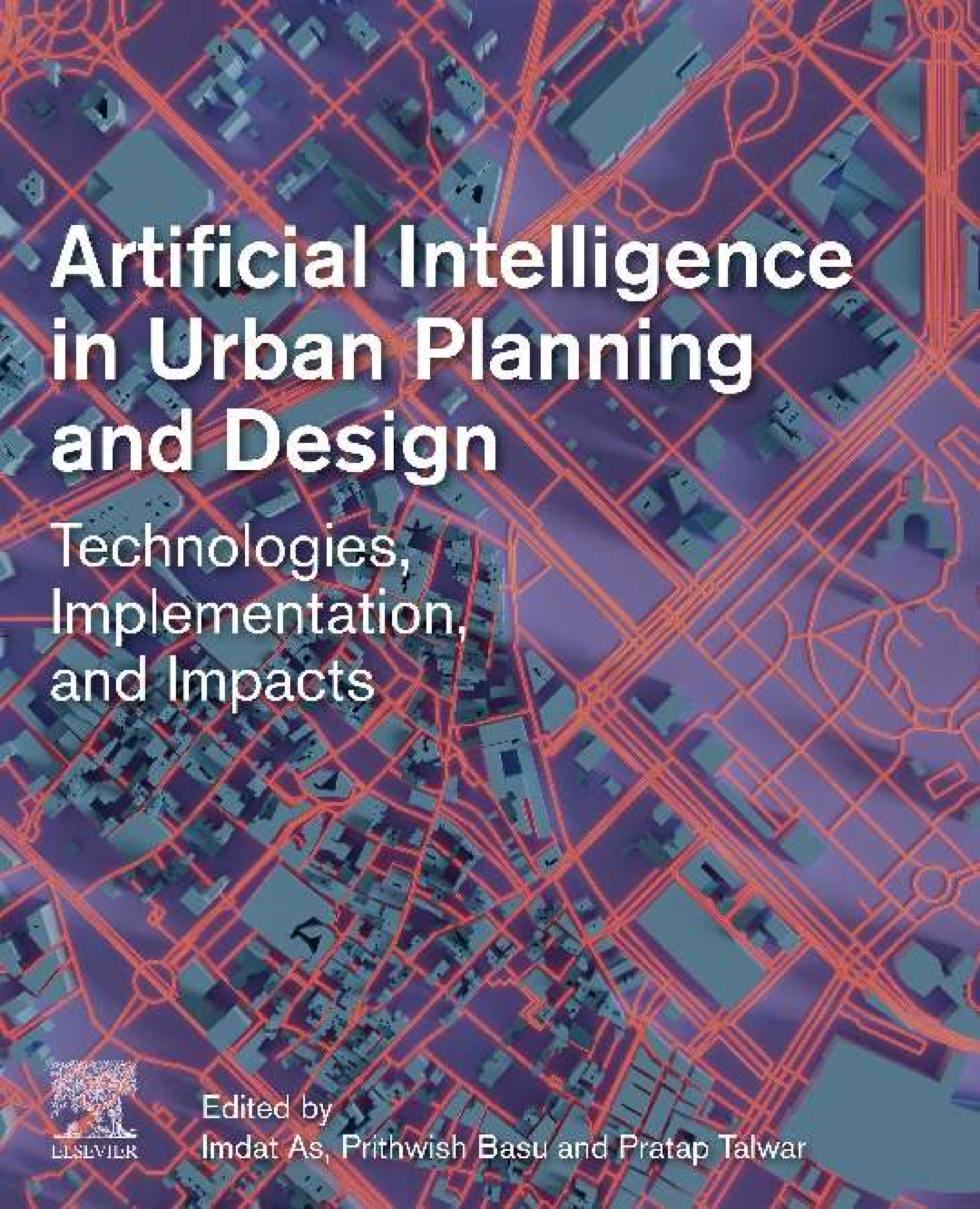


Artificial Intelligence in Urban Planning and Design

Technologies, Implementation, and Impacts

ELSEVIER

Edited by
Imdat As, Prithwish Basu and Pratap Talwar

ARTIFICIAL INTELLIGENCE IN URBAN PLANNING AND DESIGN

This page intentionally left blank

ARTIFICIAL INTELLIGENCE IN URBAN PLANNING AND DESIGN

Technologies, Implementation, and Impacts

Edited by

IMDAT AS
Faculty of Architecture, Istanbul Technical University, Istanbul, Turkey

PRITHWISH BASU
Network and Cyber Technologies, Raytheon BBN, Cambridge, MA, United States

PRATAP TALWAR
Thompson Design Group, Boston, MA, United States

ELSEVIER

Elsevier
Radarweg 29, PO Box 211, 1000 AE Amsterdam, Netherlands
The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, United Kingdom
50 Hampshire Street, 5th Floor, Cambridge, MA 02139, United States

ISBN: 978-0-12-823941-4

For information on all Elsevier publications
visit our website at https://www.elsevier.com/books-and-journals

Publisher: Joseph P. Hayton
Acquisitions Editor: Kathryn Eryilmaz
Editorial Project Manager: Sara Valentino
Production Project Manager: Maria Bernard
Cover Designer: Mark Rogers

Typeset by STRAIVE, India

Contents

5. Urban form analysis through morphometry and machine learning

Jinmo Rhee

6. AI-driven BIM on the cloud

Wanyu He, Jackie Yong Leong Shong, and Chuyu Wang

3
AI in urban scale research

7. Deep learning in urban analysis for health

David William Newton

8. Spatial design of energy self-sufficient communities

Mina Rahimian, Lisa Iulo, and Jose Pinto Duarte

9. The image of the city through the eyes of machine reasoning

Elcin Sari, Cengiz Erbas, and Imdat As

10. Optimizing urban grid layouts using proximity metrics

Fernando Lima, Nathan C. Brown, and Jose Pinto Duarte

4
Case studies in urban design and planning

11. Image analytics for urban planning: The case of the Barcelona Superblock

Aldo Sollazzo

12. Complexity science-based spatial performance analyses of UNStudio/DP Architects' SUTD Campus and WOHA's Kampung Admiralty

Anjanaa Devi Sinthalapadi Srikanth, Benny Chin Wei Chien, Roland Bouffanais, and Thomas Schroepfer

13. Understanding urban leisure walking behavior: Correlations between neighborhood features and fitness tracking data

Özgün Balaban

14. Spacemaker.Ai: Using AI in developing urban block variations

Jeffrey Landes

15. Möbius evolver: Competitive exploration of urban massing strategies

Patrick Janssen, Tung Do Phuong Bui, and Likai Wang

16. Adaptive master plans: Flexible modular design strategies

Martin Bielik, Reinhard Koenig, and Sven Schneider

17. SASAKI: Filling the design gap—Urban impressions with AI

Thiyagarajan Adi Raman, Justin Kollar, and Scott Penman

18. KPF: A retrospective view on urban planning AI for 2020

Snoweria Zhang, Kate Ringo, Richard Chou, Brandon Pachuca, Eric Pietraszkiewicz, and Luc Wilson

This page intentionally left blank

Contributors

Imdat As TUBITAK International Fellow, Istanbul Technical University, Istanbul, Turkey

Özgün Balaban Chair of Design Informatics, Faculty of Architecture and the Built Environment, Delft University of Technology, Delft, The Netherlands

Martin Bielik Bauhaus-University Weimar, Chair of Computer Science in Architecture and Spatial Planning, Weimar, Germany

Roland Bouffanais University of Ottawa, Ottawa, ON, Canada

Nathan C. Brown Department of Architectural Engineering, College of Engineering, The Pennsylvania State University, University Park, PA, United States

Tung Do Phuong Bui Department of Architecture, National University of Singapore, Singapore

Mark Burry Swinburne University of Technology, Melbourne, VIC, Australia

Benny Chin Wei Chien Singapore University of Technology and Design, Singapore, Singapore

Richard Chou Kohn Pedersen Fox (KPF), New York, NY, United States

Jose Pinto Duarte Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, Department of Architectural Engineering, School of Engineering Design, Technology and Professional Programs, College of Engineering, The Pennsylvania State University, University Park, PA, United States

Cengiz Erbas TUBITAK International Fellow, Hacettepe University, Ankara, Turkey

Wanyu He Florida International University, The College of Communication, Architecture + The Arts, Miami, FL, United States; Shenzhen Xkool Technology Co., Ltd., Shenzhen, China

Lisa Iulo Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, Department of Architectural Engineering, School of Engineering Design, Technology and Professional Programs, College of Engineering, The Pennsylvania State University, University Park, PA, United States

Patrick Janssen Department of Architecture, National University of Singapore, Singapore

Geoff Kimm Swinburne University of Technology, Research Fellow, Smart Cities Research Institute, Melbourne, VIC, Australia

Reinhard Koenig AIT Austrian Institute of Technology, Digital and Resilient Cities, Vienna, Austria; Bauhaus-University Weimar, Professorship for Computational Architecture, Weimar, Germany

Justin Kollar Department of Urban Studies and Planning, Massachusetts Institute of Technology, MA, United States

Jeffrey Landes Autodesk Spacemaker.ai, Cambridge, MA, United States

Neil Leach Florida International University, Miami, FL, United States; Tongji University, Shanghai, China; The European Graduate School, Visp, Switzerland

Fernando Lima Department of Architecture, Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, The Pennsylvania State University, University Park, PA, United States

David William Newton College of Architecture, University of Nebraska-Lincoln, Lincoln, NE, United States

Brandon Pachuca Kohn Pedersen Fox (KPF), New York, NY, United States

Scott Penman Sasaki, Boston, MA, United States

Eric Pietraszkiewicz Kohn Pedersen Fox (KPF), New York, NY, United States

Mina Rahimian Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, Department of Architectural Engineering, School of Engineering Design, Technology and Professional Programs, College of Engineering, The Pennsylvania State University, University Park, PA, United States

Thiyagarajan Adi Raman Sasaki, Boston, MA, United States

Jinmo Rhee Carnegie Mellon University, Codelab, School of Architecture, Pittsburgh, PA, United States

Kate Ringo Kohn Pedersen Fox (KPF), New York, NY, United States

Elcin Sari Middle East Technical University, Department of City and Regional Planning, Ankara, Turkey

Sven Schneider Bauhaus-University Weimar, Chair of Computer Science in Architecture and Spatial Planning, Weimar, Germany

Thomas Schroepfer Singapore University of Technology and Design, Singapore, Singapore

Jackie Yong Leong Shong Florida International University, The College of Communication, Architecture + The Arts, Miami, FL, United States; Shenzhen Xkool Technology Co., Ltd., Shenzhen, China

Aldo Sollazzo IAAC, Barcelona, Spain; Noumena, Barcelona, Spain

Anjanaa Devi Sinthalapadi Srikanth Singapore University of Technology and Design, Singapore, Singapore

Chuyu Wang Shenzhen Xkool Technology Co., Ltd., Shenzhen, China

Likai Wang Department of Architecture, National University of Singapore, Singapore

Luc Wilson Kohn Pedersen Fox (KPF), New York, NY, United States

Snoweria Zhang Kohn Pedersen Fox (KPF), New York, NY, United States

Preface

Urban planning and design is a complex field of study that combines a wide variety of disciplines. City planners, urban designers, architects, and landscape architects work together to solve demanding urban issues. They have to study the city at a range of scales from zoning laws to transportation and infrastructure networks, to buildings, street furniture, and lighting. The range of man-made urban intervention can be clustered into three main layers: firstly, houses, shops, factories, etc., secondly, overground infrastructure, e.g., road networks, railways, light polls, etc., and finally, underground technical infrastructure, e.g., sewage, waterworks, heat, gas, electricity, etc. Engineers contribute to developing and maintaining this complex grid of urban construction and infrastructure. Besides the actors who work with the physical tissue of the city, others study intangible forces. Economists, scientists, operations researchers, and sociologists study the organization, growth, and decline of cities—the flow of goods and services, aspects of market forces—and the effects of the urban environment such as climate change on human behavior—evolving social values, human interactions, and the exodus and migration of individuals and groups.

Thus, the field of urban design and planning relies traditionally heavily on large amounts of data. Planners use spreadsheets to come up with spatial analysis, evaluate projections, assumptions, and make estimates and predictions. In the latter half of the 20th century, geographic information systems (GIS) tools were introduced to the field that could integrate geographic information with layers of data, and translate them into tables, graphs, and maps—in order to make it easier to gather, manage, and analyze them. In parallel, groundbreaking developments in artificial intelligence (AI) revolutionized many fields of data-driven research in computer science applications. The familiarity of utilizing urban data to develop urban design and planning solutions naturally lent itself to the introduction of AI to the field.

Over the last decades, the field of AI went through three waves of development, transitioning from symbolic or rule-based AI, e.g., expert systems, genetic algorithms, swarm intelligence, etc., to statistical reasoning, e.g., support vector machines, Bayesian reasoning, and artificial neural networks, to a hybrid of both approaches, e.g., robotics. AI research broadly consists of supervised and unsupervised learning, generative algorithms, and reinforcement learning. Supervised learning approaches train on labeled data and perform classification and prediction tasks, whereas unsupervised learning trains on unlabeled data and detects significant patterns. On the other hand, generative algorithms train or transform a generative model to create unprecedented samples. And finally, reinforcement learning interacts with stochastic environments to gather training data and learns a model that makes utility-optimizing decisions.

In the last decade, AI captured the public imagination thanks to developments in deep learning—a branch of AI that uses artificial neural networks that loosely mimic the inner workings of the human brain. A deep neural network (DNN) consists of layers of artificial neurons that are stacked on top of each other. When a DNN is trained with enough data samples, it can discover internal representations of objects, e.g., the system can be trained with cat images and can identify cats in new images that it has not seen before. Deep learning systems discover latent patterns and relationships in big data that are often not apparent to humans. They are being used in a variety of everyday applications, from image, voice, and video recognition systems, to self-driving cars, language translation, and online recommendation systems.

In this book, we explore the promising use of AI as it relates to urban planning and design, illustrate various technologies that have come to fruition, showcase their implementation opportunities and challenges, and discuss their impact on our built environment. Organized into four parts: real-world projects, this book provides a broad overview: (1) theoretical and historical background, (2) AI-based tools, methods, and technologies, (3) AI in urban planning and design research, and (4) case studies of AI used in real-world projects. It contains 18 illustrated contributions examining AI-based urban planning and design work from around the world, including the United States, Europe, and Asia.

Content

In Part 1 of the book, we situate AI within the overall context of urban planning and design, and discuss how AI approaches differ and relate to the traditional toolkit of urban planners and designers. In the opening chapter, Mark Burry offers a new agenda for AI-based urban planning and design. Neal Leach sews connections between the seminal moment of DeepMind's AI-AlphaGo software beating a professional human Go player, with the limits it exposes vis-a-vis human creativity in developing urban planning and design solutions. Thomas Schroepfer, lays out the fundamentals of complexity science, to form the basis to deal with the nature of complex and multiobjective problem sets in almost any urban challenge.

In Part 2, we present a survey of state-of-the-art AI-based tools, methods, and technologies. We highlight the ones that have been particularly explored in urban planning and design—with examples of where and how they have been used. Geoff Kimm gives a classification, overview, and evaluation of various novel AI tools. Jinmo Rhee offers an alternative approach to urban form analysis through morphometry and machine learning. Wanyu He et al., of XKool, a well-known Chinese start-up, demonstrates a novel tool, where building information modeling (BIM) is augmented with additional AI-based datasets on the cloud, and illustrates its use in various urban scale projects.

In Part 3, we offer an insight into the application of AI in urban scale research. David Newton correlates health-related problems, e.g., various diseases, with urban form by analyzing satellite imagery through AI. Mina Rahimian et al. use deep learning to unearth the intertwined relationship between urban form and energy demand in San Diego, California, to achieve energy self-sufficient communities. Elcin Sari et al, illustrate a novel machine reasoning (MR) tool that can discover significant urban components (ala Kevin Lynch) from various city layouts that are highly ranked in some quality-of-life indexes, and Fernando Lima et al. employed an evolutionary multiobjective optimization method driven by proximity metrics to generate novel urban grid layouts.

In Part 4, we showcase the use of AI in various capacities in real-world urban design and planning projects. We structured this part into three categories: The first set of contributors present AI as an *analysis* tool where they give novel insights into the complex problem sets of urban challenges. The second set of contributors examine AI as an *assistant* in urban design and planning processes, e.g., in optimizing various aspects of land use, orientation, climate, etc., and the last set of contributors explore AI as a *generator* that directly offers actionable idea items, e.g., to generate unprecedented urban blocks within a boundary condition in a free manner. In the first section, Aldo Solazzo uses image analytics to collect and analyze data in order to understand how people are living and using urban spaces in the renowned Barcelona Superblocks. Thomas Schropfer shows us how to use complexity science to analyze UNStudio & DP Architect's Singapore University of Technology and Design (SUTD) campus and WOHA's Kampung Admiralty Buildings; and Ozgun Balaban presents a case study where he analyzes Urban Singapore through fitness tracking. In the second section, Jeffrey Landes of Spacemaker.ai demonstrates how one can use AI to optimize 3D urban layouts for a given site in Istanbul. Patrick Janssen et al. demonstrate the Mobius Evolver that uses an evolutionary algorithm where one urban massing solution competes against another. Reinhard Koenig et al. use digital adaptive master plans (AMPs) to develop city layouts in Ethiopia and Singapore. AMPs are parametrically controlled three-dimensional urban design models that can automatically adapt to different boundary conditions and planning requirements. In the third section, Thiyagarajan Adi Raman et al. of SASAKI use generative adversarial networks (GANs) to develop novel impressionistic aerial imagery (also known as urban impressions) to "sketch out" early ideas for urban design. Finally, Snoweria Zhang et al. of Kohn, Petersen, and Fox (KPF) showcase three case studies that offer an AI-based speculative narrative framework to analyze and develop ideas in regards to conventional urban design workflows.

AI research is constantly evolving, and its applications in urban design and planning will surely mature over time. We hope that this collection of articles will offer an exciting and informative introduction to this fascinating topic to planners and designers, architects, AI researchers, and engineers involved in urban planning and design projects.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of Raytheon BBN. This book does not contain technology or technical data controlled under either the U.S. International Traffic in Arms Regulation or the U.S. Export Administration Regulations.

This page intentionally left blank

Acknowledgments

We are indebted to many people and institutions who generously gave their time, offered encouragement, and provided support. We are grateful to Istanbul Technical University and Raytheon BBN for their support during the execution of this book, which allowed us to shape our thinking about the specific topics of AI in urban planning and design. We also thank the Scientific and Technological Research Council of Turkey (TUBITAK) for supporting the formation of the City Development through Design Intelligence (CIDDI) Lab at Istanbul Technical University, which gave us physical and human resources to deal with pressing issues on the "future city." In May 2021, we organized a "Future City Summit" together with BIM4Turkey, and contributors of this book presented their work at this conference. The worldwide participation in this event exceeded our expectations. We are very grateful to all those who participated, and to all those who organized this exciting summit with us, especially Mehmet Sakin, Furkan Filiz, the cofounders of BIM4Turkey, and many of their colleagues, who worked diligently to put this event together. We also thank our publishers, Brian Romer, Sara Valentino, and Ivee Indelible at Elsevier, for their patience and attentive help in these difficult times of the pandemic, and lastly we thank Ana Batista for giving her feedback and guidance in completing this book.

This page intentionally left blank

PART 1

Theoretical foundations

This page intentionally left blank

CHAPTER

1

A new agenda for AI-based urban design and planning

Mark Burry

Swinburne University of Technology, Melbourne, VIC, Australia

Embracing AI to recalibrate the master plan

Looking down from the window seat in a circling jet at the *new world's* suburban sprawl and the *developing world's* informal developments, how confronting these traffic-engineered tracts are, bereft of any sense of joyful and inspiring urbanity. They are uncivil expressions of entirely logical or informally derived arrangements of housing, schools, shops, parks and sports fields, articulated with congested highways. They may or may not meet economic, social, planning and building codes, standards, and constraints but they provide little else—certainly not cultural enrichment. Where are the boulevards and the town squares? Where are the retirees, young lovers, parents with prams, and dog-walkers supposed to stroll? Not to mention children knocking about with a football, the neighborhood gossips, matchmakers, and buskers!

Entirely new creative avenues beckon for steering toward sustainable urban transformation, striving to boost social equity and civic amenity along the route. By placing the citizen at the helm of a team of multidisciplinary experts for codesigning responses to urban densification, we could tackle a key challenge: how will future cities and precincts be designed with people rather than for people? A worthy goal is to enable the community identify more acutely what is important to them toward establishing viable alternative pathways to accommodate inevitable change. How can we subsume the NIMBY (Not In My Back Yard) mindset with a more positive YIMBY outlook—where the "Y" of YIMBY stands for "Yes!" (Lake, 1993)? How can the various national, state, and local urban development planning, design, construction, and management sectors come together in a new kind of conversation? How might we coopt AI along with emerging and maturing information and communication technologies (ICT) to centralize the citizen voice away from *consultation* closer to *active participation*? What are the optimal social creative, economic, and technological criteria needed to

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00005-6

construct a digitalization framework for innovative approaches to planning and urban design? How might such a platform provide the people most affected by the expert's decisions the necessary agency to help formulate positive transformations to backyards: denser precincts yet greater amenity?

The master plan and, by definition, its two-dimensional physical characterization ("the plan") is another key issue: how do we coopt rapidly developing AI technologies to move from conventional planning to multidimensional master planning? A fundamental paradigm shift beckons planning and urban design professionals to engage fully with today's smarts to anticipate future urban exigencies more effectively and with greater confidence than has been possible to date. How might AI render urban sustainability challenges visible and intelligible to the communities subjected to the pressures of urban growth? Can AI tools be created to assist planning and urban design professionals in codesigning improved civic amenity for our cities and regions with the citizens? What is the evolving role for planning and urban design professionals in the new digital ecosystem of data collection, data analytics, data visualization, artificial, augmented reality (AR) and virtual reality (VR), game changers to the way we master plan, design, build, and manage our cities? Who will specify and build the urban futures digital workbench to serve as a shared research platform and collaborative design framework, capturing and cementing the public's contributions to help shape sustainable urban growth and accepting increased population density?

The future of work: AI and the disruption of planning and urban design practice

Perpetually unfinished business

As cities change, so does society, convulsing with the implementation of every technological shift as it occurs, disrupting urban design, construction, and city management systems and services in its wake (Burry, 2020). In "The Rise and Fall of American Growth" social economist Robert J Gordon notes that since the 1850s civil society has evolved from an almost universal condition of having no access to any of the facilities and modern conveniences that we take for granted today regardless of their position in society (Gordon, 2017). These include not having indoor sanitation, central heating and cooling, getting around the city other than by foot or horse, artificial lighting beyond candles and lamps, electricity to power domestic appliances, and no wider communication with the world at large other than by letter. Nevertheless, the speed of change and its ensuing complexity have been demonstrably at a pace beyond our human capability to stay a step ahead: we have become used to adapting to human-initiated change and accepting the unintended negative consequences as inevitable, through being unable to keep up with the pace.

What is so different today than a decade ago, for instance?

Always complex systems, cities have become complex adaptive systems (Karakiewicz, 2020). Rapid digitalization during the last three decades has seen a technological shift permeating almost every aspect of urban life. The digitalization of the city fabric and associated systems yields the *smart city.* The smart city combines the *Internet of Things* (IoT)—the data collecting sensors connected to electronic devices enabled by *information communication technology* (ICT) to help urban designers, construction companies, and city systems and services managers do more for the citizen with less (Mora and Deakin, 2019). The global smart city movement is predicated on ICT being the greatest sustainability change agent at the experts' disposal. But the same blossoming personal technology is also increasingly in the hands of the nonexpert urban dwellers: the "smart citizen," with access to radically different facilities to influence planning and urban design decision-making, such as Australia's *National Urban Research & Development Platform* (iHUB), an urban observatory designed to gaze deep into possible urban futures and described later in the chapter.

A perennial problem for all designers is the client being limited naturally to *what they know*, with a limited appetite to experiment on something wholly unfamiliar to them, however potentially enriching it might be. Exploiting the combination of Artificial Intelligence with games technologies, for example, could help end users ascertain their fundamental needs and responsibilities for themselves. In deference to Carl Frey and Michael Hammer, AI can be harnessed to augment extant human creative ability, and not necessarily supplant it (Hammer, 1990; Frey, 2019). Frey, however, in his 2019 book also warns of a re-emergence of the eponymous "technology trap" thus:

> One reason economic growth was stagnant for millennia is that the world was caught in a technology trap, in which labor-replacing technology was consistently and vigorously resisted for fear of its destabilizing force. Could countries in the industrial West experience a return of the technology trap in the twenty-first century? … Proposals to tax robots in order to slow down the pace of automation now feature in the public debate on both sides of the Atlantic. And unlike the situation in the days of the Industrial Revolution, workers in the developed world today have more political power than the Luddites did. In America, where Andrew Yang [2020 USA Presidential hopeful] is already tapping into growing anxiety about automation, an overwhelming majority now favor policies to restrict it. The disruptive force of technology, Yang fears, could cause another wave of Luddite uprisings: "All you need is self-driving cars to destabilize society.… [W]e're going to have a million truck drivers out of work who are 94 percent male, with an average level of education of high school or one year of college. That one innovation will be enough to create riots in the street. And we're about to do the same thing to retail workers, call center workers, fast-food workers, insurance companies, accounting firms."

Unpacking artificial intelligence for planners and urban designers

For planners and urban designers who are aware of artificial intelligence's pole position in digitally disrupting their practices but wholly unfamiliar with its components, this section peeks under the bonnet. This is a loose and informal taxonomy grouped in categories that span between "fundamental" and "little immediate relevance." It is by no means comprehensive, and naturally there will be disagreement around both my plain English definitions and assessment of relative utility. The intention is not to provide a textbook approach here; the 26 AI components described below, some of which are only subtly different from each other, together lay out the field and the potential for AI to enhance planning and urban design practice very significantly—if not prevented from doing so by the Neo-Luddites Frey warns us of (Fig. 1.1).

In terms of the *future of work*, it seems that we are at a crossroads where those practitioners disinclined to take up the opportunities AI offers them could be left in the slow lane, as Thomas Siebel alerts us to:

> The coming two decades will bring more information technology innovation than that of the past half century. The intersection of artificial intelligence and the internet of things changes everything. This represents an entire replacement market for all enterprise application and consumer software. New business models will

FIG. 1.1 126 components of artificial intelligence that currently impact planning and urban design practice. They are ranked between "fundamental" (identified in red, *gray in print version*) clockwise to "currently least relevant" (identified in pale gray). *No Permission Required.*

> emerge. Products and services unimaginable today will be ubiquitous. New opportunities will abound. But the great majority of corporations and institutions that fail to seize this moment will become footnotes in history. (*Siebel, 2019*)

In the fast lane—fast because at the very least AI affords more speed and efficiency—will be practitioners skilled in making AI components work for them and, regrettably, newly minted subprofessionals enfranchised through AI to offer new and manifestly valuable services such as urban analytics, applications of smart technology, and visualization. The danger comes from the elevation of an individual with splinter skills gifted, say, in computer graphics but inexperienced in assaying the significance of what they are showing and how it is being presented—the talented ignoramus. The brief discussion on AI and expertise at the conclusion of this chapter will consider this outlook a little more fully.

Fundamental AI components for disrupting planning and urban design practice

1. Machine learning (ML) uses artificial intelligence to enable systems to self-learn, adapt, and improve from experience without having been explicitly programmed through prior experience. Computer programs with ML access data and sift through it in order to learn from the insights that emerge in the process. Raw data, observation, direct experience, or instruction initiates the learning process enabling patterns to emerge from the data, thereby facilitating more effective decision-making. ML facilitates computers' automatic learning without human input enabling vast pools of data to be processed with far greater speed and precision.

Classic ML algorithms considered text as a sequence of keywords migrating to semantic analysis mimicking human ability to comprehend the text's meaning.

Planners and urban designers disposed to producing design software ML could track the designers' decisions and begin to automate routine decisions. Software produced for clients could be enabled to innately track their choices and learn from them, guiding the client toward an improved understanding of what is at stake.

2. Neural Networks (NNs) are predicated on machine learning and are at the core of deep learning algorithms (see Section 3 below). Their name is derived from the structure of the human brain, in the sense of matching the concept derived from our understanding of the way the brain's neurons intercommunicate. Artificial neural networks (ANNs) consist of node layers, one or more layers below, and an output layer. Each node is conceived as an artificial neuron connecting to a neighbor with an associated weight and threshold. Only when a node has an output that exceeds a given threshold value will it activate and transmit data to the next network layer or else it simply remains inactive and does not transmit.

Generative adversarial networks (GANs) are a class of machine learning in which two competing Neural Networks—one the generator and the other the discriminator are pitted against each other in a cooperative zero-sum game: one side's gain is the other's loss, from which to learn. Effectively, GANs create their own training data sets. The generator's role is to artificially produce outputs that could be mistaken for real data. The discriminator's goal is to identify which of the outputs it receives have been created artificially. The GAN learns to generate new data with the same statistics as the training set. Training a GAN using a range of photographs, for example, new photographs can be generated that look at least superficially authentic to the human eye having absorbed many key characteristics extracted from the training set.

Neural networks are used extensively to problem solve and seek options. Their extended use offers designers and planners unprecedented opportunities to mine data for the purposes of attaining deeper insights and situational awareness as inputs to decision-making and design. For those seeking to augment human creative skillsets with AI GANs offer a treasure-trove of possibilities. A set of images from a renowned architect, for instance will lead to creative but dissimilating apparently authentic outcomes.

3. Deep learning is a subset of machine learning being a neural network with at least three layers. Neural networks are designed to mimic but not imitate the human brain in terms of learning from the big data sources it trawls through. A single neural network can significantly zero in on and make predictions, while the additional sublayers can assist with optimization, refinement, and ultimately accuracy.

Deep learning is fundamental to any artificial intelligence application aimed at improving automation and autonomous analytical or practical tasks independent of direct human involvement. The technology supporting deep learning can be found today in familiar products and services including digital assistants and chatbots, financial fraud detection, voice-controlled personal assistants such as Apple's Siri and Amazon's Alexis, and driverless vehicles.

With Machine learning embedded into design software as well as software intended to help the client produce a better-informed brief by drawing out the client's less obvious priorities, deep learning offers rich dividends.

4. Autonomous systems can change their behavior during operation in response to unanticipated inputs. Inbuilt "intelligence" lies at the core of such systems. Their integration enables the system to perceive, process, recall, learn, and decide on appropriate courses of action autonomously. Examples include computation that can improve human performance at games such as Chess and Go, facilitating drones and robots to adapt their flight paths and tasks according to information received while in action, self-driving vehicles, and advanced manufacturing.

For the urban designer and planner, the opportunities are not immediately obvious. Design software could begin to learn from the designer's decisions and make suggestions. Software for clients could track their predilections and, working in conjunction with the designer's inbuilt constraints, be guided toward their optimal option.

5. Pattern recognition comes from computer algorithms using machine learning to detect patterns otherwise invisible within data sets. In representing patterns as knowledge or statistical information, the data can be classified.

Pattern recognition systems are trained using labeled training data. Looking for *unknown knowns* is achieved from labels attached to specific input values leading to a pattern-based output. Without labeled data being available, *unknown unknowns* are sought and more sophisticated computer algorithms are deployed, thereby taking the art beyond that which is practically possible using the human brain unaided.

A Holy Grail for designers and planners is accessing the unknown unknowns that potentially lead to different sets of decisions and ultimately outcomes than would be made based on traditional data analysis. Pattern Recognition has the potential to reveal these unknowns, but designers nevertheless require new skills to see value in territory unfamiliar to them.

6. Simulation modeling enables research that requires a virtual environment to simulate physical systems in operation from which useful insights can be drawn. Simulation Modeling typically looks at systems in operation such as population dynamics, airports, cargo fleets, and traffic systems.

Simulation modeling is a prototyping environment where changes to a system can be safely tested and assessed, ideal for multicriteria inputs, decision support, and risk mitigation.

The three principal frameworks to simulation modeling are discrete event simulation (DES), system dynamics (SD), and agent-based modeling (ABM).

Simulation modeling is fundamental and in pride of place for both urban designers and planners when enhanced by various categories of AI. Along with AR and VR leaps in functionality, the opportunities to simulate and test future scenarios are an extraordinary asset. At the time of the writing, "digital twins" are center stage; the more they can be enriched through AI, the greater capability we will have to be more accurate in predicting the future, and planning and designing a better one. AI-enhanced simulation will help planners and urban designers anticipate and avoid what might have been unanticipated consequences from poor decision-making.

7. Social network analysis unpacks the behavior of individuals at the microlevel, the network structure from the pattern of relationships at the macrolevel, and how the two interact. Social networks both form and constrain opportunities for individual choice while individuals can simultaneously initiate, build, sustain, and dismantle relationships determining the network's global structure along the way.

The instrumental value of the relationships under investigation determines which network structures and positions generate robust opportunities or, conversely, sturdy constraints.

Social relationships create social capital as an opportunity structure. Many measures for characterizing and comparing network structures and positions within networks can be derived through social network analysis.

When social network analysis is directly harnessed by the planners and urban designers as part of their digital workbench, professional practice will fundamentally change in response. Notably, the social capital behind planning and design decisions will have a far higher level of participation and therefore a more influential role.

8. The Internet of things (IoT) describes a network of connectable devices including computers, sensors, digital and mechanical, and ICT-enabled objects. With attached unique identifiers (UIDs), animals and people can be part of the network capable of data transfer over an electronic network independent from direct human-to-human or human-to-computer communication.

Any IoT network can be conceived of as an ecosystem of Internet-enabled smart devices with embedded systems which incorporate processors, sensors, and communication hardware. The network can collect data from their environments, process it, and transmit it back to an IoT gateway either analyzed locally or sent to the cloud to be analyzed remotely. IoT devices can communicate with each other and act accordingly on the information they receive and process, mostly without the intervention of humans beyond setting them up and providing them with instructions and accessing the data.

While planners and urban designers are not directly involved with IoT, the impact it has had already in the smart city—even at the trivial level of smart car parking—will increasingly influence the way our cities operate. As censors proliferate and vast data sets become ever vaster, the professions will have a far deeper insight into how cities operate instrumentally, and how humans work, recreate, and dwell. Accessing the data and drawing fresh insights from it will increasingly need to involve the planner and designer directly lest others more agile to change step in (and on) their shoes.

9. Image analytics, also known as *computer vision* or *image recognition*, can pull information automatically from a single or a vast collection of images. AI is incorporated as algorithms that can automatically extract specified or unspecified data from an image or set of images and process it.

Logical analysis is the core to image analytics facilitating the interpretation of information from nontextual material including diagrams and graphics and is not limited to photographs.

Significant time will be saved as planners and urban designers embrace image analytics. It is not simply a matter of avoiding tedious work; just as dermatologists now have more success in spotting skin cancers through AI and image recognition, so too will urban professionals be able to spot otherwise imperceptable differences. Image recognition applied to satellite images from different time periods will spot changes and provide measurements more accurately and in less time than humans are capable of, even with an abundance of time that they simply do not have.

10. Graph analytics is applied to structured, unstructured, numeric, or visual data to derive decision influencing insights. It is a relatively new application of AI and is used to analyze graph-based data akin to Social Network Analysis since it is an analysis based on entities or graph nodes. These can be products, devices, operations, or end users, for example.

Graph analytics is being deployed globally by enterprises requiring assistance in gaining impactful insights in highly networked situations, including for the detection of fraud, marketing, real-time supply chain management, and the optimization of search engines.

Graph analysis enhanced through AI offers planners and urban designers ways of understanding data, interpreting it, and communicating it meaningfully to nonexperts. The future professional will need to be on top of developments in the field lest the accounting firms step in.

11. Visualization refers to representing data graphically in ways that facilitate interacting with these representations to gain insights that are otherwise not easy to see, if at all without the intervention of AI. From the outset, computer graphics have provided a powerful mechanism for creating, manipulating, and interacting with data representation. Data visualization through graphs and tables has been part of human analytical endeavor well before the arrival of the computer. Their prior existence attests to the human need to represent data graphically to identify trends, for example, just as computer-aided AI-assisted visualization points to the opportunities we have for deep-diving into data not available predigitalization.

Visualization of data is a fundamental requirement for planners and urban designers. As AI computation becomes faster and more sophisticated, the opportunities to understand and persuade through 4D visualization will continue to grow.

AI components deemed to be very useful

12. Real-time emotion analytics or emotion AI and opinion mining involves the analysis of human sentiment. Essentially, real-time emotion analytics examines different human brain states using natural language processing, computational linguistics, data (text) mining, and biometric analysis.

At its core, a sentiment analysis program separates inputs including text, speech, and facial expression into categories. Positivity, negativity, and neutrality are determined as primary sentiments leading to deeper analysis of emotions including enjoyment, happiness, disgust, anger, fear, disbelief, and surprise. One precursor to the analysis is quantifying input data using algorithms to read and process it. The second is psychological research to aid identification of which expression equates to which emotion.

As an adjunct to chatbot capability, planners and urban designers can dive even deeper toward understanding clients and end users' requirements using *real-time emotion analytics*. Sentiment analysis of written material will reveal particularities with greater facility, and aural exchanges between client groups and experts can be guided more meaningfully by using AI to pick up collective nuances that might otherwise be hidden from view.

13. Natural language processing (NLP) is the ability of machines to read, comprehend, and derive meaning from human languages as a branch of AI. The disciplines of data science and linguistics come together with a scalability deployable in many industries.

As computers grow faster and more powerful, NLP has progressed in leaps and bounds. With ever-increasing precision, practitioners across a broad range of disciplines are benefiting, including health, media, finance, human resources, and security industries.

With AR and VR technologies continuing to evolve rapidly, new types of conversation are possible between the client, planner, and designer when speculating on possibilities. NLP facilitates unexpected meaning being drawn from an AI-assisted *reading between the lines*.

AI components deemed to be potentially useful

14. Chatbots are digital agents that can responsively interact with human "chat" with ever greater sophistication, as the AI support becomes more powerful. Typically, a chatbot takes the role of a human respondent in a call center in both business-to-consumer (B2C) and business-to-business (B2B) contexts. Initially handling simple information requests to direct the caller to the person best placed to handle a more complex enquiry, chatbots are rapidly improving their performance. They afford companies opportunities to handle more enquiries during peak hours, as well as being able to extend 24/7 customer service at a relatively low cost.

Chatbots can be "stateless" or "stateful." A stateless chatbot handles each interaction as a fresh conversation, whereas a stateful chatbot can reengage with earlier interactions and build on them accordingly.

Chatbots will develop to the extent that client groups will be able to be consulted more readily and in greater numbers than through the current reliance on workshops, town halls, roundtables, and questionnaires. Operating on a 1:1 basis, chatbots will be neutral note takers as they deep-dive into each client representative and end user's unique set of experiences and desires.

15. Neuromorphic computing imitates the physiology of the human brain and central nervous system through creating "spiking neural networks." A cascading chain of spikes is created as each neuron activates its neighbor in sequence. As a process, it mimics the capacity of the brain and uses biological neurons to send and receive signals to sense the body's feelings and movement. When compared with conventional methods in which computation within systems is affected as binary expressions of yes/no or 0/1, neuromorphic computation has greater flexibility. Spiking neurons do not function in any particular sequence.

In mimicking the brain, neuromorphic computing has the potential for more creative approaches to processing unfamiliar objects or people without prior knowledge before taking autonomous action.

For designers curious to find routes for AI to augment their creative processes or planners wanting to home in on and speculate on unanticipated outcomes, neuromorphic computing is an alternative to following set pathways.

16. Thought-controlled gaming deploys neuro-technology and brain-computer interfaces (BCIs) to connect the human mind to devices. Their complexity and delicacy have led to neural implants and bionic prosthetics in medicine. In the entertainment industry, similar capability is possible through noninvasive electroencephalography (EEG) devices using sensors touching the scalp. These have sufficient sensitivity to measure fluctuations of voltage from the brain's neurons as they activate.

Once the user's brain waves have been detected and calibrated, the BCI can distinguish between their normal state through frequency and location and predetermined action. Coded software is programmed to link specific thoughts with intended movement. With the user focusing on moving forward, for instance, the program affects an advance, a turn to the right or left similarly executed by the program. As the technology develops, wheelchairs, vehicles, and robots are enabled with thought-controlled telepresence en route to entirely new suites of computer-based gaming.

As gaming begins to inculcate client-designer briefing processes, it is remotely possible, however, that thought-controlled gaming might enrich simulations and *what-if?* scenario testing.

17. Real-time universal translation (RTT)uses AI to translate instantly between two languages—in real time. At its most basic, RTT will reveal the salient facts, leaving the user the task of making sense of the communication enhanced by an awareness of context. With increasing sophistication, fluency is improving to levels where complete sense is made in translation, if not the nuances associated with elegant writing style. For call centers and service desks, RTT increasingly offers a fluency between hundreds of the world's languages meaning that companies and organizations can connect with distant consumers, partners, and employees that hitherto could not be communicated with affordably.

Future exchanges between the many experts from diverse disciplines involved in planning and urban design—with their professional peculiarities, might be enriched if real-time universal translation can evolve to read and translate nuance that might otherwise escape attention. Similarly, the client's voice along with the end user would be given added value by the same means.

18. Audio analytics is akin to speech recognition and real-time emotion analytics when AI is coopted to analyze and comprehend audio signals such as speech, extraneous sounds, birdsong, for example

There are already a wide variety of applications in a variety of contexts including business, health care, and smart cities. The practical purpose of Audio Analytics includes end uses such as the analysis of customer satisfaction from customer support calls, media content analysis and retrieval, diagnostic aids in the health sector, patient monitoring, assistive technologies for people with a range of disabilities including hearing, audio analysis for public safety (antisocial behavior, for example) and wildlife identification.

Research allied to real-time emotion analytics is proceeding in several directions. Firstly, extracting nonverbal cues from human speech. This refers to analyzing a human voice to extract information such as speaker identification and verification, age, gender, and emotional state. Secondly, *audio understanding* aims to extract insights such as detecting audio events, recognizing audio backgrounds, and detecting audio anomalies. Thirdly, audio search mechanisms are essential for sifting through large amounts of raw audio data and metadata in order to provide descriptions and annotations of the data, querying and indexing, and ranking for retrieval.

Audio analytics will help planning and urban design professionals with subtle sentiment analysis leading to greater value extraction from verbal exchanges with clients and end users alike.

AI components deemed to be currently least relevant

19. Cognitive security refers to systems that use data mining, machine learning, natural language processing and human-computer interaction to self-learn much in the way the human brain operates. Founded on security intelligence leveraging big data analytics, cognitive security is provided by technology with comprehension, reasoning, and learning capability. In this way, the reactivity of the first generation of such systems will be supplanted by cognitive security responding proactively to detect and respond appropriately to anomalies or cyberattacks.

The most challenging security problems require human decision-making to distinguish between a false alarm and a genuine need to defend. This requires constant monitoring or expanding sets of data in real time to ensure preemptive action.

Cognitive security has little immediate relevance for planners and urban designers other than spotting errors such as code compliance. It might have the potential of assisting in avoiding traps in situations where not all traps can be defined and registered. Mistakes are routinely made through human error, and if the security aspect of cognitive cybersecurity is reconceptualized as "pitfalls," such mistakes could be substantially avoided by being picked up along the way.

20. Robotic personal assistants are automatons with varying levels of capability mimicking human movement and activity. They are ideal machinic proxies for tasks that humans prefer not to do or repetitive tasks that robots can perform with greater precision and speed, without fatigue. Typically, they are deployed to perform dirty, tedious, boring, or dangerous tasks such as household cleaning, grounds maintenance, drain inspections, and the like. With increasing sophistication and capability, their deployment is extending toward assistance with aged care, disability, and other repetitive aspects of health care. At the time of the writing, robotic humanoids can perform movements such as dancing with similar speed and agility as a human being.

Other than being aware of the rapid evolution of robotic personal assistants and the effect they will play in the design of public buildings such as hospitals, there is little obvious relevance to planners and urban designers.

21. Autonomous surgical robotics are increasingly performing operating tasks acting autonomously with partial human involvement, and in some cases, none at all. Including robots in surgery brings several advantages. Firstly, they can operate with increasing micromillimeter level precision. Secondly, they can react in real time to bio-signals during procedures. Thirdly, a combination of image recognition and other sensing capabilities offers a valuable level of computer-aided assistance.

As matters stand, while Autonomous Surgical Robotics takes some of the routine tasks from humans, the assistance provided releases humans to work more exclusively on tasks for which human skills remain paramount.

Autonomous surgical robotics is in the same class as autonomous robotic personal assistants and offers little relevance to planners and urban designers.

22. Next gen cloud robotics combines cloud computing and cloud storage with robotics, the internet and IoT technologies drawing from the benefits of the converging infrastructure and shared services. Data repositories with increasingly powerful computation, storage, and communications facilities dramatically improve robotic capability. The resulting increased autonomy reduces maintenance and overheads, as well as reliance on updates and middleware.

Increasing data transfer rates and cloud robotics means that robots can offload the tasks that do not need onboard real-time processing. This lowers onboard power consumption and costs, potentially improving operational efficiency and efficacy, speeding up operations and mobility.

Next gen cloud robotics is relevant to planners and urban designers only as much as being aware of the implications these will have on the design and construction of the future smart city. Once robots can autonomously tackle the unique one-off situation and conditions for the typical building site, we will see a profound shift in building procurement. The role of the urban designer and planner will adapt in response to a likely shift in urban economics.

23. Virtual companions offer a kinder or at least a more familiar collaborative interface between humans and IT, making the services provided appear more personalized and friendly. Well-known examples of Virtual Companions include Amazon's Alexa and Apple's Siri. Virtual Companions can be more than a speaking voice and can be embedded within artifacts such as a robotic concierge, or drones that can perform as eyes in the sky.

At its simplest, a Virtual Companion is in constant aural attendance and activates on voice command, listens, translates instructions into outcomes consistent with the service's capabilities. Given their growing sophistication in terms of AI, it is clear that friendlier interfaces between humans and machines are developing rapidly, ranging from smartphone to intelligent speaker and robot humanoids.

Perhaps the professional tools of both planners and urban designers will be enhanced by expert virtual companions accompanying them as their projects evolve.

24. Machine translation automates translation from text input in one language into a text output in another. In contrast to real-time universal translation, machine translation works with text files, whereas real-time universal translation can work with the directly spoken word and audio files.

Machine translation can work rapidly through large volumes of text well beyond the speeds of traditional translation techniques unaided by human input.

There is some potential for machine translation to help planners and urban designers interpret textual material. If we take the particularities and unique nuance within different professions as dialects if not languages, machine translation may help with interpretation across the team.

25. Soft robotics contrasts with rigid-body robots by deploying materials with mechanical and tactile properties akin to living tissue in their construction. Their design and manufacture is innovative to the extent that they do not follow the artificial assembly in serial or parallel arrangements using elementary blocks, as in the case for rigid-body robots.

There are situations in which interfacing with humans in intimate situations such as aged care, for example, where soft robotics will be less unsympathetic and confronting, leading to a growing interest in the new possibilities they offer. Their ongoing development is contingent on the developments in advanced manufacturing.

Again, AI-enhanced robotics at any level is generally remote to planners and urban designers' immediate purview and sets of priorities. They no doubt need to be aware of the likely changes to society that will result from their increasing adoption beyond the factory to the office, public facilities, and home.

26. Virtual personal assistants are similar to virtual companions in the way that they relate to humans as close to being another human being as possible. Virtual assistants (VAs) perform certain tasks that were previously only undertaken by humans enabled by semantic and deep learning including deep neural networks (DNNs), natural language processing, or prediction models. They learn from recommendations and personalization to provide humans with assistance or automate tasks for them. VAs listen to and observe behaviors and construct relevant data models and their maintenance. Once suitably set up to self-learn, they can predict and recommend actions. They can be deployed in a variety of situations including virtual personal assistants, virtual customer assistants, and virtual employee HR assistants.

Virtual personal assistants enhanced with deep learning have the potential to aid professional planners and urban designers significantly in accessing both fundamental and new knowledge.

AI enhancing traditional planning and urban design services workflow

Fig. 1.2 is a diagrammatic speculation showing how a selected number of the 26 AI components outlined above could fundamentally reshape traditional planning and urban design services workflow. It is intended to act more as a provocation than serving as an attempt to proselytize any particular preferred workflow or predict the future in any way. Coopting AI in this way augments human intelligence (HI) to "arbitrage" between both types of intelligence: human and artificial (Kimm and Burry, 2021).

The left-hand column depicts a simplified traditional workflow for urban designers working in conjunction with planners. It presumes that the client approaches the expert team with a brief which is translated to a sketch design for the client's consideration. The sketch design evolves into a developed design which, once approved by the client, is documented for legal and construction purposes. On project completion, the client assumes responsibility for the ongoing management and maintenance of the project.

Famously, architects and urban designers have been reluctant to migrate from traditional modes of working to the digital. Initially, CAD tools merely mimicked the drafting equipment

FIG. 1.2 Radically reshaping traditional planning and urban design services workflow by coopting AI. *No Permission Required.*

they replaced rather than offering paradigm-shifting software, in contrast to the way that engineers were gifted parametric design. Working with data and generative design tools have been resisted by the urban design, landscape, and architectural professions, consequently reflected in education programs that remain influenced more by a historical view of how the professions have traditionally operated; they have not been enthusiastically predicated on new ways of working enhanced by emerging digital technologies, not least AI. How many schools of planning and urban design require computer science pre- or corequisites? How many computer science graduates emerge with creative skills in the sense of synthesizing more than one viable option in response to a brief (as opposed to zeroing in on the optimal solution)? The workflow in Fig. 1.2 presumes that the design and planning team members have either acquired AI skills or know how to work with farsighted computer scientists who have the collaborative fortitude to work with creatives.

In this hypothetical model of a fully digitized planning and urban design services workflow, the role of the creative team is to build the tools that help the client build themselves a better brief, not least with the capability to include representatives of the end user community as part of their process. Using custom-adapted apps, they codesign a planning and urban design strategy. A games approach might be used, for example, deploying a variety of the 26 AI components listed above at the back end with a familiar games technology serving as the front end. Using a combination of deep learning, neural networks, social network analysis, and image analytics, the game could take all participants on a deep-dive journey into the unknown. Instead of town hall style meetings and questionnaires, end users could use play to drill down to a hidden core of what really matters to them. Given the variety of opinions and needs that the players will individually hold, the game could automatically adapt to each of them learning from their responses, becoming more attuned to their no doubt wide ranging sets of desires and priorities as they emerge along the way.

Working with these evolving deep levels of insights, the planning and urban design team builds a *digital workbench optimizer* for the client to define and fine-tune the project, based on their original aspirational brief. Chatbots, real-time universal translation, audio analytics, machine translation, and virtual personal assistance add an AI dimension to capturing notes and nuances extracted from the mixed bag of codesign workshop and roundtable participants, which will include commissioning client representatives, local government officials, planning and urban design experts and their consultants, and community participants. Whatever is captured at meetings will be added to the pools of relevant data collected via IoT and pulled from historical data. Implied preferences will be discovered, evaluated, filtered, and deployed to help the project firm up as one that best meets the needs of all.

Project description will use AI to build *digital twins* with an inbuilt design intelligence capable of uncovering relatively mundane issues such as faulty code compliance as well as more sophisticated and subtle considerations including logical inconsistencies and the Pareto optimization of conflicting parameters. Trade-offs can be weighed up and broader economic, social, and aesthetic deliberations assessed by a combination of AI and HI.

The clients and end users thus develop their own project with the urban design team providing a creative overlay ensuring that a human dimension drives the digital workbench optimizer, not a machine. The emerging digital twin will serve the life of the project long after construction is completed and the buildings occupied. The digital twin will also capture all the relevant building information (BIM) and precinct information (PIM) as its virtual construction evolves. Rather than being restricted to a passive encapsulation of information, the digital twin will have AI embedded in all its functions as a living and responsive representation of the project as it develops, and as a simulacrum of real-life conditions once occupied including decay, repair, rejuvenation, and obsolescence as time goes on.

Construction continues to respond to the opportunities of automated processes at a slow pace with the bespoke nature of architectural projects and uncertain site conditions blamed for relatively little gains in productivity during the last 30 years compared with general manufacturing (McKinsey, 2017). Offsite prefabrication has greater automation through robotic assembly than does onsite building. As AI capability improves with real-time assessment of site condition, advances in cooperative robotics and autonomous systems, pattern recognition, IoT, and next gen cloud robotics will lead to considerable advances in robotic construction onsite.

Finally, on completion, facilities management for the project will be a potential extension to the planning and urban design team's role. As AI will help maintain the project, monitor and manage energy, water, and waste management to a greater extent, the design team will facilitate change as a creative response to the unexpected change in circumstances, such as a global pandemic. Imagine if the world's CBDs had been conceived as complex adaptive systems and managed as AI-enabled digital twins during the COVID-19 pandemic? Before the dramatic resource implications began to play out, limiting economic losses could have been handled proactively rather than the typical reactive responses, essentially conditioned by the current human dimension to city operations.

AI-assisted citizen jury sandpit

Working with *citizen juries* drawn from the communities involved, the alternative workflow could be used to model speculatively diverse densification strategies set over the next 30 years, formulated for testing as alternative plausible and implausible scenarios. The triangulated team comprising key stakeholders, experts, and end users could play in a codesign sandpit such as iHUB, shown in Fig. 1.3. Working closely with the relevant local government with carriage of precinct development, for example, other government agencies, peak bodies, consultancies, charities, NGOs and NGAs, and community representatives could work with visual material being their *lingua franca*. The community could have AI-enhanced visualization tools to convert a NIMBY predisposition to an alternative YIMBY mindset through actively participating in the codesign of the sustainable urban interventions that typically would be rejected out of hand.

Rapidly evolving AI is speeding up our capability to deep-dive into data and extract valuable fresh and often unexpected insights. Together these combine with wholly new ways to share data for absorption between groups of individuals made up from disparate disciplines and interests. In combination, these emerging technologies make for a more intelligible exchange between experts and nonexperts through their mutual interaction with innovative visualization setups. The innovative and newly inaugurated iHUB facility in Australia is the physical sandpit, the *National Urban Research & Development Platform*, hosted at Swinburne University of Technology is an urban observatory designed to gaze deep into possible urban futures. The facility is part of a national network involving five universities based in four states and Australia's major metropolitan cities. iHUB is a cutting-edge facility that addresses Seamer's plea for the public to be made "*aware of the issues and their potential solutions*" by

FIG. 1.3 iHUB is a rapidly reconfigurable planning and urban design decision-making facility where key stakeholders, experts, and the public can interact and participate in project design. Every participant can display their device simultaneously on high resolution "pods" shown here in one of three reconfigurable layouts: "**breakout**" mode. The facility can be rapidly transformed into "**lecture**" and "**boardroom**" modes. As AI matures to support applied human creative intelligence radically new project planning, design, and delivery workflows are made possible through shared access to the "digital workbench optimizer" in the iHUB. This federally funded lead facility is based at Swinburne University of Technology in Melbourne, Australia, and is associated with four similar facilities in Brisbane, Sydney, and Perth. It is scheduled to open in 2022. *No Permission Required.*

offering an innovative platform for the issues to be unpacked (Seamer, 2019). iHUB fuses AI to emerging data gathering, computation and visualization technologies to afford groundbreaking opportunities for the public to participate with experts in urban planning, design, construction, and management around the table. This innovative mode of shared decision-making can lead to future cities being codesigned cooperatively with citizens rather than directorially on their behalf. It also provides a state-of-the-art platform to enable this research program to meet its ambition of connecting most of Australia's key parametric urbanism and urban digitalization researchers, not just those based in Melbourne where our team is located. iHUB also provides the essential platform for engagement with an extensive international network.

AI and the challenges to expertise

Speculating on the future is a foolish scientific option at the time of the speculation—the present, given that only the future will prove whether part or all of any prediction is borne out. Frey points to the "technology trap" discussed above. Other commentators such as Tom Nichols point to a potential "death of expertise" (Nichols, 2018):

> These are dangerous times. Never have so many people had so much access to so much knowledge and yet have been so resistant to learning anything. In the United States and other developed nations, otherwise intelligent people denigrate intellectual achievement and reject the advice of experts. Not only do increasing numbers of laypeople lack basic knowledge, they reject fundamental rules of evidence and refuse to learn how to make a logical argument. In doing so, they risk throwing away centuries of accumulated knowledge and undermining the practices and habits that allow us to develop new knowledge.

Will AI provide the confidence in a general sense of expertise that human expertise specifically has lost to many apparently rational and educated people?

Resistance to change is not necessarily a preternatural characteristic of planning and urban design professions, but there is ample evidence of a lack of agility. Such a dramatic change to the creative workflow as proposed above is unlikely to appear anytime soon. But the AI components are there and already making spectacular incursions into professional practice, as the chapters in this book amply demonstrate. At the very least, the 26 AI components detailed above, and the many others that could have been identified here, not only exist but are advancing in sophistication at an astonishing rate. Each is like a jewel, becoming more faceted and polished as computer science continues to advance and computational power and speed improve. Some of the jewels become more brilliant than others at any moment in time. At the time of the writing, for example, to those craving the arrival of AI with creative potential exceeding the human mind, GANs appear to offer considerable potential. Tomorrow's shinier jewel might be cooperative robotics, or it could be complex adaptive systems, or most likely it will be something not currently in view.

AI is a polarizing force with its well-argued skeptics such as Kate Crawford (Crawford, 2021) contrasting with its proselytizers including Stuart Russell and Peter Norvig (Russell and Norvig, 2022). The intention of this chapter has been to unpack AI as a set of discrete components—bright shiny jewels seem an appropriate metaphor. AI is here and not going away. The principal challenge for the planning and urban design profession is not to obsess on any single AI component, but to think as broadly as possible on how to improve general workflows for creative project delivery, and greater reduction of tedious tasks thereby freeing up quality time for the creative thinking that human intelligence still excels at. Let us hope that future well-informed planning and urban design professionals are enabled to participate in threading the various AI jewels into a necklace that arbitrages human and artificial intelligence. Different mindset, skills formation, interdisciplinary flexibility, and optimism are required, but emerging work from around the globe is evidence of where we can go in this exciting domain.

Acknowledgment

The author expresses his appreciation for the generous research support for the iHUB facility provided by the Australian Research Council (ARC) and Swinburne University of Technology. Thank you Awnili Shabnam for graphics support.

References

Burry, M.C. (Ed.), 2020. Urban Futures: Designing the Digitalised City. In: Architectural Design, John Wiley and Sons, London, UK.

Crawford, K., 2021. Atlas of AI: Power, Politics, and the Planetary Costs of Machine Learning (ML). Yale University Press, New Haven, CT.

Frey, C.B., 2019. The Technology Trap: Capital, Labor, and Power in the Age of Automation. Princeton University Press, Princeton, NJ.

Gordon, Robert, 2017. The Rise and Fall of American. Growth: The U.S. Standard of Living Since the Civil War. Princeton University Press, Princeton. In press.

Hammer, M., 1990. Reengineering work: don't automate. Harv. Bus. Rev. 68.

Karakiewicz, J., 2020. Perturbanism in future cities: enhancing sustainability in the Galapagos Islands through complex adaptive systems. Archit. Des. 90 (3), 38–43. https://doi.org/10.1002/ad.2566. Wiley.

Kimm, G., Burry, M., 2021. Steering into the skid: arbitraging human and artificial intelligences to augment the design process. In: Proceedings of the 40th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA).

Lake, R.W., 1993. Planners' alchemy transforming NIMBY to YIMBY: rethinking NIMBY. J. Am. Plan. Assoc. 59 (1), 87–93. https://doi.org/10.1080/01944369308975847. Informa UK Limited.

McKinsey, 2017. The Case for Digital Reinvention. Available at: https://www.mckinsey.com. (Accessed 30 September 2021).

Mora, L., Deakin, M., 2019. Untangling Smart Cities: From Utopian Dreams to Innovation Systems for a Technology-Enabled Urban Sustainability, first ed. Elsevier Inc.

Nichols, T., 2018. The Death of Expertise: The Campaign Against Established Knowledge and Why it Matters, first ed. Oxford University Press, United States.

Russell, S., Norvig, P., 2022. Artificial Intelligence: A Modern Approach, fourth ed. Pearson, London, UK.

Seamer, P., 2019. Breaking Point: The Future of Australian Cities. Black Inc, Melbourne, Australia.

Siebel, T.M., 2019. Digital Transformation: Survive and Thrive in an Era of Mass Extinction. Rosetta Books, New York, NY.

CHAPTER

2

AI and the limits of human creativity in urban planning and design

Neil Leach

Florida International University, Miami, FL, United States; Tongji University, Shanghai, China; The European Graduate School, Visp, Switzerland

Introduction

The game of Go is simple enough in terms of its rules, but infinitely complicated in terms of strategy, in that the number of potential legal board positions is greater than the number of atoms in the universe (Moyer, 2016). As a result, it is a game that has long been considered one of the greatest challenges for AI, and the obvious next challenge for AI, following the triumph of IBM's supercomputer Deep Blue in a chess match with the then world chess champion, Gary Kasparov, in 1997. However, to take on one of the world's best players at Go would not be an easy challenge, as it would be technically impossible to use the same techniques in a match of Go as used in the match of chess against Kasparov, no matter how extensive the computational resources. Deep Blue was a hard-coded expert system that needed to be programmed for every single potential move. Such were the numbers of potential moves in the game of Go, however, that even if all the computers in the world were programmed for millions of year, this would not be enough to calculate the next move (Bolojan, 2021). What was required, then, was a completely different approach.

The challenge was taken up by DeepMind Technologies, a company based in London, and owned by Google. Fortunately, AI techniques have been developing at a rapid pace in the intervening years since Deep Blue's triumph over Kasparov, and learning systems have now been introduced that go well beyond the limitations of the expert systems deployed in Deep Blue. Machine learning—and deep learning especially—have become increasingly powerful. The issue, now, has become how to harness the extraordinary capabilities of learning systems to address the sheer range of possibilities afforded by the game of Go (Fig. 2.1).

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00013-5

FIG. 2.1 Lee Sedol and AlphaGo. Lee Sedol playing in the fourth match of the DeepMind Challenge Match against DeepMind's artificial intelligence program AlphaGo, on March 13, 2016, in Seoul, South Korea. *No Permission Required.*

AlphaGo v Lee Sedol

AlphaGo is a deep-learning computer program developed by DeepMind that depends on a Monte Carlo tree search algorithm, a policy neural network, and a value neural network. As Daniel Bolojan explains:

> You have a policy network, which is a neural network, you have a value network and you have a tree search, which is a Monte Carlo tree search algorithm. On one side, the value network provides an estimate of the value of the current state of the game – what is the probability of the black stone to ultimately win the game, given the current state? The output of the value network is then the probability of a win. On the other hand, the policy network provides guidance regarding which action to choose, given the current state of the game. The result is a probability value for each possible legal move, where higher probability values correspond to actions that have a higher chance of leading to a win. So the two networks are continually learning, by playing a game against each other. And the last component of this, of course, is the tree search, which looks to different variations of the game, and tries to define which move is most likely to succeed. So the policy network scans the positions to try to identify interesting spots to play, and it builds a tree of variations, and uses the value network to determine how promising is the outcome of that particular variation (Bolojan, 2021).

What is especially significant about AlphaGo is that reinforcement learning was used so that AlphaGo would "teach" itself to play Go, by playing a vast number of matches against itself (Silver et al., 2016). The big advantage here is that AlphaGo learns the game afresh, unconstrained by traditional thinking. As Demis Hassabis, CEO of DeepMind, has noted: "Deep Blue is a hand-crafted program where programmers distilled the information from chess grandmasters into specific rules and heuristics, whereas we've imbued AlphaGo with the ability to learn, and then it's learnt it through practice and study, which is much more human-like" (Byford, 2016).

However, this might be perhaps a little disingenuous, if we are to believe Stuart Russell. According to Russell, AlphaGo cannot learn by deep learning alone. He claims that AlphaGo also has a few handcrafted features, and—like Deep Blue—was also trained on a database of previous matches played by humans. As such, the two programs might not be quite as dissimilar as is often thought. As Russell comments:

> AlphaGo, and its successor AlphaZero, created a lot of media attention around deep learning with stunning advances in Go and Chess, but they're really a hybrid of classical search-based AI and a deep-learning algorithm that evaluates each game position that the classical AI searches through. While the ability to distinguish between good and bad positions is central to AlphaGo, it cannot play world-champion-level Go just by deep learning (Russell, 2018).

Nonetheless, the significant advances made in deep learning suggested that AlphaGo would at least stand a chance of beating one of the world's best Go players. Accordingly, a match was arranged between AlphaGo and one of the leading Go players in the world, Lee Sedol, Korean 9-Dan professional Go player, to take place in Seoul, Korea, over several days in March 2016.

The match between AlphaGo and Lee consisted of five games, with most Go experts—including Lee himself—predicting that the human player would win easily. From the very beginning, however, it became clear that this would not be the case, with Lee losing the Game 1 somewhat inauspiciously. Game 2, however, proved to be the turning point. After Game 1, Lee was surprised, but after Game 2 he was lost for words: "Yesterday, I was surprised. But today I am speechless. If you look at the way the game was played, I admit, it was a very clear loss on my part. From the very beginning of the game, there was not a moment in time when I felt that I was leading" (Metz, 2011).

The biggest talking point of the whole match, however, was a remarkable move, Move 37, played by AlphaGo in this game:

> In Game 2, Lee exhibits a different style, attempting to play more cautiously. He waits for any opening that he can exploit, but AlphaGo continues to surprise. At move 37, AlphaGo plays an unexpected move, what's called a "shoulder hit" on the upper right side of the board. This move in this position is unseen in professional games, but its cleverness is immediately apparent. [Go player] Fan Hui would later say, "I've never seen a human play this move. So beautiful" (Moyer, 2016).

Beautiful, beautiful, beautiful—Hui kept repeating (Metz, 2011). What this move challenges is the very nature of creativity. Moreover, it has also served to change fundamentally our understanding of the game of Go, by introducing a number of previously unknown moves (Kohns, 2017).

> And Lee? *He gets up and walks out of the room.* For a moment it's unclear what's happening, but then he re-enters the game room, newly composed, sits down, and plays his response. What follows is a much closer game than Game 1, but the outcome remains the same. Lee Sedol resigns after 211 moves (Moyer, 2016).

It is clear that AlphaGo was deploying a long-term strategy in its various moves. It made a number of moves that were initially dismissed by experts as "slack moves" in that at first they did not seem to make any sense. In the longer term, however, it became clear that these "slack moves" were actually setting the scene for a series of subsequent—and strategically devastating—moves.

In the end, the match proved to be somewhat one-sided. Although Lee did manage to win one game, AlphaGo went on to win the match fairly conclusively by 4 games to 1. The result sent shockwaves through the Go community.

The Sputnik moment

A match of Go taking place in South Korea involving a professional player largely unknown in the West, playing a game almost unheard of in the West, could hardly be expected to create much of a stir, except perhaps within the AI community. It could be argued, however, that this match proved to be one of the most significant events in the entire history of AI.

In China, AlphaGo's triumph over Lee was an event that triggered a huge interest in AI. After all, the game of Go was invented in China more than 3000 years ago, and remains hugely popular there. The Chinese nation was clearly transfixed by the match. There was an estimated television audience of 280 million for this event, a significant proportion of which were in China (Kohns, 2017). And the victory of AlphaGo over Lee sent a seismic shock through the whole nation. The impact of the match on China should not be understated. It was a huge wake-up call for them. As Lee notes, "Overnight, China plunged into an artificial intelligence fever" (Lee, 2018). In what has been described by Kai-Fu Lee as China's "Sputnik Moment," the Chinese government realized after the match that it was lagging behind the West in a technology that held vast potential (Simonite, 2018). The original "Sputnik moment" was, of course, the moment when the States was jolted into action in the Space Race, after being seriously embarrassed by the success of the Soviet Union in launching a satellite into space (Leach, 2014).

The Chinese government promptly decided to initiate an ambitious and rapid program of investment in AI (Mozur, 2017). On October 18, 2017—a year and a half after the match—Chinese President Xi Jinping announced a new plan for China to invest in AI with a view to overtaking the States in AI development by 2030 (Thomson and Bremmer, 2018). Kai Fu-Lee astutely observes, "If AlphaGo was China's Sputnik moment, the government's AI plan was like President John F. Kennedy's landmark speech calling for America to land a man on the moon" (Lee, 2018). In fact, some have argued that China has already surpassed the States, if judged on the basis of the number of articles published on AI, and looks set to claim the top spot for most cited papers by 2025 (Schoenick, 2019).

If, then, the original sputnik moment in the States led to the Space Race that was itself a manifestation of the Cold War, would not the second sputnik moment in China lead to the AI race, which is itself a new form of Cold War? "No," says Lee, "this is not a new Cold War" (Lee, 2018). Although AI can be used for military purposes, its true value lies in opening up to a new technology that will surely benefit the whole of humanity. Instead of the Cold War, the comparison should be with the Industrial Revolution or the invention of electricity. But it most certainly was, as Lee so aptly observes, both a "game" and a "game changer," at least as far as China was concerned (Lee, 2018).

Nor can we overlook South Korea, the country in which the match itself was played, and where the match also had a significant impact on AI funding. On 17 March—just 2 days after the match—the South Korean government pledged 1 trillion won ($863 million) into research in AI over the next 5 years. South Korean President Park Geun-Hye expressed her gratitude for the match, "Above all, Korean society is ironically lucky, that thanks to the

"AlphaGo shock," we have learned the importance of AI before it is too late" (Zastrow, 2016).

Architectural lessons

AlphaGo, then, had a huge impact beyond Go playing circles. It triggered a worldwide race to develop AI and spawned investment on a huge scale. But what might architects and urban planners learn from AlphaGo?

Here, let us take a look at two of the leading companies developing AI-based architecture and urban design tools, Xkool and Spacemaker AI, and consider how they might have been influenced—directly or indirectly—by the match between Lee and AlphaGo (Figs. 2.2–2.4).

Xkool

In 2016, the same year as AlphaGo's triumph over Lee Sedol, Xkool Technology (Xkool) was founded by two architects, Wanyu He and Xiaodi Yang. Xkool claims to be "the world's first innovative technology company that uses cutting-edge technologies such as deep learning, machine learning and big data to successfully apply artificial intelligence to urban planning and architectural design, is based on its own core algorithm technology and in architectural design." For sure, Xkool stands out from other rival companies working with AI through the sheer investment it has made in deep-learning techniques. We can see evidence of this in their use of StyleGANs and other deep-learning techniques to generate architectural designs.

Given the extraordinary interest in AI that the match generated in that country, one might surmise that any AI start-up based in China would have been well aware of the match. Indeed, this was the case.

For Xkool, however, it was not AlphaGo itself so much as the next generation in the series, AlphaGo Zero, that really left its mark. What is stunning about the development of AlphaGo Zero is not only that it taught itself to play Go without being given any prior knowledge, but also the sheer speed at which it did so. AlphaGo Zero effectively trained itself through reinforcement learning, playing 4.9 million games of Go against itself (Kennedy, 2017). That is a rate of almost 20 games of Go per second—a rate that is utterly incomprehensible for human beings.

Indeed, it was precisely as a direct result of the success of the AlphaGo ZERO initiative, that Xkool developed a new technique using reinforcement learning that meant they did not need to rely on datasets of existing buildings. Instead, the system was capable of extracting its own rules from previous examples, and generating options that were genuinely innovative:

> In 2017, the official publication of AlphaGo ZERO showed research results that promoted the application of reinforcement learning technology in developing intelligent design tools. It freed design tools from the limitations of the database of real cases towards a direct use of initial models generated by rules they have learnt in confrontation and iteration. By repeating this process, a model that best meets (or even exceeds)

FIG. 2.2 Xkool. StyleGAN-generated building images. *No Permission Required.*

human designers' expectations and has a true potential for exploring the unknown is finally generated (He, 2019).

In their latest stage of development, Xkool now sees the role of AI as being broken down into four distinct stages: recognition, evaluation, reconstruction, and generation (He, 2020). "Recognition" is used to search for complex and hidden patterns in the data generated by cities. Of course, humans are also capable of patterns, but the sheer amount of data makes it impossible for them to do so effectively, and there are often "blind spots" in any analysis

FIG. 2.3 Xkool. StyleGAN-generated building images. *No Permission Required.*

undertaken by humans. The next step, "evaluation," involves detecting patterns in this data, such as pedestrian movement or traffic flow. This can help to reveal problems, such as traffic congestion or a lack of public facilities. After that comes "reconstruction," a background process that helps to form a basic understanding of the challenge. The development of this technique allowed Xkool, for example, to launch a platform, "Non-Existing Architectures," in 2019, that was able to generate relatively convincing "hallucinations" of buildings based on a massive dataset of building images. However, reconstruction can only operate at a relatively basic level, to produce little more than impressionistic designs. It therefore depends on

FIG. 2.4 Xkool3. Xkool, StyleGAN-generated building image. *No Permission Required.*

the final step, "generation," to provide a more detailed and refined output. "Generation" is similar to the process of turning a rough sketch into a detailed design.

Xkool has developed two tools for this. Firstly, at an urban scale they have developed their Intelligent Dynamic Urban Planning and Decision-Making Platform, an integrated dynamic platform which allows the overall plan for urban planning proposals to be modified, as each component part is itself modified. Secondly, at an architectural scale, they have introduced Koolplan, an AI assistant to generate more detailed floor plans and elevations (Fig. 2.5).

FIG. 2.5 KoolPlan. KoolPlan generated design (2019). KoolPlan is an AI assistant for floor plans and façade design that allows for more refined detailing. *No Permission Required.*

Koolplan offers designers a range of possible options from which to choose their preferred solution, a significant improvement on earlier shape grammar techniques that only offer designers a single solution (He, 2020).

As a result, Xkool is now not far from developing a fully automated process for generating actual architectural drawings.

Spacemaker AI

In late 2016—the same year that Xkool was founded—Spacemaker AI (or "Spacemaker" for short) was launched in Oslo by architect, Håvard Haukeland, computer engineer, Carl Christensen, and financial analyst, Anders Kvale. In November 2020 it was announced that Spacemaker had been acquired by Autodesk for $240 million (O'Hare, 2020).

The primary intention of Spacemaker is to find the smartest way to realize the potential of any building plot. Spacemaker is intended to be used primarily by property development professionals. As Steve O'Hear puts it, "Described as 'the world's first' AI-assisted design and construction simulation software for the property development sector, Spacemaker claims to enable property development professionals, such as real-estate developers, architects, and urban planners, to quickly generate and evaluate the optimal environmental design for any multibuilding residential development (Fig. 2.6). To achieve this, the Spacemaker software crunches various data, including physical data, regulations, environmental factors, and other preferences" (O'Hare, 2020).

Compared to Xkool, however, Spacemaker is not so reliant on deep-learning technologies. Christensen describes their approach as being similar to how a self-driving cars works. A self-

FIG. 2.6 Spacemaker figure. Lund Hagem Architects, Tjeldbergvika Development, Svolvaer, Norway (2019) Spacemaker AI was used to optimize sun conditions, sea views, wind, daylighting, and noise conditions. *No Permission Required.*

driving car relies on AI, but it also relies on many other technologies. Spacemaker is experimenting with a number of different technologies, including deep learning, with a view to incorporating more advanced AI. Although the Spacemaker team does not disclose full details of what they use, for the moment it would seem that their primary focus is on topological and machine learning, rather than deep learning:

> It's a real mix-up of different things, because the core idea is to bring everything together in one platform. So we do use a lot of machine learning, but we do use other algorithms and ways of modeling the world as well. And we generally say that it is AI like a self-driving car is an AI. It's a lot of different things coming together to create a result. So we do use generative design. We use optimization. We use simulation models of the world. We use machine learning models for many things, like surrogate models for understanding the physical environment – for example, how you would change a design to make it better for many factors at once (Christensen, 2019).

The premise behind Spacemaker is that the design of buildings in an urban setting is becoming increasingly challenging for architects and urban planners. There is simply too much data and complexity for the human mind to comprehend. And this is where Spacemaker comes in. The Spacemaker team sees its role as translating architecture to mathematics. To this end, Spacemaker has developed an engine that generates, optimizes, and analyzes buildings of different solutions based on input data and preferences defined by the user (Fig. 2.7).

Once the site has been defined, and the various constraints and parameters have been inputted, the AI engine is then engaged, and the architect is presented with a range of optimized solutions. "So that means that architects are now able to explore a really wide variety of

FIG. 2.7 Spacemaker rendering 2. Schmidt Hammer Lassen Architects, Molobyen Development, Bodø, Norway, 2019–20. Spacemaker AI was used to optimize the design, taking into account a variety of factors. *No Permission Required.*

alternative solutions for a site, instead of only a handful of solutions. And at the same time the solutions that they are looking at are aimed at maximizing space utilization while also satisfying requirements and regulations in the area. This means that the architect can work in a completely different way, in a much more informed and iterative process" (Chowdhry, 2019). What results is not simply a change in the design process itself. It also represents a change in the way that architects design, whereby the AI becomes an "invisible assistant."

Spacemaker also offers a platform that uses the cloud to allow the various stakeholders in a project to come together to study "surrogate models" of the proposed building. This allows them to "trade off" various performance factors in real time, so that they can quickly find the solution that suits them best. Importantly, the platform allows users to *explore* different options. Hence, the name of Spacemaker's recently released generative platform, *Explore*. Kara Vatn describes how their platform, *Explore*, operates: "With *Explore*, architects and urban planners can continuously generate and review different site proposals, and focus in and iterate at both a macro and micro level. Users can make changes at any point in the planning process and immediately see the impact and alternative options for their site, all in one fast and uninterrupted workflow" (Vatn, 2020).

Not only does their platform serve to increase the range of options, but it also suggests options, some of which might not be immediately apparent. In fact, on occasions the platform can come up with suggestions that no architect would ever have imagined, but that nonetheless offer the best solution. Haukeland cites a particular example of a project, affectionately known as their "Giraffe" project, where the computer was able to find the complete opposite of what an experienced architectural mind might have thought appropriate (Fig. 2.8):

> The places where the architects thought that it would be smart to build tall buildings, and the places where they thought it would be smart to build a dense wall, all the things that they intuitively thought would be

FIG. 2.8 Spacemaker rendering 3. NREP, Proposal for Okernvelen, Norway, 2020 (the "Giraffe" project). Spacemaker AI was used to develop seemingly counterintuitive proposals in terms of the handling of sun, view, and noise conditions. *No Permission Required.*

> smart – because they had hundreds of projects of experience – were flipped around. Because when you get the complexity of thinking of a multi-objective organizational problem... you are really not able to see the patterns that a computer can find. So what happened was that the computer was able to find a pattern as to how to solve that site that you would never come up with yourself (Vatn, 2020).

I would suggest that architecture and urban planning could be conceptualized within two different—yet interrelated—frameworks.

One would be what we might call "design," by which we might refer to the aesthetic aspect of design—what a design "looks like." The other would be the strategic planning side of design—the massing and other models that are intended as ways to explore a site from a strategic point of view. It is this latter aspect—the strategic planning behind a design—that echoes the way in which a game such as Go is played. The game of Go is all about strategy. No one is concerned too much about what the board or pieces on the board look like.

I would therefore argue that parallels can be drawn between Move 37 in Game 2 of the match between AlphaGo and Lee Sedol, and the way that Spacemaker has discovered that AI can occasionally generate architectural and planning solutions that might not seem to make much sense at first sight—solutions that echo the "slack moves" of AlphaGo. Again, the possibility had always existed, but—like move 37 in the AlphaGo match—no one had thought about it before. What this suggests is that from a strategic point of view, urban planning and the game of Go might have more in common, than at first might seem apparent.

The limits of human creativity

The time has long gone when human beings might expect to beat AI at a game of Chess or even Go. By extension, it could be claimed that AI should be better than human beings at offering strategies for urban planning. In many cases, after all, the sheer complexity of issues of operating at an urban scale makes urban planning extremely challenging for human beings. It is here that AI can offer a powerful tool that becomes an extension of human intelligence, enabling architects to enhance their own abilities, so as to meet the challenge.

Interestingly, this has a special appeal for developer clients who see AI-based tools, such as Spacemaker, as offering "customer value"—or, to use a term popular in the industry itself, "return on investment." Indeed, as Haukeland observes, developer clients are now beginning to insist that architects use AI in the design process, so that they find the most effective and efficient solution for their client: "The developers really want architects to use Spacemaker. That technology is something they want. It is a requirement from their clients" (Vatn, 2020).

This seemingly throwaway comment should not be underestimated. This surely is the single most important factor that will lead to the AI revolution in architectural profession. Clients will want architects to use AI in order to maximize their "return on investment" and optimize the performance of their buildings. It is as simple as that. Forget progressive aesthetics, forget experimentation. The lasting impact of AI will be guaranteed, once the majority of clients start to insist on their architects using AI. Thereafter, we could predict that architects will begin to brand themselves in terms of their practice-based use of AI, in order to attract clients, much as they now brand themselves as being LEED or BREEAM certified in terms of environmental sustainability.

What implications might this have for the future? Perhaps the analogy of the self-driving car might offer some insights. Self-driving cars are likely to have a huge impact on driving. In fact, Toby Walsh predicts that human beings will eventually be banned from driving, as a result of the introduction of self-driving cars (Walsh, 2018). As self-driving cars become more available, Walsh argues, we will drive less and less. As a consequence, our driving skills will diminish, so that insurance premiums will increase. Gradually, we will become resigned to not driving, to the point that young people might not even bother to learn to drive. Finally, driving itself will be banned.

Change, of course, is often incremental, just as the development of the self-driving car is happening gradually over time. In the case of a Tesla car, for example, this takes the form of regular software updates. What is perhaps most interesting about Walsh's prediction, however, is his comment about our change of attitudes: "We won't be allowed to drive cars any more, and we will not notice or even care" (Walsh, 2018).

AI, of course, will make architecture and urban design easier, just like self-driving cars. The question that arises, then, is whether architecture will follow the model of self-driving cars. Might we even see parallels between the increase in insurance premiums for drivers as a result of self-driving cars that will prove themselves more reliable and safe than human drivers, as Walsh predicts, and a rise in professional indemnity insurance for architects, who choose not to use AI? After all, apart from "return on investment," risk assessment is another factor that needs to be considered, an area where AI is likely to be far more reliable.

With self-driving cars, however, the driver eventually becomes redundant. If we adopt the same model for architecture, might this not mean that eventually the architect would also become redundant? (Leach, 2021) Might this not mean that the architect will also disappear eventually, just as the human driver will disappear? And, if so, might we not notice or even care?

What became of Lee himself after his match against AlphaGo? In November 2019, Lee retired from professional Go, on the basis that he would never be able to beat AI in the future: "This is an entity that cannot be defeated" (Yonhap News Agency, 2017). We have already seen that AI has proved more effective than urban planners. For sure, the role of urban planners would seem to be at risk. But might architects not find themselves in the same situation eventually?

Learning from Move 37

Of all the moves made in the match between AlphaGo and Lee, there was one particular move—Move 37 in Game 2—that stood out for its innovation. What, then, can we learn from Move 37? For sure, this was the move that made Lee think that AlphaGo could indeed be "creative." As European Go champion Fan Hui comments, "When AlphaGo chose that move, I assumed that it had made a mistake. I immediately looked to see Lee's reaction. At first, he seemed to smile – as though he too thought it had made a mistake – but as the minutes rolled by it was clear that he was starting to realize its brilliance. In fact, after the match, he said that when he saw this move he finally realized that AlphaGo was creative" (Hassabis and Hui, 2019).

Hassabis goes even further: "Anyone can play an original move on a Go board by simply playing randomly. Yet a move can only be considered truly creative if it's also effective. In that sense, Move 37's decisive role in game two represents a move of exquisite computational ingenuity that not only changed the game of Go forever, but also came to the enormous creative potential of AI" (Hassabis and Hui, 2019).

Indeed, such was the brilliance of AlphaGo's play, that Lee even began to question the creativity of moves made by humans that were previously thought to be creative: "AlphaGo showed us that moves humans may have thought are creative, were actually conventional" (Kohns, 2017).

The real challenge, however, is whether human beings would even recognize the full "creativity" of AI. The chances are that—if AI is too "creative" we human beings would not even able to grasp its "creativity," much like the "slack moves" of AlphaGo that escaped the analyses of experts. By a curious irony, this was already predicated by Alan Turing before the term "artificial intelligence" had even been conceived. In his famous article, "Computing Machinery and Intelligence," with the question, "Can Machines Think?" (Turing, 1950) In fact Turing speculates that eventually machines should be able to do anything that a human can do, to the point that they should be able to write sonnets:

> We have to have some experience with the machine before we really know its capabilities. It may take years before we settle down to the new possibilities, but I do not see why it should not enter any one of the fields normally covered by the human intellect, and eventually compete on equal terms. I do not think that you can even draw the line about sonnets (Turing, 2015).

Turing, however, goes on to add an interesting qualification, surmising that human beings might not be able to fully appreciate these sonnets: "Though the comparison is perhaps a little bit unfair, because a sonnet written by a machine will be better appreciated by another machine" (Turing, 2015).

Rethinking creativity

In his famous paper, "Computing Machinery and Intelligence," Turing speculates about the possibility of developing machines that might be capable of thinking (Turing, 1950). He describes a technique to judge whether the intelligence of a "thinking machine" could match the intelligence of human beings. Initially named after a popular party game, the "Imitation Game," this technique has since become known as the "Turing Test" (Hodges, 2021). The clever aspect of the Turing Test is that we do not have to define terms such as, "a machine" or "to think." Instead, a simple game is played between a judge, a human being, and a computer program. The challenge is for the computer program to compete against the human being, take part in a conversation, and answer questions set by the judge. If the computer program manages to convince the judge that it is human, it passes the Turing Test.

According to the philosopher, John Searle, however, AI cannot think. AI does not possess consciousness, even though it might *appear* to do so. To illustrate his point, Searle uses his famous "Chinese Room" thought experiment (Searle, 2009). Searle invites the reader to imagine that he is locked in a room, equipped with an instruction manual that allows him or her to translate English text into Chinese. The only problem is that he does not understand Chinese. By following the right instructions, theoretically he might be able to produce a convincing Chinese translation of the English text. As such, to anyone outside the room, he might *appear* to understand Chinese, even though he does not. Now imagine, by way of comparison, an AI computer program designed to translate Chinese. The program is able to take English characters as input and generate Chinese characters as output. How is this any different to the situation with AI? AI might *appear* to possess consciousness, but it does not. Neither Searle inside the room, nor the computer understands what they are doing. The weakness of the Turing Test, then, is that the computer might pass the test by merely *appearing* to think like a human being. It is simply a question of fooling the judge.

Let us go back to Move 37. For sure, with this move AlphaGo *appears* to be creative. But how is this different to Searle's "Chinese Room" thought experiment? Substitute "consciousness" for "creativity," and we find ourselves in a very similar situation. "From outside the room," as it were, AlphaGo *appears* to be creative, just as Searle appears to understand Chinese. But what if AlphaGo is not creative at all? Some might even claim that AlphaGo was merely conducting a search for the most effective move—and a Monte Carlo search was used, after all, in its "decision" making process.

Indeed, according to Melanie Mitchell, AI cannot be called "creative," in that in order for it to be truly creative, it would need to be *aware* that it is being creative and capable of appreciating its creativity. For Mitchell, at any rate, consciousness must be considered the hallmark of creativity (Mitchell, 2019). According to this logic, at any rate, AlphaGo could not be considered to be creative, since it does not possess consciousness.

But let us pursue this argument further, and apply it to human creativity. What is interesting is that Lee notes that certain Go moves made by humans are only "thought" to be creative: "AlphaGo showed us that moves humans may have *thought* are creative, were actually conventional" (Kohns, 2017). What if we were to also reflect on human creativity in terms of the Chinese Room scenario? What if, for example, human beings are merely clinging to the notion that there is something special—even mysterious—about human creativity? Indeed, as Margaret Boden has noted, creativity *appears* somewhat mysterious (Boden, 2016). But what if this were not the case? What is there were nothing mysterious about creativity? In fact we still know relatively little about what is going on inside the mind—"inside the room," as it were. What if human beings are in fact merely conducting a "search" similar to AlphaGo? In other words, what if—despite the mystique associated with it—what we call "creativity" were to be not so dissimilar to the operations of a computer? What if human beings are trying to convince themselves that human creativity is something magical, when in fact is it really quite straightforward?

"Any sufficiently advanced technology," Arthur C Clarke famously claims, "is indistinguishable from magic." But is this true?

Let us be clear. A magician does not perform magic. A magician simply conceals—by sleight of hand—what is actually happening, such that the audience is duped into thinking that it is an act of magic. Neither is technology magical. Sometimes, however, technology might *appear* to be magical, when we cannot understand how it actually operates: "Like the conjurer's trick, where the magician conceals the true devices at work, so as to fool the audience into attributing them to magic, so technology, in effacing itself, invites us to believe in its magical potential" (Leach, 1999).

Might the same principles apply to creativity?

As yet, we simply do not fully understand how the mind works. The mind, like creativity itself, remains somewhat mysterious. Surely, we will never be able to understand what creativity is, until we understand fully how the mind itself works. We can only judge it by outward appearances, like the figures outside the room speculating on whether the figure in Searle's "Chinese Room" thought experiment understands Chinese.

Is creativity, then, like magic? Does it even exist?

Beauty, it is often said, is in the eye of the beholder. But should we not say that beauty actually exists in the *mind* of the beholder, as some have claimed? (Wargo, 2011). Perception, after all, is not just a question of sight. Perception itself is always already mediated (Clark, 2016; Seth, 2021). Or, as Slavoj Zizek argues, everything comes to us through the "maze of the imagination" (Zizek, 2002).

Is creativity, then, like beauty? Do perceptions of creativity not exist in the *mind* of the beholder?

Is creativity, then, merely *perceived* creativity?

And is this not the ultimate lesson of AlphaGo?

References

Boden, M., 2016. AI: Its Nature and Future. OUP, Oxford.

Bolojan, D., 2021. Creative AI Augmenting Design Potency, DigitalFUTURES CDRF. Available at: https://www.youtube.com/watch?v=r65IHo-TwCs&t=4272s.

Byford, S., 2016. DeepMind Founder Demis Hassabis on How AI Will Shape the Future. The Verge.

Chowdhry, B., 2019. Designing Better Cities With Artificial Intelligence. Seattle. Available at: https://interaction19.ixda.org/program/talk-designing-better-cities-with-artificial-intelligence-bilal-chaudhry/. (Accessed 3 February 2019).

Christensen, C., 2019. Global PropTech Interview #5 With Carl Christensen, Co-founder of Spacemaker AI. Available at: https://www.youtube.com/watch?v=hvmus_VUtQ8&app=desktop. (Accessed 2 December 2019).

Clark, A., 2016. Surfing Uncertainty: Prediction, Action and the Embodied Mind. Edinburgh University Press, Edinburgh.

Hassabis, D., Hui, F., 2019. AlphaGo: moving beyond the rules. In: Wood, C., Livingston, S., Uchida, M. (Eds.), AI: More Than Human. Barbican International Enterprises, London.

He, W., 2019. From competition, coexistence to win-win—relationship between intelligent design tools and human designers. Landsc. Archit. Front., 76–83.

He, W., 2020. Urban experiment: taking off on the wind of AI. Archit. Des. 90 (3), 95–99.

Hodges, A., 2021. The Alan Turing Internet Scrapbook. Available at: https://www.turing.org.uk/scrapbook/test.html. (Accessed 25 September 2021).

Kennedy, M., 2017. Computer Learns to Play Go at Superhuman Levels 'Without Human Knowledge. Available at: https://www.npr.org/sections/thetwo-way/2017/10/18/558519095/computer-learns-to-play-go-at-superhuman-levels-without-human-knowledge.

Kohns, G., 2017. AlphaGo The Movie. Available at: https://www.alphagomovie.com/.

Leach, N., 1999. Millennium Culture. Ellipsis, London.

Leach, N., 2014. Space Architecture: The New Frontier for Design Research. Wiley, London, p. 232.

Leach, N., 2021. The Death of the Architect. Bloomsbury, London.

Lee, K.F., 2018. AI Superpowers: China, Silicon Valley, and the New World Order. Harper Business, New York.

Metz, C., 2011. The Sadness and Beauty of Watching Google's AI Play Go. Wired.

Mitchell, M., 2019. Artificial Intelligence: A Guide for Thinking Humans. Farrar, Straus and Giroux, New York.

Moyer, C., 2016. How Google's AlphaGo Beat a Go World Champion. The Atlantic. Available at: https://www.theatlantic.com/technology/archive/2016/03/the-invisible-opponent/475611/.

Mozur, P., 2017. Beijing Wants A.I. to Be Made in China by 2030. New York Times, New York. Available at: https://www.nytimes.com/2017/07/20/business/china-artificial-intelligence.html. (Accessed 20 July 2017).

O'Hare, S., 2020. Spacemaker, AI Software for Urban Development, Is Acquired by Autodesk for $240 Million. TechCrunch. Available at: https://techcrunch-com.cdn.ampproject.org/c/s/techcrunch.com/2020/11/17/spacemaker-ai-software-for-urban-development-is-acquired-by-autodesk-for-240m/amp/. (Accessed 17 November 2020).

Russell, S., 2018. Architects of Intelligence: The Truth About AI From the People Building It. Packt Publishing, New York.

Schoenick, C., 2019. China May Overtake US in AI Research. Available at: https://medium.com/ai2-blog/china-to-overtake-us-in-ai-research-8b6b1fe30595. (Accessed 13 March 2019).

Searle, J., 2009. Chinese room argument. Scholarpedia, 3100. https://doi.org/10.4249/scholarpedia.3100.

Seth, A., 2021. Being You: A New Science of Consciousness. Dutton, London.

Silver, D., et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature 529 (7587), 484–489. https://doi.org/10.1038/nature16961. Springer Science and Business Media LLC.

Simonite, T., 2018. Tencent Software Beats Go Champ, Showing China's AI Gains. Wired. Available at: https://www.wired.com/story/tencent-software-beats-go-champ-showing-chinas-ai-gains/.

Thomson, N., Bremmer, I., 2018. The AI Cold War That Threatens Us All. Wired. Available at: https://www.wired.com/story/ai-cold-war-china-could-doom-us-all/.

Turing, A., 1950. Computing machinery and intelligence. Mind 236, 433–460.

Turing, D., 2015. Prof: Alan Turing Decoded. Pitkin Publishing, Norwich.

Vatn, K., 2020. Introducing Explore, A Creative Toolbox for Architects and Developers. Medium. Available at: https://blog.spacemaker.ai/introducing-explore-a-creative-toolbox-for-architects-and-developers-4d1a8df1318d. (Accessed 41 May 2020).

Walsh, T., 2018. Machines that Think: The Future of Artificial Intelligence. Prometheus, Buffalo, NY.

Wargo, E., 2011. Beauty is in the Mind of the Beholder. Association for Psychological Science. Available at: https://www.psychologicalscience.org/observer/beauty-is-in-the-mind-of-the-beholder.

Yonhap News Agency, 2017. Go Master Lee Says He Quits Unable to Win Over AI Go Players. Available at: https://en.yna.co.kr/view/AEN20191127004800315. (Accessed 27 November 2017).

Zastrow, M., 2016. South Korea Trumpets $860-Million AI Fund After AlphaGo 'Shock'. Nature. Available at: https://www.nature.com/news/south-korea-trumpets-860-million-ai-fund-after-alphago-shock-1.19595.

Zizek, S., 2002. From virtual reality to the virtualisation of reality. In: Leach, N. (Ed.), Designing for a Digital World. Wiley, London.

This page intentionally left blank

CHAPTER

3

Complexity science for urban solutions

Anjanaa Devi Sinthalapadi Srikanth[a], *Benny Chin Wei Chien*[a], *Roland Bouffanais*[b], *and Thomas Schroepfer*[a]

[a]**Singapore University of Technology and Design, Singapore** [b]**University of Ottawa, ON, Canada**

Introduction

Everyone who lives in an urban environment is (consciously or not) affected by its planning and design. Cities have now been recognized as nuclei for innovation, expertise, and opulence; they can be considered as "concentrations of social interactions in space" (Garfield, 2019). As cities grow larger in population and size, they exhibit three key characteristics—complexity, diversity, and intelligence (Güell, 2006; Camagni, 2003; Fernández-Güell et al., 2016)—that offer a glimpse of both the potential of cities and the problems that they face today.

Many urban issues, ranging from wealth inequity to environmental sustainability, are usually tackled independently of each other (Bettencourt and West, 2010) despite their obvious interdependencies. This practice continues the convention of disciplines following a centralized order, which was largely the norm up to the 19th and 20th centuries (Batty and Marshall, 2012). Urban planning in the 20th century was characterized by a rigorous top-down approach, despite notable critics, including Christopher Alexander, who railed against the simplistic urban models of "tree-like" hierarchies and Jane Jacobs, who called for more diversity and citizen-centric design that reflected the realities of urban life. Facing today's climate emergency, it seems clear that such outdated planning and design strategies are ineffective in satisfactorily addressing many of today's problems.

The need for cities to become smarter in problem-solving cannot be overstated. It is important that concurrent trends in urbanization, economic growth, technological progress, and environmental sustainability act as drivers in urban planning and design thinking processes (Naphade et al., 2011). Batty et al. (2012) call for an "integration that enables system-wide effects to be tracked, understood and built into the very responses and designs that characterize the operations and functions of the city." Christopher Alexander, in "Notes on the Synthesis of Form," details the "use of a structure-preserving mathematical decomposition of complex

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00017-2

design problems into hierarchies of simpler problems which could be readily solved, then recomposed into a complex solution" (Taylor, 2019). His proposed methodology of automating the deconstruction processes based on a holistic and comprehensive understanding of all the factors (Doug, 1994) has influence on and applications in both the computation and design fields. His intent is similar to that of (Bettencourt and West, 2010), whose approach to the study of cities is to "understand their dynamics, growth and evolution in a scientifically predictable, quantitative way." This highlights the need for and potential of artificial intelligence (AI) in urban planning and design today.

Internet of Things (IoT) technology is already ubiquitous in many cities worldwide, with wide-ranging applications in urban planning and design that are based on real-time data collection. In a more dominant role, AI tools and techniques can be tapped into for tackling multiple issues across urban scales, to integrate a conscious top-down approach to planning with site-specific bottom-up solutions. In the following, we detail a complexity science-based methodology that employs machine learning (ML) to quantitatively analyze spaces and activities in high-density urban built environments, with the goal of understanding the efficacy of their use and shortcomings to inform better future planning and design decisions.

Artificial intelligence (AI) in the built environment

Digitization, through the installation of sensors, computational cores, and different telecommunication systems (Alvarez, 2017), has resulted in an unprecedented scale of urban data generation. It is predicted that by 2023, machine-to-machine (M2M) connections, such as smart meters, video surveillance, healthcare monitoring, transportation, and package or asset tracking, will be 14.7 billion in number or 50% of the total devices and connections (Cisco, 2020). AI can be used, beyond processing such large amounts of data, for cognitive computing integration (Allam and Dhunny, 2019), which makes it pervasive in urban environments and led to the "smart city" concept.

The idea of the "smart city" has accompanied the rise of IoT. Harrison et al. (2010) essentially view it as information and communication technologies that can help cities to address their problems as well as increase their competitiveness and efficiency (Batty et al., 2012). Kitchin (2014) provides one definition of the smart city as "the prioritization of data capture and analysis as a means for underpinning evidence-informed policy development, enacting new modes of technocratic governance, empowering citizens through open, transparent information, and stimulating economic innovation and growth." In the smart city framework, AI can inform urban planning and design processes, e.g., in transport planning, with progress in intelligent transport systems (ITS) and the exploration of automated vehicle technology. AI helps account for unpredictability in transport planning, where users' behavior is too difficult to model by traditional analytical methods (Abduljabbar et al., 2019; Gopalakrishnan et al., 2021). Intelligent prediction methods are used in ITS subsystems such as advanced traveler information systems, traffic management systems, public transportation systems, and commercial vehicle operations (Mahamuni, 2018; Abduljabbar et al., 2019). They are based on the use of historical data that has been extracted from sensors on roads, which is input to ML and AI algorithms (Mahamuni, 2018). AI is also used by ride-sharing service companies such as Uber and Didi Chuxing to predict passenger demand (Yao et al., 2018). Through avoiding empty vehicles, the use of AI in this context can help to reduce energy consumption and traffic congestion. In the long run, the use of AI in smart city planning and design is expected to generate many important benefits for the urban environment and its socioeconomic development.

The use of AI is currently being explored in urban planning and design in many ways. Incorporating ML in cloud-based platforms such as Google Earth Engine and ArcGIS Cloud aCarto has enhanced urban analytical methods through satellite imagery (Goldblatt et al., 2018). AI is also a powerful tool that can support decision-making; through the lens of generative urban design, AI can be used to model processes that lead to a solution to many problems. Quan et al. (2019) have argued that the system as a "smart design framework" has four main components: human problem initialization stage (problem clarification), human-system interface stage (mathematical representation of the problem dimensions), system optimization stage (computational algorithms that drive design exploration) and human-system interaction stage (result interpretation and visualization), in which heuristic algorithms (such as genetic algorithms, simulated annealing, tabu searches, etc.) and other AI search techniques can be used for optimization. Although they are applied more commonly in architectural than in urban design due to the dynamic and complex nature of urban problems (Quan et al., 2019), they allow for providing the planner and designer with multiple urban form iterations to intuit (Gopalakrishnan et al., 2021). For example, street network generation using deep learning techniques has been experimented with (Hartmann et al., 2017). This can influence methods of urban visualization but is currently not widespread in the industry due to the difficulties in interpreting the results (Miao et al., 2020).

AI-aided urban planning and design is both an important tool for improving existing cities as well as a tenet for future cities. A popular example of the use of AI in the generation of a masterplan is Masdar City in the United Arab Emirates, where the planning of personal rapid transit and autonomous vehicle systems was coupled with the planning and design of spaces from the very beginning of the project. Future cities such as Neom in Saudi Arabia and Beiyang AI Town in China will intrinsically link the emergent urbanism and lifestyle with AI techniques (Cugurullo, 2020; Gopalakrishnan et al., 2021).

At the architectural scale, the exploration of AI began with early efforts to use computation for generative form compositions and representation (Stiny and Gips, 1972). The evolution of AI led to integrated building systems documentation, complex formal representations, and experiments in decision support systems based on multiobjective optimization engines resulting in a wider design space (Keough and Benjamin, 2010). Decades of computational advancement, recent open-source sharing, and the availability of distributed cloud computing have rapidly increased the experimental creation of tools with analytical, optimization, and generative design capabilities. The advent of IoT devices with embedded sensors has allowed for the sensing and responding to the built environment and human activity in complex spatial networks at many scales (Gopalakrishnan et al., 2021; Manivannan et al., 2020).

As computational systems have emerged as a fundamental keystone in architectural design, they have extended the capacity of traditional processes, while challenging design conventions and praxis (Rocker, 2006). The development of computational design tools has changed the way machines can inform and actively interact with the design process. Computational systems have greatly reduced labor time, improved design quality, and reduced cost by helping planners and designers to work more efficiently. The progressive adoption of technological solutions has transformed the architecture, engineering, and construction (AEC) industry in many ways: first by introducing computer-aided design (CAD) software, then by exploring new construction techniques through parametric tools, and now by introducing statistical computing capacities such as big data and AI.

AI techniques can be applied to several design problems such as building massing, orientation, façade design, thermal comfort, daylighting, life cycle analysis, structural design analysis, energy, and cost (Machairas et al., 2014). Recent examples include the linking of CAD packages to simulation engines, such as the DIVA plug-in that links the Rhinoceros software to the Radiance software (Lagios et al., 2010) or design tools that integrate solar radiation, energy and wind flow analysis modules, such as project Vasari by Autodesk Labs (Gopalakrishnan et al., 2021).

Current planning and design research has also explored the development of new interfacing tools and ML models. For example, a multicriteria genetic algorithm was used to optimize architecture desk layouts in offices by evaluating existing office design (Anderson et al., 2018). These heuristic algorithm-based optimizations can influence the design of a building's envelope according to simulated energy performance (Tuhus-Dubrow and Krarti, 2010) as well as expected energy performance (Chronis et al., 2012). Heuristic algorithms are also useful for geometrical form optimization, and for accounting construction costs (Rudenauer and Dohmen, 2007) and real-estate value (Alfaris and Merello, 2008). In this context, AI has been employed to optimize structural geometry and was able to identify the optimum solution out of approximately 30,000 possible designs (Flager et al., 2009; Gopalakrishnan et al., 2021).

Recent projects by research groups at Autodesk, including Project Discover and Autodesk@MarRS, have explored the use of computational systems in urban planning and design as part of a "generative design" process by using computational capabilities to generate feasible solutions and to explore larger solution spaces based on robust and rigorous models that meet required design conditions and performance criteria. A number of tools are now available for planners and designers who seek to incorporate genetic algorithms in the design process, most notably Galapagos for Rhino Grasshopper (Rutten, 2013) and Optimo for Revit Dynamo, where traditional parametric 3-D modeling programs can be augmented by libraries that add ML capabilities (e.g., artificial neural network, nonlinear regression, k-means clustering, etc.) to be used in conjunction with spatial data modeling (Gopalakrishnan et al., 2021).

Complexity science and urban systems

In the 21st century, the rise of the smart city paradigm has significantly contributed to the understanding of the intrinsic complexity (Naphade et al., 2011) of urban environments. The complexity of cities makes an interdisciplinary approach to the planning and designing of cities and their dynamics increasingly imperative, as argued by Batty and Marshall (2012), who evince that the idea of a bottom-up approach became important at the same time as the notion that "many different systems being claimed by different disciplines were part of a more generic whole." The need for a holistic approach to problem-solving in the context of urban planning and design calls for an understanding of the complex patterns that are visible in the city as we study social networks, transportation networks, spatial networks, etc., through the lens of complexity science (Batty, 2009; Gopalakrishnan et al., 2021; Manivannan et al., 2020). Mitchell (2014) states: "The 'study of complexity' refers to the attempt to find common principles underlying the behavior of complex systems—systems in which large collections of components interact in nonlinear ways. Here, the term nonlinear implies that the system cannot be understood simply by understanding its individual components; nonlinear interactions cause the whole to be 'more than the sum of its parts.'"

One way to understand this is to view the city as a network of resource flows (Kennedy et al., 2011) and its buildings as a network of interconnected programmatic spaces and circulatory paths, or nodes and links, within the superstructure of the urban spatial network (Gopalakrishnan et al., 2021).

Key aspects of spatial network analysis

Scale of spatial networks

Scale is a fundamental concept in all space-related analysis (Sheppard and McMaster, 2008; Jiang and Anders Brandt, 2016; Boeing, 2018). In studies of social interactions, population movements and urban structure, two of the most common types of spatial networks, include two scales, between and within cities. The analysis of intercity networks is focused on the interactions and connectivity between cities within a region. This type of analysis treats every city as a single node. The information on the city is gathered and aggregated as an indivisible object (Alderson and Beckfield, 2004; Neal, 2011). The intracity spatial network analysis is focused on the heterogeneity within a city, that every part of a city could have different urban functions or roles (Jiang and Claramunt, 2004; Chin and Bouffanais, 2020). Thus, these analyses allow us to understand and uncover the underlying structure of the city. Examples for intercity and intracity networks are shown in Fig. 3.1.

Fig. 3.1A and B are examples for intercity and intracity networks. The colors show the community detection result (modularity-based) and sizes of nodes indicate betweenness centrality. Both community detection and betweenness centrality are network analysis techniques, which will be discussed in the next section of this chapter (Section: Analysis of spatial networks). Fig. 3.1A shows the airline network in Southeast Asia. Each node is an airport and represents a city. The large nodes include SIN (Singapore), CGK (Jakarta, Indonesia), KUL (Kuala Lumpur, Malaysia), MNL (Manila, Philippines), RGN (Yangon, Myanmar), and SGN (Ho Chi Minh, Vietnam). Fig. 3.1B shows the public transport (including train and bus) network between subzones (an administrative level) in Singapore. The community detection result returned five communities that grouped the subzones according to their physical locations, e.g., the light green subzones at the bottom left corner are mainly located in the western part of Singapore, whereas the majority of orange subzones at the bottom right corner are located in the eastern part. The other three communities at the top (green, blue, and purple, gray, light gray in print version) contained other subzones that were located in the northern, central, and northeastern parts. The mixed patterns in community detection results indicated strong connectivity between these regions.

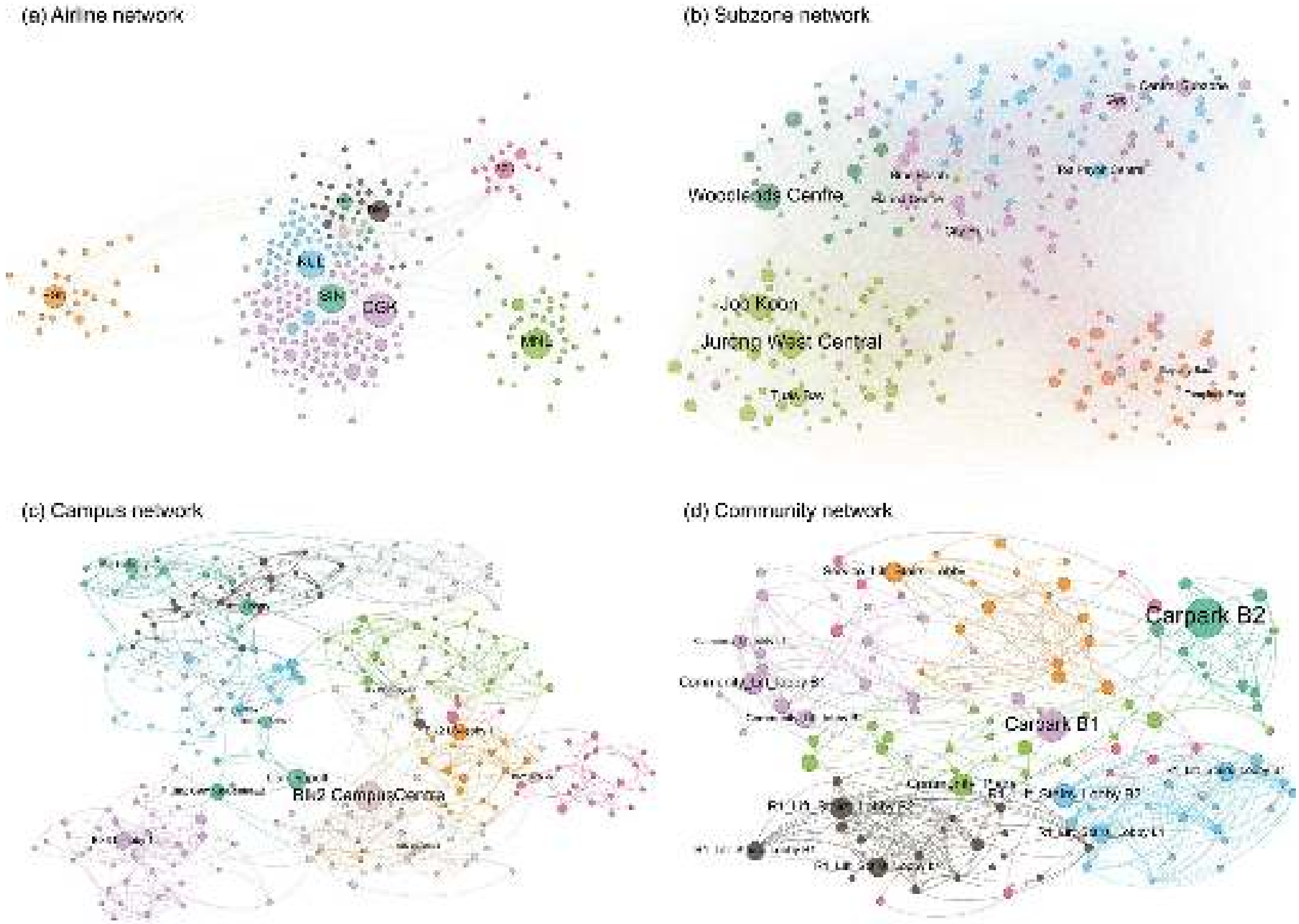


FIG. 3.1 Spatial network examples of three different scales: (A) an airline network, where cities are nodes; (B) a public transportation network within a city, where nodes are the subdistricts (subzones); (C) a university campus network, where nodes are the spaces within the buildings; and (D) a vertically integrated building, where nodes are spaces of different programs. Sizes of nodes indicate the community detection and betweenness centrality results. *The calculations and figure generations were generated in Gephi.*

As many cities are increasingly arranged vertically, urban space should be analyzed in a higher resolution because different types of space could be vertically overlapped. For example, in Singapore, there are residential towers that were built on top of bus interchanges. In this situation, the horizontal subdivision of space (such as the subzones in Singapore, Fig. 3.1B) is not suitable for the analysis of space. In a vertical urban space, the subdivision could be even smaller spaces with distinguishable functions, i.e., micro-spaces, e.g., shops, lift lobbies, gardens, classrooms, or houses. The focus of the analyses of these micro-space networks is on understanding their microlevel spatial interactions and structure. For example, how people move between the shops, or which locations are more accessible. Fig. 3.1C shows the adjacent relationships between micro-spaces of the Singapore University of Technology and Design (SUTD) Campus. The campus is designed in a way that fosters connectivity between the various buildings and programs, e.g., through multiple sky-bridges at different levels. The community detection result of the campus (Fig. 3.1C) shows block structure, i.e., most of the communities (nodes with the same color) are formed by spaces in the same block. At the same time, the whole campus network also shows a strong connectivity between blocks. Fig. 3.1D shows an example of a spatial network in a vertically integrated building, Kampung Admiralty, a high-density mixed-use development for the elderly in Singapore. The two groups of nodes at the bottom (gray at the bottom left and blue, light gray in print version, at the bottom right) indicate the two residential towers of Kampung Admiralty, which are separated from the public spaces and facilities of the development to maintain the privacy of the residents. The towers are only connected to the public spaces and facilities and to each other on Level 6 (Sky Garden) and on the ground level; the green nodes, gray in print version (center) are the community spaces that are mainly located on the ground level, whereas the orange nodes, gray in print version (top middle) are the public spaces at Level 6, which include a sky garden, a playground, and walkways that connect the residential and commercial spaces; nodes at the top right corner are mainly composed of the basement car park, whereas the top left corner contains the nodes of the central service lift lobbies. These examples show that a basic network analysis of space networks can reveal the structure of the functions in the buildings.

Similar to geographical and spatial studies, in spatial network analysis, the concept of scale is important for the identification of the research question and the study of object definition processes: in other words, what spatial unit is appropriate for accessing a specific research problem, and what unit would then lead to the questions of what can be explained and to what extent the results can be interpreted. In addition, the scale of study also implies the spatial boundary, i.e., what the limits of the study are. Therefore, it also indicates the edges of the cases and where edge effects may occur.

Common types of spatial networks

A spatial network (graph) can be defined as $G\ (V, E)$, where V is a set of nodes (also known as vertices), and E is a set of links (also known as edges). In addition, a spatial network can be categorized by its links' direction (i.e., undirected vs directed) and links' weight (i.e., unweighted or weighted); by the definition of connectivity (topologically adjacent, accessibility, or visibility); and if it is a dual representation network.

Directional and weighting

While the analysis of spatial networks applies concepts from network analysis and graph theory, there are several ways to define a spatial network. Direction and weightings are two main aspects of a network. An undirected network means that the links are mutual, i.e., two nodes are connected bidirectionally, e.g., the accessible network is established by a network without any one-way connections. For a directed network, the links are shown as arrows, indicating that each link only flows in one direction, e.g., space users can go from one node to another through a directed link, but not in the opposite direction ; if the flows are accessible between two nodes, two links with opposite directions are needed. Weights could be added to links and nodes, but usually they are used to describe the links' weight. An unweighted network means that the weights of links are the same. On the other hand, a weighted network is used to describe links that are not uniform, i.e., some links have higher weights than others. The weight of links can be used to describe the intensity, cost, and capacity between connected nodes.

Adjacency, accessibility, and visibility

Three basic types of relationships are commonly used to represent the interaction of spaces. The spatial adjacency network is the most intuitive network. It defines each space as a node and a link is generated between every two directly connected spaces. In other words, a link in the adjacent network indicates that the two nodes are not only next to each other but also connected (e.g., through an open door or a hallway). An example is given in Fig. 3.2A. It shows the adjacency network of an integrated community building. Accessibility is one of the important relationships in spatial network analysis studies. The accessibility in this form of analysis is defined through a cost function, i.e., a threshold in distance, moving time, or transport fare: for example, the accessibility from residential blocks to medical facilities, which can also be described as the accessibility between different building programs. Fig. 3.2B shows the 50-m reachable network of a community building. In addition to accessibility, visibility network analysis is a method to access the intervisibility relationship between nodes that has been developed from the spatial analysis theories of space syntax (Turner et al., 2001; Jiang and Claramunt, 2002).

Dual representation

Dual representation networks (also known as dual graphs) focus on the relationship of the connections (Añez et al., 1996; Batty, 2013). Technically, the dual representation of a network converts the links to nodes and establishes links through the relationships of node-sharing in the original network. For example, in a typical street network, the streets are represented as links and the intersections (endpoints of streets) as nodes. A dual representation of the street network would be a network with streets defined as nodes, and links represented as the relationship between streets, i.e., street-street connectivity networks (Jiang and Liu, 2009). While the dual representation network focuses on the relationships between the connections, it is useful for the analysis of the linkages themselves, e.g., the evaluation of traffic in connections (Hu et al., 2008), or the assessment of the attractiveness of each connection (Wen et al., 2017). An example for dual representation in a community building is shown in Fig. 3.2C.

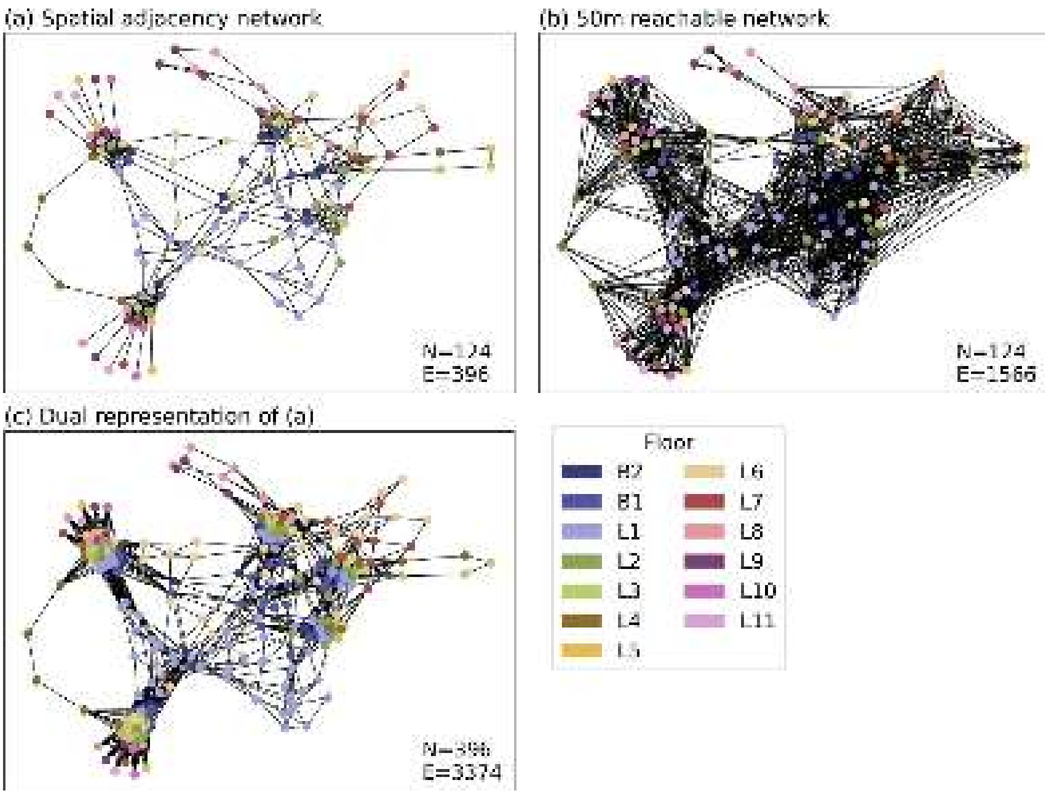


FIG. 3.2 Three types of commonly used spatial networks in Kampung Admiralty, Singapore: (A) spatial adjacency network, (B) reachable network, and (C) dual representation network. *Networks were generated and visualized in Python.*

Analysis of spatial networks

The analysis of complex networks is a combination of methods and algorithms used to uncover their structure. A complex network is composed of two main elements—the nodes which act as agents, and the links which capture the complex relationships or interactions between the nodes. Three basic and classical analyses of complex network studies include the measurement of the importance of nodes, measurements of the criticality of links, and the identification of communities.

Measurements of the importance of spatial nodes

The main purpose for measuring the importance levels of nodes is to identify the key players exhibiting significant influence as a result of complex interactions. Using different definitions of "main players" or "significance," there are three basic centrality measurements that have been frequently discussed in the relevant literature, including "degree," "closeness," and "betweenness" (Barrat et al., 2004). Fig. 3.3 shows an example of the three centrality measurements for the SUTD Campus network.

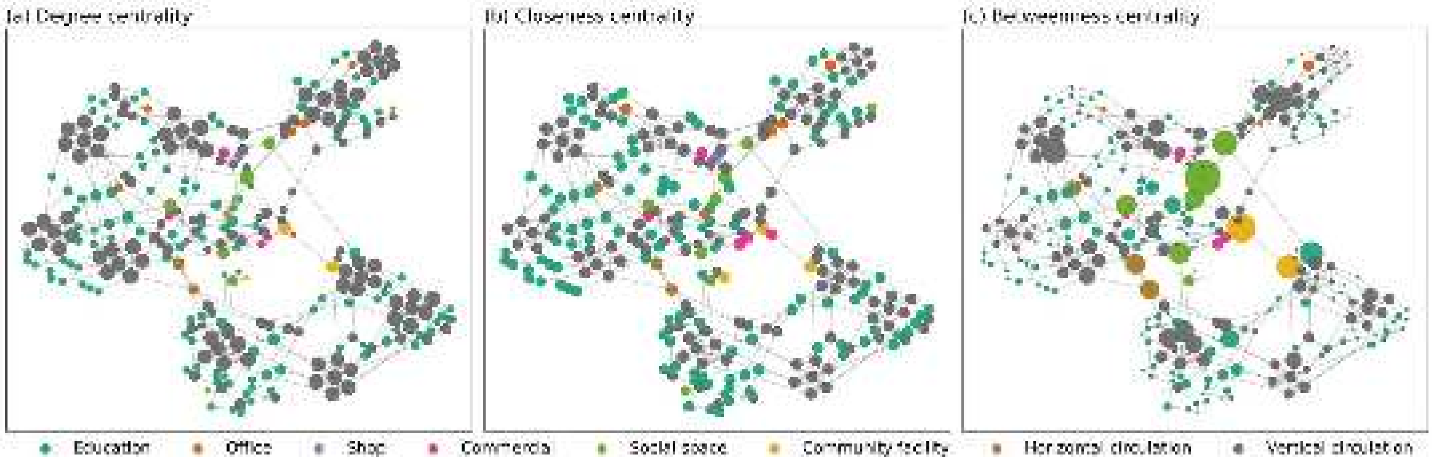


FIG. 3.3 The demonstration of (A) degree centrality, (B) closeness centrality, and (C) betweenness centrality for the SUTD Campus network. The calculation of the shortest path in (B) and (C) have considered the actual distance between the centroid of the spaces. *Calculated and visualized in Python.*

Degree centrality is the most basic measurement of a node's significance. By definition, it is the number of neighbors a node has. The higher the degree centrality, the more neighbors a given node has, hence the more influencing power it potentially holds. This measure is useful in finding the most connected spaces or influential individuals within a spatial or social network by ranking all nodes within a network. The calculation of degree centrality can be useful for the effective planning of active social spaces that act as critical connectors in the built environment.

Closeness centrality measures the distance from one source node to all other nodes, i.e., how close a node is to all others. The Small World Problem, a famous experiment conducted by Milgram (1967), stated that every two people in the United States can be connected through approximately three friendship links, meaning that on average, everyone can reach everyone else through two people. Thus, the question about heterogeneity between people arises, i.e., is any of them closer to everyone else? The calculation of closeness centrality first determines the step counts of the shortest path from one source node to all other nodes (namely farness). The inverse of the summation of farness is closeness. A node with high closeness can reach the whole network with the least efforts (steps). So, closeness centrality can help in identifying spatial clusters within a building or any spatial development, highlighting the spatial influencing power of distribution of nodes. For example, an international airport is connected to more places in fewer steps (transfers) than a domestic airport in the same country, because domestic airports rely on the former to reach international destinations.

Betweenness centrality is identifies the "bridge-like" nodes within a complex network. A node with high betweenness centrality acts as a "broker." It controls the connectivity of some nodes that "hide" behind it. For example, a bridge between two islands would have high betweenness because all flows from one island will need to go over the bridge to reach the other other. Technically speaking, betweenness measures the levels of criticalness of a node in terms of being "in between" all pairs of nodes. The calculation of this measurement needs to identify the shortest path of all pairs of nodes and count the number of nodes appearing in these shortest paths. Previous studies used betweenness as a measurement of vulnerability (Ducruet et al., 2010). The concept behind this is that when high betweenness nodes are removed (e.g., because they malfunctioned or are attacked), the network could break into pieces or the connection could be increased as the flows would need to be rerouted to a new shortest path structure. In the context of studying human movement, a high betweenness centrality measure (e.g., Fig. 3.4) indicates that a node is part of many shortest routes, which typically translates to increased human movement and interactions.

Other than the centralities measurements, there are two groups of advanced algorithms that are frequently used for assessing the importance of nodes. The first group is used to uncover the core and peripheral structure of complex networks. One of the most recognized methods in this area is the so-called *k-shell decomposition* (Carmi et al., 2007; Kitsak et al., 2010). The concept of *k-shell decomposition* is that core nodes have links to each other; thus, if a node's neighbor is a peripheral node, there is a high probability that it is also a peripheral node. Technically, the calculation process starts by setting the k-value to 1, and iteratively removing nodes with degree equal to k, until all nodes' degree centrality is higher than k; all the removed nodes belong to the k-shell group; then, the k-value is increased by 1 and the nodes removal and k-shell assigning process is repeated until all nodes are processed. The k-shell values can be used to differentiate the nodes from core, periphery, or any hierarchy of levels

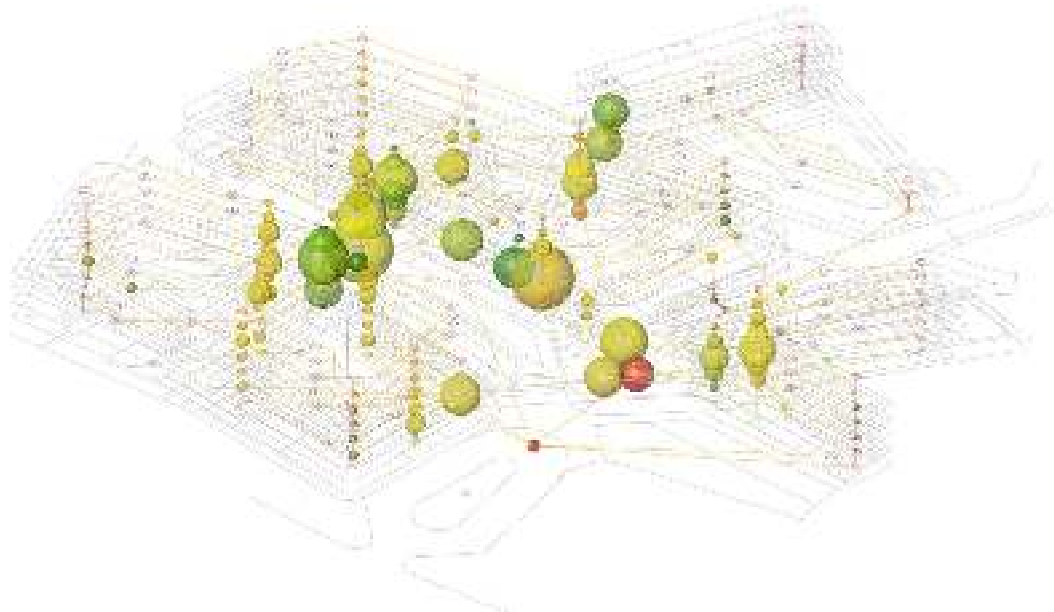


FIG. 3.4 Betweenness centrality diagram of the SUTD Campus network. The calculation of betweenness centrality includes the actual distance in searching for the shortest path. *Calculated in Python and visualized in Rhinoceros, Grasshopper.*

in between, i.e., nodes with higher *k*-shell values have a larger probability to be cores, and vice versa. In a spatial network, the top-level core nodes are the nodes surrounded by second-level core nodes, hence, they can be used to identify the regional cores or the most influential nodes (Kitsak et al., 2010; Chin and Bouffanais, 2020).

The second group of advanced algorithms is utilized in iterative process calculations to penetrate networks. It includes Google's *PageRank* algorithm (Brin and Page, 1998) and the Hyperlink-Induced Topic Search (HITS) algorithm (Kleinberg et al., 1999). The reason for developing these advanced algorithms was to improve the measurements of the importance of nodes at a global level through the penetration of the whole network and the consideration of the direction of edges (for directed networks). These algorithms were developed for the identification of key webpages in the World Wide Web. PageRank uses a large number of "random surfers" who move within a network and count them on each page in every step. After surfers move randomly for a certain time, the number reaches an equilibrium state that indicates the constant number of surfers appear at each page. The mathematics of the PageRank algorithm is closely related to that of a Markov chain process. In spatial network analysis, PageRank has been used and modified in previous studies. Modifications include Place Rank (El-Geneidy and Levinson, 2011) that considers the flow of population, EpiRank (Huang et al., 2019a,b) and Geographical PageRank (Chin and Wen, 2015) that considers the distance decay effect.

Measurements of the criticalness of links

In the discussion of the significance of links, previous studies focused on the criticalness of each link within the network, i.e., which links are more critical than others (Barrat et al., 2004; Onnela et al., 2007; Papakyriazis and Boudourides, 2001). The concept of criticalness and vulnerability of links are related to the concept of strong and weak ties in social network analysis (Granovetter, 1973). A strong tie (bond) in a social network indicates a strong bonding between a group of people—everyone knows everyone else in the group very well—whereas a weak tie (bridge) indicates more potential opportunities—a person with more weak ties indicates that he/she knows more people from outside the groups, which results in more information from other groups (Granovetter, 1973; Hansen, 1999; Gee et al., 2017). This is similar to the concept of betweenness centrality; thus, the most intuitive way to measure the criticalness of links is through applying the betweenness centrality measurement to them, namely edge-betweenness (Girvan and Newman, 2002; Newman and Girvan, 2004).

A link is more critical or vulnerable than others if its removal would break the network into two components or increase the separation of nodes (e.g., diameter, average closeness). These critical link have been defined as "bridges" (or "global bridges") in previous studies (Bollobás, 1998; Huang et al., 2019a,b). On the other hand, if the removal of a link would not separate the nodes at the two ends, i.e., the alternative path to connect the two nodes is short, then it is less vulnerable and is known as "bond." To inspect the hierarchical structure from bridge to bond, previous studies have also defined a multilevel local bridge (Huang et al., 2019a,b; Huang and Chin, 2020). The hierarchical structure is determined through the length of the alternative path after the removal of the target link, i.e., if the alternative path is as long as the average path length of all pairs of nodes, the link is assigned as a global bridge (highest level); if the alternative path length is shorter than that, it is considered as the second highest local bridge, etc.

Detection of community structure

Besides the analysis of nodes and links, one of the other main analyses for network structure is community detection (Girvan and Newman, 2002). Similar to the clustering analysis in spatial analysis that aims to find points that are near to each other, the main purpose of detecting communities is to identify nodes that are densely connected to each other. Some examples are shown in Fig. 3.1. For instance, in the airline network of airports in Southeast Asia (Fig. 3.1A), domestic airports are usually connected to each other but not linked to those in other countries. This forces them to form a densely connected structure within their country and only link to airports outside through brokers (international airports). For example, the green nodes at the bottom right corner of the network are the airports in the Philippines, the red nodes at the top right are the airports in Vietnam, and the orange nodes on the left are airports in Myanmar.

In order to detect communities in a complex network, the measurement of modularity is introduced (Newman and Girvan, 2004; Newman, 2006). Qualitatively, modularity is a measurement for the quality of nodes partition. Quantitatively, modularity compares the number of links in a community (both ends are in the same community) to the distribution of links at random (in the same community on the basis of chance). The modularity measurement is typically used along with a heuristic algorithm for nodes grouping (Clauset et al., 2004;

Guimera et al., 2004, 2005; Blondel et al., 2008). The Louvain method—the currently most popular modularity-based community detection method—is a greedy algorithm that iteratively merges the communities and calculates the changes of modularity (Blondel et al., 2008). Using a simulated annealing heuristic algorithm, Guimera et al. (2004) developed another way to detect the optimal partitions of nodes with a fluctuation process.

Due to the limitations of the modularity calculation, the modularity-based methods do not capture the effects of direction and flow structure in a directed network. Therefore, the MapEquation algorithm has been introduced to better understand the effects of flow in a directed network (Rosvall et al., 2009). Similar to PageRank, MapEquation uses a random surfer process in the calculation. In other words, the partition results of MapEquation tend to maximize the flows of random surfers more within and less in between partitions. Since the concept of the MapEquation algorithm is more aligned with the nature of population flow, it can delineate better partitioning results in a transportation flow or population movement network (Zhong et al., 2014; Chin and Bouffanais, 2020).

Computational social science and its AI applications

Comparing and correlating the various importance measurements and empirical statistics data (e.g., actual population flow, socio-demographic, disease cases) allows for the identification ofthe significance of spaces regarding their programs and locations. Several previous studies have been conducted to analyze population movements at the urban scale. For example, Wen et al. (2017) integrated a genetic algorithm to analyze the traffic flow data and the dual representation of the road network structure using a modified PageRank algorithm to obtain a spatial distribution of spatial attractiveness. The results were subsequently used to discuss traffic congestion and delineate the traffic impact area (Wen et al., 2016). Other research has studied daily round trip commuting patterns and integrated the data with several infectious diseases, including 2009 H1N1 influenza, enterovirus cases, and 2003 Severe Acute Respiratory Syndrome, to assess the disease spreading risk of the two directions of commuting, i.e., from home to the workplace and back (Huang et al., 2019a,b; Chin and Huang, 2020). In a study of a campus network, researchers used the class attending timetable data of individual students to establish a flow network in between campus buildings. The study delineated the campus into multiple zones using community detection methods and analyzed the separation levels through a campus isolation scenario simulation process to access the effects of campus isolation to control the spreading of diseases (Wen and Chin, 2015).

These computational analyses of network measures and empirical statistics allow for the identification of parameters for the planning and design of size, colocation, and placement of social spaces within larger building or spatial developments. Combined with the nodes' spatial attributes such as floor area, height, openness, visibility, etc., it allows for the further identification of the factors that influence the effectiveness of these spaces in terms of their use. The many possibilities and parameters of spatial distributions at multiple scales can benefit from complexity science-based methods that map and analyze spatial networks with greater quantitative measures, types of intelligence, and a rich collation of data sources. In addition, a variety of datasets from different fields of research as well as the ubiquity of smart IoT devices provide the basis for new methods of sensing and analyzing actual space use in the built environment.

The study of space use is interdisciplinary in nature and also draws from computational social science. The latter is a subfield of the social sciences that uses computational methods to study social phenomena. To evaluate urban and architectural space use, these include the tracking of human activities in the built environment to better understand intertwined social, spatial, and temporal behaviors. The computational methods employed in this context are mainly based on algorithms that allow for the building of predictive models that use tracking data. In addition, statistical techniques and simple computational processes are employed to study the relationship between humans and the built environment they inhabit (Alessandretti et al., 2018).

ML is considered to be a subset of AI and it can be applied in two important ways: (a) human activity recognition (Lara and Labrador, 2013), and (b) location prediction (Zafari et al., 2019). Both of these applications are based on supervised methods that use training data to predict the class of interest, e.g., running, walking, or specific locations (rooms, etc.). This can be done offline (passive prediction after data collection is complete) or online (active prediction during data collection). Online predictions, on the one hand, are helpful for active interaction with the user or for real-time decision-making. However, they are computationally intensive and rely on real-time and incomplete data. Offline predictions, on the other hand, allow researchers to analyze the complete dataset and provide the flexibility of tweaking models for better prediction accuracy. Offline methods are therefore more suitable for researchers who study long-term behavior of humans that requires devices to be energy efficient. However, unsupervised ML methods such as clustering and pattern recognition can also be useful for the understanding of human activity patterns such as the

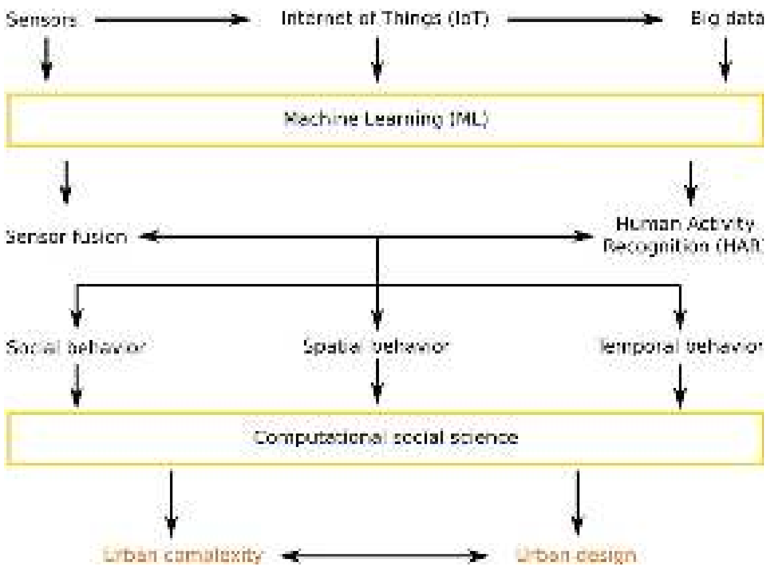


FIG. 3.5 Application of ML in studying the social and spatiotemporal behaviors of humans in the built environment.

identification of important nodes or attractive places and the delineation of traffic impact areas (Wen et al., 2016, 2017).

Wearable devices, including mobile phones, smart watches, and smart glasses, have become an important part of our everyday life. Social science researchers and urban planners have used large-scale availability of big data generated by these mobile devices to track humans and to study their behavior in the built environment. The study of human mobility has led to important developments in our understanding of human behavior, including the descriptions of their daily mobility patterns in cities, "burstiness" of individual and collective behavior, and simple mathematical models of their displacement (Barthélemy, 2011; Manivannan et al., 2020). All of these have helped to inform the planning and design of cities, e.g., through the appropriate placement of facilities and the provision of connections between important places.

Mobile sensors (e.g., inertial measurement unit, IMU) that consist of an accelerometer and gyroscope along with a barometer and magnetometer, are the predominantly found built-in sensors in mobile phones (Lara and Labrador, 2013; Manivannan et al., 2020). The data from these sensors can be processed and used to recognize many activities, such as running, walking, standing, sitting, sleeping, climbing stairs, etc. The identification of these activities within the context of their location can help to understand how a particular space is used. Barometer sensors are sensitive to change in elevation and have been used to recognize vertical displacement through elevators, escalators, and stairs (Manivannan et al., 2020). The identification of vertical mobility can indicate the choice of users regarding vertical mobility modes and their time of use during the day can, e.g., help to avoid vertical traffic congestion, and the average vertical displacement height can help make decisions about the allocation of facilities on appropriate building levels (Manivannan et al., 2020).

Location-based sensors including GPS, Bluetooth, Wi-Fi access points, and Radio Frequency Identifier (RFID) can be used to identify the location of users in indoor or outdoor environments (Zafari et al., 2019). Peer-to-environment sensing systems developed using these sensors can be used for tracking and navigation. Due to the environmental obstacles (such as walls, plants, etc.), the receive signal strength indication (RSSI) measured at the receiver end from these sensors is unreliable as an indicator of distance (Zafari et al., 2019). Hence, ML is used to convert the radio signal available in each location and is studied over time and the revealed patterns of these signals can be used with supervised ML algorithms to predict their corresponding location.

The application of ML can thus be used to study the socio-spatial behavior of humans in the built environment and inform urban planning and design. As such, it can be an integral part of evidence-based approach. The framework shown in Fig. 3.5 summarizes the application of tools and techniques from computational and information science to understand social and urban structures and to facilitate urban development. The first layer consists of (big) data from the built environment and human activities, which were collected by sensors and the IoT. The ML methods are applied to these data to identify patterns, leading to sensor fusions and HAR. Further analyses can provide a deeper understanding of space users in terms of their social, spatial, and temporal behaviors. The integration of these analyses can also contribute to computational social science which then can help to further develop urban applications of complexity science (Manivannan et al., 2018; Bouffanais and Lim, 2020; Chin and Bouffanais, 2020).

Summary

In this chapter, we described a new complexity science-based approach to the understanding of the dynamics, growth, and evolution of cities in a scientifically predictable, quantitative way. We discussed innovative AI-aided urban planning and design methods and tools and how these have already been and can be applied in the future. We further described spatial network analysis and common types of spatial networks as well as computational social science and its application to urban planning and design problems. The complexity science-based approach to analyzing the dynamics of cities described in this chapter allows us to uncover and understand their underlying structure and can lead to more informed urban planning and design decisions in the future.

Acknowledgments

The authors would like to thank Chirag Hablani, Srilalitha Gopalakrishnan, and Daniel Kin Heng Wong from the Singapore University of Technology and Design for their contributions to this chapter.

References

Abduljabbar, R., et al., 2019. Applications of artificial intelligence in transport: an overview. Sustainability 11 (1), 189.
Alderson, A.S., Beckfield, J., 2004. Power and position in the world city system. Am. J. Sociol. 109 (4), 811–851.
Alessandretti, L., Lehmann, S., Baronchelli, A., 2018. Understanding the interplay between social and spatial behaviour. EPJ Data Sci. 7 (1), 36.
Alfaris, A., Merello, R., 2008. The generative multi-performance design system. In: ACADIA Proceedings: Silicon +Skin: Biological Processes and Computation, pp. 448–457.
Allam, Z., Dhunny, Z.A., 2019. On big data, artificial intelligence and smart cities. Cities 89, 80–91.
Alvarez, R., 2017. The relevance of informational infrastructures in future cities. J. Field Actions 17, 12–15.
Anderson, C., et al., 2018. Augmented space planning: using procedural generation to automate desk layouts. Int. J. Archit. Comput. 16 (2), 164–177. https://doi.org/10.1177/1478077118778586.
Añez, J., De La Barra, T., Pérez, B., 1996. Dual graph representation of transport networks. Transp. Res. B Methodol. 30 (3), 209–216.
Barrat, A., et al., 2004. The architecture of complex weighted networks. Proc. Natl. Acad. Sci. 101 (11), 3747–3752.
Barthélemy, M., 2011. Spatial networks. Phys. Rep. 499 (1–3), 1–101.
Batty, M., 2009. Complexity and emergency in city systems: implications for urban planning. Malays. J. Environ. Manag. 10 (1), 15–32.
Batty, M., 2013. Big data, smart cities and city planning. Dialogues Hum. Geogr. 3 (3), 274–279.
Batty, M., Marshall, S., 2012. The origins of complexity theory in cities and planning. In: Portugali, J., et al. (Eds.), Complexity Theories of Cities Have Come of Age: An Overview With Implications to Urban Planning and Design. Springer, Berlin Heidelberg, pp. 21–45.
Batty, M., et al., 2012. Smart cities of the future. Eur. Phys. J. Spec. Top. 214 (1), 481–518.
Bettencourt, L., West, G., 2010. A unified theory of urban living. Nature 467 (7318), 912–913.
Blondel, V.D., et al., 2008. Fast unfolding of communities in large networks. J. Stat. Mech. Theory Exp. 10, P10008.
Boeing, G., 2018. Measuring the complexity of urban form and design. Urban Des. Int. 23 (4), 281–292.
Bollobás, B., 1998. Modern Graph Theory. Springer Science & Business Media, Berlin Heidelberg.
Bouffanais, R., Lim, S.S., 2020. Cities—try to predict superspreading hotspots for COVID-19. Nature 583, 352–355.
Brin, S., Page, L., 1998. The anatomy of a large-scale hypertextual web search engine. Comput. Netw. ISDN Syst. 30 (1–7), 107–117.
Camagni, R., 2003. Incertidumbre, capital social y desarrollo local: enseñanzas para una gobernabilidad sostenible del territorio. Investig. Reg. J. Reg. Res. (2), 31–57.
Carmi, S., et al., 2007. A model of Internet topology using k-shell decomposition. Proc. Natl. Acad. Sci. 104 (27), 11150–11154.

Chin, W.C.B., Bouffanais, R., 2020. Spatial super-spreaders and super-susceptibles in human movement networks. Sci. Rep. 10 (1), 1–19.
Chin, W.C.B., Huang, C.Y., 2020. Comments on 'EpiRank: modeling bidirectional disease spread in asymmetric commuting networks' for analyzing emerging coronavirus epidemic patterns. medRxiv.
Chin, W.C.B., Wen, T.H., 2015. Geographically modified PageRank algorithms: identifying the spatial concentration of human movement in a geospatial network. PLoS One 10 (10), 1–23.
Chronis, A., et al., 2012. Performance driven design and simulation interfaces: a multi-objective parametric optimization process. In: Symposium on Simulation for Architecture and Urban Design (SimAUD) 2012, pp. 81–88.
Cisco, 2020. Cisco: 2020 CISO benchmark report. Comput. Fraud Secur. 3 (4).
Clauset, A., Newman, M.E., Moore, C., 2004. Finding community structure in very large networks. Phys. Rev. E 70 (6), 066111.
Cugurullo, F., 2020. Urban artificial intelligence: from automation to autonomy in the smart city. Front. Sustain. Cities 2, 38.
Doug, L., 1994. Christopher Alexander: an introduction for object-oriented designers. ACM SIGSOFT Softw. Eng. Notes, 39–46. https://doi.org/10.1145/181610.181617. Association for Computing Machinery (ACM).
Ducruet, C., Lee, S.W., Ng, A.K., 2010. Centrality and vulnerability in liner shipping networks: revisiting the Northeast Asian port hierarchy. Marit. Policy Manag. 37 (1), 17–36.
El-Geneidy, A., Levinson, D., 2011. Place rank: valuing spatial interactions. Netw. Spat. Econ. 11 (4), 643–659.
Fernández-Güell, J.M., et al., 2016. How to incorporate urban complexity, diversity and intelligence into smart cities initiatives. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer Verlag, Spain, https://doi.org/10.1007/978-3-319-39595-1_9.
Flager, F., et al., 2009. Multidisciplinary process integration & design optimization of a classroom building. Electron. J. Inf. Technol. Constr. 14, 595–612.
Garfield, M., 2019. Luis Bettencourt on the Science of Cities. Available at: https://open.spotify.com/episode/1pgspyxZhG357pt8RMzBc3.
Gee, L.K., et al., 2017. The paradox of weak ties in 55 countries. J. Econ. Behav. Organ. 133, 362–372.
Girvan, M., Newman, M.E., 2002. Community structure in social and biological networks. Proc. Natl. Acad. Sci. 99 (12), 7821–7826.
Goldblatt, R., et al., 2018. Artificial Intelligence for Smart Cities: Insights From Ho Chi Minh City's Spatial Development. Available at: https://blogs.worldbank.org/opendata/artificial-intelligence-smart-cities-insights-ho-chi-minh-city-s-spatial-development. (Accessed 20 March 2021 (Accessed 0 March 2021).
Gopalakrishnan, S., et al., 2021. Mapping emergent patterns of movement and space use in vertically integrated urban developments. In: Symposium on Simulation for Architecture and Urban Design (SimAUD) 2021 Proceedings.
Granovetter, M.S., 1973. The strength of weak ties. Am. J. Sociol. 78 (6), 1360–1380.
Güell, J.M.F., 2006. Planificación estratégica de ciudades: nuevos instrumentos y procesos. Reverté.
Guimera, R., Sales-Pardo, M., Amaral, L.A.N., 2004. Modularity from fluctuations in random graphs and complex networks. Phys. Rev. E 70 (2), 025101.
Guimera, R., et al., 2005. The worldwide air transportation network: anomalous centrality, community structure, and cities' global roles. Proc. Natl. Acad. Sci. 102 (22), 7794–7799.
Hansen, M.T., 1999. The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. Adm. Sci. Q. 44 (1), 82–111.
Harrison, C., et al., 2010. Foundations for smarter cities. IBM J. Res. Dev. 54 (4), 1–16.
Hartmann, S., et al., 2017. StreetGAN: towards road network synthesis with generative adversarial networks. In: Computer Science Research Notes. University of West Bohemia, Germany. Available at http://wscg.zcu.cz/.
Hu, M.B., et al., 2008. Urban traffic from the perspective of dual graph. Eur. Phys. J. B 63 (1), 127–133. https://doi.org/10.1140/epjb/e2008-00219-5. China.
Huang, C.Y., Chin, W.C.B., 2020. Distinguishing arc types to understand complex network strength structures and hierarchical connectivity patterns. IEEE Access 8, 71021–71040. https://doi.org/10.1109/ACCESS.2020.2986017. Taiwan: Institute of Electrical and Electronics Engineers Inc.
Huang, C.Y., Chin, W.C.B., Fu, Y.H., et al., 2019a. Beyond bond links in complex networks: local bridges, global bridges and silk links. Phys. A Stat. Mech. Appl., 536. https://doi.org/10.1016/j.physa.2019.04.263. Taiwan: Elsevier B.V.

Huang, C.Y., Chin, W.C.B., Wen, T.H., et al., 2019b. EpiRank: modeling bidirectional disease spread in asymmetric commuting networks. Sci. Rep. 9 (1). https://doi.org/10.1038/s41598-019-41719-8. Taiwan: Nature Publishing Group.

Jiang, B., Anders Brandt, S., 2016. A fractal perspective on scale in geography. ISPRS Int. J. Geo Inf. 5 (6). https://doi.org/10.3390/ijgi5060095. Sweden: MDPI AG.

Jiang, B., Claramunt, C., 2002. Integration of space syntax into GIS: new perspectives for urban morphology. Trans. GIS 6 (3), 295–309. https://doi.org/10.1111/1467-9671.00112. Sweden: Blackwell Publishing Ltd.

Jiang, B., Claramunt, C., 2004. Topological analysis of urban street networks. Environ. Plann. B Plann. Des. 31 (1), 151–162. https://doi.org/10.1068/b306. Sweden: Pion Limited.

Jiang, B., Liu, C., 2009. Street-based topological representations and analyses for predicting traffic flow in GIS. Int. J. Geogr. Inf. Sci. 23 (9), 1119–1137. https://doi.org/10.1080/13658810701690448. Sweden.

Kennedy, C., Pincetl, S., Bunje, P., 2011. The study of urban metabolism and its applications to urban planning and design. Environ. Pollut. 159 (8–9), 1965–1973. https://doi.org/10.1016/j.envpol.2010.10.022. Canada.

Keough, I., Benjamin, D., 2010. Multi-objective optimization in architectural design. In: Spring Simulation Multiconference 2010, SpringSim'10. United States., https://doi.org/10.1145/1878537.1878736.

Kitchin, R., 2014. The real-time city? Big data and smart urbanism. GeoJournal 79 (1), 1–14. https://doi.org/10.1007/s10708-013-9516-8. Ireland.

Kitsak, M., et al., 2010. Identification of influential spreaders in complex networks. Nat. Phys. 6 (11), 888–893. https://doi.org/10.1038/nphys1746. United States: Nature Publishing Group.

Kleinberg, J.M., et al., 1999. The web as a graph: measurements, models, and methods. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer Verlag, United States, https://doi.org/10.1007/3-540-48686-0_1.

Lagios, K., Niemasz, J., Reinhart, C.F., 2010. Animated building performance simulation (ABPS): linking Rhinoceros/Grasshopper with Radiance/Daysim. In: Presented at Fourth National Conference of IBPSA-USA.

Lara, O.D., Labrador, M.A., 2013. A survey on human activity recognition using wearable sensors. IEEE Commun. Surv. Tutorials 15 (3), 1192–1209. https://doi.org/10.1109/SURV.2012.110112.00192. United States.

Machairas, V., Tsangrassoulis, A., Axarli, K., 2014. Algorithms for optimization of building design: a review. Renew. Sustain. Energy Rev. 31, 101–112. https://doi.org/10.1016/j.rser.2013.11.036. Greece: Elsevier Ltd.

Mahamuni, A., 2018. Internet of Things, machine learning, and artificial intelligence in the modern supply chain and transportation. Def. Transp. J. 74 (1), 14–17.

Manivannan, A., et al., 2018. Are the different layers of a social network conveying the same information? EPJ Data Sci. 7 (1). https://doi.org/10.1140/epjds/s13688-018-0161-9. Singapore: SpringerOpen.

Manivannan, A., et al., 2020. On the challenges and potential of using barometric sensors to track human activity. Sensors 20 (23), 1–36. https://doi.org/10.3390/s20236786. Singapore: MDPI AG.

Miao, Y., Koenig, R., Knecht, K., 2020. The development of optimization methods in generative urban design: a review. In: SimAUD: Symposium on Simulation for Architecture & Urban Design, pp. 247–254.

Milgram, S., 1967. The small world problem. Psychol. Today 2 (1), 60–67.

Mitchell, M., 2014. How Can the Study of Complexity Transform Our Understanding of the World? Available at: https://aidontheedge.wordpress.com/2014/01/27/how-can-the-study-of-complexity-transform-our-understanding-of-the-world.

Naphade, M., et al., 2011. Smarter cities and their innovation challenges. Computer 44 (6), 32–39. https://doi.org/10.1109/MC.2011.187. United States.

Neal, Z., 2011. Differentiating centrality and power in the world city network. Urban Stud. 48 (13), 2733–2748. https://doi.org/10.1177/0042098010388954. United States.

Newman, M.E.J., 2006. Modularity and community structure in networks. Proc. Natl. Acad. Sci., 8577–8582. https://doi.org/10.1073/pnas.0601602103.

Newman, M.E., Girvan, M., 2004. Finding and evaluating community structure in networks. Phys. Rev. E. https://doi.org/10.1103/physreve.69.026113. American Physical Society (APS).

Onnela, J.P., et al., 2007. Structure and tie strengths in mobile communication networks. Proc. Natl. Acad. Sci. 104 (18), 7332–7336.

Papakyriazis, N.V., Boudourides, M.A., 2001. Electronic weak ties in network organisations. In: 4th GOR Conference, pp. 17–18.

Quan, S.J., et al., 2019. Artificial intelligence-aided design: Smart Design for sustainable city development. Environ. Plan. B Urban Anal. City Sci. 46 (8), 1581–1599. https://doi.org/10.1177/2399808319867946. South Korea: SAGE Publications Ltd.

Rocker, I.M., 2006. When code matters. Archit. Des. 76 (4), 16–25. https://doi.org/10.1002/ad.289. Conde Nast Publications, Inc.

Rosvall, M., Axelsson, D., Bergstrom, C.T., 2009. The map equation. Eur. Phys. J. Spec. Top. 178 (1), 13–23. https://doi.org/10.1140/epjst/e2010-01179-1. Sweden.

Rudenauer, K., Dohmen, P., 2007. Heuristic Methods in Architectural Design Optimization. pp. 507–514.

Rutten, D., 2013. Galapagos: on the logic and limitations of generic solvers. Archit. Des. 83 (2), 132–135. https://doi.org/10.1002/ad.1568.

Sheppard, E., McMaster, R.B., 2008. Scale and geographic inquiry: contrasts, intersections, and boundaries. In: Scale and Geographic Inquiry: Nature, Society, and Method. Wiley Blackwell, United States, pp. 256–267, https://doi.org/10.1002/9780470999141.ch13.

Stiny, G., Gips, J., 1972. Shape Grammars and the Generative Specification of Painting and Sculpture. The Best Computer Papers of 1971. pp. 125–135.

Taylor, D., 2019. Toward a Theory of Design as Computation. Available at: https://doriantaylor.com/toward-a-theory-of-design-as-computation. (Accessed 21 January 2021 (Accessed 201 January 2021).

Tuhus-Dubrow, D., Krarti, M., 2010. Genetic-algorithm based approach to optimize building envelope design for residential buildings. Build. Environ. 45 (7), 1574–1581. https://doi.org/10.1016/j.buildenv.2010.01.005. United States.

Turner, A., et al., 2001. From isovists to visibility graphs: a methodology for the analysis of architectural space. Environ. Plann. B Plann. Des. 28 (1), 103–121. https://doi.org/10.1068/b2684. United Kingdom: Pion Limited.

Wen, T.H., Chin, W.C.B., 2015. Incorporation of spatial interactions in location networks to identify critical georeferenced routes for assessing disease control measures on a large-scale campus. Int. J. Environ. Res. Public Health 12 (4), 4170–4184. https://doi.org/10.3390/ijerph120404170. China: MDPI AG.

Wen, T.H., Chin, W.C.B., Lai, P.C., 2016. Link structure analysis of urban street networks for delineating traffic impact areas. In: Advances in Complex Societal, Environmental and Engineered Systems. Springer, Cham.

Wen, T.H., Chin, W.C.B., Lai, P.C., 2017. Understanding the topological characteristics and flow complexity of urban traffic congestion. Phys. A Stat. Mech. Appl. 473, 166–177. https://doi.org/10.1016/j.physa.2017.01.035. Taiwan: Elsevier B.V.

Yao, H., et al., 2018. Deep multi-view spatial-temporal network for taxi demand prediction. In: 32nd AAAI Conference on Artificial Intelligence, AAAI 2018. United States. AAAI press. Available at https://aaai.org/Library/AAAI/aaai18contents.php.

Zafari, F., Gkelias, A., Leung, K.K., 2019. A survey of indoor localization systems and technologies. IEEE Commun. Surv. Tutorials 21 (3), 2568–2599. https://doi.org/10.1109/COMST.2019.2911558. United Kingdom: Institute of Electrical and Electronics Engineers Inc.

Zhong, C., et al., 2014. Detecting the dynamics of urban structure through spatial network analysis. Int. J. Geogr. Inf. Sci. 28 (11), 2178–2199. https://doi.org/10.1080/13658816.2014.914521. Switzerland: Taylor and Francis Ltd.

PART 2

AI tools and techniques

This page intentionally left blank

CHAPTER

4

Classes of AI tools, techniques, and methods

Geoff Kimm

Swinburne University of Technology, Research Fellow, Smart Cities Research Institute, Melbourne, VIC, Australia

Introduction

Cities are sophisticated, intricate organizations of nested spatiotemporal artifacts and relationships. That statement by itself may seem trite; nonetheless, cities are recognized to be complex systems with properties of self-organization, nonlinearity, discontinuity in change, feedback loops, adaptation, and a propensity toward continual disequilibrium (Batty, 2009; Walloth, 2016).

Innovation systems are themselves complex systems, and the pace of innovation in artificial intelligence (AI) is seen by experts to be accelerating (Grace et al., 2018; Katz, 2006). The complexity and diversity of the domain of contemporary AI is reflected in pressing current issues. These include skills shortages that reveal the multidisciplinary nature of modern AI practice; large language models that can generate convincing text on any topic even from limited and relatively unstructured data; the increasing focus on dedicated neuromorphic AI chips by manufacturers including the giants NVIDIA and Intel; growing use of AI in manufacturing; a forming focus on regulation of AI and its applications; and the development of nation-level AI strategies (Patience, 2021). Thus, in this chapter we find ourselves trying to discuss tools, techniques, and methods of the complex, dynamic field of AI, a nebulous target, in a context that is itself complex.

Fischer et al. identify a number of challenges in placing AI into general practice (Fischer et al., 2020). For deep learning, they include intrinsic challenges such as confidence measures on AI outcomes and the black box nature of AI; system engineering challenges such as data quality issues that may skew the accuracy of AI training; and interpretability and confidence challenges aligned with entrusting control to an AI system. Each of the challenges like these may apply to AI in urban design and planning practice and are potential axes on which to

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00012-3

measure and group that AI. Similarly, AI can be classified as analytical, human-inspired, and humanized, according to its respective qualities of cognitive, emotional, or social intelligence, and, from a perspective of its evolutionary stage, as Artificial Narrow, General, and Super Intelligence (Haenlein and Kaplan, 2019). Even for the seemingly straightforward task of identifying classes of algorithmic tools or AI methods, real-world practice contexts blur boundaries and suggest diverse grouping schema. The use of artificial intelligence in the city is as much about the mind of the human urban design and planning practitioner, and the desires and capabilities of that practitioner in concert with evolving societal wants and expectations, as it is about how it works internally. Moreover, within the complexities of cities there are many different perspectives—equally valid—from urban design and planning professionals, citizens, government, and even, notionally, the machine.

This chapter hence approaches the task of classifying tools, techniques, and methods of AI in urban design and planning by employing three complementary viewpoints. Initially, AI tools are discussed as classes or clades of algorithms in terms of their essential algorithmic mechanisms. Subsequently, AI techniques are classed through a reductionist approach that discusses AI in urban design and planning from the notional perspective of the machine using Russell and Norvig's classification of simple reflex, model-based, goal-based, utility-based, and learning agents (Russell and Norvig, 2020). Finally, AI methods are considered, alongside a snapshot of selected real-world applications, from the perspective of the human practitioner in which they are considered more by their teleological aspects of purposes served and potentials in practice rather than their underlying mechanics directly. The chapter begins with defining AI in broad, nonanthropocentric terms to encompass basic tools and techniques that may not commonly be thought of as AI.

A working definition of AI in urban planning and design

Consideration of classes of AI tools, techniques, and methods for AI in urban planning and design must be grounded in a working definition of that AI. A popular concept of AI itself is a machine that can do those things that otherwise a human intelligence (HI) would be required to do. Oxford Reference, for example, defines artificial intelligence as the "theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages." (Oxford Reference, 2021). Taken literally, this definition implicitly argues that the AI we develop should be a simulacrum of human intelligence—that it should ape the decisions of a human planner or designer, and potentially even the decisions of the human denizens of the subject urban environments (insofar that they may be involved in the planning and design process).

This similitude is a laudable goal for those many tasks in which AI must indeed closely produce the outputs of a human mind, such as mimicking an artistic style or affective computing in a humanoid robot that should display empathy. In the diverse applications of AI that may be found across the planning and design of built environments, such fidelity of reproduction need not be strictly applied and may not be the most efficient, effective, or even most feasible use of capabilities of AI.

A definition of AI is therefore used in this chapter that allows for a nuance of unique human and machine roles and that is not prescriptive of the application context or scope of sophistication. Russell and Norvig, in the 4th edition of their textbook *Artificial Intelligence—A Modern Approach*, provide a definition centered on the idea of an *intelligent agent* (Russell and Norvig, 2020). In their definition, an agent receives stimuli or inputs (*percepts*) from its *environment* via *sensors*. The agent in turn performs *actions* by mapping percept sequences to outputs.

The adaptable, nonanthropocentric definition is useful in the built environment as, to be seen below, contemporary AI produces fragmented workflows of machine-tractable tasks, produces intelligence that is different from human intelligence in order not just degree, and is subject to continual change in how it is perceived.

Current AI workflows in the built environment are fragmented into specific machine-digestible subparts. AI largely automates particular tasks rather than jobs on the whole (Kaplan, 2016), and technology applications in the urban domain often emerge in opportunistic ways only and not in response to any strategic or formal plan (Dowling et al., 2019). Architecture, a built environment profession that is near kin to urban planning and design, relies in the main on AI to undertake specific, independent roles that are not the outcome of an overarching system that may be applied to general contexts, problems, or projects (Mrosla and von Both, 2019). An AI that would address the entirety or near entirety of urban design and planning, and that could understand context and nuance, would require a near human level intellect that current technology cannot provide. Moreover, although AI is making inroads in built environment workflows (Leach, 2019; Mrosla and von Both, 2019), claims that contemporary AI may replicate a human output in any field are often predicated in a simplistic definition of the subject human activity (Fjelland, 2020).

AI is not limited to some witless or dull role in urban design and planning practice, however, and AI may fundamentally produce outcomes that are beyond human intelligence. This is not necessarily in the sense of being smarter than a human, or super intelligent, but instead of tending toward solutions that are not those a human intelligence might naturally seek out. This may seem counterintuitive: if an AI is to produce something "beyond human intelligence," surely it must be smarter. AI may seek solutions for which the significant difference is in order rather than degree. Machines undertaking tasks that typically require human intelligence indicate that there are alternatives to solving those challenges and do not imply necessarily that computers are intelligent (Kaplan, 2016). Fjelland observes one opposite view in the literature on developing AI: aspects of reasoning that are considered central to human thinking need not appear in AI outcomes; correlation may be a sufficient proxy for causality in many situations, and statistical and big data techniques processing sufficient real-world examples may produce actionable but fundamentally nonhuman outcomes (Fjelland, 2020).

What may be classed as AI at any one time is dynamic. The classification of intelligent behavior in a machine, or even in a human peer, is continually shifted and redefined as the trick of its calculation is learned (Minsky, 1958). As AI becomes subsumed into built environment practice as a tool, it is no longer taken as AI. There is a sliding window of what is viewed as AI, akin to the Overton window, centered on AI premised as a novel artifact; ahead lie fanciful or at least highly speculative applications, and behind are those applications that have become so embedded in practice and quotidian workflows that they are no longer explicitly recognized as AI. As seen in the section on techniques, very simple tools that are nonetheless AI may be used in urban computing.

Tools: Algorithmic clades in urban planning and design

The essential tool of the AI-enabled urban designer or planner is the algorithm itself, yet there is in the literature no clear consensus on classification schema of AI tools in urban design and planning. For instance, Newton, discussing AI in the context of computational generative design, delineates five categories with a firm computer science focus on the mechanism of computation (Newton, 2019a). Newton defines optimization and search algorithms used in architectural design to encompass tasks of plan generation, building massing, and building envelope optimization. Natural processes such as chemical reactions or the patterning of animal coats motivate physically based algorithms. Generative grammars build formal outputs through repeated application of prescriptive rules. Probabilistic algorithms undertake operations that are weighted by previous examples. Finally, deep generative models are founded in neural networks.

In contrast, Wu and Silva, looking at urban land dynamics, identify four categories that overlap with Newton's organization only in part (Wu and Silva, 2010). Their category of artificial life corresponds to Newton's physically based algorithms. Intelligent stochastic optimization processes include evolutionary approaches such as genetic algorithms. Artificial neural networks and other methods encompass "evolution computing including spatial DNA." Knowledge-based intelligent systems include expert systems that mimic the informed decision-making of humans.

The differing groupings of Newton and of Wu and Silva illustrate the lack of a canonical classification of use of AI tools in urban design and planning. By considering the mechanics of the algorithm itself, some specific foremost approaches can be nonexhaustively identified from the practice landscape: evolutionary algorithms, deep learning, generative grammars, and agent-based modeling. These will be referred to and illustrated with example uses in subsequent sections.

Evolutionary algorithms

Evolutionary algorithms are inspired by the biological metaphor of natural selection (Russell and Norvig, 2020). A digital population of individuals, each of which represents a solution to a problem, is evaluated against a fitness function that tests how well an individual satisfies the described problem. Successive generations are created from the best-performing individuals to form a new generation of individuals to be evaluated. Just as Darwin's finches and their beaks evolved to meet the conditions of the respective islands to which they are endemic (Fig. 4.1), evolutionary approaches in built environments can be well suited to responding to the specific challenges of a problem context and can produce seemingly novel outcomes.

Deep learning

Computational problem-solving tools that rely on the explicit specification of domain logic or rules can perform well for simple, well-understood tasks and certain structured contexts such as the playing of chess. Early AI research into one example, expert systems, revealed limitations of relying on the formal specification of rules to address complex, real-world problems for which necessary access to professional contextual advice is restricted or for which the method to generate a solution manually is intractable (Haenlein and Kaplan, 2019). Deep

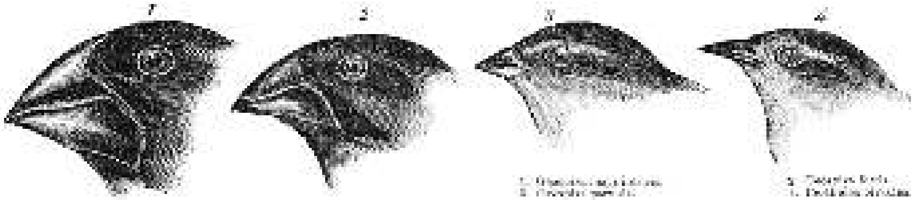


FIG. 4.1 Charles Darwin's finches of the Galápagos Islands. *Modified from a contemporary illustration of John Gould.*

learning exploits artificial neural networks of many layers between inputs and outputs (hence the term "deep") and turns this problem on its head: instead of outputs being found through carefully constructed chains of rules, the neural network is trained to produce an output on appropriate example data.

Its applications are diverse. Outcomes can range from predictive—"that image is likely an example of Koolhaas"—that may be elementary for a human expert to explain (if indeed an expert could formally describe the steps they take to find a solution), to generative (Fig. 4.2)—"this building image I, the machine, have produced is in the style of Koolhaas." However,

FIG. 4.2 AI-generated building images from XKool Technology's "Nonexisting Architectures" project, Shenzhen, 2019. *From XKool Technology and From He, W., 2020. Urban experiment: taking off on the wind of Al. Archit. Des. 90 (3), 94–99. https://doi.org/10.1002/AD.2574.*

deep learning has a limitation of *explainability*; whereas expert systems can disclose the sequence of logic that led to a particular outcome, deep learning in general is a black box and does not explain how a particular decision is derived. In built environment design applications for which human understanding of outcomes is vital, such opacity can require the role of a human designer to, shaman-like, interpret and give meaning to the whims of the machine (Kimm and Burry, 2021).

Generative grammars

Generative grammars, in the sense used by (Newton, 2019a), iteratively apply a system of transformative rules from a starting state until a halting condition is met. In built environment applications, the subclass of shape grammars is typically used to produce 2D or 3D form by operating on lines, circles, faces, and other geometric primitives. Its utility for urban designers or planners allows for facilitating exploration of form generation through a visual mode that is intuitive to those users, and the ability to modify, add to, or subtract from primitive forms in response to rules set by the user themselves. The classic example of generative grammars in design, reproduced among others by Grasl and Economou with graph grammars (Grasl and Economou, 2010), is the generation of floor plans in the style of Palladian villas (Fig. 4.3).

Agent-based modeling

Agent-based modeling describes the behavior of a complex system through the interaction of its constituent parts (Manzo and Matthews, 2014). Each part or agent is typically autonomous—it is in effect its own computer program—and reacts in response to its own goals and its observation of the model environment and the behaviors of other agents. The characterization of the overall system is hence an emergent property of the bottom-up actions of the agents as a collective. The flexibility of agent-based modeling, which is due in part to facilitating simulation through the description of mechanisms rather than an encompassing mathematical formula, and the fine control over the level of simulation abstraction it offers to the user, makes it a practical built environment tool for challenges such as pedestrian and traffic modeling (Fig. 4.4). Agent-based modeling does, however, have aspects that may limit its usefulness, or that at least need to be acknowledged in its use, including sensitivity to starting conditions that may only be imprecisely known and a potential variability of outcomes for constant parameter sets (Manzo and Matthews, 2014).

Techniques: A machine's-eye view of the city

Through what techniques may these algorithmic tools be applied? The classification of Russell and Norvig defines intelligent agents of increasing sophistication of mapping percepts of the computational environment to actions: *simple reflex agents*, *model-based reflex agents*, *goal-based agents*, and *utility-based agents,* as well as *learning agents* that can encapsulate each and improve its performance (Russell and Norvig, 2020). These agents encompass the basic principles of the majority of intelligent systems, and are hence found in use of AI in

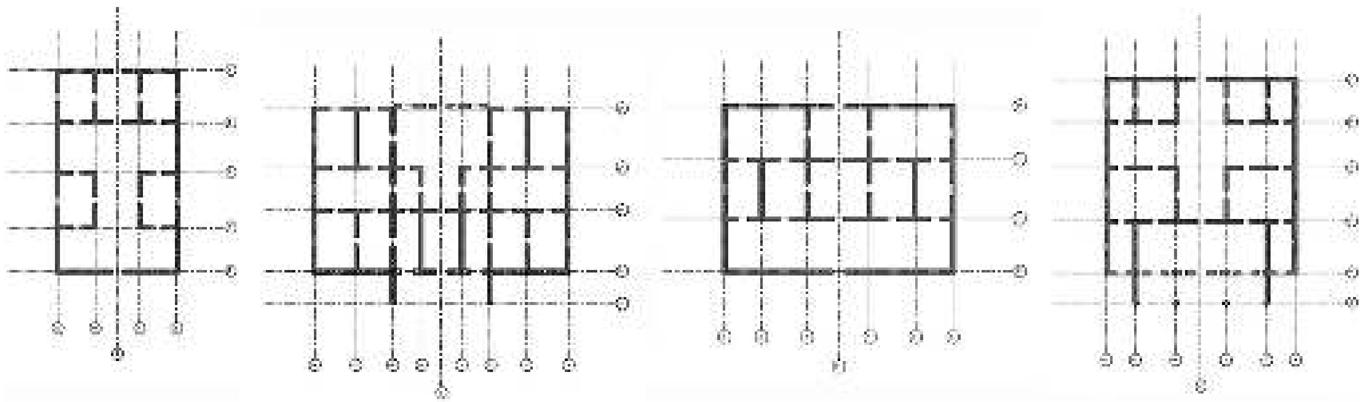


FIG. 4.3 Four Palladian plans created with generative grammars. *From Grasl, T., Economou, A., 2010. Palladian graphs: using a graph grammar to automate the Palladian grammar. In: 28th ECAADe Conference Proceedings, pp. 275–283.*

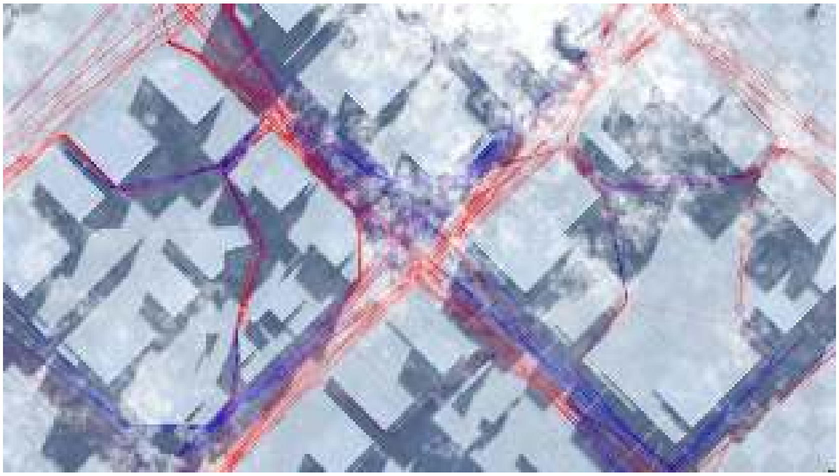


FIG. 4.4 Agent-based modeling in the Unity game engine to map pedestrian thermal comfort. *G. Kimm, 2020.*

built environments. The classification and its agent definitions have previously been referred to in urban design and planning computing for land use change simulation by agent-based modeling, intelligent envelopes for high-performance buildings, and rapid urban design prototyping for generating urban layouts (Capeluto and Ochoa, 2017; Miao et al., 2018; Ralha et al., 2013). It is adapted here to provide one conceptual framework of how AI tools may be applied in concert with the objectives of the urban designer or planner.

Simple reflex agents

Many issues in urban environments and design can be addressed by AI whose understanding of the world is limited to what it may observe in any one instant. S*imple reflex agents* are the most elementary of agents in Russell and Norvig's classification. They act in response to the current percepts alone and do not consider any percept history in their calculations. The classic example given by Russell and Norvig is of a robotic vacuum cleaner that has percepts of its current location and the cleanliness of that location, and follows simple instructions of sucking or turning left or right depending on immediate percept values.

Although such a simple mode of response may seem trivial, it is nonetheless important in diverse applications across urban planning and design. For urban service provision, the deployment of sensor technologies by local councils in the domains of smart living, mobility, or environments is a common response (Dowling et al., 2019). These sensors, such as for parking, smart pole infrastructure including lighting that is responsive to pedestrian activity, waste bin use and overflow, and pedestrian patronage monitoring, can all operate with such simple AIs. In urban simulation, simple reflex agents can support modeling like evacuation simulation, social behaviors, or urban growth.

The mechanism of the condition-action rules, or mapping of percept or action, need not be trivial in itself. While an elementary bin use sensor may be implemented with basic logic

FIG. 4.5 Urban greenery of Singapore mapped by the Treepedia tool of MIT Senseable City Lab, 2020. *From MIT Senseable City Lab, with permission.*

circuits, simple reflex agents can also use sophisticated digital models in their computation. *Treepedia*, an MIT Senseable City Lab project, determines green view indexes from Google Street View images for urban locations, and allows urban planners and designers to comprehend and manage the urban distribution of greenery (Fig. 4.5) (Cai et al., 2018). Its analysis has no understanding of previous conditions in its digital environment of Google Street View images—it does not consider for a current location what may be the adjacent percept images along the street nor what may be a past image. However, its semantic analysis of the Google Street View images—or in lay terms what classification it gives to each pixel as greenery or not—employs deep learning trained on data sets of labeled street scenes.

Model-based reflex agents

The amnesiac or in-the-moment nature of simple reflex agents may not suit certain applications. Using the sensor examples above, what if the pedestrian activated lighting of a smart pole should respond to the direction of a pedestrian's movement, so that it would not trigger due to pedestrians merely moving past, or if deep learning image processing should be applied not to an essentially static data set such as Google Street View but to live remote sensing data such as from a satellite? Such applications require the intelligent agent to have at least some awareness of the past of its environment as experienced through its percepts. *Model-based reflex agents* can address such contexts by maintaining an internal representation of the environment that is developed through its percepts. The intelligent urban agent, which may otherwise only partially observe its environment, may hence take action on conditions outside its immediate perception.

Goal-based agents

The smart pole with a responsive lighting example, now extended with a model-based reflex agent, can account for pedestrian movement. However, it still can only act on a somewhat expanded but still limited knowledge of its environment. In some circumstances, it would need to understand something about the objectives of the urban planner or designer: it needs a goal. *Goal-based agents* can combine information on desirable outcomes with the internal model to achieve those objectives. The responsive lighting of the smart pole, thus extended, could produce more sophisticated behavior by considering what action it may take in the real world, with effects tested against its internal model of the world, will progress it to its goal: it could, for example, time its lighting state against observed pedestrian circulation patterns.

Utility-based agents

Many urban issues addressed by AI involve the automation of routine behavior—the provision and use of everyday services or logistics and the like—and AI can predict the corresponding routine patterns that operate on short cycles (Batty, 2018). For less orderly urban problems, an objective may be less clear, and an intelligent agent could potentially produce more than one valid solution. Urban environments are complex systems and their planning and design necessarily involve trade-offs and accommodation of rivalrous interests under conditions of uncertainty (Burry et al., 2019). Consideration of the long-term urban issues to meet economic and social equity goals under unknown, changeable, and complex conditions, cannot yet be automated by contemporary AI (Batty, 2018).

Utility-based agents extend goal-based agents by, rather than testing merely whether an action will move toward a goal, testing an action how *well* it will contribute to meeting a goal. Utility is here is in the sense Russell and Norvig employ of "happiness." In the programmatic context of an agent, this is how happy an action may make it with respect to meeting a goal; in a broader urban computing context, it is how well an agent's solutions contribute positively to increasing the economic and social factors of a city. The designer of an urban computing tool may consider and analyze utility in city-scale terms when deciding on what should be the measure of utility of the agent. To continue the smart pole example, the lighting system could now, by considering its internal happiness, respond to considerations of energy use and light pollution versus safety and thus maximize the utility in that respect.

The utility approach can be illustrated with agent-based modeling. Raubal used agent-based modeling of perceptual wayfinding for people in unfamiliar environments (Raubal, 2001). Each utility-based agent in the urban computing tool, one per pedestrian agent in the simulation, developed a model incorporating beliefs about its environment. The overall model could explain the wayfinding behavior of people in an unfamiliar building, and the resulting practical tool could uncover where and why wayfinding problems occur on the basis of the existing and proposed wayfinding cues in an environment. Nejat and Damnjanovic employed utility-based agents in agent-based modeling of housing reconstruction behavior following disasters (Nejat and Damnjanovic, 2012). Each agent updates its belief about precinct recovery and land values by observing the reconstruction decisions of near neighbors, and decides for itself if it should invest in reconstruction or delay development. The simulation, for which real-world data is scarce, demonstrated that reconstruction can cluster around nuclei of early rebuilders. In both these examples, the utility-based agents, each by developing a model incorporating extrinsic factors garnered through its percepts, were able to take actions on the basis of utility, and hence can provide to urban designers and planners valuable and novel data and evidence that would otherwise remain uncovered.

Learning agents

A learning agent can incorporate, and refine the behavior of, each of the proceeding four agents so that they may work in previously unknown contexts and become more knowledgeable than their initial experience would allow (Russell and Norvig, 2020). Treepedia, the Senseable City Lab project used to illustrate the simple reflex agents above, also employs a learning agent model to identify the green view components of street scene images. Generative adversarial networks, which automate the machine production of seemingly creative and genuine design compositions and are a promising avenue for AI in design (Leach, 2019), are within the technique of learning agents.

In our smart pole example, the intelligent agent for the responsive lighting might be trained on collected noise data to respond to signals associated with undesirable or unlawful events, such as breaking glass, or might continuously refine its behavior via sensing pedestrian circulation through a public space to illuminate likely paths.

Methods: A snapshot from the practitioner's desktop

Cities are structures that operate across human, social, political, and ecological domains. Historically, cities have been characterized by the metaphors of insect hive or family, viewed as urban machinery to be stabilized in its operation as an engineering problem, imbued with organic characteristics analogous to ecosystems or organisms, or seen as information exchange networks akin to nervous systems (Bettencourt, 2015). These have in common an implicit acknowledgement that a city is a complex system and interacts at spatial and temporal scales.

They are highly heterogeneous and exhibit nonlinear behavior in which small changes may have nonproportional effects (Fuentes, 2015). With respect to the consideration of scale alone, for instance, a city that doubles in size may see its per capita socioeconomic outputs, including violent crime rates and innovation metrics, increase by 10%–20%, whereas infrastructure and built space volume decreases by a similar per capita amount (Bettencourt, 2015).

For the human urban planning and designer practitioner looking at specific or well-defined urban contexts, the tools and techniques of the previous sections can provide a clear guide to aid use of AI. With respect to the city as a complex system, and the interrelation of urban design and planning practice with it, reductionist perspectives may not be as useful.

AI methods in urban design and planning are hence defined in this section by a teleological filter in terms of consideration more of purposes served and potentials in practice than the mechanics of the tools and techniques themselves. They are discussed as intersecting, loose-fit axes on which urban computing approaches may be positioned as emergent, integrating, generative, and augmenting.

Emergent

For addressing some urban issues, simple tools can be entirely adequate, and their very simplicity and accessibility are an advantage. A smart pole with responsive lighting, for example, could be implemented most efficiently as a simple sensor-oriented system by a local council considering development time, a rollout of thousands of units, and subsequent maintenance and support. Many organizational concerns and short-term activities of city administrations—land allocation, transportation system design, and urban service creation using the best available technology while operating within physical, financial, and political constraints—can be conceptually described as "simple" problems susceptible to common, established ICT and engineering solutions (Bettencourt, 2015).

However, the fundamental nature of urban computing problems is complex: they are either simple with an inexorable shift or inevitable drift to the complex or they are complex in themselves. Bettencourt proposes that what is a simple problem will inevitably become complex and gives as illustration a simple problem of coordinating a transit system that inevitably turns complex as it is entwined in a web of public aspirations that rise in lockstep with economic and human progress (Bettencourt, 2015). The simple tools of the smart pole inevitably create more connections and lead to more complex systems: the use of urban computing is in coevolution with society and shifts exceptions.

The urban computing practitioner must have an effective grasp of complex modeling. Not many designers nor planners have sound software development expertise, and few programmers are skilled or even experienced in the urban design and planning domain (Derix et al., 2012). However, the simple can be an aid to complexity of modeling and outcomes. Emergent information-processing, or broad organization that arises from distributed, elementary components, in natural systems gives rise to sophisticated outcomes—consider elaborate insect hives of social insects or the distributed, parallel processing of the human brain—and are found in human-constructed models such as cellular automata, genetic algorithms, and agent-based modeling (Crutchfield and Mitchell, 1995; Silva, 2011). In design computing in particular, the ability of simple rules to give rise to complex, emergent behavior has been exploited extensively, and its emergence is manifested in many urban AI techniques including cellular automata, agent-based systems, evolutionary computation, and neural networks (Knight, 2003; Brunner, 2002).

Consider cellular automata, a special case of agent-based modeling, in which high-level, complex patterns emerge from bottom-up, localized interactions, and that are accessible and illustrate emergence well (Li and Yeh, 2002). Cellular automata are n-dimensional arrays of discrete cells that periodically update according to rules of their own state and those of their neighbors (White and Engelen, 1993). Each cell may represent a spatial unit—for instance, a square decameter in a remote sensing analysis application or a square decimeter in a floor plate daylight analysis—and individual arrays may be overlaid and cross-linked to model distinct attributes of a scenario (Silva, 2011). Wolfram identifies qualities of cellular automata that are beneficial for the urban computing practitioner: they are simpler than equivalent mathematical functions, they have a clear correspondence between their computational process and the physical process they model, and they can produce outputs with a high degree of fidelity to real-world systems (Wolfram, 1984). The property of cellular automata to, through emergent behavior, identify and quantify processes, patterns, and phase transitions through computation (Silva, 2011), has been used to undertake diverse urban computing scenarios that would otherwise be done by much more complex modeling, if done at all.

This emergence of complex behavior, which may otherwise require intricate modeling systems, can be exploited by the urban computing practitioner. As shown in the previous section on utility-based agents by the work of Nejat and Damnjanovic (2012) as well as Raubal (2001), agent-based modeling can be implanted with complex AI techniques to exhibit emergent behavior. Simpler models may also form the base units of complex systems through which emergent behavior arises. Aschwanden et al. developed crowd simulation for urban planning simulations to evaluate occupancy movement of proposed urban designs (Aschwanden et al., 2008). Their approach exploited the Massive Prime software suite, used by Weta Workshop in animating the Lord of the Rings, for agent-based modeling of precinct scenarios. Each agent employed a straightforward model of control responses mapped from percepts of social dynamics, buildings and other obstacles, terrain, a directive "flow" vector field overlay, and attractive and repulsive locations. The "brain" of the agent follows simple rules (Fig. 4.6); for example, the terrain navigation behavioral model may select responses of going up or down depending on if the current location is too high or too low.

Moreover, the choice of the technology or algorithm to use is not exclusive and different types may be harnessed together. For instance, Li and Yeh used artificial neural networks with cellular automata to find the conversion probabilities between land uses of cropland, orchards, development sites, built-up areas, forest and water in a simulation of the developing city of Dongguan, China (Li and Yeh, 2002). The networks could then sit within the cells of the cellular automata array to replace the traditional transition rules. By utilizing an artificial neural network, the elaborate task of finding the transition rules between cell states could be automated, which would typically be done with trial and error or traditional statistical methods, and can be very difficult when multiple land use types need to be considered.

The GAMA (GIS Agent-based Modeling Architecture) software platform provides an accessible method for the urban designer or planner to explore emergence for themselves. It occupies an approachable midpoint between applications geared to the skills of computer scientists versed in high-level programming languages and those applications that lessen the programming burden and required algorithmic knowledge by providing graphical scripting at the expense of depth and comprehensiveness of outcomes (Taillandier et al., 2019). GAMA's bespoke scripting language and support for importing urban data sets and 3D models allows users with foundational skills in algorithmic design to explore the emergence of macroscopic behaviors from the essential individual units of a system (Fig. 4.7).

FIG. 4.6 The visual perceptual field of a pedestrian agent in the agent-based modeling of Aschwanden et al. (2008). The rating information in the graph overlay shows the left sector is to be avoided. *From Aschwanden, G., Halatsch, J., Schmitt, G., 2008. Crowd simulation for urban planning. In: 26th ECAADe Conference Proceedings, pp. 493–500.*

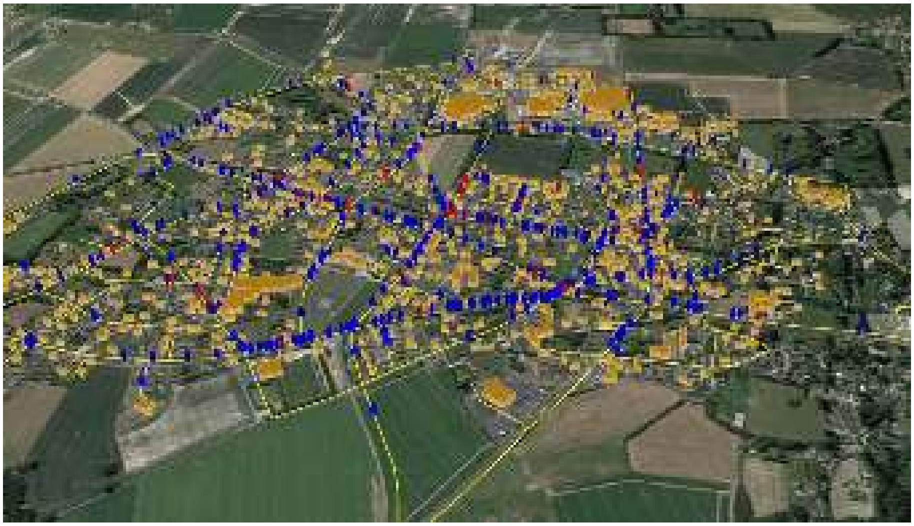


FIG. 4.7 Agent-based modeling in the GAMA software platform. *Screenshot of the GAMA software.*

Integrating

Currently, AI tools in urban planning and design suffer from the more general limitations of AI as they address only specific stages and narrow tasks. Just as there is no "Architectural Artificial Intelligence" that may understand and address the entire context of a project (Mrosla and von Both, 2019), there is no urban computing AI that can understand and integrate the entirety of the planning and design needs of cities as complex systems. Indeed, although a building—the common focus at the architectural scale—can be a complex system (Lachhab et al., 2017), cities operate at a larger scale and may be nested systems of systems and highly open (Walloth, 2016).

The ability of emergent behavior in AI to model intractable city issues currently addresses complexity in a narrow sense: the resulting tools work on closely defined areas such as land use change. Design computing tools also must address cities that are complex in breadth and in which diverse and disparate urban elements must be integrated. This is still a task for the human intelligence of the urban designer and planner: AI may 1 day encompass those intricacies of the cities, but for now it is the urban designer and planner who must integrate across the human, social, political, and ecological domains within and with the aid of AI-enabled tools.

Topos, a New York start-up, provides one example of this in practice (Topos, 2019). The Topos platform leverages multiple AI technologies, such as machine vision and natural language processing, to garner and fuse heterogeneous urban data and can answer questions on the similarity or otherwise of disconnected urban spaces. In Australia, Archistar combines cadastral, remote sensing, and other data with AI (Archistar, 2021). The platform allows built environment professionals to identify sites of interest, generate residential and commercial candidate designs through AI, and test those against performance and amenity design criteria (Fig. 4.8).

FIG. 4.8 Multicriteria feasibility testing in Archistar, August 2020. *From Archistar Pty. Ltd., With permission.*

Spacemaker, a Norwegian start-up acquired by Autodesk in 2020, provides AI-enabled cloud-based software to real estate developers, urban designers, and architects (Spacemaker, 2021). In their platform, users can apply their human experience and design intuitions to integrate across diverse cartographic, planning, and environmental design criteria and analyses (Fig. 4.9). Similarly, Delve, a product of Alphabet's Sidewalk Labs, provides software in which real estate development and urban professional teams can generate high-performing designs alternatives against programmatic, environmental, and financial considerations (Delve by Sidewalk Labs, 2021). Yet it is still the expert human user who must integrate across multitudinous express and latent urban consideration to prioritize outcome criteria and limit the range of essential input parameters.

The AI-assisted integration of the complexities of cities need not be only of statistical or spatial data. Recent developments in natural language processing greatly increase its ability to assimilate loosely structured data to produce lucid results. The 175 billion parameter *GPT-3* language model, released in 2020, is able to generate convincing synthetic text on a given topic, is capable of responding to questions on general knowledge, and can process simple reasoning and arithmetic challenges (Brown et al., 2020). Such outcomes point the way to an integrative mode of AI operation that is little explored in urban computing.

Generative

Alan Turing, the computer scientist, in his eponymous test proposed that a machine could be considered to be intelligent if it could deceive a human observer into thinking it is the human partner in a text-based conversation (Turing, 1950). The Turing Test, since it was proposed in 1950, has been extended from its conversational textual basis to other modes and media. In the field of artistic creativity, AI had by 2010 already strongly passed the Turing test for noninteractive examples of expression, and occasionally for "behavioral" examples (Boden, 2010). Arguably, AI is already capable of producing artifacts that would pass a Turing test for urban design and planning; however, these may be of narrow scope and their ability to pass as of human origin under scrutiny may in some measure be due to the mediocre standards set by some extant urban design and planning in the real world.

Moreover, much AI is a black box, including in built environment contexts, and its mapping of input to output can be inscrutable (Leach, 2019; Kimm and Burry, 2021). Perhaps defining what happens within that black box is not important for applied design computing—it may be taken as resembling Schrodinger's cat—and the observer may not know if the creative spark is alive or dead until the box is opened (if indeed it ever is). Whether or not its outputs are truly creative is beyond the scope of this discussion, and perhaps also for pragmatic purposes the routine activities of the urban planner or designer; however, modern machine learning approaches certainly evince what appears at least a superficial level of creativity and that is certainly generative.

Minsky viewed "creativity" as synonymous with those processes that had not been mechanized and hence understood (and warned that a view of creativity as an inexplicable "gift" might lead to nothing remaining on the list of human creative talents once all possible machines had been examined) (Minsky, 1958). The systems view of creativity of Csikszentmihalyi models creativity as a process in which existing cultural artifacts are

FIG. 4.9 The Autodesk Spacemaker® cloud platform. *Autodesk screen shots reprinted courtesy of Autodesk, Inc.*

transformed by an individual and the outcomes are assessed and filtered by society to form foci for further creative iteration (Csikszentmihalyi, 1988). Such views position creativity, from a *pragmatic* perspective of an urban designer and planner, as a process that is fundamentally generative on precedent and mechanizable.

Generative methods used in built environment design and planning have been primarily in the classes of cellular automata, genetic algorithms, shape grammars, L-systems, and agent-based models (Duarte et al., 2012; Singh and Gu, 2012). In deep learning, generative adversarial networks have, since their inception in 2014, demonstrated capacities that are at least superficially creative (Leach, 2019). Their use in built environments now extends to tasks including generation of conceptual building design as spatial connectivity graphs, images of buildings that imitate example styles, 3D building massing quantized as voxels, and architectural floor plans (As et al., 2018; He, 2020; Newton, 2019a,b). Research has demonstrated that GANs may be applicable in built environment design even when trained on small data sets (Fig. 4.10) (Newton, 2019b), which mirrors the approach of humans to novel problems and suggests application to urban environmental issues in which a project's context might be highly specific or unique and corresponding or relevant precedent might be thin.

In these generative applications, the role of the practitioner can be to filter and winnow the outputs. The generative methods can be prolific, but their results may be scattershot: the outcomes may be inappropriate on a spectrum ranging from merely containing incongruous atavistic artifacts from the training data or precedents to being incomprehensible in part or whole. While these AI abilities are still nascent and relatively crude, AI development in general has exceeded Moore's Law since 2012: prior to that year, the computing resources

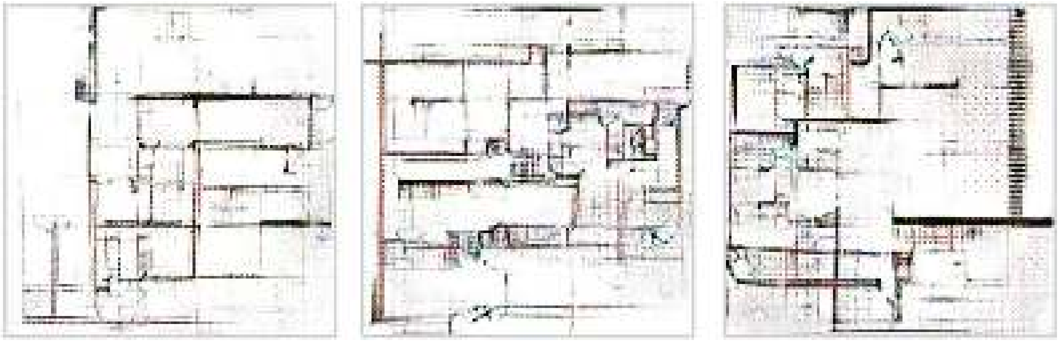


FIG. 4.10 Plans generated by a GAN trained on a small data set of Le Corbusier's single-family residential projects. *From Newton, D., 2019. Deep generative learning for the generation and analysis of architectural plans with small data sets. In: Proceedings of 37 ECAADe and XXIII SIGraDi Joint Conference. https://doi.org/10.5151/PROCEEDINGS-ECAADESIGRADI2019_135.*

dedicated to training instances of selected large models doubled every 2 years, but since that year the rate is doubling every 3.4 months (Perrault et al., 2019). The generative derivations of AI may 1 day present a serious challenge to the creative intuition of the urban practitioner (Kimm and Burry, 2021). Until such a time, the designer or planner in the loop is needed. In this, the human works to direct, winnow, interpret, apply, and further develop results (Burry et al., 2019; Woodbury et al., 2017).

Real-world exemplars of built projects that use generative design in this sense with the designer or planner in the loop are as yet thin on the ground. The Living, an Autodesk research-based design practice, used generative design in optimizing energy and financial considerations for a residential neighborhood layout project of 7000 m^2 in Alkmaar, the Netherlands (Nagy et al., 2018). Their research exploited a genetic algorithm to explore a solution space of building orientations and heights, road access, house unit type mix, and parking provision. Design fitness goals including solar energy potential of the building roofs and project profitability for the developer were formulated in consultation with the client. The tool produced project layout strategies on the axes of the design goals, and selected varied outcomes were reviewed with the client. A preferred layout was then developed for a final design.

Augmenting

The ultimate power of AI is yet to be determined and contemporary AI is not yet ready to supplant human intelligence. In some tasks, AI can approach or exceed the powers of the human mind, such as the translation of closely related languages, the visual recognition of objects in image data sets, or the composition of photorealistic portraits. Such powers are, however, only weak or narrow AI—they replicate only part of the human mind, or address but a clearly and closely defined task.

Artificial General Intelligence—"systems that show behavior indistinguishable from humans in all aspects and that have cognitive, emotional, and social intelligence"—has yet to be achieved, despite having been often predicted by experts since the 1950s (Haenlein and Kaplan, 2019). However, this kind of machine intelligence is forecast by experts to be as likely as not by circa 2060 (Grace et al., 2018). Subtasks that are relevant to urban design and planning were anticipated by the surveyed experts to be handled competently much sooner by AI. Computer games or virtual worlds are merely one type of simulation, and any urban system that is computable may be represented in those forms. The experts in the study of Grace et al. predicted an AI would be able to reasonably explain the decisions it takes in a computer game by the mid-2020s and by the early 2030s would be able to, after dwelling in and interacting with a virtual environment, deduce the formulas of its governing laws. Herbert Simon, as summarized by Duarte et al., proposed in 1969 that the laws governing human design behavior might be discovered, just as natural sciences have effectively uncovered the rules regulating natural orders (Duarte et al., 2012). The potential of AI to uncover the 'laws' of cities and the human interventions within them may be great and in the future may challenge the traditional role of the urban planner or designer.

Despite the increasing powers of AI and any threat that AI might represent to the role of the human urban computing practitioner, the interplay of AI and society is itself a system that is not in equilibrium. Feedback loops exist between new AI advances and technologies and the ways in which society chooses to exploit those: AI changes society, yet simultaneously society changes the use and direction of AI. In this, AI is in a persistent state of novelty that may be exploited by the human urban computing practitioner (Kimm and Burry, 2021). Thus, there is a continuing and resilient gap between the capabilities of AI and the demands of society that the human urban design and planning profession can *arbitrage*. Arbitrage here is used in the sense of exploiting that gap to persistently maximize the utility afforded by their professional role.

XKool Technology, a Shenzhen-based start-up founded in 2016, is one company that is augmenting the practice of human urban designers and planners in this sense of arbitrage. Its *AI Design Cloud Platform*, as well as exploratory testbeds such as its *Intelligent Dynamic Urban Planning and Decision-Making Platform*, integrates AI models as digital assistants to aid decision-making (He, 2020). These virtual aides respond to the criteria of the designer and present options that may be filtered and modified (Fig. 4.11). In the vision of the AI-enabled workflows of XKool, designers maintain their authority despite the increasingly sophisticated AI by developing a working comprehension of essential AI tools and techniques, leading to future cities that are still molded by a human will augmented by technology.

A fuzzy landscape

The perspectives offered in this section—emergence, integrating, generative, and augmenting—are four fuzzy axes against which AI methods can be positioned according to their use to the urban designer or planner rather than by the underlying tools and techniques directly. They offer one nonexhaustive view of clustering AI methods based on a snapshot of contemporary practice and state of the art with respect to how design computing can elevate the work of the urban practitioner. As AI develops—and those developments cannot be predicted clearly or conclusively—those alignments will change, just as will the nature of the value of the urban practitioner as their professional role evolves.

FIG. 4.11 The XKool cloud platform integrating AI models as digital assistants, 2020. *From XKool Technology and From He, W., 2020. Urban experiment: taking off on the wind of Al. Archit. Des. 90 (3), 94–99. https://doi.org/10.1002/AD.2574.*

Conclusions

The three perspectives detailed in this chapter offer distinct though complementary classifications of AI in urban planning and design as tools, techniques, and methods. The algorithm is the essential tool of the AI-enabled urban designer or planner. Although there is no canonical classification of those AI tools in urban design and planning, four particular algorithmic classes or clades are discussed: evolutionary algorithms, deep learning, generative grammars, and agent-based modeling.

Techniques are considered as a framework for tools by applying Russell and Norvig's *intelligent agent* schema of simple reflex, model-based reflex, goal-based, utility-based, and learning agents. The framework provides a machine's eye view of the city in terms of digital model inputs and outputs and how the computational mapping between those may be formulated in concert with the objectives of the urban planner or designer.

Positioning AI against the practice of urban planners and designers presents AI methods in a teleological approach that focuses more on its potentials and the purposes to which it is put than on the actual underlying digital mechanisms. Each of the alignments of emergent, integrating, generative, and augmenting discussed are methods by which tools and techniques may elevate human professional roles that are themselves changing in feedback with evolving technology and societal expectations.

The schemas of tools, techniques, and methods are three of many possible. Within the city, there are a multitude of credible perspectives on AI in planning and design, and participant interests span a spectrum from concern only on human effects of AI outcomes to responsibility for the internal minutiae of algorithms. Consequently, any number of classification schemas may be possible. On human-oriented themes, a classification could address matters such as the relatability of machines in urban roles and the uncanny valley, affective computing, codesign, or explainable decision-making. A classification could structure ethical challenges including protection of privacy, intellectual honesty and creative rights, prevention of unintended algorithmic bias, or support of meaningful and dignified human work. Or a classification could center on the role of AI in preparatory, feasibility, design, implementation, operation, and other project phases. Against the intricacies of the city as a complex system, and the increasing sophistication of AI, no single schema can encompass all purposes and a diverse abundance of classifications is needed to meet the evolving ambitions of urban designers and planners.

Acknowledgments

The author was supported in this work by an Australian Government Research Training Program Scholarship.

References

Archistar, 2021. Available at: https://archistar.ai/. (Accessed 21 September 2021).

As, I., Pal, S., Basu, P., 2018. Artificial intelligence in architecture: generating conceptual design via deep learning. Int. J. Archit. Comput. 16 (4), 306–327. https://doi.org/10.1177/1478077118800982.

Aschwanden, G., Halatsch, J., Schmitt, G., 2008. Crowd simulation for urban planning. In: 26th eCAADe Conference Proceedings, pp. 493–500.

Batty, M., 2009. Cities as complex systems: scaling, interaction, networks, dynamics and urban morphologies. In: Meyers, R.A. (Ed.), Encyclopedia of Complexity and Systems Science. Springer, Berlin, pp. 1041–1071.

Batty, M., 2018. Artificial intelligence and smart cities. Environ. Plan. B Urban Anal. City Sci. 45 (1), 3–6. https://doi.org/10.1177/2399808317751169.

Bettencourt, L., 2015. Cities as complex systems. In: Furtado, B.A., Sakowski, P.A.M., Tóvolli, M.H. (Eds.), Modeling Complex Systems for Public Policies. Institute for Applied Economic Research, pp. 217–236.

Boden, M.A., 2010. The turing test and artistic creativity. Kybernetes 39 (3), 409–413. https://doi.org/10.1108/03684921011036132.

Brown, T.B., et al., 2020. Language models are few-shot learners. Adv. Neural Inf. Proces. Syst. 33, 1877–1901.

Brunner, K., 2002. What's emergent in emergent computing? In: Cybernetics and Systems 2002: Proceedings of the 16th European Meeting on Cybernetics and Systems Research. vol. 1, pp. 189–192.

Burry, M., Cruz, C., Kimm, G., 2019. Avoiding the color gray: parametrizing CAS to incorporate reactive scripting. In: Kvan, T., Karakiewicz, J. (Eds.), Urban Galapagos, pp. 137–154, https://doi.org/10.1007/978-3-319-99534-2_9.

Cai, B.Y., et al., 2018. Treepedia 2.0: applying deep learning for large-scale quantification of urban tree cover. In: IEEE International Congress on Big Data, pp. 49–56, https://doi.org/10.1109/BIGDATACONGRESS.2018.00014.

Capeluto, G., Ochoa, C.E., 2017. What is a real intelligent envelope? In: Green Energy and Technology. Springer, pp. 1–20, https://doi.org/10.1007/978-3-319-39255-4_1.

Crutchfield, J.P., Mitchell, M., 1995. The evolution of emergent computation. Proc. Natl. Acad. Sci. U. S. A. 92 (23), 10742–10746. https://doi.org/10.1073/PNAS.92.23.10742.

Csikszentmihalyi, M., 1988. Society, culture, and person: a systems view of creativity. In: Sternberg, R.J. (Ed.), The Nature of Creativity: Contemporary Psychological Perspectives. Cambridge University Press, pp. 325–339.

Delve by Sidewalk Labs, 2021. Available at: https://www.sidewalklabs.com/products/delve. (Accessed 10 September 2021).

Derix, C., et al., 2012. Simulation heuristics for urban design. In: Arisona, S.M., et al. (Eds.), Digital Urban Modeling and Simulation. Springer, pp. 159–180, https://doi.org/10.1007/978-3-642-29758-8_9.

Dowling, R., McGuirk, P.M., Gillon, C., 2019. Strategic or piecemeal? Smart city initiatives in Sydney and Melbourne. Urban Policy Res. 37 (4), 429–441. https://doi.org/10.1080/08111146.2019.1674647.

Duarte, J.P., et al., 2012. City induction: a model for formulating, generating, and evaluating urban designs. In: Arisona, S.M., et al. (Eds.), Digital Urban Modeling and Simulation. Springer, pp. 73–98, https://doi.org/10.1007/978-3-642-29758-8_5.

Fischer, L., et al., 2020. Applying AI in practice: key challenges and lessons learned. In: Holzinger, A., et al. (Eds.), Machine Learning and Knowledge Extraction. Springer, pp. 451–471, https://doi.org/10.1007/978-3-030-57321-8_25.

Fjelland, R., 2020. Why general artificial intelligence will not be realized. Palgrave Commun. 7 (1), 1–9. https://doi.org/10.1057/S41599-020-0494-4.

Fuentes, M., 2015. Methods and methodologies of complex systems. In: Furtado, B.A., Sakowski, P.A.M., Tóvolli, M.H.E. (Eds.), Modeling Complex Systems for Public Policies. Institute for Applied Economic Research, Brasília, pp. 55–72.

Grace, K., et al., 2018. When will AI exceed human performance? Evidence from AI experts. J. Artif. Intell. Res. 62, 729–754. https://doi.org/10.1613/JAIR.1.11222.

Grasl, T., Economou, A., 2010. Palladian graphs: using a graph grammar to automate the Palladian grammar. In: 28th eCAADe Conference Proceedings, pp. 275–283.

Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. Calif. Manage. Rev. 61 (4), 5–14. https://doi.org/10.1177/0008125619864925.

He, W., 2020. Urban experiment: taking off on the wind of Al. Archit. Des. 90 (3), 94–99. https://doi.org/10.1002/AD.2574.

Kaplan, J., 2016. Artificial intelligence: think again. Commun. ACM 60 (1), 36–38. https://doi.org/10.1145/2950039.

Katz, J.S., 2006. Indicators for complex innovation systems. Res. Policy 35 (2), 893–909. https://doi.org/10.1016/J.RESPOL.2006.03.007.

Kimm, G., Burry, M., 2021. Steering into the skid: arbitraging human and artificial intelligences to augment the design process. In: Proceedings of the 40th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA). vol. 1, pp. 698–707.

Knight, T., 2003. Computing with emergence. Environ. Plann. B. Plann. Des. 30 (1), 125–155. https://doi.org/10.1068/B12914.

Lachhab, F., et al., 2017. Energy-efficient buildings as complex socio-technical systems: approaches and challenges. In: Nemiche, M., Essaaidi, M. (Eds.), Nonlinear Systems and Complexity. Springer, pp. 247–265, https://doi.org/10.1007/978-3-319-46164-9_12.

Leach, N., 2019. Do robots dream of digital sheep. In: Proceedings of the 39th Annual Conference of the Association for Computer Aided Design in Architecture, pp. 298–309.

Li, X., Yeh, A.G.-O., 2002. Neural-network-based cellular automata for simulating multiple land use changes using GIS. Int. J. Geogr. Inf. Sci. 16 (4), 323–343. https://doi.org/10.1080/13658810210137004.

Manzo, G., Matthews, T., 2014. Potentialities and limitations of agent-based simulations. Rev. Fr. Sociol. 55 (4), 653–688.

Miao, Y., et al., 2018. Computational urban design prototyping: Interactive planning synthesis methods—a case study in Cape Town. Int. J. Archit. Comput. 16 (3), 212–226. https://doi.org/10.1177/1478077118798395.

Minsky, M., 1958. Some methods of artificial intelligence and heuristic programming. In: Proceedings of Symposium on the Mechanization of Thought Processes. Her Majesty's Stationary Office, pp. 3–28.

Mrosla, L., von Both, P., 2019. Quo vadis AI in architecture?—survey of the current possibilities of AI in the architectural practice. In: Proceedings of 37 eCAADe and XXIII SIGraDi Joint Conference., https://doi.org/10.5151/PROCEEDINGS-ECAADESIGRADI2019_302.

Nagy, D., Villaggi, L., Benjamin, D., 2018. Generative urban design: integrating financial and energy goals for automated neighborhood layout. In: 2018 Proceedings of the Symposium on Simulation for Architecture and Urban Design.

Nejat, A., Damnjanovic, I., 2012. Agent-based modeling of behavioral housing recovery following disasters. Comput. Aided Civ. Inf. Eng. 27 (10), 748–763. https://doi.org/10.1111/J.1467-8667.2012.00787.X.

Newton, D., 2019a. Generative deep learning in architectural design. Technology|Architecture + Design 3 (2), 176–189. https://doi.org/10.1080/24751448.2019.1640536.

Newton, D., 2019b. Deep generative learning for the generation and analysis of architectural plans with small datasets. In: Proceedings of 37 eCAADe and XXIII SIGraDi Joint Conference., https://doi.org/10.5151/PROCEEDINGS-ECAADESIGRADI2019_135.

Oxford Reference, 2021. Artificial Intelligence. Available at: https://www.oxfordreference.com/view/10.1093/oi/authority.20110803095426960.

Patience, N., 2021. 2021 AI and Machine Learning Outlook. S&P Global. Available at: https://www.spglobal.com/marketintelligence/en/news-insights/blog/2021-ai-and-machine-learning-outlook.

Perrault, R., et al., 2019. The AI Index 2019 Annual Report. Human-Centered AI Institute, Stanford University.

Ralha, C.G., et al., 2013. A multi-agent model system for land-use change simulation. Environ. Model Softw. 42, 30–46. https://doi.org/10.1016/J.ENVSOFT.2012.12.003.

Raubal, M., 2001. Agent-Based Simulation of Human Wayfinding: A Perceptual Model for Unfamiliar Buildings (PhD diss). Vienna University of Technology.

Russell, S.J., Norvig, P., 2020. Artificial Intelligence: A Modern Approach, fourth ed. Pearson.

Silva, E.A., 2011. Cellular automata and agent base models for urban studies: from pixels to cells to hexa-dpi's. In: Yang, X. (Ed.), Urban Remote Sensing: Monitoring, Synthesis and Modeling in the Urban Environment. Wiley, pp. 323–334, https://doi.org/10.1002/9780470979563.CH22.

Singh, V., Gu, N., 2012. Towards an integrated generative design framework. Des. Stud. 33 (2), 185–207. https://doi.org/10.1016/J.DESTUD.2011.06.001.

Spacemaker, 2021. Available at: https://www.spacemakerai.com/. (Accessed 10 September 2021).

Taillandier, P., et al., 2019. Building, composing and experimenting complex spatial models with the GAMA platform. GeoInformatica 23 (2), 299–322. https://doi.org/10.1007/S10707-018-00339-6.

Topos, 2019. Available at: https://topos.com/. (Accessed 24 August 2021).

Turing, A.M., 1950. Computing machinery and intelligence. Mind, 433–446.

Walloth, C., 2016. Emergent Nested Systems: A Theory of Understanding and Influencing Complex Systems as well as Case Studies in Urban Systems. Springer Nature.

White, R., Engelen, G., 1993. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ. Plan. A. 25 (8), 1175–1199.

Wolfram, S., 1984. Computer software in science and mathematics. Sci. Am. 251 (3), 188–203.

Woodbury, R., et al., 2017. Interactive design galleries: a general approach to interacting with design alternatives. Design studies 52, 40–72. https://doi.org/10.1016/J.DESTUD.2017.05.001.

Wu, N., Silva, E.A., 2010. Artificial intelligence solutions for urban land dynamics: a review. J. Plan. Lit. 24 (3), 246–265. https://doi.org/10.1177/0885412210361571.

This page intentionally left blank

CHAPTER

5

Urban form analysis through morphometry and machine learning

Jinmo Rhee

Carnegie Mellon University, Codelab, School of Architecture, Pittsburgh, PA, United States

In this chapter, we explore morphometry—a quantitative approach to shape and its correlation to variations in shape—in the context of architectural and urban form analysis. This exploration centers on how this concept can be seen as a distinctive approach to form studies, tracing latent granular patterns of urban types and fabrics, and in the process, changing our understanding of city space.

Conventional approaches such as qualitative visual observation and measurement are predominantly descriptive, focusing on compositional aspects, but overlooking the richness in the layers of information that may help in understanding various urban phenomena. We posit an approach that represents urban form as material containing data, knowledge, and immanent relations in the physical formation of the urban elements. This approach relies on morphometry, which is based on curation and quantitative processing beyond mere geometrical properties, in order to explore urban form through its rich layers of information.

We argue that conventional form studies in architecture and urban design engender morphometry, and that morphometric analysis is quintessentially embedded in these studies. Adapting from disciplines where morphometry intersects with computational methods for form analysis, we show that architectural and urban form analysis can be expanded by incorporating artificial intelligence. To demonstrate this, we rely on the methodological commonality between urban form analyses and morphometry. By adapting an analytical framework from modern morphometry (Marcus, 1990; Reyment, 1985), we have developed a machine- and deep learning-based framework for urban form analysis. We apply this framework to Pittsburgh, a mid-sized city in the state of Pennsylvania in the United States. The analysis allows for a granular distinction between urban forms, and consequently for a detailed categorization of urban types that are not recognized by conventional analysis.

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00007-X

Urban form—A basic definition

Form has long been central to architecture and to considerations of the city. Despite the absence of a concrete and agreed to definition for architectural and urban form, as both Cairns et al. (2012) and Oliveira (2016) have argued, we consider architectural form as "the point of contact between mass and space" (Bacon, 1976). Form relates to the physical appearance of buildings; according to Cairns et al. (2012), it was "the key preoccupation in the development of modern architecture." Moreover, the study of form is the principal engagement of architectural theory and practice, for example, one can look at symbolism in architectural form (Venturi et al., 1972), generation of structurally optimized form (Otto et al., 2010), or the advent of style in their extreme manifestation (Schumacher, 2008).

The study of form is not solely confined to architecture; it extends to urbanism, urban form, pattern, fabric, and morphology (Brown, 2004; Koetter and Rowe, 1979; Rossi, 1982; Ungers, 2011). Research into architectural form has focused on qualitative visual observations, and on measurements such as size, dimension, symmetry, proportion, repetition, rhythm, syncopation, dynamic equilibrium, and such. From the ancient Greek to the Renaissance and Modern periods, these features have been developed into orders of architectural form, and have fascinated architects in their desire to lean toward numerical principles in design. For instance, Marcus Vitruvius Pollio, a Roman author and architect, argued that "proportion is a correspondence among the measures of the members of an entire work, and of the whole to a certain part selected as standard." (Pollio et al., 2001) He introduced the aesthetic point of ratios "governing the dimensions of the human body" (Mitchell, 1989) and proposed that "building should be derived from the basic module by used of a system of ratios related to that of the body" (Mitchell, 1989). Andrea Palladio, Italian Renaissance architect active in the Venetian Republic, also developed his architectural design based on the five class orders and the ratios (Palladio, 1965). Even in Modern, Le Corbusier borrowed the classical idea about the proportion to invent his theory and design architecture (Corbusier, 1986), such as Golden Rectangle (Singley, 2019).

In contemporary architectural design and studies, architects have tended to systematically generate rationalized form (Mitchell, 1989), "expand their formal repertoire" (Schumacher, 2016), and implement the convoluted form assisted with computer programs (Singley, 2019). Although the shape of form is steadily more complex, the treatment of form as geometry or shape alone tends to neglect the rich layers of information that may help understand various urban phenomena. The geometry of a form only highlights the value of its appearance.

Certain notable architects have not focused on form, for instance, Mies van der Rohe, the famous Modernist architect, refused to recognize form as something distinct from design (Schulze and Windhorst, 2012). On the other hand, certain others stress the value and potential of form in design, for example, Christopher Alexander, the influential British-American architect and design theorist, argued that "the ultimate object of design is form" (Alexander, 1964).

Architects who follow the Modernist sentiments commonly point out that form studies that focus on the shell and shape of the architecture or urban form, blur the value of space (Kwinter, 2003). However, neither the Modernist dictum: "form must follow function" (Sullivan, 1896) nor the Miesian disregard for form, seeing it instead as a by-product of construction (Neumeyer, 1991), detract from its conventional and continuous importance in buildings and within the city. The value of form is not in its appearance, shell, or shape, but in its potential for integrating materiality from the built and other urban phenomena within the urban space.

Urban form is composed by a aggregation of the natural environment, human activities, physical products, street systems, plot systems, and building systems as well as social, cultural, and economic aspects of city (Kropf, 2017; Oliveira, 2016). Urban form analysis is not merely about interpreting or extracting the process of formation and transformation of urban form based on tacit knowledge and experience. It is about tracing the complex patterns of the physical, environmental, economic, social, cultural, and political interactions of form and its context. To this end, we posit that urban form as an aggregate complex, as a material containing information, knowledge, and at times immanent relations about the physical configurations of urban elements. Within this view, form needs to be systematically curated in its data form than described by its appearance.

One of the more renowned historical representations of urban form showing aggregation is Giambattista Nolli's figure-ground map of Rome (Giambattista, 1748). This map depicts public-private space configurations in the 16th century Rome. Unlike typical maps that represent urban elements such as buildings, plots, squares, and streets as individual objects, his map merges the ground-level private spaces and represents them as solid black figures, which foreground the ground-level public spaces enclosed by them. This distinct representation helps capture, visually and temporally, porosity and connectivity of Rome's public spaces such as squares and plazas.

These days, representations of urban form are not limited to figure-ground maps. A notable modern-day method is street network analysis (Andres, 2010). Using statistical and computational methods, street network analysis focuses on extracting patterns of street networks from geospatial data and articulating their nodes to analyze various urban such as complexity, connectivity, or accessibility. The studies who use street network analysis assume that the street network pattern is a critical factor that both influences and is influenced by the formation of a city. For example, a study by Geoff Boeing (2018), an urban morphologist, analyzes the centrality of three distinct districts in the United States; he found that different street centrality patterns demonstrate hidden weights of intersections in neighborhood scale by topological features of streets.

Such maps allow us to represent and reveal the formal characteristics of city space in different ways, and in that sense, they represent distinct ways of curating urban form. This then enables us to reveal and understand the formal characteristics of city space. Nolli developed a new reveal of urban form through drawings of merged private spaces. On the other hand, Boeing uses graphs and statistics to produce an alternate and distinctive understanding of street network patterns. Based on such distinct modes of curation and the different methods of reveal, urban form can be considered as a material containing information about the physical formation of urban elements which the complex urban phenomena may appear through. These phenomena can be related to social, cultural, historical, economic, or political aspects of urban space.

Analyzing the complex information embedded within urban form also requires quantitative processing of the curated form data. Although aforementioned analysis and research show novel ways of curating urban forms, their methods for processing form hardly guarantee the complexity needed to analyze the relations between urban form and urban phenomena. In this regard, we consider a morphometric approach, described below, to the curation and quantitative processing of form data in order to explore the rich layers of information in urban form.

Urban morphometry

Morphometry, a branch of morphology, refers to the quantitative analysis of form through measurement, and has been employed in such diverse fields as ecology, geology, archaeology, cosmology, and design studies (Reyment and Elewa, 2010). Traditional morphometric methods focus on the physical features such as size, shape, ratio, mass, and area. In these methods, form data typically comprise size measurements (Marcus, 1990). When architectural and urban form are analyzed, they also include such features as shape, configuration, repetition, structure, articulation, or connection. In this sense, architectural and urban form analysis could be (re)viewed as morphometric.

An example of traditional morphometric analysis in architecture is seen in the analysis of Greek classical order. The type of order in architecture is defined with respect to formal features of columns: size of fluting, shape of volute, ratio between base, shaft, capital, and abacus. In the past, this type of analysis and definition of order entailing formal aesthetic balance through proportions was a key process in design. Even in the early 20th century, traditional methods of morphometry were central to the analysis and design of architectural form. Modernist architects have widely used and referred to ratio, size, shape, and configuration in their design and analysis works (Weber and Larner, 1993). This heavy focus on the measurement and proportion of form became an axis of detraction from the form in architectural and urban design.

Another axis of value detraction is based on an accentuation of architectural and urban forms as shell, as designers gain greater accessibility through computers in controlling form. Specifically, designers have focused on the study of "mechanisms of formation" (Somol et al., 1994) as well as on the generation of forms using computers.

Aside from architecture and urban design, with the increasing accessibility of computers to morphometry, other disciplines have expanded form analysis to incorporate advanced statistical methods such as multivariate statistics and machine learning (Reyment and Elewa, 2010). Recently, neuroimaging, medical imaging, and geography have been employing artificial intelligence (AI) technologies and deep learning to produce algorithms for form analysis (Dramsch et al., 2020; Goceri and Goceri, 2017). The use of advanced methods in these diverse fields has demonstrated the analytical potential of computation to uncover complex relationship patterns between differing forms and in predicting changes. For example, Nicola Dinsdale, a medical science researcher in the Image Analysis Group, and her colleagues studied patterns of human brain's functional and formal changes by aging. Deep learning is employed as a tool to trace, segment, and predict morphological features from changes in brain by aging (Dinsdale et al., 2021).

We intend to learn from these disciplines to expand form analysis in architecture and urban design. That is, we will use morphometry combined with AI technologies to apply to urban form analysis. As a grounding for this proposition, we focus on the commonality between morphometry and urban form analysis: both modern morphometry and urban form analysis are concerned with representation and classification of types based on morphological properties. For our research, we adapted an analytical framework from modern morphometry. We propose to augment this morphometric framework with AI technology and apply it to urban form analysis to investigate urban patterns and types. The following section illustrates a possible morphometric approach to urban form analysis. It is important to note that the research described in the following section were conducted prior to developing the concept of urban morphometry. This research uses a similar methodological approach to form analysis as morphometry.

Context-rich urban analysis and generation using machine learning

In Rhee et al. (2019), we explore the analytical and generative potential of machine learning methods on urban form in Pittsburgh, Pennsylvania using context-rich urban datasets. Pittsburgh is not a metropolitan-scale city as such although it has complex city structures owing to an accumulation of historical changes. We have identified a homogeneity within urban forms and have categorized 23 different distinguishable urban types. Additionally, the trained deep learning model, we can generate Pittsburgh style urban form according to the different types.

Constructing a custom form dataset

Assuming an urban form comprises a collection of individual urban elements, we can construct custom urban form data by extracting information about each building from a public Geographic Information System (GIS)). The urban form dataset reflects an immediate urban context and consists of raster images of a building footprint and its neighboring building footprints, street networks, and terrain. Instead of relying upon satellite or map images, we developed a bespoke representation scheme, termed Diagrammatic Image Dataset (DID) (Rhee, 2018). It is called a diagrammatic image as the representation is abstracted with the proper configuration of features, and this is comparable to other types of urban form data such as satellite images or digital map images. For example, the target building footprint is always placed on center of a color image and represented as a colored solid from a gradient ranging from yellow to red. The taller the building, the more reddish it is. Immediate building footprints to the target building are represented in black solids. Street networks are represented as blue line segments of varying width. The wider the roads, the thicker lines are (see Fig. 5.1).

There are two major advantages to the DID scheme: curation of information and low noise. We can specify the analysis by including just those elements to focus on, and excluding those that we do not. As DID only synthesizes necessary and targeted information into a dataset, the dataset has low noise. For instance, supposed segmented satellite images are considered; we can remove unnecessary information such as trees and cars during preprocessing. Despite advances in image segmentation, a certain amount of noise will always be present in the dataset. However, data synthesized only with the necessary information will have information refined according to the data constructor's intentions.

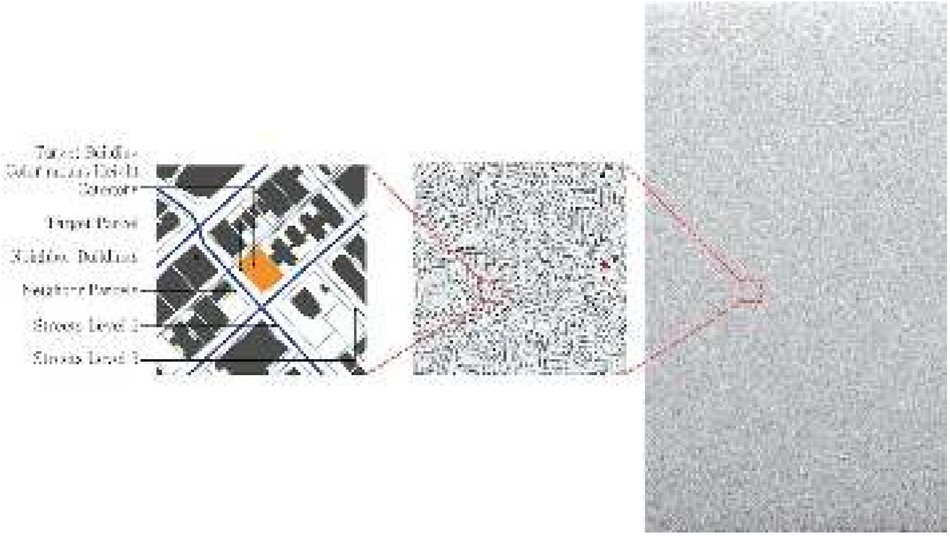


FIG. 5.1 45,852 Urban form data in the custom-curated dataset. A custom scheme called Diagrammatic Image Dataset is applied to construct urban form data for Pittsburgh, PA. Each data is a raster image that includes a target building on the center of the image and its immediate urban context. (Right) Total dataset includes 45,852 diagrammatic images, arranged by density, (Middle) zoom-in of several urban forms in the dataset, (Left) configuration of data in the dataset. *No permission required.*

Identification of urban types

Each data has 786,432 (512 pixels × 512 pixels × 3 channels) dimensions and the dataset, called DID-PGH (Rhee, 2019a,b,c,d), has a total of 45,852 urban forms. For improved efficient performance from standpoint of dimensionality reduction, the image size of the original data was decreased to 28 × 28 pixels" (Rhee, 2019a,b,c,d). In general, higher-resolution images will result in better projection and clustering in dimensionality reduction algorithms as they contain more detailed information. However, this generalization does not work for every dataset. Some information in high-resolution images acts as noise and thus, disturbs feature extraction.

As a way of dimensionality reduction, feature projection techniques are employed to preserve the principal variables while decreasing the data dimensions, typically, PCA (Principal Component Analysis) and t-SNE (t-distributed Stochastic Neighbor Embedding. PCA uses linear transformation and is not appropriate for projecting major features of a complex dataset. Therefore, we adopted a t-SNE algorithm with convolutional networks to calculate nonlinear principal components.

Data that has been dimensionality reduced by the t-SNE algorithm has three feature axes, which can be visualized in three-dimensional space. Each point in data space has three distinct feature values, which refers to urban form. Likewise, urban form data can be mapped onto a point in data space which is determined by its morphological features. The closer the

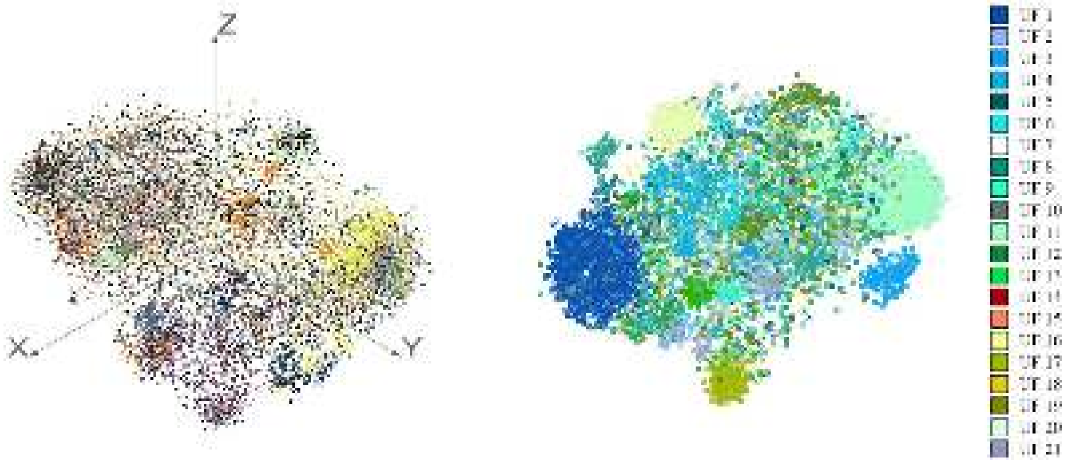


FIG. 5.2 Distributed and clustered urban form data. Distribution of urban form data in data space by t-SNE algorithm (left) and clustering results of the distributed urban form (right). The distributions and clustering are based on not geospatial location but similarity of urban form in DID-PGH. The color of points in the left distribution represents the neighborhood to which each data point belongs. The color of points in the right distribution represents the urban types based on their similarity. *No permission required.*

distance between two points, the more similar are their corresponding urban forms. We can do a density-by-distance analysis using a DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm to find core samples of high-density data points of DID-PGH. The result of this analysis is that Pittsburgh shows 21 distinct urban types that shares morphologically similar urban context conditions. The result of clustering is the latent pattern of urban form in Pittsburgh (see Fig. 5.2).

Evaluation of inductively defined urban types

Without proper evaluation methods, it is difficult to intuitively understand and translate meaning of patterns from their clustering. Thereby, we devised two evaluation methods: direct and indirect. Direct evaluation qualitatively and quantitatively verifies patterns by mapping them onto two-dimensional map space. Extracting typical conditions of each urban type and visiting sites where different types are conflicting on the map, we confirmed that clustering reasonably had distinguished different types of urban forms. Indirect evaluation is using generation for testing that dataset is trainable, its features are extractable, and machine can capture generation principles based on the pattern (see Fig. 5.3). In this section, we will address these two evaluation methods in details and provide an example project using deep learning with the same datasets of urban analysis for illustrating the concept of indirect evaluation.

From the results of clustering, a data-driven map of urban types can be generated. We can remap the clusters to the geospatial map space by differently coloring each building footprint

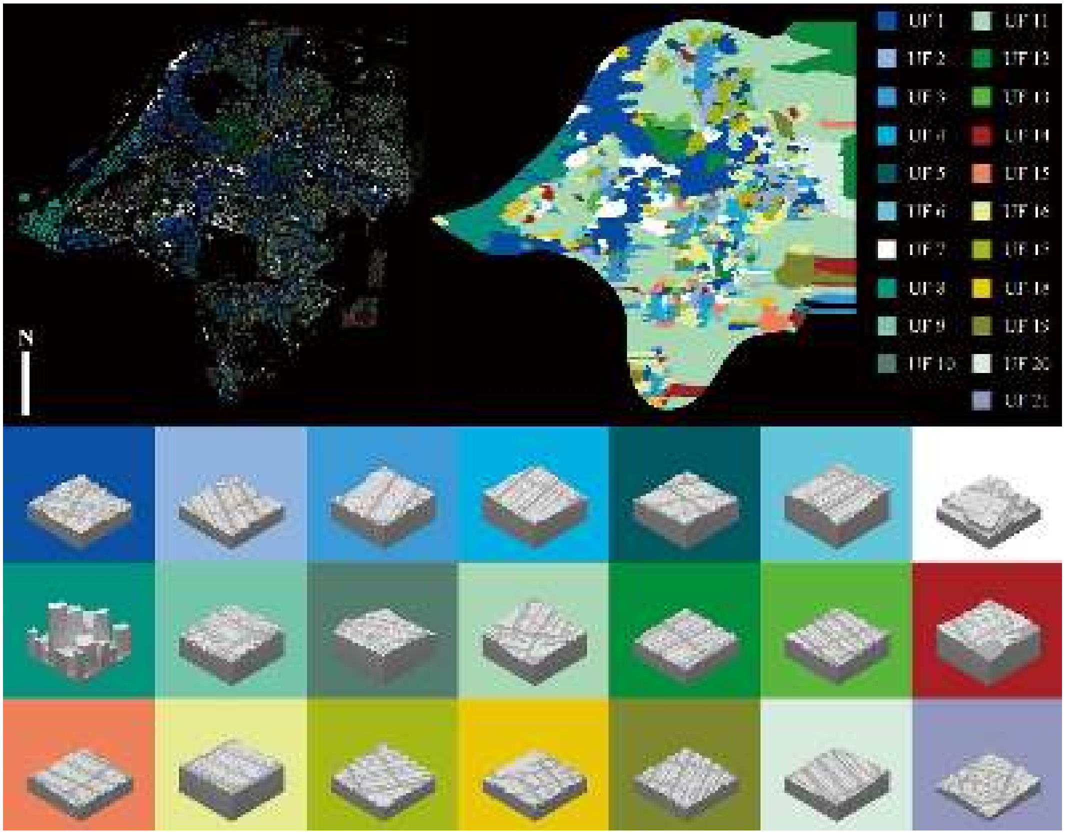


FIG. 5.3 Map by different morphological urban types and typical conditions of urban types in Pittsburgh. The map is generated by remapping the distribution and clustering results from data space to 2D geospatial map space (top-left). Using KNN for defining the boundaries of the types, a map for urban fabric in Pittsburgh, PA is constructed (top-right). Representative conditions of 21 different urban types are investigated to evaluate the distribution and clustering results (bottom). *No permission required.*

according to type. By processing the building footprints with KNN (K-Nearest Neighbors) algorithm, we can map the urban fabrics in Pittsburgh. The map projects urban patterns from data space to two-dimensional space. This projection helps us understand the urban structure of Pittsburgh by granularly visualizing the urban fabrics.

Based on the map, distinctive characteristics of 21 urban types are examined both qualitatively and quantitatively. Qualitative examination of spatial features involved reconstructing 3D models of typical context conditions of urban types by sampling the center of the largest type boundaries. Quantitatively, distinctive characteristics of each urban type are examined by using spatial quality descriptors and statistical values such as occupancy rate (%), occupancy rank, average height (m), average area (m^2), average density, average building occupancy, and average stories (Rhee et al., 2019).

With these descriptors and values, we can make qualitative descriptions for each type. For example, "Urban Type 11" is the most common in Pittsburgh. It has a certain number of empty parcels and no distinctive shape of urban blocks. "Urban Type 1" is the second most common—it is street-centered and has orthogonal intersecting spaces with differing sized urban blocks. "Urban Type 8" is the most vertically distinctive type consisting of high-rise buildings with grid street networks. This type is mainly distributed in Downtown Pittsburgh. "Urban Type 2" and "Urban Type 3" have rectangle-shaped blocks along the main streets and two rows of parcels. "Urban Type 7" has relatively higher density than other urban types. There is no generalized shape that can be specified for this urban type, each block in this type is represented by the shape of buildings such as a hospital, school, government office, shopping mall, etc. (Rhee, 2019a,b,c,d; Rhee et al., 2019).

To confirm these characteristics, we sampled several points where urban types of conflict. By site surveying for investigating borders between different urban types at the point, we can deduce whether urban forms with different characteristics are well distinguished and we can test the reliability of urban pattern in urban form analyses. We photographed and recorded the situations of conflicts among urban fabrics. By comparing the photographs with the results of the qualitative and quantitative examination on the urban pattern, we have confirmed that the points have different urban spaces and forms. This means the pattern form clustering is reliable and granular enough to catch the detailed difference between urban forms.

Another way to evaluate the pattern is by **generation**. For this, analytical machine learning models are used to discover latent patterns in the urban forms of Pittsburgh. Patterns are essentially constructed by abstracting high-dimensional form data in the image format. Evaluating reliability in patterns can be restrictive in that machine learning is a black-boxed model. Instead, we trained a generative deep learning model to see if generative principles are captured; if morphological principles are successfully captured in the process of abstraction in a deep neural network, the network will be able to create new urban forms. Observing the results of generated forms, we can assure the reliability of the abstraction process and expand this method to general urban form analysis.

To test this assumption, we developed a design experiment to synthesize a new urban fabric based on urban patterns. We trained a generative deep neural network with the same dataset. Three different generative models were tested with the dataset: VAE (Variational Auto-Encoder), GAN (Generative Adversary Networks), and WGAN (Wasserstein Generative Adversarial Networks).

VAE comprises two sets of neural networks: encoder and decoder. The encoder is trained to capture features of the input data and compress them into a latent vector. The decoder is trained to decompress and reconstruct the latent vector to the original form of the input data. One of benefits of VAE is the ability to construct a latent space of data based on their features. Like a dimensionality reduction algorithm, the space keeps the features of each data point and represents data into lower dimensions. However, results of generation from VAE decoding are generally blurred or smudged (see Fig. 5.4).

GAN too has two sets of neural networks: generator and discriminator. The generator is trained to generate data similar to the valid data, by synthesizing random vectors. The discriminator is trained only to discriminate whether the generated data are real or fake with

FIG. 5.4 Generation test for model selection. Image generation from three different deep neural networks. Without any additional training techniques, WGAN tends to generate detailed images than VAE or GAN within same training time. *No permission required.*

respect to the valid data. Since the generator synthesizes results from random vectors, GAN hardly constructs a latent space of the input data, but it generally results in better quality compared to VAE.

WGAN is an improved GAN with Wasserstein distance as the loss function, which scores how similar generated data is to the valid data (Arjovsky et al., 2017). This new discriminator is referred to as a critic. WGAN tends to produce more detailed images than GAN.

In our model selection test, WGAN results showed sharper images and better capture of morphological features than from other two models (Fig. 5.4). For generating cleaner urban fabric images, we trained a WGAN-GP (Wasserstein Generative Adversarial Networks—Gradient Penalty) (Gulrajani et al., 2017) with DID-PGH (Rhee and Veloso, 2021). WGAN-GP is an advanced model of WGAN with a gradient penalty on the norm of weights from the critic networks. Due to the gradient penalty, the model converges faster and is more stable than a WGAN (see the top image of Fig. 5.5).

Considering the size and complexity of the image data, we set the *Z*-dimension, or compressed feature size, of WGAN to 100. WGAN was trained for about 11,000 batches (15 epochs) with batch size 64. The model optimizer is "ADAM" (Kingma and Ba, 2017), and the learning rate is 2.0E-4. The model has no dropout layers, and both critic and generator use Leaky Rectified Linear Unit as the activation function. The losses reduced significantly until 3000 batches, and after that, the changes were subtle (see the bottom image of Fig. 5.5).

The trained model was embedded in a software prototype, Urban Structure Synthesizer (USS) (Rhee, 2019a,b,c,d) to help designers generate a new urban fabric. The prototype provides sliders to change the features of the new urban fabric. For instance, by increasing the value on the 11th slider, the urban form in a fabric becomes more orthogonal; and by increasing the value on the 25th slider, the urban form becomes more merged and has larger buildings. The prototype also has a computer vision-based 3D reconstruction function. Once an urban fabric image is synthesized, the prototype can trace the outline of building footprints and mean heights. By importing this traced information, users can reconstruct urban forms in a 3D modeling software. USS also can detect and determine the urban type of the synthesized urban form. USS projects the abstracted representation of the synthesized urban form image

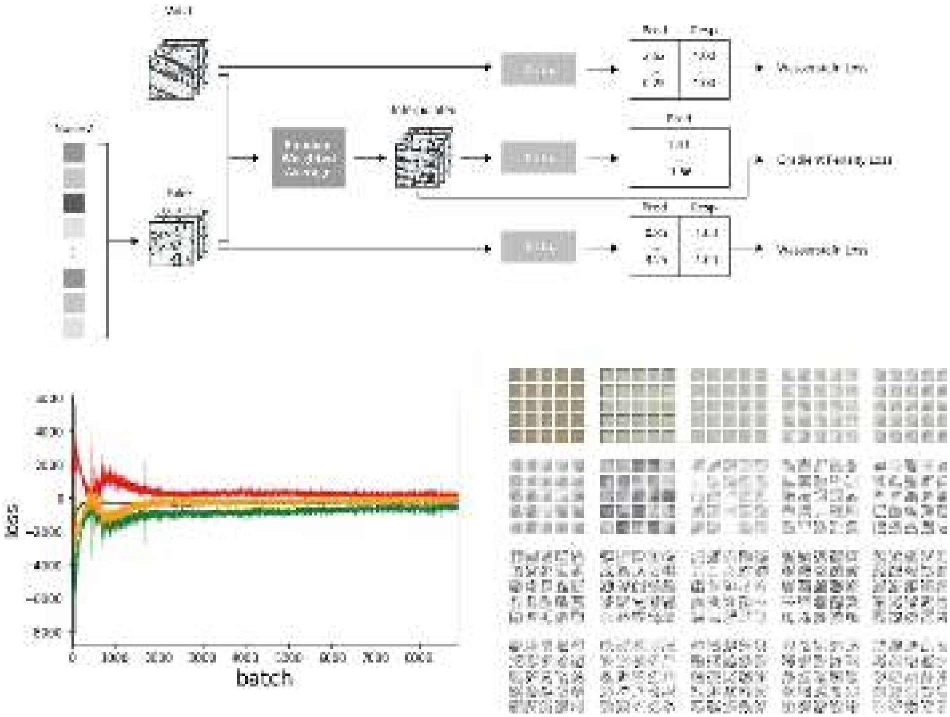


FIG. 5.5 WGAN model structure (top) and learning results (bottom). To generate sharper and detailed image of urban form, the model uses Wasserstein distance and gradient penalty. Losses drop until about 700 batches, rise at about 1000 batches, start to be converged again, and become stable after 3000 batches. *No permission required.*

into the latent space, or *Z*-space, where the urban pattern exists. By calculating the distance between the synthesized and existing urban form data, USS can identify the most similar urban form. As this function works as guidance to generation, users can synthesize a new urban fabric according to a specific urban type (Rhee and Veloso, 2021) (see Fig. 5.6).

The design task of this experiment was to insert synthesized urban fabrics based on the morphological qualities of downtown Pittsburgh into the typical low-rise residential area. Through USS, we were able to synthesize downtown-like urban fabrics that have triangular grids and high-rise buildings in the middle of a residential area that has rectangular grids and low-rise houses. The result of the experiment not only shows the generation of a specific type of urban fabrics, but also the gradual changes of urban forms at the periphery of two different fabrics (see Fig. 5.7).

This experiment with USS illustrates data abstraction using machine learning as a working method to investigate urban form types, to capture generative principles of form features, and to distinguish the urban types. During the design experiment, users could interact with the USS prototype to determine the urban type of a synthesized urban fabric.

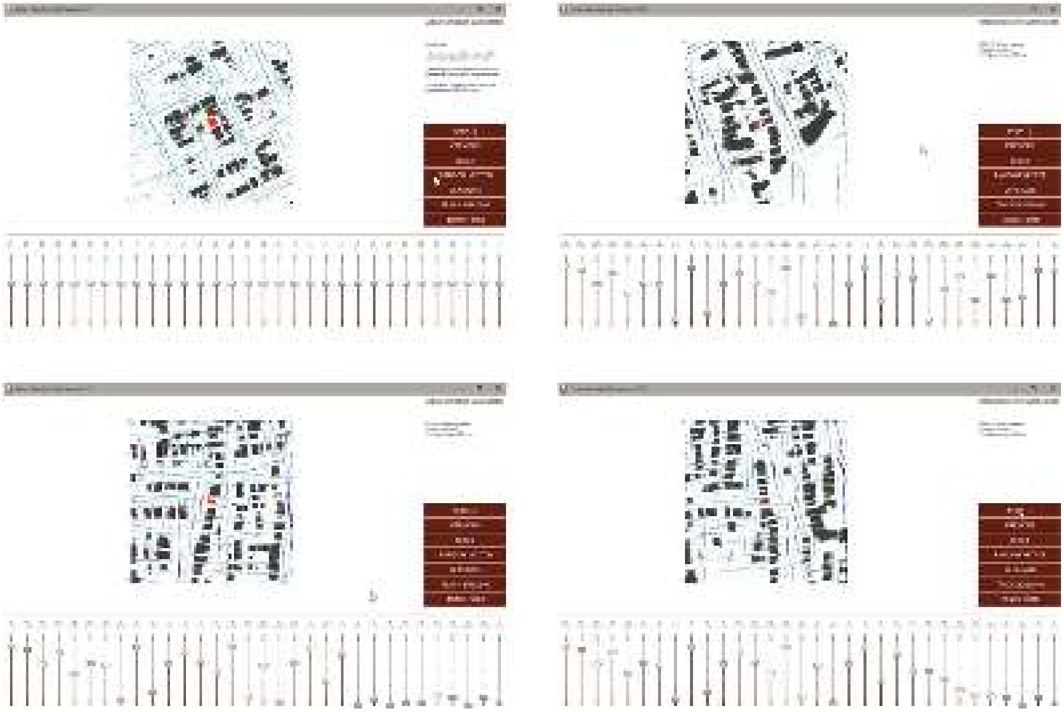


FIG. 5.6 Screen captures of user interface in urban structure synthesizer. Urban Structure Synthesizer generates different urban fabrics with urban type distinguisher from the trained generative deep neural network. *No permission required.*

This entire experiment with designer interaction is based on the urban patterns from the analytical machine learning of existing urban forms.

Urban morphometry with advanced statistics

The research project presented in this chapter demonstrates how to employ and tweak the framework of form analysis in morphometry of other disciplines for investigating urban patterns and types. First, we define urban elements related to urban forms and collect their information. By curating this information with a diagrammatic representation, we can synthesize a custom urban form dataset. A neural network-based t-SNE algorithm is used to extract and abstract features of each data. After clustering the abstracted data, several distinctive but latent urban types are discovered. By remapping the results of clustering into real-world map space, a granular urban pattern can be generated.

We also developed two different evaluation methods on the pattern derived from the abstraction of form data: direct and indirect evaluation. Direct evaluation is comparison between the results from computer calculation and real-world situation. This evaluation requires qualitative and quantitative examination on types from dimensionality reduction

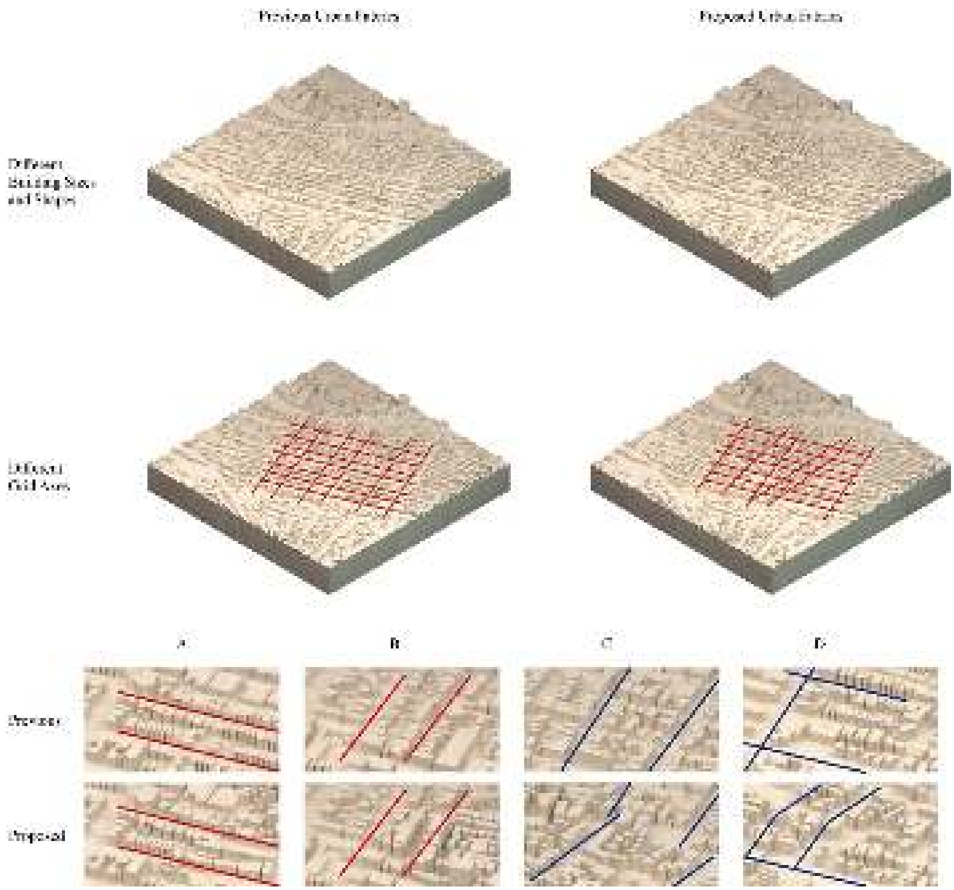


FIG. 5.7 Comparison of existing and proposed urban fabrics by USS. The proposed fabrics have gradual changes in street patterns and building forms (top). Detailed view and analysis of the gradual changes (bottom). *No permission required.*

and clustering. It also requires records of real-world to be used as a comparison group. We visually and statistically examined 21 different urban types, conducted a field study to observe conflicts between the types, recorded urban form configuration through photographs, and compared them with the results of our examination.

Indirect evaluation uses generation to qualitatively confirm and analyze how a statistical modelgeneralizes principles of form features. Generative model can construct a latent space of form data by abstracting features of a dataset. By exploring latent space we not only synthesize new forms but also provide distinctions of their type. For our research, we trained a generative model with Pittsburgh urban form data and synthesized new urban fabrics with the real-time guidance of type distinction. Downtown-like synthesized urban fabrics are inserted in a typical residential area. Generating a specific type of urban fabrics works as circumstantial evidence that the characteristics of urban form data are well abstracted.

Our research shows the potential for analytical methods in morphometry to be applied to urban form studies. Specifically, the analytical framework with learning algorithms can take full advantage of urban data: large size and high accessibility. Since learning algorithms are data-hungry, implementing them in an urban form study requires a lot of data to discover morphological patterns of a city, which is, basically, a collective space of public and private urban elements. A city has an abundance of information on urban forms and elements. Framing the information into data can satisfy the huge demand of data for learning patterns of forms. Another advantage is that urban form-related data is already highly accessible through public or civic data platforms like GIS and census data from governments. Commercial 3D map and metaverse services are also highly available to urban form data collection.

Large accessible urban form data and processing tool with AI not only increase accuracy and granularity of urban form analysis but also contribute to unveiling latent knowledge of urban form. These approaches focus on each urban form in the format data, aggregate each data feature, and draw patterns of the form data. Unlike categorizing by preexisting systems such as neighborhood boundary, building programs, and zones, we can construct data by defining formal features of each building within their urban context and statistically processing the data to investigate types by patterning the data. This is a bottom-up view of city space, which can change the understanding of complexity in city space, beyond our traditional top-down view of urban form analysis. In other words, morphological characteristics of an entire city can be investigated more rigorously by observing features of individual elements constituting the urban space.

By applying morphometric analysis method to urban form study, we can discover granular and high-resolution urban form patterns. Methodological advances in form analysis with AI technology allowed us to thoroughly analyze city structure, urban fabrics, and urban forms in detail. However, the form data used for investigating urban form types and patterns only include features of physical appearances. Although this method can contribute to statistical examination of urban form, it is limited in its investigation of the principles or dynamics in urban forms. In other words, it is hard to reason why urban forms in a city construct the shape of the pattern, what factors affect the characteristics of urban form, how an urban factor influences urban forms and types, etc.

To conclude in order to fully treat the identity of urban form, it should be integrated and analyzed with the relationship to nonphysical factors, which, in a city, can be represented as sociocultural data reflecting various urban phenomena and closely related to changes of urban form. Integration between formal and nonformal data can precisely deal with complex relationships between urban phenomena and forms through patterning as shown above. For this, one of the more central prerequisites will be how we curate and process formal and nonformal urban data. Any future study should plane to explore technical and design-based experiments on data curation conducted by regarding representations of nonphysical urban data and how to integrate them with form data. Developing AI models should be accompanied by data curation to handle integrated form data. Based on such experiments where sociocultural principles embedded in the form are uncovered using such integration and artificial intelligence technology, morphometric analysis on urban form would become a core computational method in urban morphology.

References

Alexander, C., 1964. Notes on the Synthesis of Form. Harvard University Press, Cambridge.

Andres, S., 2010. Path and Place : A Study of Urban Geometry and Retail Activity in Cambridge and Somerville, MA. Massachusetts Institute OF Technology, Massachusetts. Available at: https://dspace.mit.edu/handle/1721.1/62034.

Arjovsky, M., Chintala, S., Bottou, L., 2017. Wasserstein GAN. arXiv:1701.07875 [cs, stat]. Available at: http://arxiv.org/abs/1701.07875. (Accessed 8 December 2019).

Bacon, E.N., 1976. Design of Cities, A Studio Book, Revised ed. Penguin Books, New York.

Boeing, G., 2018. Measuring the complexity of urban form and design. Urban Des. Int. 23, 281–292. https://doi.org/10.1057/s41289-018-0072-1.

Brown, D., 2004. Encyclopedia of 20th century architecture. Ref. Rev. 18 (7), 46. https://doi.org/10.1108/09504120410559825.

Cairns, S., Crysler, C.G., Christopher, G., Heynen, H., 2012. The SAGE Handbook of Architectural Theory, Architectural Theory. SAGE Publications, Los Angeles.

Corbusier, L., 1986. Towards a New Architecture. Dover Publications, New York.

Dinsdale, N.K., et al., 2021. Learning patterns of the ageing brain in MRI using deep convolutional networks. Neuroimage 224. https://doi.org/10.1016/j.neuroimage.2020.117401, 117401.

Dramsch, J.S., Moseley, B., Krischer, L., 2020. 70 years of machine learning in geoscience in review. In: Advances in Geophysics. Elsevier, pp. 1–55. Available at: https://www.sciencedirect.com/science/article/pii/S0065268720300054. (Accessed 11 August 2021).

Giambattista, N., 1748. Map of Rome, Earth Sciences & Map Library. University of California, Berkeley. Available at: https://www.lib.berkeley.edu/EART/maps/nolli.html. (Accessed 20 September 2021).

Goceri, E., Goceri, N., 2017. Deep learning in medical image analysis: recent advances and future trends. In: IADIS International Conference Big Data Analytics, Data Mining and Computational Intelligence 2017 (part of MCCSIS 2017). Available at: http://www.iadisportal.org/digital-library/deep-learning-in-medical-image-analysis-recent-advances-and-future-trends. (Accessed 11 August 2021).

Gulrajani, I., et al., 2017. Improved training of Wasserstein GANs. In: Advances in Neural Information Processing Systems 30. Curran Associates, Inc, pp. 5767–5777. Available at: http://papers.nips.cc/paper/7159-improved-training-of-wasserstein-gans.pdf. (Accessed 8 May 2020).

Kingma, D.P., Ba, J., 2017. Adam: A Method for Stochastic Optimization. arXiv:1412.6980 [cs]. Available at: http://arxiv.org/abs/1412.6980. (Accessed 14 November 2020).

Koetter, F., Rowe, C., 1979. Collage City. MIT Press, p. 185.

Kropf, K., 2017. The Handbook of Urban Morphology. Wiley, Chichester, West Sussex.

Kwinter, S., 2003. Who's afraid of formalism? In: Phylogenesis: Foa's Ark. Actar, pp. 96–99.

Marcus, L.F., 1990. Traditional morphometrics. In: The Michigan Morphometric Workshop. Rohlf and F. L. Bookstein.

Mitchell, W.J., 1989. The Logic of Architecture : Design, Computation, and Cognition. MIT Press, Cambridge, MA.

Neumeyer, F., 1991. The Artless Word : Mies Van der Rohe on the Building Art. MIT Press, Cambridge, MA.

Oliveira, V., 2016. Urban Morphology: An Introduction to the Study of the Physical Form of Cities, The Urban Book Series. Springer International Publishing. Available at: https://www.springer.com/gp/book/9783319320816. (Accessed 17 October 2020).

Otto, F., Songel, J.M., Otto, F., 2010. A Conversation with Frei Otto, english ed. Conversations: A Princeton Architectural Press Series, Princeton Architectural Press, New York.

Palladio, A., 1965. The Four Books of Architecture. Dover Publications, New York.

Pollio, V., et al., 2001. Vitruvius : Ten Books on Architecture, first pbk ed. Cambridge University Press, New York.

Reyment, R.A., 1985. Multivariate morphometrics and analysis of shape. J. Int. Assoc. Math. Geol. 17 (6), 591–609. https://doi.org/10.1007/BF01030855.

Reyment, R.A. Elewa, A.M.T. (2010) "Morphometrics: an historical essay," in Morphometrics for Nonmorphometricians. Berlin, Heidelberg: Springer, pp. 9–24. doi:https://doi.org/10.1007/978-3-540-95853-6_2 (Accessed 1 August 2021).

Rhee, J., 2018. Architectural Diagrammatic Image Dataset for Learning. Available at: https://jinmorhee.net/jinmorhee_3-multimedia/DID_1.html. (Accessed 5 August 2021).

Rhee, J., 2019a. Context-Rich Urban Analysis Using Machine Learning: A Case Study in Pittsburgh, PA. Carnegie Mellon University, Pittsburgh, PA. Available at: https://kilthub.cmu.edu/articles/thesis/Context-rich_Urban_Analysis_Using_Machine_Learning_A_Case_Study_in_Pittsburgh_PA/8235593.

Rhee, J., 2019b. Context-rich Urban Analysis Using Machine Learning—A Case Study in Pittsburgh, PA. Available at: https://www.jinmorhee.net/jinmorhee_3-multimedia/contextrichurban.html. (Accessed 5 August 2021).

Rhee, J., 2019c. Diagrammatic Image Dataset—Pittsburgh. Available at: https://jinmorhee.net/jinmorhee_2-multiimage/didpgh.html. (Accessed 5 August 2021).

Rhee, J., 2019d. Urban Structure Synthesizer (Prototype). Available at: https://jinmorhee.net/jinmorhee_3-multimedia/uss.html. (Accessed 5 August 2021).

Rhee, J., Veloso, P., 2021. Generative design of urban fabrics using deep learning. In: The 26th International Conference of the Association for Computer Aided Architectural Design Research in Asia (CAADRIA). 1. The Association for Computer Aided Architectural Design Research in Asia (CAADRIA), pp. 31–40. Available at: http://papers.cumincad.org/cgi-bin/works/paper/caadria2021_053. (Accessed 30 March 2021).

Rhee, J., Cardoso Llach, D., Krishnamurti, R., 2019. Context-rich urban analysis using machine learning—a case study in Pittsburgh, PA. In: The 37th eCAADe and 23rd SIGraDi Conference. Architecture in the Age of the 4th Industrial Revolution—Proceedings of the 37th eCAADe and 23rd SIGraDi Conference. http://papers.cumincad.org/cgi-bin/works/paper/ecaadesigradi2019_550. (Accessed 12 September 2019).

Rossi, A., 1982. The Architecture of the City. MIT Press, Cambridge, MA and London, England, p. 202. Available at: https://mitpress.mit.edu/books/architecture-city.

Schulze, F., Windhorst, E., 2012. Mies Van der Rohe : A Critical Biography. New and revised edition, The University of Chicago Press, Chicago.

Schumacher, P., 2008. Parametricism as Style—Parametricist Manifesto. Biennale, Venice.

Schumacher, P., 2016. Formalism and formal research. In: ARKETIPO—International Review of Architecture and Building Engineering.

Singley, P., 2019. How to Read Architecture : An Introduction to Interpreting the Built Environment. Routledge. Available at: https://www.taylorfrancis.com/books/9780429262388. (Accessed 10 August 2020).

Somol, R.E., et al., 1994. What is the status of work on form today? ANY: Archit. New York (7/8), 58–65. Available at: http://www.jstor.org/stable/41846103. (Accessed 9 September 2020).

Sullivan, L.H., 1896. The Tall Office Building Artistically Considered. Lippincott's. Available at: http://archive.org/details/tallofficebuildi00sull. (Accessed 5 July 2020).

Ungers, O.M., 2011. Morphologie: City Metaphors, Bilingual ed. Buchhandlung Walther Konig GmbH & Co. KG. Abt. Verlag, p. 132.

Venturi, R., Izenour, S., Scott Brown, D., 1972. Learning from Las Vegas, Facsimile ed. The MIT Press, Cambridge, MA.

Weber, R., Larner, S., 1993. The concept of proportion in architecture: an introductory bibliographic essay. Art Doc. J. Art Libr. Soc. North America 12 (4), 147–154. Available at: http://www.jstor.org/stable/27948585. (Accessed 11 August 2021).

CHAPTER

6

AI-driven BIM on the cloud

Wanyu He[a,b], Jackie Yong Leong Shong[a,b], and Chuyu Wang[b]

[a]Florida International University, The College of Communication, Architecture + The Arts, Miami, FL, United States [b]Shenzhen Xkool Technology Co., Ltd., Shenzhen, China

Introduction

Since the Renaissance, the representation of architectural projects has evolved from hand drawings, computer renderings, and geometric modeling to building information modeling (BIM)—i.e., juxtaposing various information in one comprehensive digital data model. Currently, the construction industry remains labor-intensive, especially for the preliminary stages of a project, such as planning and design. The lack of individual competence, effective corporate management, and innovation capabilities lead to a minimal contribution to the designers' core competitiveness and substantial development. The architectural design profession still depends strongly on the manual labor force, which is neither sustainable nor productive. In this chapter, we suggest that AI-driven BIM on cloud (ABC) can solve productivity issues by integrating BIM with big data, AI, and cloud computing. We will showcase several case studies that have demonstrated how ABC has assisted construction projects within China.

Background

Thanks to the rapid development of information technologies, BIM software companies have experienced breakthroughs and innovations in improving the working progress of urban planning and architectural design. In general, some companies focus on improving existing functions, whereas some resort to challenging the existing workflow or business models, such as cloud platforms that connect designers and clients to improve communications. Although these developments aim to raise the productivity of the industry by applying new technologies, the effect is one-sided and not fully satisfying. Our question is whether BIM can solve the fundamental efficiency problem within the construction industry? Before we

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00009-3

discuss this and go further, we need to recall the definition of BIM. In a narrow sense, BIM is literally understood as a digitized building model that consists of information relating to the physical and functional properties of a building. But in a broad sense, BIM not only represents the model itself but also serves as *modeling*—the progress of creation and utilization of information synchronically across several stages (Borrmann et al., 2018) BIM also indicates *management* that supports the control and organization of data throughout the project's life cycle, such as visualization, scheme comparison, sustainability analysis, and construction site supervision.

BIM's rise and bottlenecks in China

China began its exploration of BIM at the beginning of this century. Several top-down policies have been published promoting BIM. In 2011, the Ministry of Housing and Urban-Rural Development (MOHURD) developed a standard for BIM (2011–2015 Informatisation Development Outline of Construction Industry, 2011) and further strengthened BIM's position as one of the top five technologies it perceived significant for the following 5 years (2016–2020 Informatisation Development Outline of Construction Industry, 2016) In accordance with the General Office of the State Council's ambition to realize more sustainable development for the construction industry, MOHURD further defined BIM as the only leading technology in developing the industry, and attached several seminal case studies (10 New Technologies in Construction Industry (2017 edition), 2017). Later in 2020, MOHURD claimed that BIM is significant when combined with advanced technologies such as AI, cloud computing, innovative site supervision, and so on (Guidance on Promoting the Coordinated Development of Intelligence Construction and Building Industrialization by MOHURD and Other Departments, 2020).

BIM was introduced to China in 2011, but ever since, the use of BIM in China is struggling. We will discuss several key facts about BIM's current application in China. Generally speaking, BIM is used in large-scale and complex construction such as public buildings and infrastructure. The complexity of building information surpasses what conventional CAD drawings can handle, and BIM is aimed to convey the information efficiently and accurately. For example, at the Shanghai Tower, built in 2017, the design team understood early on that it was impossible to accomplish such a "Super Project" if they would solely rely on traditional drawing methods, which would lead to many construction errors and a high number of costly change requests—due to the massive information load of this project (just its design development (DD) phase includes about 150,000 drawings). Therefore, they decided to use BIM technologies, project management tools, and relevant technology applications. In the end, they successfully built the tower utilizing BIM throughout the life cycle of the building, e.g., from design and construction, to operation and maintenance.

With the encouragement and support from the central government, BIM enjoys promising outcomes in China. In 2020, a survey regarding BIM adoption in China shows that BIM applications in public building projects reached nearly 74%, and public residential construction projects nearly 61% of penetration (Editorial Committee of BIM Application Analysis Report of China Construction Industry (2020), 2020) Although infrastructure and industrial construction reached nearly 34% and 28% of BIM penetration respectively, we expect that BIM adoption will continue to grow, i.e., using BIM for complex engineering tasks will gradually become a norm.

However, BIM adoption still has some resistance in private residential construction, which has a larger market size in China. In order to shorten the housing delivery schedule and maximize turnover, residential projects already developed a relatively established mechanism with proven business models, standardized dwelling products, and 2D-based communication workflows among majority stakeholders such as developers, design institutes, and contractors. With this machinery, the relative simplicity of residential buildings makes the transformation to BIM more difficult. Regular CAD drawings can support the entire construction cycle, and the cost can still be controlled. There is no motivation to support change in terms of workflow or shift to BIM software that requires a higher learning curve. Secondly, BIM adoption requires design and construction units to invest in recruiting and training BIM-proficient professionals, which increases manpower costs. Last but not least, developers act as clients who do not necessarily require a BIM model delivered from downstream parties, the underlying reasons being that it will further increase the budget, or they do not need to use its advantages further down the line for operations and maintenance. These factors are actually similar to barriers BIM experiences in other countries (Barriers to Implementation of Building Information Modeling (BIM) to the Construction Industry: A Review, 2018) As the government aims to solve real estate's debt crises, several policies have been promoted in recent years such as tougher lending practices. Therefore, developers turn their attention to solve capital raising and debt issues rather than move to costly technology implementation.

In summary, BIM has been relatively well promoted and used in complex and larger public construction projects in China; however, in the simpler residential building space, regular CAD drafting still acts as a major information carrier for constructing buildings.

BIM software's adoption

BIM is not equivalent to a geometric model but aims to bridge information from the design team to the construction team, by allowing each party to interoperate information during their period of contribution to the BIM model. Besides human participants, BIM software plays a significant role in connecting people and building information. In contrast with CAD software using graphical elements, BIM software uses model elements, allowing it to process richer information such as economic indicators, construction time, cost, and product manufacturer. As equipped with a higher level of structure, BIM software can organize, manage, and exchange information.

In China, various segments of the construction industry have different preferences for the use of BIM-related software. An American software company, Bentley has various types of BIM-related software product matrix which have been widely used in infrastructure construction since the past decade. At present, Bentley can be seen almost in every subdivision in the field of infrastructure construction (roads, bridges, airports, and industrial plants), and in projects of large central enterprises and state-owned enterprises (China Railway, China Metallurgical, CNOOC, and Shougang). Besides, French software company Dassault serving aircraft, ships, and cars manufacturing industry began to capture China's market with its BIM software, i.e., CATIA, in recent years.

In private construction projects, such as residential buildings, BIM-related software mainly refers to Revit by Autodesk and ArchiCAD by Graphisoft. In addition to Revit, Autodesk offers additional programs such as Dynamo, Insight, and NavisWorks to cover all the stages of a building's life cycle. Autodesk's comprehensive functions and earlier introduction of BIM into the market caused it to enjoy a higher market share of China's residential projects. One of the factors lies in the strong foundation in the era of 2D drawing laid Autodesk AutoCAD; on the other hand, Revit which integrates architecture, structure, MEP, and HVAC, is also more compatible with the departmental organization of design institutes in China. As for complex large-scale public construction projects, such as stadiums, five-star hotels, and commercial complexes, the adoption of BIM software is relatively diversified. For instance, Bentley's OBD (OpenBuilding Designer), CATIA, Revit, ArchiCAD, and Digital Project are some of the adopted software tools used in China. Besides foreign software, local BIM software and plug-in providers such as PKPM, Glodon, XKool, and Tangent are also growing to support more seamless adoption in response to local demands. This localized research and development trend is intensifying more as people get more aware of local technologies.

However, such a wide range of BIM software choices at a glance create varieties and competitiveness, but they will also become impediments in pursuing the ideal BIM vision. One of the key obstacles is data exchange. To ensure data can interoperate with each other, data from different BIM software must be translated into a medium format, in which the current mainstream neutral exchange standard is IFC. IFC is not the panacea, it does cause data loss and misrepresentation when semantic information differences exist (Interoperability analysis of IFC-based data exchange between heterogeneous BIM software, 2018) But this interoperability issue is expected to be solved by a "common BIM platform" that fully supports IFC schema, allowing models from multiple disciplines to be integrated without any data loss. More ideally, this one platform (or multiple platforms with the same kernel) with one BIM model could be utilized by multiple stakeholders throughout the entire building project life cycle, rather than using several respective programs with different kernels at different stages.

Does BIM enhance productivity?

In 2004, well-known representatives from the architectural, engineering, construction, building management, and operations sectors, and technology, and building products industries (forming the Architectural and Engineering (AE) Productivity Committee) met to address inefficiencies in the field (Collaboration, Integrated Information, and the Project Lifecycle in Building Design, Construction and Operation, 2004). They proposed a new collaboration framework that emphasizes owner leadership, integrated project structure, open information sharing, and BIM. The core initiative was to establish a mechanism based on an open exchange of information that unifies the stakeholders from the beginning of the project with shared objectives and results in an optimal outcome.

BIM promotes sharing information among collaborative teams. When the information is shared early in the project process, i.e., planning and design stage, it is most likely to achieve good outcomes in terms of delivery time and cost. Ideally, in such a mechanism, the main design decision-making efforts (which is the most cost-sensitive) can happen at the earlier stages of the project, giving collaborators maximum opportunity for good design decisions, thereby avoiding huge cost overruns (such as design changes, reworks, or termination) in later stages. As BIM technology continues to be developed, the vision of the AE Productivity Committee, especially in terms of data exchange, is gradually being realized.

But BIM still needs to pay more attention on how to achieve optimized design solutions. The design stage mainly includes project planning (predesign), conceptual design (schematic design), design development, and construction documents. Among them, project planning involves major cost planning, wherein developers need a feasible design solution to justify whether to acquire the land or not. This is intensified in China nowadays after rigorous financing policy, developers start requiring predesign solutions (or feasibility studies) that consist of defined aboveground housing unit numbers, building layouts, underground volumes, car park lots, and even structural solutions (which normally occur in the later stages of the project) in order to narrow down uncertainties and potential cost overruns. Meanwhile, in order to control land use, the government cut down land available for development. Therefore, feasibility studies early on became even more important for developers. This in fact greatly pressurized participants in the predesign stage to include business analytics, and pressured architects, urban planners, and engineers to develop feasibility studies to ensure the feasibility of investment at the very beginning and connecting both abstract numeric indicators with physical geometric entities (even considering aesthetic value).

Although the design tool has changed from pen and ruler to computer modeling today, the essence of design workflow remains unchanged; it still mainly depends on manpower to acquire design solutions from many design objectives and regulatory constraints. The role of design, in feasibility studies, is more suited to the concept of multiobjective optimization. Designers need to understand the project constraints (such as planning regulations, design codes, and given housing type) and objectives (such as maximizing plot ratio and minimizing construction cost). Hence design, in this case, is like the concept of operational research, looking for the optimum solution to a complex problem. To manually enhance the solution-finding process and quality is indeed difficult if not impossible. In practice, designers have to spend the majority of their time on data collection and understand building codes, zoning laws, etc., in order to rationally design a building, which squeezes the time that one could spend on the design.

AI-driven building information model on the cloud

Traditional CAD software tools can no longer satisfy the expectations that the contemporary building industry requires. Meanwhile, due to expensive BIM software procurement, higher learning costs, and low demands from clients in China, BIM is mainly applied in the final stages of the design, that is, BIM is merely used to “replicate” the design after it is finalized. In this way, there is no essential difference between BIM and CAD in the design stage. Hence BIM can only present its value in the construction document stage, but its participation in the early cost-sensitive design stage is almost nonexistent. BIM carries essential data about the design; however, information alone cannot completely generate optimal solutions for multiobjective problem sets. Therefore, alternative information technologies such as big data, AI, and cloud computing are crucial to integrating with BIM in order to achieve advanced performance.

Big data

Before starting the process of designing, one needs to conduct site analysis, which includes land use plan by the government, infrastructure (such as road and major public transportation hubs), facilities (such as education and cultural centers, healthcare services, retails, and landmark), geographical and natural resources (topography information, greenery, and waterscape), existing building, and frequently updating data such as housing price trends, demographic structure, and population circulation.

Integrating big data will allow BIM software to carry out site analysis similar to what geographic information systems (GIS) software does, such as noise analysis, potential economic zones, the field of vision analysis, and what GIS still does not cover such as housing plan suggestions. BIM models with big data could carry out more realistic simulations. For instance, the visitor data in a shopping mall could be collected through a series of distributed WiFi probes to study the visiting pattern, the learned patterns can later be integrated with agent-based modeling (AMB) in order to simulate and predict the circulation of visitors. Thus, such BIM integration can be useful in evaluating visitor density, evacuation efficiency, and storefront economic values (see Fig. 6.1), which could all result in optimizing storefront-divisions, visibility, and accessibility. On the other hand, housing data records in BIM will have semantic value (such as floor plan's geometry, room configuration, window orientation, and construction area) that could perfectly match with housing value trends from third-party data suppliers. The above analysis will further assist AI in design generation.

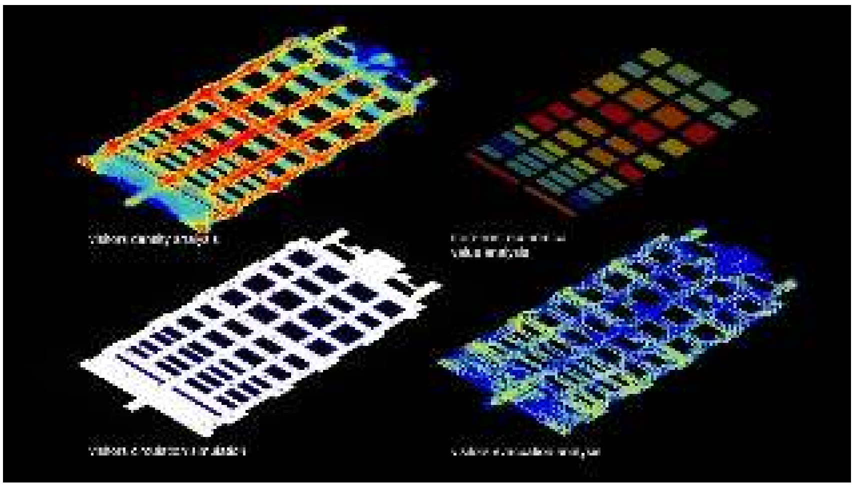


FIG. 6.1 Big data simulation and analysis in a shopping mall BIM model. The visitors' pattern is used to simulate the circulation that helps to evaluate density, evacuation efficiency, and storefront economic value. *From Shenzhen XKool Technology Co., Ltd.*

Artificial intelligence

Since the concept of artificial intelligence (AI) was proposed in the middle of the last century, AI algorithms began to solve various practical problems. Earlier AI integrated software tools such as expert systems have been proven to be ideal tools to improve production efficiency in many industries due to memory and computing ability that assisted humans to solve complex problems in the real world (Hadi, 2011; Liao, 2005) From the perspective of problems types, traditional algorithms are good at solving problems that can be clearly constrained by mathematical formulas, while AI algorithms (in the contemporary context it refers more to machine learning algorithms) are adept at solving complex or even abstract problems that cannot be fully expressed through mathematical formulas. Take the problem of finding the maximum number of boxes a container can hold as an example. If the size of the boxes and the container are given, it can be well solved by a typical linear programming algorithm; but without knowing the size of boxes that fill the container, the problem becomes complicated and it is hard to express all constraints in mathematical formulas. In this case, we need to resort to AI algorithms.

AI technologies can assist BIM to generate optimum design solutions. The highly structured BIM software architecture allows the input (such as the surrounding big data and regulatory requirements such as plot ratio) and the building element generative module (integrated with the compliance checking module) could be well-defined and related together without misrepresentation. The building generative module could generate housing units configuration, building form and planning layouts, room layouts, building facades with components, site plan drawings, and so on.

Generative modules based on AI algorithms such as evolutionary algorithms mimic the natural selection theory (Deb and Deb, 2014) The mechanism, in brief, is as follows: it firstly generates initial groups of design solutions (generation 1) based on input, later based on selection objectives (such as maximized housing unit A) filter out disqualified solutions among generation 1, later generate another group (offspring) with variation based on the survived solutions. This process is repeated until the most optimum design scheme is found, and this algorithm has been tested and practiced in the design profession. Take a museum form-finding as an example. Based on the target site's surrounding information such as topography and wind orientation and speed records, a series of museum's potential forms are generated and their performance in terms of ventilation, accessibility, and field of vision, is tested (Fig. 6.2).

On the other hand, AI can also help machines to understand unstructured data. With the development of big data technology, it is likely that in the near future, the input of design will take into account more diversified data, such as hand-sketching, point clouds, street views, regulatory wordings, and even 2D CAD-based geometric information that initially exists in an unstructured form. If these unstructured data can be effectively processed and associated with BIM data, it will greatly reduce the onerous work of parameters key in BIM modeling. Algorithms such as Markov random field (Zhu et al., 2017) and Natural Language Processing (NLP) technique (Shuai et al., 2016; Salama and El-Gohary, 2016) can realize the retrieval, extraction, analysis, and even mapping the semantics with unstructured data, bridging them effectively with BIM.

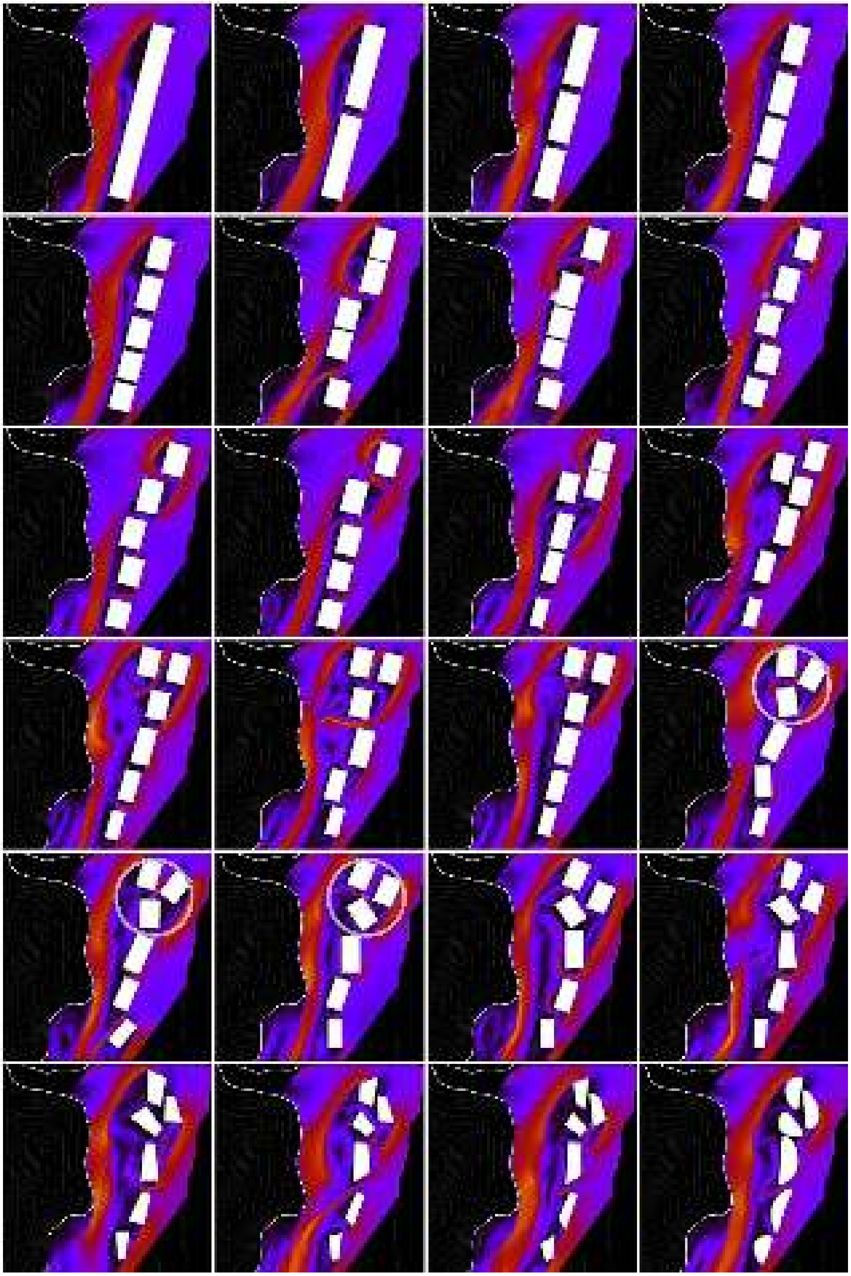


FIG. 6.2 AI-generation for a Chengdu museum's form study. A series of forms has been tested with variations in division, shape, orientation, and polygon corner. The initial scheme is displayed at the top left, whereas the final scheme is displayed at the bottom right. *From Shenzhen XKool Technology Co., Ltd.*

Cloud computing

The higher demand for feasibility studies requires more specialties to move forward to exchange information, this will encourage an increase in the requirements on BIM adoption in earlier stages of the project, resulting in a significant increase in IT costs, such as BIM software procurement, computer configuration, and network capabilities.

Software deployed in the cloud has changed the ordinary software business model. By gathering the scale of requirements, cost-sharing and computational resources' flexible allocation are realized. Enterprises can subscribe on-demand to reduce the recruitment of IT technicians, in-house physical system maintenance costs, and equipment depreciation. This further lowers the threshold for project participants to use BIM. This promotes one of the highest technical implementation points of BIM ideals, which is BIM integration for the whole life of a building. BIM giants such as Autodesk and Graphisoft are already foreseeing this and are gradually moving to the cloud. Therefore, BIM with cloud computing realizes real-time editing of digital models, supporting information sharing, and collaborative work synchronously.

In a nutshell, the above-stated technologies integrated with BIM propose a paradigm shift, AI-driven building information model on cloud (ABC). From the initial stage of the project, it could do site analysis more in-depth, thus generating optimum design solutions in BIM based on big data, AI, and regulatory and industry standards. In contrast with the purely manual modeling method, ABC with AI generative module shortens the model creation and solution finding period. In addition, cloud computing provides economical subscription and computational resources. It also promotes the interoperability of the digital model that enables real-time visualization, coediting, sharing, and exchange among stakeholders on the cloud.

Case studies

Dutch architect Rem Koolhaas claims that: "Our contemporary world is extraordinarily complex that a construction company alone is already inadequate to produce enough wisdom to understand and deal with different conditions, unknown situations and complex contexts." (Rem Koolhaas and David Gianotten on Countryside, 2017) It can be inferred from his speech that conventional design methods and approaches are no longer following the fast-changing and complicated contemporary world. Cities or buildings can only test their performance after being materialized. If the design has large defects, the remedy might be costly. Therefore, state-of-the-art information techniques that allow virtual testing before realization is believed could meet the diverse needs in the fast-changing environment. The ABC paradigm will be further explored in the following cases by XKool.

Case 1: Multidimensional urban digital platform

The 2017 Shenzhen-HongKong Urbanism\Architecture Bi-City Biennale exhibition was organized by the Shenzhen Municipal People's government held in one of Shenzhen's urban villages, Nantou Old Town (Exhibition Venue Design Concept | Curating in Nantou: A Case of Village/City Coexistence and Regeneration, 2018). As housing demand grows rural lands with collective ownership are transformed into plot areas that can house a maximum number of buildings. The Nantou Urban Village is one such area that has affordable rentals and attracts a variety of people to live and work. To investigate the opportunity and risk due to such a densified living, regional residents' circulation data were collected by WiFi probes with permission installed around the village in several specifically planned positions. The WiFi probes could record any hardware device that could be covered by their searching range in real-time. Besides these huge dynamic data, the static information such as land, traffic network, building model, and facilities of the site was also used in BIM software for simulation purposes.

Data is collected 24 h/day and recorded on a *Multidimensional Urban Digital Platform* that can discover the living patterns of villagers (as well as visitors). The device detects the residents' daily schedule within the observable zone. The unique ID of the device (MAC address) helps track the circulation sequence. On the other hand, data helps to spot the potential high-density area in a specific time, which helps the village manager to narrow down the further inspection area (Fig. 6.3).

This cloud-based platform visualizes the data collected and shows results in real-time during the exhibition period. Furthermore, a mobile application that connects to the same cloud server is also provided to visitors and local residents (Fig. 6.4). Besides displaying all the exhibition points and main tourist POIs in the village, it also helps visitors to navigate within the village by planning suitable visit routes as these visiting points are scattered distributed. Furthermore, the visitors and residents could use the app to glimpse several refurbishment options models in AR when they navigate (either physically or virtually) to targeted risk areas as stated above. Overall, these explorations are aimed to expand the boundary of conventional BIM by integrating it with big data and the cloud. Due to the data collected beyond the building scale, the data platform serves between BIM and city information modeling (CIM), pushing its original stage to a wider scope.

Case 2: XKool AI design cloud platform

In 2016, XKool launched an intelligent design platform, *XKool AI Design Cloud Platform*. It is based on the ABC paradigm and integrates several common construction design work tasks, which include checking, scheme generation, editing, reviewing, collaboration, and exporting data. It aims to improve design effectiveness and efficiency specifically for designers who participate mainly in real estate projects by generating optimum design schemes through AI, real-time compliance checking, and supporting multiple formats of input and output without disconnects from current mainstream design software.

Initially, platform users could choose to upload the target land boundary or hand-drawn map (when the detailed cadastral land parcel's geometry data have not been published). Once the site's location is selected, the surrounding information such as building geometry, road networks, and existing POI information could be queried and displayed for more perception intuition about the site. Several site analyses could be carried out including but not limited to housing price trends, economic value, potential population density, noise analysis, sight view analysis, and mobility analysis. With these analyses, designers can better understand the site conditions without paying actual visits, and even gain insight into potential risks and opportunities that could influence the design quality.

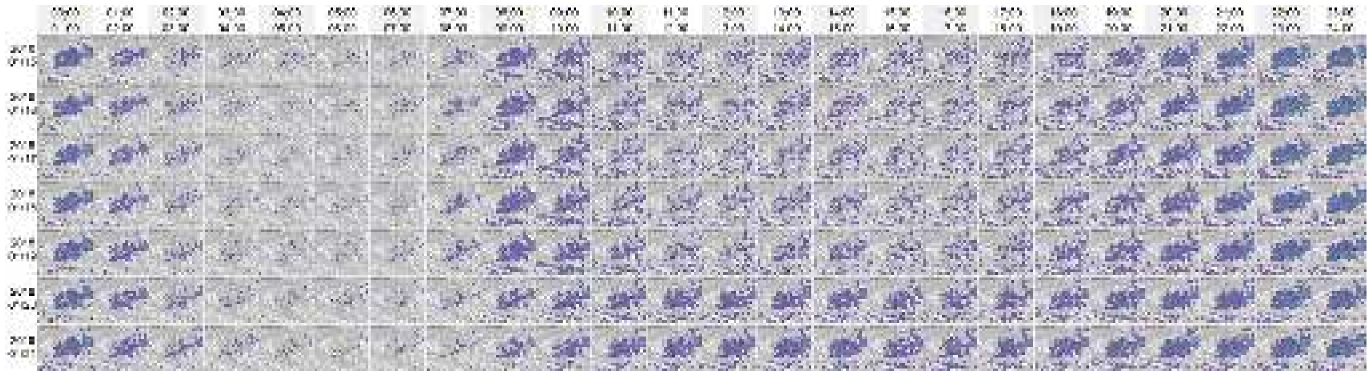


FIG. 6.3 Heatmap visualization of Nantou Urban Village. The image shown is the regional population 24 h data collected in a week via WiFi probes and visualized in the heatmap in which it is better to represent the changes of concentration and area. *From Shenzhen XKool Technology Co., Ltd.*

FIG. 6.4 Mobile application of Multidimensional Urban Digital Platform. From left to right represents the exhibition map, smart navigation for visiting points, and overlay of 3D model displayed in AR. *From Shenzhen XKool Technology Co., Ltd.*

Next, the project objectives (plot ratio, housing unit configuration, building block number) and constraints (density, height limit, setback limit, minimum daylighting duration) will be set for the parameters for the multiobjective optimization generative and compliance check modules. Designers could choose either to define the land subdivision by themselves or by machine, in order to define the location of main road networks and minimize the generation area for various latent planning schemes. AI-integrated generative module will output the planning schemes consisting of building block(s) identical to the housing unit plan designated by designers who have uploaded to the library previously, thus reducing the building model creation cost. These planning schemes in the BIM structure will be exhibited in ranking after being qualified with regulatory rules and satisfy the objectives as much as possible. When the generated outcome still does not match the requirement, this platform, which is also equipped with common editing tools, allows manual modification in terms of geometry and attributes, enabling real-time compliance checking when adjusting the model (Fig. 6.5). These procedures can be repeated until the desired plan is obtained.

At the urban planning or project planning level, this platform is able to generate planning schemes from scratch and assist in achieving an optimum solution. Take a particular case as an example, the original scheme (solely done by the designer) has six buildings that could not comply with daylight regulation (Fig. 6.6). However, with the aid of the platform, disqualified buildings could meet the compliance check. The difference between manual and machine is that the latter can keep testing each possibility by changing within hundredths of a meter and/or rotation degree. Such diminutive adjustment is hard for humans when looking for a globally optimized solution.

FIG. 6.5 Screenshot from XKool AI Design Cloud Platform. The AI-generated schemes are sorted according to satisfaction toward objectives. *From Shenzhen XKool Technology Co., Ltd.*

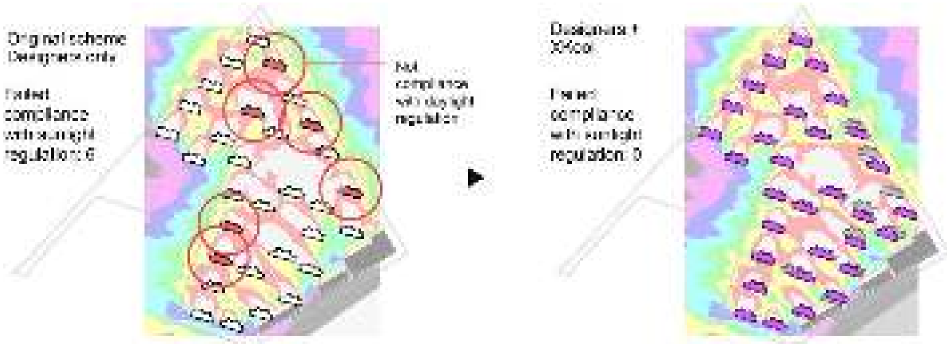


FIG. 6.6 Optimum planning scheme before and after. The left represents the planning scheme done solely by designers, whereas the right represents the optimized planning scheme by the design platform. *From Shenzhen XKool Technology Co., Ltd.*

Besides the planning scale, the platform also covers smaller scales. A generative model is trained by deep learning using data from millions of housing plans to study the relationship between housing structure attributes (i.e., housing size, room configuration, entrance position, and balcony orientation) and the geometry of various rooms (i.e., living room, kitchen, dining room, bedroom, balcony, and corridor). This generative model could generate several floor plans using just the given numerical parameters (Fig. 6.7). Meanwhile, a classifier model can also match the given floor plan outline (in CAD) and tries to match it with the current BIM

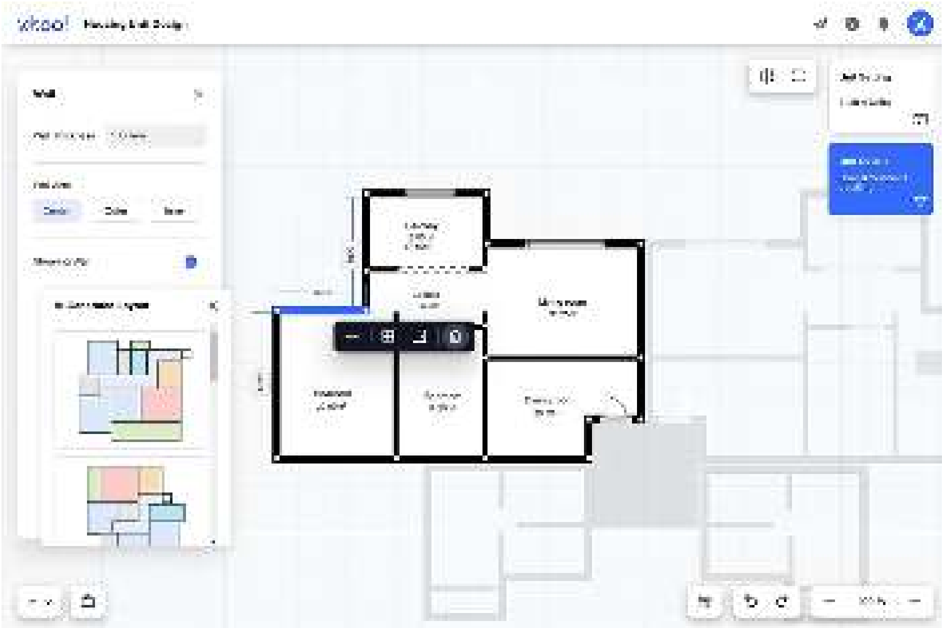


FIG. 6.7 Screenshot from XKool AI Design Cloud Platform. The platform can generate and recommend plans for users' consideration, which will be used for design development. *From Shenzhen XKool Technology Co., Ltd.*

housing model in the database library; this technique involves the use of AI algorithms such as convolutional neural network (CNN) that have been widely adopted in the classification task nowadays.

Case 3: Kooltect prefabrication design cloud platform

In recent years, standardized and industrialized prefabricated buildings have been regarded as a key standard that proves to a great extent construction efficiency, the ability to cope with rising labor costs, construction quality, and low-carbon emissions. Based on the ABC paradigm, *Kooltect Prefabrication Design Cloud Platform* is aimed to empower the prefabrication industry. Starting from the prefabricated container unit, users can quickly view the existing units from the manufacturer, such as a single apartment with a single container, a one-room apartment with two containers, or a special unit to deal with the corner space. After the appropriate unit module is selected, one can edit the exterior and interior layout.

In contrast with traditional design workflow that requires multidisciplinary collaboration, the platform allows a few professions to join at the previous stage as the logic of each specialty is already coded. When the container unit boundaries or indoor layout is adjusted, the algorithm enables the components such as structure, MEP, and HVAC to react accordingly. For instance, once the indoor layout is determined, the system will calculate ventilation requirements and propose HVAC equipment, including air duct size, inlet and outlet size, location, and so on (Fig. 6.8). The duct system is also generated in the ceiling and condensate pipes

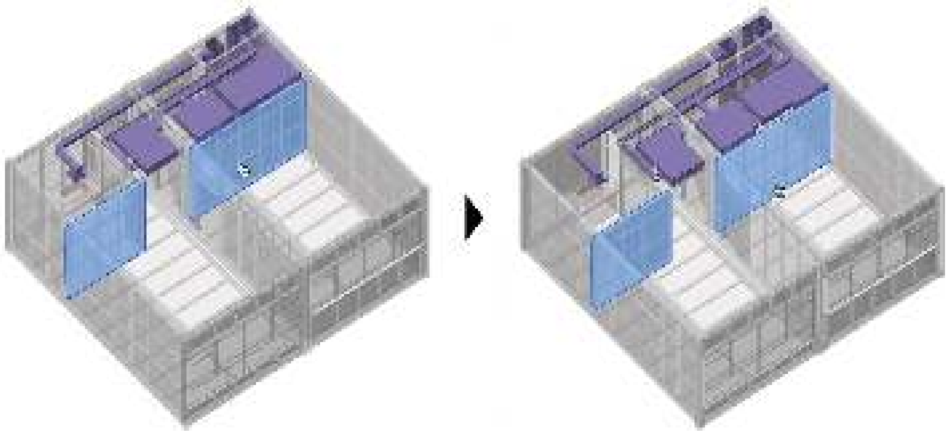


FIG. 6.8 HVAC equipment adjustment according to changes of partition wall. HVAC equipment and connectors could be adjusted when the space is modified by pulling or pushing the partition wall. *From Shenzhen XKool Technology Co., Ltd.*

required for air conditioning. Finally, the HVAC system of each residential unit is connected, forming a well-connected system within the building.

Once the container unit is defined, the platform's assemble module will further generate several assembling schemes with the given site and unit. Unlike the planning generation mentioned earlier, this module will assemble the container units both horizontally and vertically, and comply with the rules too (Fig. 6.9). The assemble generative module also deals with

FIG. 6.9 Screenshot from Kooltect Prefabrication Design Cloud Platform. The selected container units assemble both horizontally and vertically, forming several building blocks. *From Shenzhen XKool Technology Co., Ltd.*

multiobjectives as optimization needs to consider maximum construction area, unit numbers, building density, plot ratio, cost, rental price, and rate of return. After defining the assemble schemes, users are also allowed to go back and modify the container unit, and thus change the unit block simultaneously. This exchangeable operation ensures the flexibility of the model creation, in other words, real-time synchronous design at different scales is achieved.

Conclusions

The trend of informatization and digitalization in the construction industry is irreversible. BIM is still undergoing continuous development to meet the demands of current projects by integrating advanced technology. In this regard, ABC might be one of the paradigms to be tested in the market. In the future, it is expected that BIM will continue to collaborate with technologies such as robotic construction, 5G, blockchain, virtual reality, and the Internet of Things. Last but not least, the current adoption of BIM in China still needs attention to issues such as the client's awareness of BIM, the business model, the accessibility of stakeholders, the user-friendliness of the BIM software interface, and the effectiveness and efficiency of the AI design algorithm.

References

10 New Technologies in Construction Industry (2017 edition), 2017. Available at: http://www.mohurd.gov.cn/wjfb/201711/t20171113_233938.html. (Accessed 30 August 2021).

2011–2015 Informatisation Development Outline of Construction Industry, 2011. Available at: http://www.mohurd.gov.cn/wjfb/201105/t20110517_203420.html. (Accessed 30 August 2021).

2016–2020 Informatisation Development Outline of Construction Industry, 2016. Available at: http://www.mohurd.gov.cn/wjfb/201609/t20160918_228929.html. (Accessed 30 August 2021).

Ahmed, S., 2018. Barriers to implementation of building information modeling (bim) to the construction industry: a review. J. Civil Eng. Constr. 7 (2), 107–113. https://doi.org/10.32732/jcec.2018.7.2.107.

Borrmann, A., et al., 2018. Building Information Modeling, first ed. Springer International Publishing, Switzerland, https://doi.org/10.1007/978-3-319-92862-3.

Collaboration, Integrated Information, and the Project Lifecycle in Building Design, Construction and Operation, 2004. Available at: https://kcuc.org/wp-content/uploads/2013/11/Collaboration-Integrated-Information-and-the-Project-Lifecycle.pdf. (Accessed 1 September 2021).

Deb, K., Deb, K., 2014. Multi-Objective Optimization. Springer US, Boston, MA, pp. 403–449, https://doi.org/10.1007/978-1-4614-6940-7_15.

Editorial Committee of BIM Application Analysis Report of China Construction Industry (2020), 2020. BIM Application Analysis Report of China Construction Industry (2020). China Architecture & Building Press.

Exhibition Venue Design Concept | Curating in Nantou: A Case of Village/City Coexistence and Regeneration, 2018. Available at: http://2017.szhkbiennale.org.cn/EN/News/Details.aspx?id=10001013. (Accessed 2 September 2021).

Guidance on Promoting the Coordinated Development of Intelligence Construction and Building Industrialization by MOHURD and Other Departments, 2020. Available at: http://www.mohurd.gov.cn/wjfb/202007/t20200728_246537.html. (Accessed 30 August 2021).

Hadi, A.S., 2011. Expert Systems. Springer, Berlin, Heidelberg, pp. 480–482, https://doi.org/10.1007/978-3-642-04898-2_240.

Huahui, L., Deng, X., 2018. Interoperability analysis of IFC-based data exchange between heterogeneous BIM software. J. Civ. Eng. Manag. 7 (24), 537–555. https://doi.org/10.3846/jcem.2018.6132.

Liao, S.-H., 2005. Expert system methodologies and applications—a decade review from 1995 to 2004. Expert Syst. Appl. 28 (1), 93–103. https://doi.org/10.1016/j.eswa.2004.08.003.

Rem Koolhaas and David Gianotten on Countryside, 2017. Available at: https://msd.unimelb.edu.au/events/mtalks-rem-koolhaas-and-david-gianotten-on-countryside. (Accessed 2 September 2021).

Salama, D.M., El-Gohary, N.M., 2016. Semantic text classification for supporting automated compliance checking in construction. J. Comput. Civ. Eng. 30 (1), 04014106. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000301. American Society of Civil Engineers.

Shuai, L., Hubo, C., Kamat, V.R., 2016. Integrating natural language processing and spatial reasoning for utility compliance checking. J. Constr. Eng. Manag. 142 (12), 04016074. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001199. American Society of Civil Engineers.

Zhu, Q., et al., 2017. Robust point cloud classification based on multi-level semantic relationships for urban scenes. ISPRS J. Photogramm. Remote Sens. 129, 86–102. https://doi.org/10.1016/j.isprsjprs.2017.04.022.

This page intentionally left blank

PART 3

AI in urban scale research

This page intentionally left blank

CHAPTER

7

Deep learning in urban analysis for health

David William Newton

College of Architecture, University of Nebraska-Lincoln, Lincoln, NE, United States

Introduction

Over the last hundred years, the number of people living in urban areas has increased dramatically, making the link between the design of our cities and human health a pressing global issue (United Nations, Department of Economic and Social Affairs, Population Division, 2019). According to the United Nations, 56.2% of the world's population now resides in cities and the World Health Organization (WHO) projects that the number will increase to 66% by 2050. In parallel to this massive urbanization of our species, diseases such as obesity, diabetes, and high blood pressure have increased significantly among urban populations (WHO, 2016). In addition to significant physical health problems, urbanization has also been linked to increasing rates of mental illness. Analysis by the WHO estimates that mental illnesses, such as depression and anxiety, make up 12% of the global disease burden, and this figure is projected to increase as more and more world's population moves into cities. The combined cost to society of treating these physical and mental diseases globally is estimated to be in the trillions of dollars (WHO, 2016). A key component in mitigating the impact of these diseases on society at large is developing a better understanding of how the design of the built environment impacts human health. Developing urban analysis methods that allow urban planners and designers to better understand this relationship is, therefore, crucial to the design of healthier cities.

The increasing urbanization of our species has also been accompanied by a revolution in information collection, processing, and analysis powered by the integration of global computer networks into the fabric of our everyday lives. From the smartphones in our hands to the global satellite networks above our heads, a vast informational infrastructure generates

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00018-4

around 2.5 quintillion bytes of data each day. Among this deluge of data, are a multiplicity of data collection technologies that provide information on the state of the built environment. Remote sensing technologies are a major source of such data, which use aerial and satellite platforms to observe the surface of the planet from a bird's-eye view. From this vantage point, data in the form of aerial photographs, light detection and ranging (LIDAR) images, radio detection and ranging (RADAR) images, hyperspectral images, and thermal images can be captured in real-time documenting the change of the built environment over days, months, and years. These image-based datasets can be extremely large requiring new methods and technologies to systematically extract useful information. A variety of disciplines, from earth science to epidemiology, have used advances in machine learning to automate the analysis of large image-based datasets in order to better understand a range of phenomena (Tsagkatakis et al., 2019). The allied design fields, however, have largely relied on traditional inferential statistical methods—which require significant amounts of manual labor to extract features from images for tasks like regression and classification. These large image-based datasets, therefore, offer a rich and largely untapped resource for the allied design disciplines to better understand the link between human health and the built environment in a world that is becoming increasingly urbanized.

There has been significant progress in the field of machine learning in the development of methods capable of working with large image-based datasets for analysis, identification, and prediction tasks. Deep learning is a subfield of machine learning that uses layers of artificial neurons to build mathematical models from datasets that have been demonstrated to outperform competing approaches on a number of these tasks. For example, researchers have trained deep learning models to accurately identify objects, such as cars, people, exoplanets, and even skin cancer from photographs. Researchers have also begun to explore the use of remote sensing datasets, such as satellite imagery, in order to build models of natural and man-made landscapes that can aid in understanding and predicting phenomena as diverse as geological disasters and poverty (Liu and Wu, 2016; Piaggesi et al., 2019). Their application in the realm of urban analysis has been more limited, but some of the areas they have been used to analyze include: identifying urban land use (Zhang et al., 2019); predicting urban growth (Jaad and Abdelghany, 2020); and estimating human health measures, such as obesity (Maharana and Nsoesie, 2018). Their application in understanding the link between human health and the built environment has been especially limited, but existing research has demonstrated their potential for both estimating health measures, as well as identifying correlations between the visual features in the built environment and health.

The application of deep learning to urban health analysis is, therefore, in its early stages, but offers new and promising capabilities in using large image-based datasets to better understand the built environment and its effects on human health. This chapter will introduce and explore some of these capabilities, providing the allied design fields with a roadmap of this emerging area of research, its potentials, and current challenges. The chapter begins with a brief overview of existing research related to urban morphology and health, in which precedent work using traditional methods as well as deep learning are introduced. Next, research is presented demonstrating methods for the use of discriminative and generative deep learning processes for both urban health estimation and analysis. The chapter then concludes with a discussion of key challenges and directions for future work in this emerging field of research.

Urban morphology and health

Existing research in urban planning and health has established a variety of links between the physical characteristics of the built environment and human health. In terms of physical health measures, previous research has found significant correlations between characteristics of urban morphology, such as density and street network pattern, to rates of obesity (Lopez-Zetina et al., 2006; Marshall et al., 2014). These characteristics have also been found to be linked to increased rates of diabetes (Marshall et al., 2014) and asthma (McConnell et al., 2006). The work done so far suggests that neighborhoods and cities that are more walkable tend to be correlated with improved health outcomes for the diseases mentioned.

There has also been a growing body of work that has discovered significant correlations between urban morphology and mental health. Research looking at how urban density effects mental health has found a positive correlation between high rates of urbanization and high rates of mental illness (Peen et al., 2010). Street network proximity has been linked to neurological diseases such as non-Alzheimer's dementia, Parkinson's disease, Alzheimer's disease, and multiple sclerosis (Yuchi et al., 2020). In contrast, proxies for lower density, such as access to green spaces, water features, natural views, and natural light, have been found to correlate to low rates of anxiety and depression (Braubach, 2007; May et al., 2009; Garrett et al., 2019).

The picture that emerges from this growing body of work is that the physical characteristics of our neighborhoods and cities have significant correlations with health. The nature of these correlations is still being studied, and it is important not to confuse correlation with causation, but the evidence suggests an important link that requires more investigation. The majority of existing research in this area has primarily used traditional inferential statistical approaches to discover correlations (Hoisington et al., 2019; Renalds et al., 2010). These approaches, however, have a limited ability to efficiently analyze large image-based datasets, such as those from remote sensing platforms.

Deep learning in urban analysis for health

In order to address some of the shortcomings of traditional statistical methods, there is a growing body of research investigating the use of deep learning in combination with remote sensing datasets to discover and better understand correlations between urban morphology and human health. This research can be broadly categorized into two categories: discriminative deep learning and generative deep learning approaches. Deep learning models are comprised of layers of artificial neurons—with each neuron being a simple mathematical function mapping inputs to an output. These simple building blocks can be connected to one another in networks in order to create models capable of representing any mathematical function. The organization of multiple layers of artificial neurons into a network to accomplish a particular task is referred to as creating a deep learning architecture. There are a large variety of architectures for both discriminative and generative deep learning that has been developed and validated by the research community with new architectures being developed every day.

Discriminative deep learning processes use labeled datasets to build models for classification and regression tasks. In cases where an input dataset is correlated with an output dataset, these processes can approximate a function that maps inputs to outputs given enough data examples and training time. Generative deep learning processes work in a different way and use large unlabeled datasets to learn the probability distribution that underlies an input dataset. This distribution can then be sampled to generate new data instances. Generative processes require less data preparation than discriminative processes because they work with unlabeled data. Discriminative and generative processes can build models from many types of large datasets (e.g., images, drawings, text, 3D models, sounds, etc.). This flexibility, coupled with their ability to work with images, makes them useful to disciplines whose data tends to be image-based, or heterogeneous, in nature.

Applications of discriminative deep learning in urban health analysis

Discriminative deep learning approaches have been most widely used by existing research in urban health analysis. They have been used in conjunction with aerial, satellite, and point-of-view images for a variety of classification and regression tasks involving demographics, health, and well-being. For example, they have been used to train models that can estimate the population of census blocks from satellite images using classification (Robinson et al., 2017). They have also been applied to regression tasks to estimate the rate of poverty in developing countries using daytime and nighttime satellite images of those countries (Jean et al., 2016). In terms of health measures, researchers have trained discriminative models on satellite images of cities to estimate rates of obesity (Maharana and Nsoesie, 2018). Researchers have also used street view and point-of-view images to estimate a broader spectrum of wellness metrics related to unemployment, education, income, and wellbeing (Suel et al., 2019).

Convolutional neural networks (CNNs) are a deep learning architecture developed for working with images and are the main architecture used by this precedent research. CNNs work by taking image data as an input and passing that data through a series of neural layers. As the images move through each layer, image data is progressively abstracted into sets of visual features that provide a compressed representation of the image data that can be used for classification, regression, or generative tasks. The layers at the beginning of the model extract low-level features (i.e., edges, corners, etc.) while the layers toward the end of the model extract high-level features (i.e., roads, buildings, etc.). CNNs learn which features best define an image for a particular task and how to extract those features from the image data through a training process involving feeding example images into the model along with the desired model output (e.g., a desired classification or regression value), calculating the error, and then using an optimization algorithm to adjust the weights associated with the CNN's mathematical model. This supervised learning process is done iteratively until the model reaches peak accuracy.

There are a large variety of CNN architectures to choose from depending on the task at hand. Previous research involving the use of satellite images for health analysis has primarily used the visual geometry group (VGG) family of CNN architectures (Simonyan and Zisserman, 2016). There are, however, a number of other architectures that offer increased accuracy in image recognition tasks that could also be chosen (e.g., Inception, Xception, ResNet). Training these CNN models, however, poses a challenge. Discriminative deep learning models require prodigious amounts of data for their training. These models are often trained on datasets that contain millions of data samples in order to reach peak accuracy in classification, or regression tasks. This can pose a challenge when working with smaller datasets.

In order to address this challenge, researchers have developed two methods that are fundamental to any deep learning training process: data augmentation and transfer learning. Data augmentation increases the size of the training dataset by creating new data instances from existing instances. In the case of an image dataset, this is done by taking an existing image from the dataset and applying operations (e.g., scaling, rotation, distorting, adding noise, etc.) to it that modify the image from its original state. The new modified image can then be used as a new training example. This simple trick seems dubious but has been demonstrated to improve model accuracy significantly and is used extensively by precedent research in urban health analysis.

Transfer learning is the other primary method used when working with small datasets (i.e., datasets in the hundreds to thousands of data points). Transfer learning saves significant computation time by repurposing deep learning models trained for one task for another similar task. This is done by using available deep learning models trained on millions of data points and then retraining only a small part of that model for the desired classification, or regression task that is similar but different from the task the model was originally trained for. Transfer learning has demonstrated impressive capabilities and allows the analytic insights developed from one dataset to be transferred to other datasets. Precedent work in urban health analysis has made use of this method extensively.

Fig. 7.1 shows an example of discriminative deep learning architecture using transfer learning for an urban health regression task involving estimating the rate of overweight adults based on satellite images of US census tracts—which are typically about the scale of a neighborhood. In the figure, the Xception CNN architecture is pictured. Xception is an architecture that is pretrained on the ImageNet database, which is an image database of over 14 million images spanning more than 20,000 object categories. The original architecture is comprised of 14 convolutional blocks (each block is made up of several neural layers) and a layer at the end that outputs a classification value. In order to adapt the model for estimating rates of obesity, the final layer of the original model is removed and replaced by a new layer that will output a regression value instead of a classification value. As Fig. 7.1 shows, the model takes satellite images of census tracts as an input, extracts features through its convolutional blocks, and then outputs a regression value estimating the rate of overweight adults in the census tract.

The training of the model involves freezing a set number of neural layers and only training a select set of layers in the model. This selective training is what saves time and finding which layers to train is a key problem. This choice is often made based on how similar the desired dataset is to the original dataset for which the model was trained. In the example given in Fig. 7.1, satellite images are significantly different than the ImageNet database used to train the original Xception architecture. ImageNet features close-up elevational views of various objects (e.g., people, plants, animals, furniture, etc.) and not views from above. In order to address this issue, multiple options are normally tested. For example, one test might explore

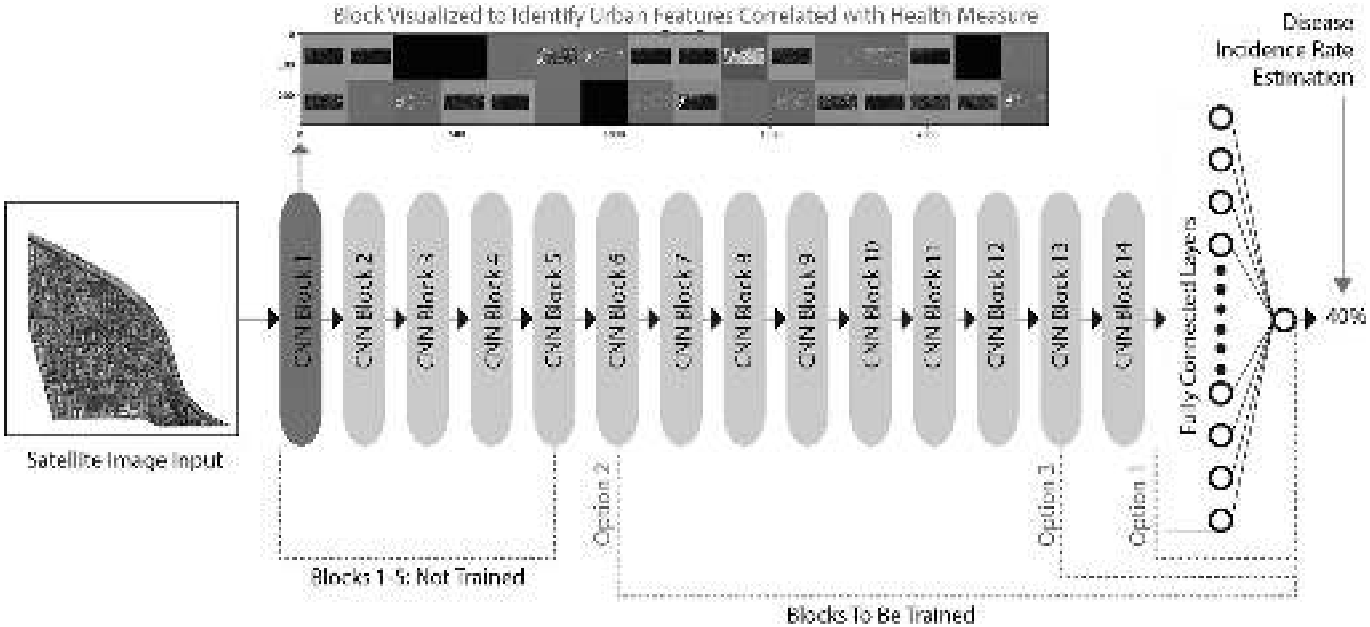


FIG. 7.1 Xception CNN architecture. The Xception CNN architecture is shown. The diagram shows that the following CNN blocks are trained on the dataset: Option 1—just the last fully connected layer; Option 2—blocks 13, 14, and the last layer; Option 3—CNN block 6–14 and the last layer. The diagram shows that block 1 is visualized to find correlations between specific urban design features and the estimated health outcome. *No permission required.*

how well a minimally modified version of the Xception architecture can perform by only training the last layer. This option saves the most computation time but assumes that the low and high-level image features learned from ImageNet will be relevant for analyzing satellite images of cities. The second test might explore the hypothesis that the low-level image features learned from ImageNet are useful but that the high-level features are not relevant. Therefore, this approach might train the last two convolutional blocks of the Xception architecture as well as the last layer. The third test might explore the hypothesis that both high-level and a proportion of low-level features may not be relevant for satellite image analysis for a particular health measure. Therefore, convolutional blocks 6 through 14, as well as the final layer, may be trained. As more layers are trained, more computational resources and time for that training are necessary. In the example, because aerial views are significantly different than elevational views, the third architecture demonstrated the lowest error in estimating rates of overweight adults but required the largest computational resources.

The existing research presented in this section establishes the efficacy of discriminative methods for estimating some health and well-being measures but there are still a number of areas that require additional study in order to realize the full potential of these processes for urban health analysis. These areas include the following: developing a greater understanding of which health measures can best be estimated with these processes; creating methods for training these models more efficiently: and developing techniques to identify specific visual features that correlate with health measures. The next section will address this last issue in more detail.

Analyzing deep learning models to find correlations

Deep learning models are often referred to as "black-box" models because their inner workings remain obscured behind hundreds of thousands, and sometimes millions, of parameters. The development of analytic methods to address this problem is currently a pressing problem for disciplines working with deep learning because such methods would allow insight into the learned correlations between dataset features and estimation values. Previous research in this area has used the visualization of individual CNN layers to identify correlated features. This approach has been used extensively in work using satellite images to estimate health (Jean et al., 2016; Maharana and Nsoesie, 2018) but has significant drawbacks. Specifically, these methods rely heavily on visual interpretation to identify features of interest and provide little information on how combinations of features might be correlated with outcomes.

Researchers in the field of machine learning have developed a variety of methods to identify possible correlations between dataset features and predicted outcomes in deep learning models. Zeiler and Fergus (2014) have developed a quantitative method involving deconvolution that highlights the portion of an image that is being activated by a particular neural unit. Nguyen et al. (2019) have used optimization techniques to find images that cause the highest and lowest activation of different neural layers. Gatys et al. (2016) have used the calculation of Gram matrices to find the neural layers most activated by a given set of images. The identified layers can then be visualized as images called feature maps that can be interpreted by an analyst to identify key visual features.

Fig. 7.2 shows an example of this last approach. In the example, a dataset of satellite images of census tracts from the state of California is first subdivided into image sets that represent high and low incidence for three different health measures: obesity, asthma, and heart disease (Newton, 2021). The average Gram matrix is then calculated for each high and low incidence image set. This is done by calculating the Gram matrix for each individual census tract image from the first convolutional block of the Xception architecture for each set and then averaging those individual Gram matrices together. Fig. 7.2 shows visualizations of the average Gram matrix calculated for each health measure. These matrices serve as a kind of spectrograph for the satellite images present in each high and low incidence set and allow each health measure to be compared. For example, obesity and heart disease show a similar pattern of activation for high incidence images, while asthma is noticeably different.

The axes of the matrix show identification numbers for the specific neural layers (i.e., feature maps) in the first convolutional block. Bright colors in the Gram matrix represent combinations of feature maps that are most active on average for a particularly high or low incidence set. These feature maps can then be visualized and interpreted to identify specific built and natural environment features that are correlated with high and low incidence rates. Gram matrices can be calculated from any convolutional block in the CNN architecture, and the choice of where to do this is an important one. For this example, the first convolutional block was chosen because it allowed for easier visual interpretation. The downside to this choice is that the neural layers at this level are involved with identifying low-level image features (e.g., edges, corners, etc.) and not high-level features (e.g., objects composed of several low-level features like street network grids, etc.).

In Fig. 7.3, the most active feature map combinations identified from the average Gram matrices for both high and low incidence rates of overweight adults are shown (Newton, 2021). The highest activating feature maps for high disease incidence are feature maps 30 and 24. Fig. 7.3 shows visualizations of these feature maps as well as overlaid analysis. Visual analysis of feature map 30 reveals that it activates most when detecting proxies for buildings and streets—such as north-south edges and the roofs of buildings—especially lighter roofing materials often associated with larger commercial and residential buildings. In contrast, feature map 24 activates in relation to the space in-between buildings, specifically darker elements in the exterior landscape of the census tract, such as asphalt surfaces (e.g., streets and parking lots), vegetation, and shadows. The highest active feature maps for low incidence are feature maps 24 and 22 as shown in Fig. 7.3. Feature map 24 is the most active for both high and low incidence rates. Feature map 22 has a similar activation behavior as 24, responding to exterior spaces. This activation pattern, therefore, focuses more on exterior space than what was seen in the high incidence case. These results indicate the CNN model is most responsive toward proxies for walkability, such as streets, shadow patterns along streets, and parking lots. These results are consistent with precedent research in urban planning and health that has found similar correlations between walkability and obesity, but this method provides a new way of identifying these correlations (Li et al., 2009; Marshall et al., 2014).

This example demonstrates a deep learning-driven mixed methods approach to identify correlations between satellite image features and disease incidence and also its limitations. The first major limitation involves the selection of where in the CNN model to calculate the Gram matrices and retrieve the feature maps. In this research, the first convolutional block was chosen because, at that stage in the model, images can still be readily interpreted through

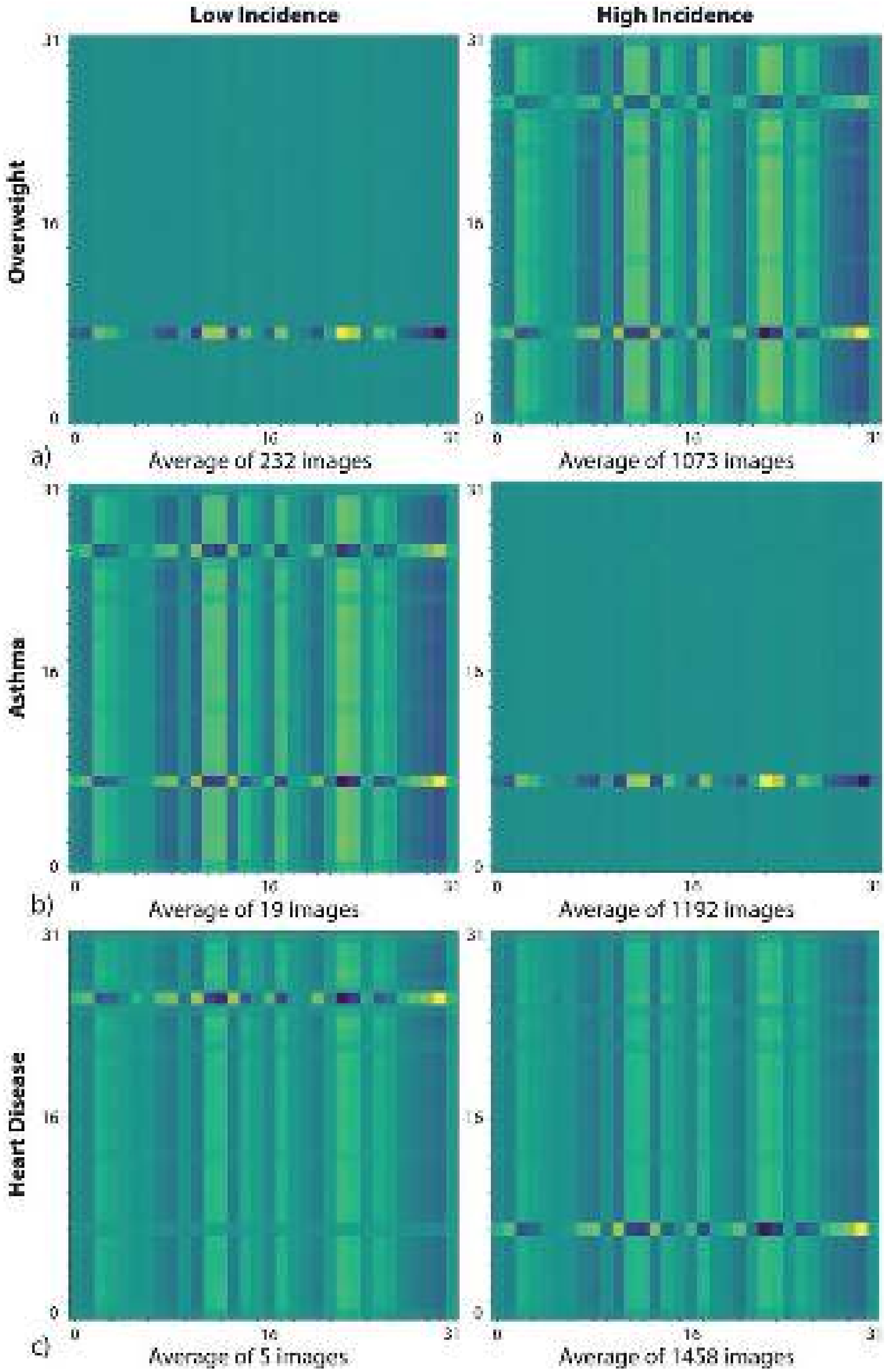


FIG. 7.2 Gram matrices. (A) Shows average Gram matrices of low and high incidence census tracts for overweight health measures. (B) Shows average Gram matrices for asthma. (C) Shows average Gram matrices for heart disease. *No permission required.*

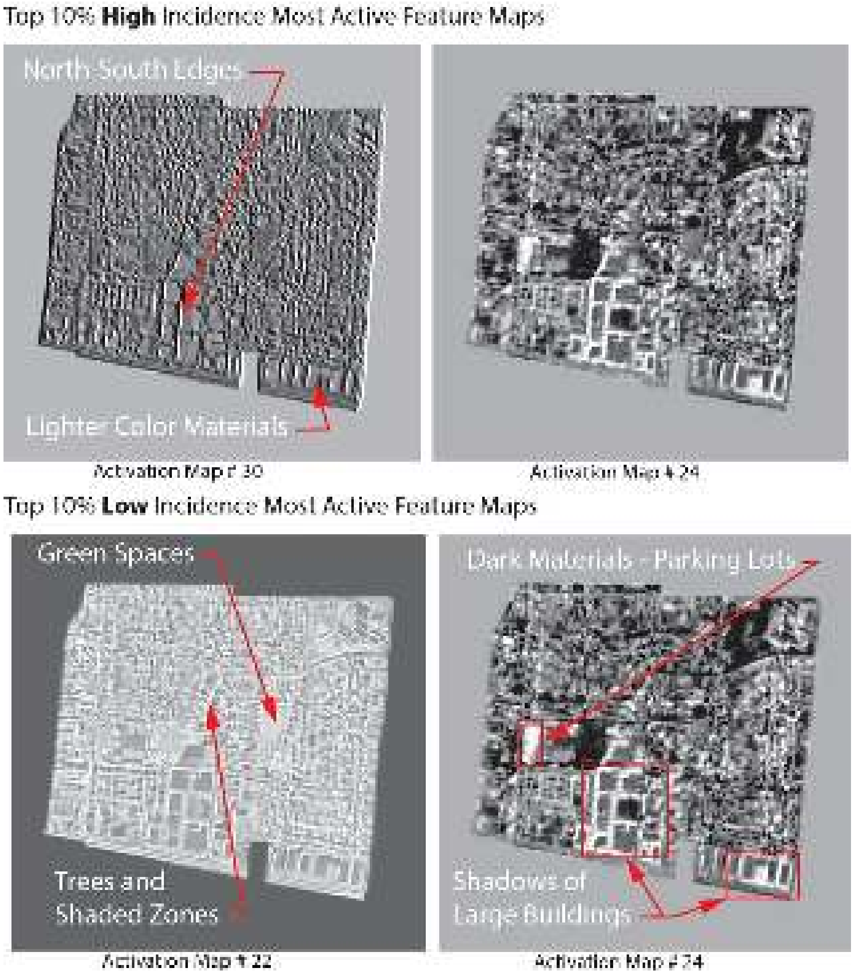


FIG. 7.3 Gram matrix analysis. A sample census tract image with a high rate of overweight adults is used as the input to the CNN model. The most active feature maps identified by the Gram matrix analysis are shown for both high and low disease incidences. Qualitative analysis is overlaid on the feature maps to identify specific visual features that are activating the model. Brighter pixel values indicate more activation in that area of the image. *No permission required.*

visual examination. The first blocks of the CNN model have neural layers that learn to find low-level features. While using these early layers from the analysis allows the feature maps produced by these layers to be human-readable, the feature maps at this stage have learned only very basic representations. This makes developing insight about how high-level features (e.g., street grid patterns, park distribution patterns, building density differences, etc.) are correlating with specific outcomes more difficult and subject to a greater level of interpretation. This issue relates to another limitation, which is the degree of interpretation needed to interpret the activation patterns at work in the feature maps identified by the Gram matrices.

Identifying the image features that are activating a particular feature map requires a careful assessment of the feature maps on a pixel-by-pixel basis. For some feature maps, the activations can be straightforward to interpret, but others require a greater degree of subjective judgment. Developing more robust quantitative methods for the analysis of CNN models to identify these features is, therefore, a pressing issue that has become the focus of an area of research called explainable, or interpretable, artificial intelligence. Recent work in this area has shown significant improvements over previous work (Linardatos et al., 2021), and with new developments occurring each year, robust tools to address this issue seem within reach.

Applications of generative deep learning for urban health analysis

Generative deep learning processes have been explored less than discriminative processes for urban health analysis by existing research. This may be due to the fact that they do not offer straightforward classification, or regression, values that lend themselves to quick interpretation, but instead can learn the statistical correlations that define one type of dataset versus another and can create new data instances based on these learned correlations. There are a wide variety of generative deep learning architectures that have been developed in the field of machine learning, such as variational autoencoders and deep belief networks. Generative adversarial networks (GANs) proposed by Goodfellow et al. (2014) are the most popular deep generative model. This popularity is due to their ability to outperform competing approaches in terms of their flexibility for image generation tasks and the quality of produced images.

GANs work through the competition of two deep neural networks: the generator network and the discriminator network. The job of the generator network is to create new data instances from noise. The job of the discriminator network is to correctly identify the fake images being created by the generator network from the real images comprising the training dataset. Both networks are trained together in an iterative manner and, if the training process is successful, the generator will gradually learn to produce new data instances that are good enough to fool the discriminator network. Fig. 7.4 shows an example of GAN architecture illustrating this deep learning architecture. In the figure, the GAN is being trained on a dataset of satellite images of census tracts. The generator network is tasked with learning to generate completely new images that resemble those in the training set. The discriminator network must, therefore, learn to accurately differentiate between data instances from the real training set and those being artificially created by the generator.

GANs have been used for a large variety of image generation tasks. For example, they have been used to generate images of human faces, bedroom layouts, and building facades. They have also been used in the creation of designs for new 3D objects like chairs and tables. Their application for urban health analysis, however, has been limited. The research that has been done in this area can be classified as residing in two different categories: (1) approaches that use GAN architectures to create completely new data instances for analysis; (2) approaches that use GAN architectures for translation between one dataset and another for analysis.

The first category involves training GANs on satellite, aerial, or map images of exemplar urban areas in order to create images of new urban plans that have been learned from the exemplar dataset. These images can then be qualitatively assessed to develop insight into

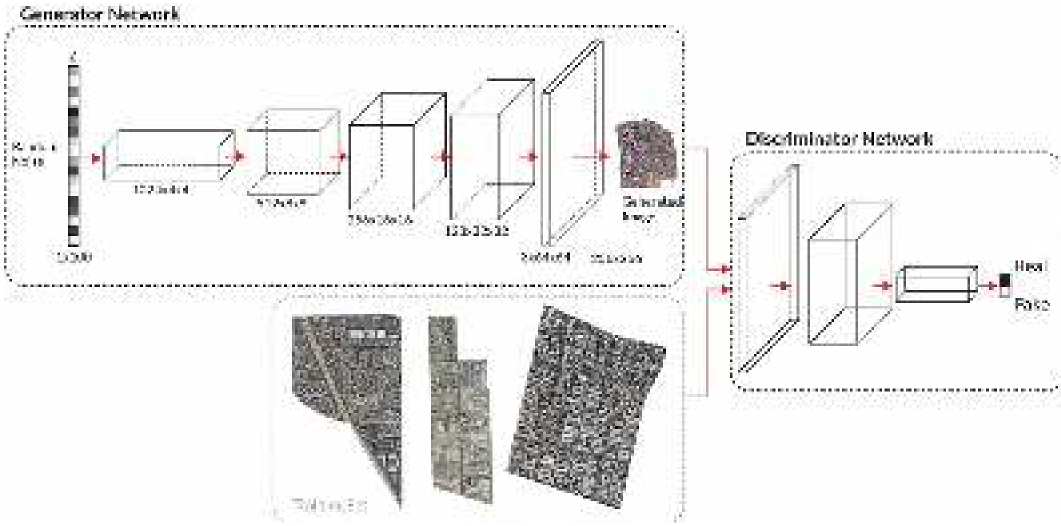


FIG. 7.4 GAN architecture. The GAN architecture is comprised of a generator and discriminator network that compete against each other. Through this competition, the generator learns the probability distribution that underlies a training set of images and can learn to create new image instances by sampling that distribution. *No permission required.*

correlations that might underpin the given set of exemplar designs. An example of this kind of approach is shown in Fig. 7.5, where a GAN is trained on satellite images of census tracts with high rates of anxiety in order to generate new census tract designs that may be correlated with that health measure (Newton, 2020). A qualitative visual analysis of these generated images reveals urban design features that may be correlated with high rates of anxiety. In part (A) of the figure, large, shaded areas can be seen indicating limited accessibility to natural light. In part (B), a dense urban grid is seen within an orange pollution-like haze. In part (C), a diagonal line looking like an airport runway or highway interrupts the density of the urban grid.

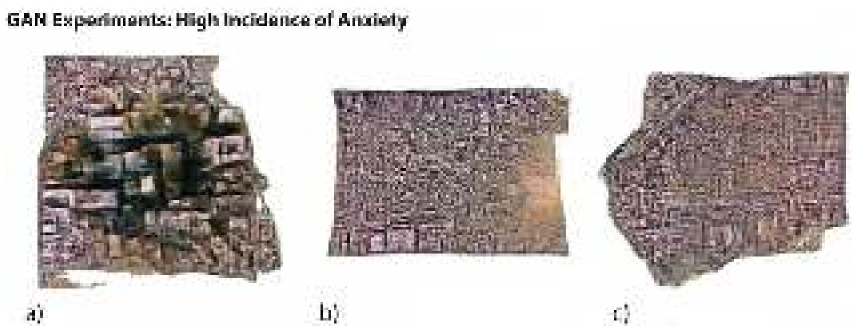


FIG. 7.5 High anxiety GAN model. Shows generated samples from a GAN model trained on the high incidence of anxiety. Parts (A)–(C) show dense urban fabric with no natural spaces and an air pollution-like haze. *No permission required.*

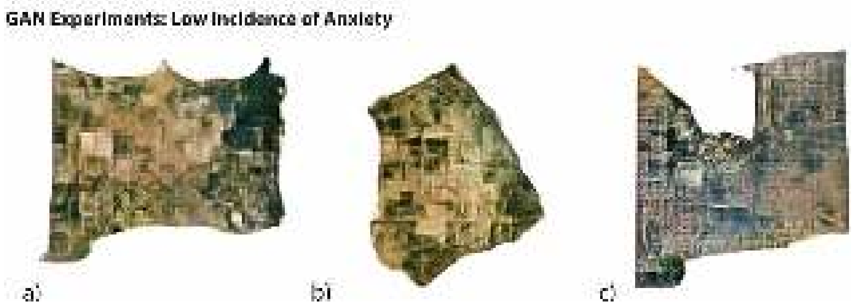


FIG. 7.6 Low anxiety GAN model. Shows generated samples from a GAN model trained on the low incidence of anxiety. Parts (A)–(C) show census tracts dominated by natural landscapes. *No permission required.*

The generated images in parts (A)–(C) of Fig. 7.5 are notable in the high levels of density they show with no green spaces or natural landscapes. In contrast, Fig. 7.6 shows the results of training a GAN on census tract images with low levels of anxiety. These images indicate that natural landscape features (e.g., green spaces, open land, mountains, water features), access to light, and medium to low density may have a meaningful correlation with low anxiety rates.

The other category of approach involves the use of GANs to train models that can translate from one set of exemplar images to another set. These translations can then be studied to identify urban design features that might be correlated with a particular outcome, such as safety, or health. For example, researchers have used this method to translate between satellite images of areas with a high incidence of bicycle accidents to areas of low incidence in order to identify urban features (e.g., street design, sidewalk design, etc.) that may be correlated with lower accident rates (Zhao et al., 2019).

Fig. 7.7 shows an example using the CycleGAN architecture for an analysis task involving depression. Parts (A), (D), and (G) of the figure show an original satellite image of a California census tract with a high incidence of depression. Parts (B), (E), and (H) show a translation of the original satellite image by the CycleGAN to be more consistent with the image feature present in low incidence images. Parts (C), (F), and (I) show a pixel-by-pixel difference between the original and the translated image—highlighting the primary features that have been changed. A qualitative visual analysis of these GAN translation results shows changes to a street grid pattern and greenspace distribution.

Comparing the results of both GAN studies to existing research can help to validate the potential correlations identified. In terms of anxiety, existing research has found that increased levels of urbanization and pollution correlated with higher rates of mental illness (Bolton et al., 2013; Chen et al., 2018; Peen et al., 2010). Further, correlations between anxiety and exposure to natural light and natural views have also been identified (Braubach, 2007; May et al., 2009). In relation to depression, previous research has also shown a significant correlation between low incidences of depression and access to greenspaces (Beyer et al., 2014; May et al., 2009; Cohen-Cline et al., 2015; Rautio et al., 2018). The results of these GAN experiments, therefore, are consistent with findings from existing research, but limitations inherent in this mixed-methods process need to be addressed to better verify these results. These

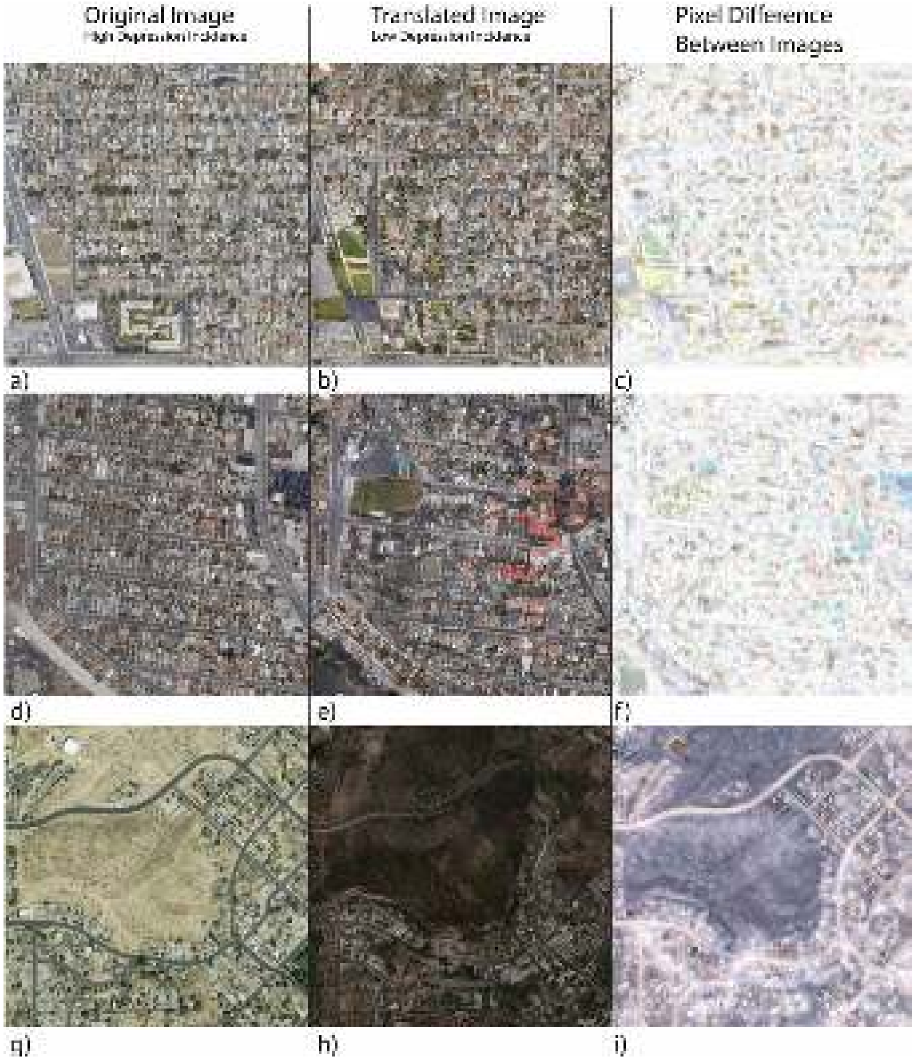


FIG. 7.7 Depression GAN model. (A, D, G) shows an original satellite image of a California census tract with a high incidence of depression. (B, E, H) shows a translation of the original satellite image by the CycleGAN to be more consistent with the image features present in low incidence images. (C, F, I) shows a pixel-by-pixel difference between the original and the translated image—highlighting the primary features that have been changed. *No permission required.*

limitations mostly stem from the qualitative visual analysis used to identify correlations. This process involves a significant degree of subjective interpretation and also does not provide detailed information on the nature and degree of the correlation between identified features and health outcomes. Integrating additional quantitative statistical methods (e.g., Pearson Correlation, etc.) to validate identified correlations is one possible way of addressing this issue. Other approaches involve developing quantitative methods of analyzing GAN models that can identify which learned visual features generated by a GAN architecture correlate most with a specific health outcome.

Existing research in this area is investigating how generative models might be used for urban health analysis, but as with discriminative deep learning processes, there are still many open questions involving how these models might be used to identify specific design features correlated with health measures, as well as, developing methods of building datasets and training models that are the most efficient.

Challenges, opportunities, and next steps

The existing research and examples presented demonstrate the potential efficacy of using deep learning with remote sensing data for urban health analysis tasks, but there are a number of important challenges that will need to be addressed by future research in order to realize the full potential of this technology to illuminate the links between the built environment and human health for the design disciplines. These challenges reside in four key areas which will be discussed in more detail below: (1) overcoming the high entry barrier to using deep learning; (2) acquiring and prepping the necessary data for deep learning; (3) developing efficient methods to train deep learning models for urban analysis; and (4) moving from an understanding of correlation to one of causation.

A key challenge in working with deep learning models is overcoming the high entry barrier needed to effectively train and analyze these models. This challenge is especially acute in the design disciplines, where knowledge of programming and machine learning is rare. Developing competencies in these areas is therefore key for the allied design disciplines if they are to more fully engage the potentials of current and future machine learning technologies for urban analysis. There are a large variety of massive open online courses in addition to publications introducing machine learning that can work as an effective stop-gap to build basic competencies in these areas, but a more strategic approach would better position the allied design fields to shape the future development and use of these technologies in the analysis of the built environment. One example of a more strategic approach could be integrating core competencies in programming, data science, and machine learning with design curriculums. This would give future practitioners and researchers in the allied design fields the foundation they need to effectively lead discussions and develop methods to extract critical insight on human health and other factors from the ever-expanding streams of data produced on the built environment.

Another important challenge in working with deep learning for urban health analysis involves acquiring the necessary remote sensing and health data to train deep learning models. Accessing quality health data for deep learning is a challenge due to the cost of collecting accurate health data and the security measures that are necessary for protecting individual privacy. Existing deep learning research involving health data has primarily used bulk anonymized data from governmental sources. These datasets are often limited in terms of geographic coverage and scale. In the United States, for example, health data is usually recorded at the county level, while data at smaller scales (e.g., census tract, neighborhood scale, etc.) is often not available. In terms of remote sensing datasets, the majority of existing research uses satellite, or aerial, images. These images, however, comprise only one data stream among many other remote sensing datasets (e.g., LIDAR images, RADAR images, hyperspectral images, thermal images, etc.) that could be useful for urban health analysis. There are also nontraditional remote sensing datasets, such as the use of social media streams that have demonstrated efficacy for urban analysis (Frias-Martinez and Frias-Martinez, 2014). These datasets are widely accessible through private (e.g., Google Earth, Bing Maps Imagery, etc.) and public sources (SGS Earth Explorer, NASA Earthdata Search, DigitalGlobe Open Data Program, etc.). The principal challenge in working with this data, therefore, is deciding which data streams might be most efficacious for a particular health analysis task and also in preparing the data (e.g., removing incomplete/damaged data instances, cropping input images consistently, etc.). The field of machine learning has attempted to address this problem in relation to classification problems through the creation of standardized datasets (e.g., ImageNet, MINST, ModelNet, etc.) that are easily accessible to the research community. These shared datasets allow researchers to save time in data collection and preparation, while also providing a more robust ability to directly compare the results of one research project to another. Developing standardized datasets for urban health analysis is, therefore, crucial for future research in this area.

The next challenge is that the training of deep learning models can be very resource-intensive—requiring large amounts of data and computing time. As discussed previously, transfer learning can dramatically reduce the amount of data and computing resources needed to train a deep learning model by making use of pretrained models trained on other image datasets that are similar in scale and view angle to a target image dataset (e.g., aerial images, LIDAR images, etc.). The problem is that remote sensing images are often very dissimilar in scale and view angle when compared to the images used to train available pretrained deep learning models. This dissimilarity makes it less efficient for transfer learning. In order to address this issue, a library of pretrained deep learning architectures is needed that are trained on remote sensing datasets. These pretrained models should be provided for different remote sensing data types, such as satellite, thermal, and hyperspectral images.

The last key challenge involves moving from an understanding of the correlation between health and the built environment to an understanding of causation. Establishing causation means demonstrating that a particular health outcome came as a consequence of some design feature in the built environment and not by chance, or due to some other hidden factor. This kind of work requires significant monetary investment and, therefore, a renewed sense of urgency by governments to prioritize research on the built environment is needed. In order to foster this kind of attention, a compelling evidence-based case must first be made correlating the built environment with human health. Deep learning workflows could provide the means to help build this case.

Addressing these challenges could allow for a new era of public health analysis and land use planning. One in which the capabilities of deep learning are used to better understand and predict the relationship between human health and its physical environs from a variety of data streams generated in our neighborhoods and cities. These predictive models could provide significant cost savings for countries around the world and help them to better deal with emerging health crises, such as pandemics. The stakes are, therefore, very high, and it is more pressing than ever that the challenges outlined be addressed in order to realize a new data-driven era of planning for our built environments.

References

Beyer, K., et al., 2014. Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. Int. J. Environ. Res. Public Health 11 (3), 3453–3472. https://doi.org/10.3390/ijerph110303453. MDPI AG.

Bolton, J.L., et al., 2013. Maternal stress and effects of prenatal air pollution on offspring mental health outcomes in mice. Environ. Health Perspect. 121 (9), 1075–1082. https://doi.org/10.1289/ehp.1306560. Environmental Health Perspectives.

Braubach, M., 2007. Residential conditions and their impact on residential environment satisfaction and health: results of the WHO large analysis and review of European housing and health status (LARES) study. Int. J. Environ. Pollut. https://doi.org/10.1504/IJEP.2007.014817. Germany: Inderscience Publishers.

Chen, C., et al., 2018. Ambient air pollution and daily hospital admissions for mental disorders in Shanghai, China. Sci. Total Environ. 613–614, 324–330. https://doi.org/10.1016/j.scitotenv.2017.09.098. Elsevier BV.

Cohen-Cline, H., Turkheimer, E., Duncan, G.E., 2015. Access to green space, physical activity and mental health: a twin study. J. Epidemiol. Community Health 69 (6), 523–529. https://doi.org/10.1136/jech-2014-204667. BMJ.

Frias-Martinez, V., Frias-Martinez, E., 2014. Spectral clustering for sensing urban land use using Twitter activity. Eng. Appl. Artif. Intell. 35, 237–245. https://doi.org/10.1016/j.engappai.2014.06.019. Elsevier BV.

Garrett, J.K., et al., 2019. Coastal proximity and mental health among urban adults in England: the moderating effect of household income. Health Place 59, 102200. https://doi.org/10.1016/j.healthplace.2019.102200. Elsevier BV.

Gatys, L.A., Ecker, A.S., Bethge, M., 2016. A neural algorithm of artistic style. J. Vis. 16 (12), 326. https://doi.org/10.1167/16.12.326.

Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. In: Proceedings of the 27th International Conference on Neural Information Processing Systems – Volume 2 (NIPS'14). MIT Press, Cambridge, MA, USA, pp. 2672–2680.

Hoisington, A.J., et al., 2019. Ten questions concerning the built environment and mental health. Build. Environ. 155, 58–69. https://doi.org/10.1016/j.buildenv.2019.03.036. Elsevier BV.

Jaad, A., Abdelghany, K., 2020. Modeling urban growth using video prediction technology: a time-dependent convolutional encoder–decoder architecture. Comput. Aided Civ. Inf. Eng. 35 (5), 430–447. https://doi.org/10.1111/mice.12503. Wiley.

Jean, N., et al., 2016. Combining satellite imagery and machine learning to predict poverty. Science 353 (6301), 790–794. https://doi.org/10.1126/science.aaf7894. United States: American Association for the Advancement of Science.

Li, F., et al., 2009. Built environment and changes in blood pressure in middle aged and older adults. Prev. Med. 48 (3), 237–241. https://doi.org/10.1016/j.ypmed.2009.01.005. Elsevier BV.

Linardatos, P., Papastefanopoulos, V., Kotsiantis, S., 2021. Explainable AI: a review of machine learning interpretability methods. Entropy 23 (1), 18. https://doi.org/10.3390/e23010018. MDPI AG.

Liu, Y., Wu, L., 2016. Geological disaster recognition on optical remote sensing images using deep learning. Prog. Comput. Sci. 91, 566–575. https://doi.org/10.1016/j.procs.2016.07.144. Elsevier BV.

Lopez-Zetina, J., Lee, H., Friis, R., 2006. The link between obesity and the built environment. Evidence from an ecological analysis of obesity and vehicle miles of travel in California. Health Place 12 (4), 656–664. https://doi.org/10.1016/j.healthplace.2005.09.001. Elsevier BV.

Maharana, A., Nsoesie, E.O., 2018. Use of deep learning to examine the association of the built environment with prevalence of neighborhood adult obesity. JAMA Netw. Open 1 (4). https://doi.org/10.1001/jamanetworkopen.2018.1535. United States: American Medical Association.

Marshall, W.E., Piatkowski, D.P., Garrick, N.W., 2014. Community design, street networks, and public health. J. Transp. Health 1 (4), 326–340. https://doi.org/10.1016/j.jth.2014.06.002. Elsevier BV.

May, D., et al., 2009. The impacts of the built environment on health outcomes. Facilities 27 (3–4), 138–151. https://doi.org/10.1108/02632770910933152. Emerald.

McConnell, R., et al., 2006. Traffic, susceptibility, and childhood asthma. Environ. Health Perspect. 114 (5), 766–772. https://doi.org/10.1289/ehp.8594. Environmental Health Perspectives.

Newton, D.W., 2020. Anxious landscapes: correlating the built environment with mental health through deep learning. In: Proceedings of the *40th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA): Distributed Proximities, Virtual Conference, October 24*–30, 2020. ACADIA, Delaware, pp. 130–139.

Newton, D., 2021. Visualizing deep learning models for urban health analysis. In: Proceedings of the 39th Annual Education and Research in Computer Aided Architectural Design in Europe (eCAADe) Conference: Towards a New Configurable Architecture, Faculty of Technical Sciences, Novi Sad, Serbia, September 8–10, 2021. vol. 1. 527, 536.

Nguyen, A., Yosinski, J., Clune, J., 2019. Understanding neural networks via feature visualization: A survey. In: Samek, W., Montavon, G., Vedaldi, A., Hansen, L., Müller, K.R. (Eds.), Explainable AI: Interpreting, Explaining and Visualizing Deep Learning. Lecture Notes in Computer Science. vol. 11700. Springer, Cham. https://doi.org/10.1007/978-3-030-28954-6_4.

Peen, J., et al., 2010. The current status of urban-rural differences in psychiatric disorders. Acta Psychiatr. Scand. 121 (2), 84–93. https://doi.org/10.1111/j.1600-0447.2009.01438.x. Netherlands.

Piaggesi, S., et al., 2019. Predicting city poverty using satellite imagery. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops. IEEE Computer Society, Italy. Available at: http://ieeexplore.ieee.org/xpl/conferences.jsp.

Rautio, N., et al., 2018. Living environment and its relationship to depressive mood: a systematic review. Int. J. Soc. Psychiatry 64 (1), 92–103. https://doi.org/10.1177/0020764017744582. SAGE Publications.

Renalds, A., Smith, T.H., Hale, P.J., 2010. A systematic review of built environment and health. Fam. Community Health 33 (1), 68–78. https://doi.org/10.1097/fch.0b013e3181c4e2e5. Ovid Technologies (Wolters Kluwer Health).

Robinson, C., Hohman, F., Dilkina, B., 2017. A deep learning approach for population estimation from satellite imagery. In: Proceedings of the 1st ACM SIGSPATIAL Workshop on Geospatial Humanities, GeoHumanities 2017. United States: Association for Computing Machinery, Inc., https://doi.org/10.1145/3149858.3149863.

Simonyan, K., Zisserman, A., 2016. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv.org. Available at: https://arxiv.org/abs/1409.1556.

Suel, E., et al., 2019. Measuring social, environmental and health inequalities using deep learning and street imagery. Sci. Rep. 9 (1). https://doi.org/10.1038/s41598-019-42036-w. Springer Science and Business Media LLC.

Tsagkatakis, G., et al., 2019. Survey of deep-learning approaches for remote sensing observation enhancement. Sensors 19 (18), 3929. https://doi.org/10.3390/s19183929. MDPI AG.

United Nations, Department of Economic and Social Affairs, Population Division, 2019. Population Division. In: World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420). United Nations, New York.

WHO, 2016. World Health Statistics 2016: Monitoring Health for the SDGs Sustainable Development Goals. World Health Organization.

Yuchi, W., et al., 2020. Road proximity, air pollution, noise, green space and neurologic disease incidence: a population-based cohort study. Environ. Health 19 (1). https://doi.org/10.1186/s12940-020-0565-4. Springer Science and Business Media LLC.

Zeiler, M.D., Fergus, R., 2014. Visualizing and understanding convolutional networks. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). United States: Springer Verlag., https://doi.org/10.1007/978-3-319-10590-1_53.

Zhang, C., et al., 2019. Joint Deep Learning for land cover and land use classification. Remote Sens. Environ. 221, 173–187. https://doi.org/10.1016/j.rse.2018.11.014. Elsevier BV.

Zhao, H., et al., 2019. Unsupervised deep learning to explore streetscape factors associated with urban cyclist safety. Smart Innov. Syst. Technol. https://doi.org/10.1007/978-981-13-8683-1_16. Australia: Springer Science and Business Media Deutschland GmbH.

CHAPTER

8

Spatial design of energy self-sufficient communities

Mina Rahimian, Lisa Iulo, and Jose Pinto Duarte

Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, Department of Architectural Engineering, School of Engineering Design, Technology and Professional Programs, College of Engineering, The Pennsylvania State University, University Park, PA, United States

Cities and energy resiliency

Urban planning and decision-making are dependent on our understanding of communities' needs and requirements. The problem, however, is that the rapid rates of urbanization along with the changing demographics and development priorities are pushing community affairs beyond the limitations of their existing state and resources. The issues that Jonathan Barnett framed over three decades ago remain true: "…urban design and planning techniques have to change because cities and suburbs are changing. What was true about cities as recently as ten years ago is no longer true, and the process of evolution goes on…" (Barnett, 1989).

The dynamics of change—whether it is environmental, developmental, or political—along with its associated complexity has resulted in the occurrence of transitional conditions in urban areas. Keeping up with the flux of change and understanding its imposed demands and challenges on communities are impractical with our reliance on traditional theories of urban development and conventional means of analysis. With the constant changes that cities face in their environmental, developmental, and political settings, today's practice of urban planning and development requires complex strategic analysis of urban areas. This necessitates changing the way we understand cities by updating the methods we use to study them and improving our ability to map and monitor complex urban dynamics.

https://doi.org/10.1016/B978-0-12-823941-4.00021-4

Considering, for instance, environmental aspects, it is hard to neglect the impact that climate change has had on cities through different forms of natural disasters (Andreson and Bausch, 2006). Natural disasters such as hurricanes and wildfires, coupled with the centralized nature of the current power grid and the aging state of its distribution system equipment, have resulted in frequent power outages that pose a threat to the everyday lives and businesses of urban dwellers (Castañeda-Garza et al., 2019).

This is not the only shortcoming associated with regional power plants. Recent reports argue that as of 2014 more than 50% of the world population are settled in urban areas and this number is expected to increase by 64%–69% by 2050 (Seto et al., 2014). The unprecedented speed of urbanization is accompanied by an increase in industrial activities, which are highly associated with economic development, income growth, and the consequent increase in energy consumption and greenhouse gas emissions (Jebaraj and Iniyan, 2006; Dodman, 2009; Seto et al., 2014).

Statistics show that urbanization and industrialization account for 75% of global energy use (Bastiononi et al., 2004) and 80% of global greenhouse gas emissions in urban areas (Grubler et al., 2012). In reviewing emission scenarios throughout history, Höök and Tang (2013) concluded that high dependence on fossil fuel-based power plants have been a primary driver of CO_2 and other greenhouse gas emissions in urban areas.

Growing environmental concerns and the frequency of natural disasters have heightened the interest in the adoption of microgrid technologies by towns and communities, in the interest of transitioning to energy-independent urban settlements (Powering a New Generation of Community Energy, 2015). Known as community microgrids, such urban settlements exercise greater control over energy production by generating energy close to its point of consumption. Community microgrids are local, decentralized power distribution systems that use various renewable and clean power sources, such as solar panels and diesel engines and storage devices like batteries, to provide electricity for buildings. The electricity circulates locally in a microgrid infrastructure; therefore, it eliminates the need to transport power over long distances. The main feature of a microgrid is that it can disconnect from the main grid and operate in island mode without needing to be fed by the main grid. Thus, when the main grid is unable to provide energy from its power plants, the cluster of buildings with a microgrid infrastructure islands itself from the main grid and operates based on the power that it generates locally (Rahimian et al., 2018).

Counter to the main advantage of localized energy provided by a microgrid, communities and urban settlements have been depending on the one-way flow of primarily nonrenewable power coming from centralized generators to a large number of users, handling only very stable outputs while being unresponsive to the fluctuations from the environment or from the users. Since energy production has mainly been a regional enterprise, the existing power grid has been designed and engineered to generate electricity by large power generators built around communities, far from the main areas of demand, with clear boundaries between its different subsystems (Villareal et al., 2014). Therefore, the existing power distribution system has had minimal direct impact on how urban settlements and communities were designed and developed. While the energy-agnostic design and development of urban areas might not have been an issue so far, with the growing interest of urban settlements in becoming energy self-sufficient and transitioning to community microgrids, the design inefficiencies of existing communities have become more evident than before (Güneralp et al., 2017).

Designing for energy self-sufficient urban settlements

Research from the 1970s onwards has communicated the different ways in which different spatial configurations of urban form change the energy performance of neighborhoods and communities. Energy performance in any energy system, including in community microgrids, has two aspects, the energy inputted to the system and the energy outputted from the system.[a] Therefore, studies in the literature fall into two categories: some assess the feasibility of utilizing various renewable energy resources as a derivative of urban form (Amado and Poggi, 2014; Compagnon, 2004; Lobaccaro and Frontini, 2014; Robinson et al., 2007; Sarralde et al., 2015), and studies in the other category assess the impact of urban form on the energy required for building operations, specifically for space heating and cooling, as these are the main cause of energy consumption in buildings (Ewing and Cervero, 2010; Fayyad et al., 1996; Lariviere and Lafrance, 1999; Pont and Haupt, 2005; Silva et al., 2017a, b; Ratti et al., 2005; Reinhert et al., 2013).

For on-site energy production, solar energy has been regarded as one of the main sources of renewable energy available to power community microgrids. Many studies have explored the different ways urban form impacts the potential of harvesting solar energy within the urban context and communities to generate photovoltaic energy. For example, a study by Sarralde et al. (2015) on different neighborhoods in London shows how optimizing a combination of nine spatial attributes of urban form (including the share of *semidetached houses*, *average building height*, *share of area covered by private gardens, site coverage, average building perimeter, average distance between buildings, standard deviation of building heights, plot ratio, and average distance between buildings*) increases the solar irradiation of roofs by 9% and of facades by up to 45%. Research by Robinson et al. (2007) studies the effect of *urban morphology* on the radiation availability of three Swiss districts by examining *the sky view factor*, *mean canyon height to width ratio*, and the *urban horizon angle* of those districts. Compagnon (2004) looks at how the *orientation* of 61 buildings in the Perolles area of Fribourg (Switzerland) affects the potential of building facades and roofs to capture solar energy. Moreover, a paper by Lobaccaro and Frontini (2014) examines the attributes of building *densification* and *shading* in urban environments as factors that affect solar availability and, therefore, the potential for utilizing photovoltaic panels in certain communities and neighborhoods.

On the other side of the energy performance equation are studies on the effect of urban form on energy consumption, which bears more nuanced complexity than that of energy production. This complexity is due to the rapid rates of urbanization that have resulted in significant changes in land use pattern and urban form (Bettencourt et al., 2007), and as a consequence have imposed different transformations to the patterns of energy consumption in cities (Bastiononi et al., 2004; Dodman, 2009; Grubler et al., 2012; Jebaraj and Iniyan, 2006).

The "Contribution of Working Group III of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change" (Seto et al., 2014) has ranked urban form as the fifth

[a] In the community microgrids referred to in this study, the solar, photovoltaic energy produced on-site is the energy input, and the energy used to operate the buildings is the energy output

contributor to greenhouse gas emissions in cities,[b] due to the impact of urban form on mobility patterns and on the energy required for heating and cooling buildings (Owens, 1986).

Newman and Kenworthy (1989) assert that research on urban form and energy demand for traveling purposes in cities has been largely investigated throughout the years. But, to date, not much literature has been dedicated to exploring the effects of urban form on energy demand in buildings and communities. Analysis in this area started in the 1960s at the Centre for Land Use and Built Form Studies at the University of Cambridge (Ratti et al., 2005). While form is not the only driver of energy demand in the built environment, there is evidence suggesting that the significance of its impact is mainly associated with the urban heat island effect,[c] change in local wind patterns, thermal comfort, and energy conservation (Chatzidimitriou and Yannas, 2015; Reinhert et al., 2013; Santamouris et al., 2001; Silva et al., 2017b).

Density has been the most cited attribute of urban form affecting energy demand due to its influence on urban heat islands (Silva et al., 2017a). Owens (1986) emphasizes *siting* and *orientation* as two important attributes since they can be adjusted to benefit from the site's microclimatic factors and free ambient energy resources. Owens (1986) also determines the importance of a community's *overall surface area (volume ratio)* as an indicator for energy demand with communities with lower surface areas tending to consume less energy. Moreover, a community's *orientation* and *layout* can change regional wind patterns impacting the rate of passive cooling and natural ventilation of buildings. In addition to density, layout, siting, and orientation (Silva et al., 2017a), find other urban attributes—including *diversity*, *green areas*, *passivity*, and *shading*—related to energy demand in buildings. In another paper, these authors identify the *number of floors*, *mix of uses*, and *floor area*, as the most energy relevant features of urban form (Silva et al., 2017b). Ratti et al. (2005) studied the effect of *urban geometry* determining that it has a low impact on energy demand, but since it was studied in isolation from other attributes, it is important to explore its significance within a wider framework.

Considering all these studies and the fact that more urban settlements are interested in becoming decentralized in terms of energy supply, research and planning communities have agreed that a new understanding of how urban design and planning can support communities' new energy needs is necessary (Cajot et al., 2017). As such, recent literature has emphasized the importance of considering an energy-conscious viewpoint when making urban planning and design decisions; accordingly, urban planners and designers are expected to consider the tradeoffs between the living qualities afforded by design solutions and their potential as high-performance energy systems, such as community microgrids (Cajot et al., 2017). Since community microgrids are contextualized in cities and urban areas, it is important to consider how the spatial structure of urban form impacts the energy required for space heating, cooling, and lighting, as well as the feasibility of adopting on-site renewable energy generators such as photovoltaic (PV) panels and wind turbines. The goal of this study is to

[b] This report ranks economic geography and income, sociodemographic factors, technology, and infrastructure as first four contributors to greenhouse gas emissions in urban areas.

[c] Due to human activities and the development of buildings, pavements and other surfaces that absorb and retain heat, many urban and suburban areas experience elevated temperatures compared to their outlying rural surroundings, which have maintained their open land and vegetation; this difference in temperature is what constitutes an urban heat island.

contribute to the understanding of how urban form impacts energy demand in communities and its significance for the spatial design of community microgrids.

Urban form and energy consumption in communities

Identifying energy-relevant attributes and indicators of urban form

This research is focused on the impact of urban form on energy demand in solar community microgrids, which can be accomplished without detailed building characteristics. In this context, the construction type or age of each individual building is not considered. The study of the complex effects of urban form on energy demand have not been rigorously and comprehensively evaluated in previous studies due to computational limitations and the lack of data-rich environments. A quantitative translation of urban form is essential to find its contribution to patterns of energy demand. From all the attributes suggested by researchers, the ones that will impact the supply and demand of energy in solar community microgrids have been selected and further studied. Based on previous literature, these attributes are briefly defined below along with relevant metrics of measurement with the purpose of quantifying urban form in community microgrids. The selected attributes range from that which previous research has shown is significant for energy demand to those that have not been deemed influential. The reason for selecting all energy-relevant spatial attributes is to understand their interaction and influence when they are in confluence as opposed to studying each attribute in isolation.

- *Density*: density has been the most researched urban attribute influencing energy demand and solar energy capture in communities (Silva et al., 2017a). Multiple descriptions of density exist depending on the intent of the research. These definitions vary from the density of the physical built environment to the density of people living or working in a given area (Ko, 2013; Silva et al., 2017a). Density in this research deals with land-use intensity and is measured per unit of area. Density is treated as a driver of energy demand by influencing the urban heat island effect and wind flow in the urban context. Denser urban environments increase the local temperature and thus increase cooling loads. Depending on the geographical location and site-specific weather conditions the urban heat island effect may be constructive or disruptive for energy demand in buildings (Taha, 1997). In the context of community microgrids, communities with higher densities facilitate the introduction of combined heat and power (CHP) systems in particular contexts (Owens, 1986).

Many density measurements of the physical built environment are the result of a fraction where the denominator is the total area of the land being measured while the numerator can vary from gross floor area and gross building footprint area to the number of rooms and the number of buildings. The measurements of density used herein are adopted from the Spacemate research (Pont and Haupt, 2005) and the literature cited by (Silva et al., 2017b):

- *Floor Space Index (FSI)*: gross floor area/total ground area.
- *Ground Space Index (GSI)*: gross area of the building footprint area/total ground area.

- *Open Space Ratio (OSR)*: gross area of unbuilt ground/total ground area.
- *Layer (L)*: average number of floors/total ground area OR (total number of floors/number of buildings)/total ground area.
- *Network Density (N)*: length of the network/total ground area.
- *Compactness*: density and compactness have very close definitions that are sometimes used interchangeably. (Ko, 2013) describes compactness as how tightly buildings stand on site. The main difference between compactness and density is that measurements of density consider the total area while compactness considers the street width, the distance between buildings, and the height of buildings.

Compactness directly impacts solar access and wind flow patterns in urban environments and therefore thermal comfort in buildings. For example, urban areas with wider streets have increased solar access and natural ventilation, while narrow streets create a wind tunnel effect. Depending on the climatic zone of the urban area, the compactness of a community or neighborhood can have different consequences for a microgrid's operation. For example, a compact form in a cold region can increase the heating demand in buildings as it blocks solar access, while also being possibly limiting for onsite PV energy generation as buildings overshadow adjacent ones. In such cases, other aspects of community design and layout should be carefully considered to manage solar access for maximum passive heating and potential PV energy generation. The compactness of a neighborhood can be measured by its aspect ratio (Ko, 2013):

- *Aspect ratio (AR)*: average building height/average street width.

Compactness is also used as an indicator of building geometry (Silva et al., 2017a). The building geometry is an important feature for energy demand since buildings' exposed surfaces directly impact heat flows between the inside and outside, as well as access to natural daylight. Researchers claim that the optimum shape for a building to minimize heat loss and maximize daylight gain is a cube (Ratti et al., 2005) and deviations from a cubic shape result in increasing heating loads. Three different but related measures of building compactness are suggested by researchers that can be applied at the community scale as well (Ratti et al., 2005; Bourdic et al., 2012):

- *Volumetric compactness (STV)*: envelope surface area/building volume.
- *Size factor (SF)*: building volume.$^{1/3}$
- *Form factor (FF)*: envelope surface area/(building volume).$^{2/3}$
- *Diversity or land use mix*: This is the second most cited attribute of urban form impacting energy demand in urban areas. It refers to the diversity of land uses and/or building types (i.e., residential, commercial, etc.) within a selected region. However, most literature that cites diversity studies its effect on traveling demand in urban areas. A diverse neighborhood or community is claimed to decrease the need for motorized travels as it brings urban activities closer to the residential context. This research is not concerned with energy demanded for traveling purposes but considers diversity as the mix of different land uses in a community. Diversity is an important feature when planning a community microgrid, since the diversity of the building load types is likely to regulate the energy

consumption peak hour; so, the microgrid infrastructure does not face periods of high energy consumption. For example, a decentralized shared energy system with a complementary mix of land uses is considered economically more beneficial due to balancing the peak hours of energy consumption (Bourgeois et al., 2015). Diversity as land-use mix is measured by the mixed-use index as proposed by van den Hoek (2008):

- *Mixed-Use Index (MXI)*: gross residential floor area/gross floor area.
- *Green areas*: the existence of green areas is not exactly a spatial feature of urban form, but is advocated to affect the urban microclimate by avoiding the urban heat island effect and, consequently, resulting in less energy demanded for space cooling[d] (Silva et al., 2017a). Depending on the geographical region of the urban area and the location where the green areas are planted, the presence of trees could also be beneficial by providing shading and solar gains and blocking unwanted wind in certain seasons. At the scale of community microgrids, simple metrics adopted from Silva et al. (2017a) and Vaz Monteiro et al. (2016) that consider width, size, and geometry may be useful for quantifying green areas:
- *Green Space Density (GSD)*: gross green space area/total ground area.
- *Green Area Geometry (GAG)*: gross green space perimeter/gross green space area.
- *Orientation*: This is a building design feature that is easy to address and useful to determine the solar gains of buildings, specifically for potential onsite PV energy generation and passive solar heating. In northern latitudes, south-facing facades are generally the most desirable to maximize solar access. North-facing facades have the lowest solar gains, while east and west orientations are exposed to direct solar gains in the morning and late afternoons, respectively. In research conducted by Hemsath (2016), the annual energy use and cost of 7000 typical Midwestern suburban homes were simulated in four different climate regions. The study shows that the cost implications of an individual home's orientation is not noticeable, whereas at the community scale, regardless of the climatic region, important savings exist in the aggregated energy usage and costs. Based on the research results of Hemsath (2016), optimizing the solar orientation of a community microgrid during the planning and design phase could potentially bring considerable reductions in a community's net energy usage and cost, which could possibly lead to longer periods of islanding.

A single building's orientation is measured by determining the building's longest axis and calculating the azimuth (Wilson, 2013). When considering the dominant orientation of a community, in addition to measuring the average orientation of all buildings, it is also important to take into account street orientation as it is claimed to influence various local conditions such as the urban heat island effect, shading, and ventilation of urban canyons (Coseo and Larsen, 2014). A street's orientation is determined by verifying its direction. Measurements of a community's orientation used in this research are as follows:

- *Community buildings' orientation*: sum of all buildings' orientation/number of buildings.
- *Street orientation*: sum of all streets' orientations/number of streets.

[d]The type of vegetation in green areas also play an important role in mitigating the urban heat island effect but since vegetation is not a feature of urban form it will not be discussed herein.

- *Shading*: it is an indicator of the effects of overshadowing by adjacent buildings as it significantly impacts the energy requirements of buildings, as well as the potential for onsite PV energy generation. Baker et al. (1992) and Ratti et al. (2005) have done extensive research on quantifying shading in urban environments. Urban horizon angle (UHA) and obstruction sky view (OSV) are two indexes that resulted from their explorations. UHA is the average elevation of the skyline from the center of the façade being considered and OSV quantifies the luminance of the obstructing facades, and they are measured as described below. Moreover, another important factor to consider when calculating shading is to identify "the ratio of radiation received by a planar surface from the sky or that received from the entire hemispheric radiating environment" (Jie et al., 2013), also known as the measurement of the sky view factor (SVF). The value of SFV is important as it defines whether the radiation that is released by building surfaces is blocked by obstructions or received by the sky; SVF = 1 means that the radiation released by a surface is totally received by the sky and SVF = 0 means the radiation is totally blocked by surrounding obstructions (Jie et al., 2013). Therefore, the value of SFV is impacted by the urban form and distribution of building in the community. Mirzaee et al. (2018) discovered a mathematical model that calculates the average SVF for an urban area as opposed to a specific point. This mathematical model is a factor of the average building density and average building height of a neighborhood. The average SVF in an area increases when the average height of buildings increases, as well as when the building density of an area increases.
  - *UHA*: average height of the opposite skyline/canyon width = tan (UHA).
  - *OSV*: average height of the opposite skyline/canyon width = cos (OSV).
  - *Sky View Factor (SVF)*: This is the value of radiation received by building surfaces. An SVF value of 1 means that the radiation released by a surface is totally received by the sky and an SVF value of 0 means the radiation is totally blocked by surrounding obstructions:
- if the average building height > 25 m then $SVF = 1.56 - (0.00572*H*D)$.
- if the average building height < 25 m then $SVF = 0.9502 + (0.00042*H) + (0.0198*D) - (0.0065*H*D)$.

  where H is the average height of the community buildings and D is the ground space index.

- *Passivity*: it is a condition of urban form that benefits from the site's ambient energy resources (solar and wind) to naturally light, ventilate, and heat building spaces. The measurement of passivity indicates the rate of passive zones (parts of a building that can be naturally lit, ventilated, and heated) in a neighborhood (Ratti et al., 2005). A simple rule of thumb for identifying the passive zones in a building is to identify those perimeter parts of each building (each floor) that lie within 6 m (or twice the ceiling height) from the façade and can let in natural daylight and airflow for ventilation (Ratti et al., 2005). To calculate the passivity of a neighborhood, the perimeter of all passive zones for each floor of each building needs to be considered. Additionally Steadman et al. (2009) argue that complementary to the passivity ratio, building depth is also an important indicator for air-conditioning requirements in buildings. Therefore, for calculating the passivity of a community two formulas are used in this research:

- *Passivity ratio*: net perimeter of all passive areas in a community/net perimeter of all nonpassive areas in a community.
- *Plan depth*: net volume of all buildings in a community/net area of all exposed walls in a community.

All attributes of urban form mentioned above, along with their indices and metrics of measurement, are summarized in Table 8.1.

TABLE 8.1 Selected attributes of urban form along with their indices and metrics.

Attribute	Index	Metric
Density	Floor Space Index	(Gross floor area)/(Total ground area)
	Gorund Space Index	(Gross area of the building footprint area)/(Total ground area)
	Open Space Ratio	(Gross area of unbuilt ground)/(Total ground area)
	Layer	(Average number of floors)/(Total ground area)
	Network Density	(Length of the network)/(Total ground area)
Compactness	Aspect Ratio	(Average building height)/(Average street width)
	Volumetric Compactness	(Envelope surface area)/(Building volume)
	Size Factor	∛Building volume
	Form Factor	(Envelope surface area)/(∛building volume∘2)
Diversity	Mixed Use Index	(Gross residential floor area)/(Gross floor area)
Green Areas	Green Space Density	(Gross green space area)/(Total ground area)
	Green Area Geometry	(Gross green space perimeter)/(Gross green space area)
Orientation	Community Building Orientation	(Sum of all buildings' orientation)/(Number of buildings)
	Street Orientation	(Sum of all streets' orientations)/(Number of streets)
Shading	Urban Horizon Angle (UHA)	(Average height of the opposite skyline)/(Canyon width) = tan (UHA)
	Obstruction Sky View (OSV)	(Average height of the opposite skyline)/(Canyon width) = cos (OSV)
	Sky View Factor	If the average building height > 25 m then SVF = 1.56 − (0.00572*H*D). if the average building height < 25 m then SVF = 0.9502 + (0.00042*H) + (0.0198*D) − (0.0065*H*D), where H is the average height of the community buildings and D is the ground space index.
Passivity	Passivity Ratio	(Net perimeter of all passive areas in a community)/(Net perimeter of all non-passive areas in a community)
	Plan Depth	(Net volume of all buildings in a community)/(Net area of all exposed walls in a community)

Artificial neural networks as a means for knowledge discovery

Researchers suggest three different methods for developing relational models explaining energy performance in the built environment[e] (Magoules and Zhao, 2016; Silva et al., 2017b):

- *Engineering methods*: In these methods, physical principles are used to calculate the energy performance of an entire building (or its sublevel components) relevant to the physicality of the building. The basis of this method is to precisely calculate the thermal dynamics and physical performance of buildings based on their structural and operational characteristics, environmental factors, and sublevel building components. Engineering models are typically associated with a great extent of complexity and detail. The main problem with this method is that to achieve accurate simulations, detailed information on building-quality parameters is required, which is unavailable to many organizations and the public. The engineering methods are known as white-box models (Tardiolli et al., 2015). In studies on buildings, white-box models are applied at a scale of a single building or part of a building (Silva et al., 2017b). Utilizing white-box models for an entire urban building stock is of high complexity and requires a considerable amount of time and data to process the manifold of energy relevant urban-scale variables that need to be considered (Tardiolli et al., 2015).
- *Statistical methods*: Also known as gray-box models, they combine physical and engineering methods with data-based, statistical modeling (Tardiolli et al., 2015). Gray-box models usually have very particular analysis methods including linear correlation, regression analysis, stepwise regression analysis, logit models, ANOVA, *t*-test, factor analysis, panel data, structural equation models, and cross-tabulation (Silva et al., 2017b) with the aim of correlating energy indexes with influencing variables.
- *Data mining methods*: Data mining is the computing process of discovering patterns and "extracting implicit, previously unknown, and potentially useful knowledge from data" (Tsui et al., 2006). According to Fayyad et al. (1996) data mining consists of "applying data analysis and discovery algorithms that produce a particular enumeration of patterns (or models) over the data." Data mining techniques originated a branch named machine learning (Silva et al., 2017b; Chen et al., 2000). Machine learning is the "science and art of programming computers so that they can learn from data" (Géron, 2017) in which "the 'machine' is able to identify and generalize patterns" from large datasets (Silva et al., 2017b). Samuel (1959) explains machine learning as giving computers (or "machines") the ability to learn without being explicitly programmed. Machine learning algorithms are essentially systems that learn and discover relational patterns and unsuspected new trends from collected data (that were not immediately apparent) and make data-driven predictions and decisions. Machine learning methods are known for working as a "black box" where a *machine learning algorithm* is constructed and "trained" to discover relational patterns and hidden structures in the input dataset (Tardiolli et al., 2015). A *machine learning model* is the outputted mathematical model that explains the discovered relational pattern in the input dataset and can be further used to make data-driven predictions and decisions on unseen examples (Tardiolli et al., 2015). In other words, machine learning is

[e]Note that explanations in these approaches are based on research on urban energy modeling.

the construction of algorithms that can learn relationships from data by developing mathematical models and make data-driven predictions or decisions accordingly.

Adopting a machine learning method is adequately useful when the problem of interest is multidimensional and complex, and solving it with conventional engineering or statistical models is extremely time- and resource-consuming. As mentioned previously, in the case of this study, researchers (Ewing and Cervero, 2010) have marked the importance of studying the *combined* impact of different attributes of urban form on energy demand rather than the influence of each individual spatial attribute. When studying the combined effect of urban spatial attributes, the problem becomes too complex for solving it with closed-form solutions. Gil et al. (2012) mark data mining as a sufficient method for analyzing the multidimensional relational complexity of urban environments. Therefore, due to the high dimensionality, complexity, and computational intensity of finding the relationship between the combination of all relevant spatial attributes of urban form and energy demand in community microgrids, a machine learning approach, more specifically an artificial neural network (ANN), has been selected for this purpose. ANNs are deemed as an effective approach to a complex application, such as in this study, since they can handle nonnormal data distributions and nonlinear relationships.

Artificial neural networks are used herein as a means of knowledge discovery on the relational complexity between urban form and energy consumption and as a powerful tool to handle nonlinear relationships and nonnormal data distributions. The comprehensive analysis offered herein is reached by studying the combined impact of "all" different spatial attributes of urban form on energy consumption rather than the influence of each individual spatial attribute. The resulting analysis leads to a set of general rules and principles for spatially designing community microgrids that yield higher energy performance. The comprehensive nature of this study is in opposition to the previous abstract and deductive modes of analysis and offers new knowledge in the field.

Mining the multidimensional impact of urban form on energy consumption

As mentioned earlier, the prerequisite for working with machine learning models is to possess a large, structured dataset. In this research—where the interest lies in identifying the relational pattern between urban form and energy consumption in community microgrids—the dataset needs to have quantifiable measures of urban form as the predictor variable and measurements of energy consumption as its response variable. For this study, San Diego County of California has been selected as a case study for two main reasons: Firstly, after Los Angeles, San Diego is the second highest ranked city in the US for total installed solar capacity as of 2019 (Bradford et al., 2019) with the ambitious goal of generating 100% of its electricity from renewable sources by 2035 according to the "City of San Diego Climate Action Plan" (The City of San Diego, 2015). Secondly, San Diego is one of the very few counties that has a rich repository of both spatial and energy data publicly available online. Aside from having a comprehensive set of GIS data representing the different physical and infrastructural layers of the county, San Diego's main utility company, SDG&E,[f] has aggregated and published energy

[f]San Diego Gas & Electric.

consumption information for the entire county from 2012 onwards and has allocated them per zip code and customer type (residential, commercial, industrial, and agricultural).

The dataset in which the ANN was trained on entails measurements of urban form and monthly energy consumption values for 110 zip codes in the San Diego County. The selected 19 indicators of urban form were measured for all zip codes in San Diego using parametric algorithms and geoprocessing tools. Additionally, monthly values of energy consumption data were obtained through San Diego's main utility company from 2012 to 2018 for each zip code. Part of the dataset is shown in Fig. 8.1; each row has the zip code number, followed by 19 numbers representing the urban form,[g] then 12 monthly values of energy consumption and then the total energy consumed in 1 year. This is repeated 7 times for each zip code, with each row representing 1 year of data from 2012 to 2018. More information on how this dataset has been processed and cleaned can be found in "A Machine Learning Approach for Mining the Multidimensional Impact of Urban Form on Community Scale Energy Consumption in Cities" by Rahimian et al. (2020).

An artificial neural network was then trained on the dataset to identify the relational pattern between urban form and community-wide net energy consumption and to deliver a predictive model. The power of neural networks lies in their predictive ability within the context in which they are trained. When using predictive modeling as such we get the answer to "what" is being predicted, but "why" certain predictions are being made is often a challenging question to answer. This is because neural networks are normally seen as a black box "whose unimaginably complex inner workings somehow magically transform inputs into predicted outputs" (Garson, 1991). Understanding the "why" behind neural networks' decision-making in predictions can be crucial in certain studies. In this research particularly, the interest lies in understanding which features of urban form and which correlations have the most influence in estimating the community's net energy consumption. With this knowledge, a set of design principles and frameworks can be developed and offered to architects and urban planners for designing new and retrofitting existing energy efficient urban settlements. However, unraveling how neural networks make certain predictive decisions has been a challenge and is still a developing field in machine learning.

Opening the black box

Among different methods proposed for interpreting neural networks, Shapley regressions are highly regarded due to their consistency and local accuracy in model inference (Štrumbelj and Kononenko, 2014; Lundberg and Lee, 2017). Shapley regressions offer a framework for statistical inference on nonlinear machine learning models where inference is achieved based on Shapley values—a method from coalition game theory (Joseph, 2019). In other words, with Shapley regression the output of any machine learning model is explained by predicting variables in linear regression. This is done by calculating the importance of a variable/feature by comparing what the model predicts with and without the feature in every combination so that

[g]It is assumed that in all these 7 years of study the urban form has remained mostly the same. Also, it is important to note that in this study, the assumption is that the community's energy demand is primarily dependent on the urban form; the effect of the construction type or age of each individual building is not considered.

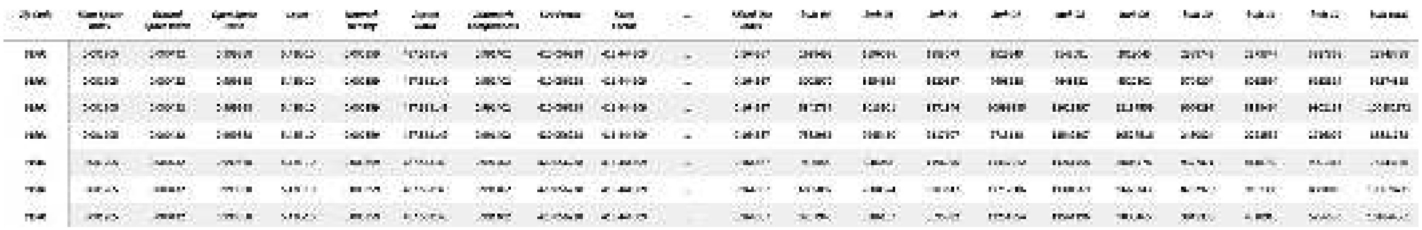


FIG. 8.1 The first several rows of the dataset, which shows urban form and energy consumption data for 7 years for one zip code in San Diego.

FIG. 8.2 Visualization showing the impact of features on the model output.

the importance of features are fairly compared. Through this method an importance value is assigned to each feature, which represents the effect of that feature on the model prediction; this value is known as the Shapley value. In this regard, Shapley value is the average marginal contribution of a feature value across all possible coalitions.

As explained by Lundberg et al. (2020) "…Shapley values are computed by introducing each feature, one at a time, into a conditional expectation function of the model's output, $f_x(S) = E[f(X) | do(X_s = x_s)]$,and attributing the change produced at each step to the feature that was introduced, then averaging this process over all possible feature orderings. Note that S is the set of features we are conditioning on, X is a random variable representing the model's M input features, x is the model's input vector for the current prediction, and we follow the causal do-notation formulation, which improves on the motivation of the original SHAP feature perturbation formulation. Shapley values represent the only possible method in the broad class of additive feature attribution methods that will simultaneously satisfy three important properties: local accuracy, consistency, and missingness.[h]"

Another advantage of this framework, also known as Shapley additive explanations (SHAP), is that it is a unified framework capable of explaining any machine learning model (Lundberg and Lee, 2017) unlike other methods of model interpretability. The SHAP framework has been implemented in the SHAP library[i] for Python, which makes it feasible to compute all possible feature combinations. To uncover the magnitude of impact that different features of urban form have on communities' net energy consumption, SHAP has been used on the final dataset with the final set of selected features.

Fig. 8.2 shows how each feature contributes to push the model output from the base value (the average model output over the training dataset) to the model output. Features pushing the prediction higher are shown in red and those in blue push the prediction lower.

Fig. 8.3 shows the impact that each urban form feature or variable has on the output, which is energy consumption, by plotting the SHAP values of every feature for every sample. In this plot, variables are ranked in descending order according to the magnitude of impact on community-wide net energy consumption, the horizontal location shows whether the effect of that value is associated with a higher or lower prediction, and color shows whether that variable is high (in red) or low (in blue) for that observation. Different correlations are

[h] Lundberg et al. (2020) describe: Local accuracy, which is equivalent to efficiency in game theory, states that when approximating the original model f for a specific input x, the explanation's attribution values ϕi for each feature i should sum up to the output $f(x)$. Consistency, which is equivalent to monotonicity in game theory, states that if a model changes so that the contribution of some feature increases, it stays the same regardless of the other inputs; that input's attribution should not decrease. Missingness is equivalent to null effects in game theory.

[i] https://github.com/slundberg/shap

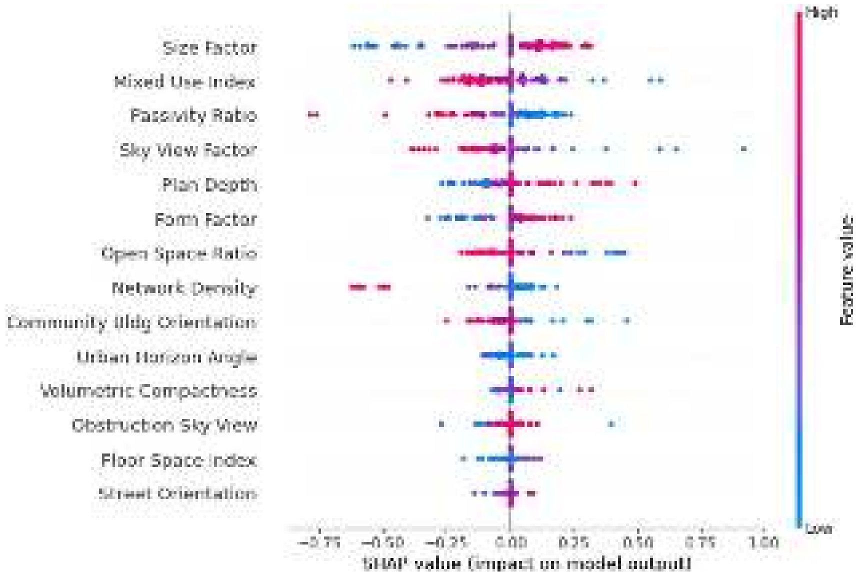


FIG. 8.3 The magnitude hierarchy of each urban form feature on energy consumption.

observed from this plot, which can be spatially and architecturally interpreted. From a high-level point of view, indicators related to the compactness of buildings within community boundary, the diversity of building functions, the shading and overshadowing resulted from building placement, and the passivity associated with community buildings have a high impact on community scale net energy demand. On the other hand, indicators related to the orientation of a community (streets and buildings) in San Diego have minimal impact on net energy consumption. An interpretation of insights and analysis of the combination of factors is provided below.

Interpreting the black box

San Diego county is home to varied climatic zones under the California Irrigation Management Information System (CIMIS) (Fig. 8.4):

- Zone 1—Coastal: mild maritime climate where winters are mild, and summers are cool with year-long moisture in the air.
- Zone 4—Coastal Inland: weather conditions are close to coastal with higher temperatures and less humidity.
- Zone 6—Upland Central: higher elevations with moist coastal air and dry interior air and moderate humidity and wind flows.
- Zone 9—Transition: marine to desert transition zone, which is a combination of warmer thermal belts and cold air basins with occasional marine influence.
- Zone 16—Mountain: with variations in sun and wind exposure and more rainfall.

FIG. 8.4 Different climate zones in San Diego County. *From San Diego County Water Authority. (2021). Water News Network. Retrieved September 24, 2021, from https://www.waternewsnetwork.com/*

- Zone 18—Desert: dry and hot days and cold night, low levels of humidity and very low rainfalls.

According to this map most urbanized areas of the county are in zones 1, 4, and 6. Therefore, in this research majority of urban form calculations, as well as the following spatial assessments, are in these three climatic zones.

Sky view factor (SVF), urban horizon angle (UHA), and obstruction sky view (OSV) are geometric parameters of urban form that relate to the degree of obstruction or of access to the sky. The energy absorbed by any given building facade comes from the sky and the radiation reflected from opposite building facades. Available daylight in buildings as well the amount of radiation absorbed by building facades are measured by SVF and UHA. Sky view factor is the value of radiation received by building surfaces defined by the ratio of the amount of sky visible with obstructions to the amount of sky visible without obstruction. An SVF value of 1 means that the radiation released by a surface is totally received by the sky, and an SVF value of 0 means the radiation is totally blocked by surrounding obstructions (Mirzaee et al., 2018). UHA determines the effect of overshadowing by adjacent buildings and is a function of the mean elevation of the skyline from a building façade (Ratti et al., 2005). Larger UHA values mean more obstruction by surrounding buildings resulting in more overshadowing. To estimate the radiation reflected from obstructing buildings, we need to know the amount of radiation that falls on the obstructing building facades through their angle of obstruction by measuring the OSV (OSV is primarily the same as UHA for the obstructing facades). The formula used for calculating SVF in this research is at an urban scale (rather than a specific point) and is a function of a neighborhood's average height and density (ground space index); this is while the measurements for UHA and OSV have been carried out for several points in a neighborhood and averaged out. This is perhaps the reason why the impact of UHA and OSV on neighborhood scale energy consumption is not quite clear in Fig. 8.3.

Mirzaee et al. (2018) have portrayed the relationship between SVF, height, and density to be not linear (Fig. 8.5).

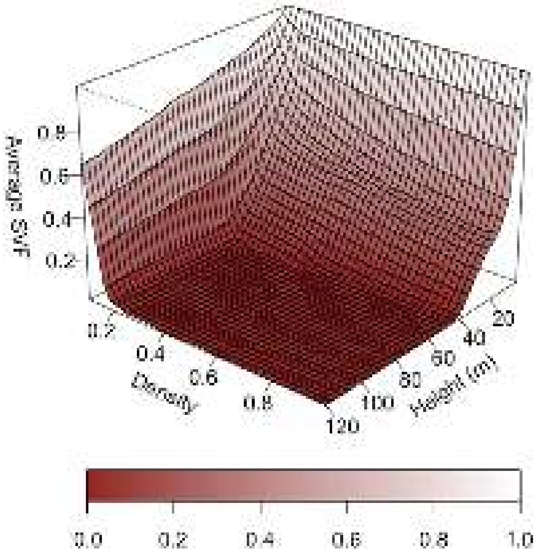


FIG. 8.5 3D visualization of the simulated relationship between average SVF, neighborhood's average building height, and average density. *From Mirzaee, S., Özgun, O., Ruth, M., Binita, K. (2018). Neighborhood-scale sky view factor variations with building density and height: A simulation approach and case study of Boston. Urban Climate, 95–108.*

However, it could generally be interpreted that those neighborhoods with shorter and more scattered buildings have more sky visibility than denser neighborhoods with taller buildings. In neighborhoods with higher values of SVF, where development dominates the natural landscape, direct radiation from the sky or reflected radiation from building facades gets trapped in the urban fabric, magnifying the urban heat island effect. From this point of view, the most urbanized areas of the county of San Diego, such as the city of San Diego and its downtown area, should experience high temperatures due to the urban heat island effect. Theoretically, this is true but in practice the effects of urban heat island in San Diego County are highly influenced by the local coastal wind patterns. These westerly winds are blown from the ocean and help disperse heat from the coastal regions to the inland areas of the county. As demonstrated in Fig. 8.6, the urban heat island (UHI) effect is manifested in the southern part of the county, and it incrementally increases in the east of the county. This means that the rising urban heat island-related temperatures of the coastal regions of San Diego County—which incorporates denser urban developments and thus has higher SVF—are moderated due to the coastal winds, while higher temperatures get blanketed in zones 9, 16, and 18.

This explains the negative correlation between SVF and energy consumption where higher values of SVF have lower values of neighborhood-scale energy consumption. The urbanized areas of the San Diego county typically experience year-long cool, breezy, mild, and pleasant weather conditions and, therefore, most buildings in that area, specifically residential buildings, do not have air-conditioning systems (Wang and Chen, 2014). This means that most of the energy is consumed for space heating in winter. However, when the SVF of a neighborhood is high, buildings are less obstructing each other and, therefore, building surfaces receive more direct radiation from the sky. When building surfaces absorb more radiation, interior spaces are passively heated, leading to minimized rates of energy consumption for space heating in colder weathers.

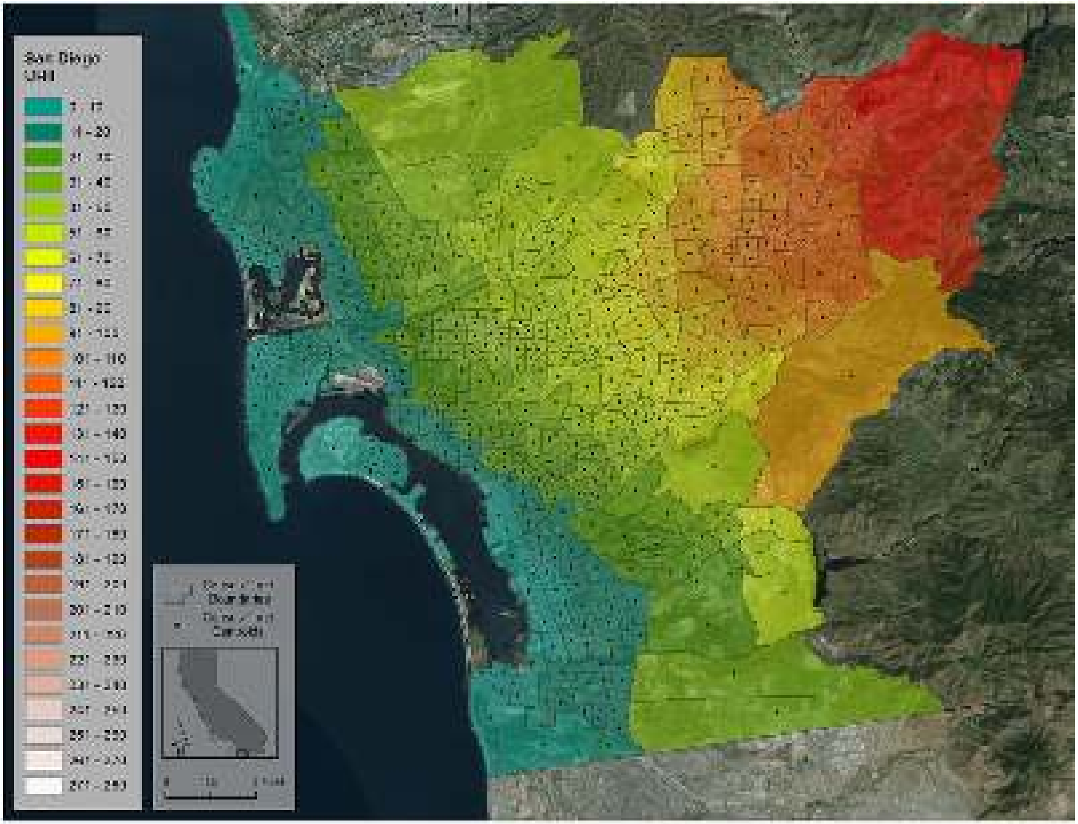


FIG. 8.6 Urban heat island index for San Diego county. *From California Environmental Protection Agency. (2021). Urban Heat Island Interactive Maps. Retrieved September 24, 2021, from https://calepa.ca.gov/climate/urban-heat-island-index-for-california/urban-heat-island-interactive-maps/*

Denser urban areas with low values of SVF result in higher values of UHA, which lead to the overshadowing of adjacent buildings. In this scenario, more energy is consumed for heating buildings in a neighborhood. This can be justified in the context of San Diego, where most operational energy used in buildings is oriented toward space heating purposes. Overshadowing passively cools the buildings and, therefore, increases the community's net energy demand for heating. Thus, in the case of developing a solar-based community microgrid in San Diego, one must consider that dense and compact neighborhoods, where the distance between buildings are minimal, increase the rates of energy demand and decrease the potential for installing PV panels on building and land surfaces, because of the effect of overshadowing. While currently PV panels are mostly installed on building roofs, not being overshaded by adjacent buildings is an important point to account for. In the case of San Diego that is in the northern hemisphere, even in scenarios where building facades are used for mounting PV cells, it is important to have south facing façades, clear from any shadows from surrounding building, to maximize the amount of produced solar energy. This is when the orientation of communities becomes important. Unlike energy consumption, community-scale PV energy production is highly dependent on the orientation of buildings and has large building facades facing south, to increase the potential for installing PV cells and, therefore, solar energy production.

Another important factor when considering energy consumption in communities is the amount of building envelope surfaces exposed to the outside environment. The building envelope is the interface between the inside and outside of buildings, where the transfer of energy between these two spaces happens. To minimize energy loss at the building scale, architects usually choose the materials of the building envelope in a way that prevents the unnecessary transfer of energy between the interior and exterior. However, researchers have found that metrics considering the relationship between building surface and volume play a significant role in urban-scale energy consumption (Ratti et al., 2005; Bourdic et al., 2012). Some indicators of this relationship considered in this study are plan depth, volumetric compactness, size factor, and form factor, all of which have shown to impact community-scale energy consumption to different extents. The fact that the combined effect of all four of these indicators impact energy consumption at the urban scale conveys the importance that building volume and exposed building surfaces play a significant role in reducing energy consumption in San Diego communities. Volumetric compactness,[j] size factor,[k] form factor,[l] and plan depth[m] have a high and positive relationship with community net energy consumption. This implies that larger building volumes demand more energy and, for a fixed volume, buildings with larger exterior surfaces have higher rates of energy consumption. Additionally, Fig. 8.3 shows that the passivity ratio—all perimeter parts of a building falling within 6 m (19.68 ft) or twice the ceiling height from the façade that can potentially be naturally lit and ventilated—has a high negative impact on energy consumption. This implies that buildings with more passive zones demand less energy. Therefore, for lower energy consumption, interior spaces need to be approximately 12 m (or less) in depth and, if a space (or a building floor area) is deeper, shorter heights can help in reducing energy demand.

According to Fig. 8.3, the open space ratio of a community has a negative relationship with net energy consumption. This means that the bigger the unbuilt area in a community, the lesser the rates of energy demand. On the other hand, floor space index, which is the ratio of gross floor area to total ground area, has a positive relationship with energy consumption, which means that buildings with larger floor areas or higher number of stories demand more energy. The reasoning behind these two relationships is clear since in any specific regional boundary, as the total number of buildings or units within a building increases, the energy demanded by the entire community increases. However, when it comes to developing a community microgrid, there is an optimal total number of buildings or operational units operating under the same microgrid infrastructure. There is no universal rule for how many operational units or buildings need to be clustered in a community microgrid. This is because the number of buildings or operational units that use energy to function is highly associated with their type of use in a microgrid context. Mixed-use index is the metric for measuring the diversity of building use inside a community and is the ratio of net residential floor area to net

[j]Community-wide net envelope surface area to building volume.

[k]Building volume$^{1/3}$.

[l]Envelope surface area/(building volume)$^{2/3}$.

[m]Net volume of all buildings in a community/net area of all exposed walls in a community.

ground floor area. The plot suggests a high and negative relationship between mixed-use index and energy consumption. This indicates that residential communities or communities with less nonresidential buildings have lower rates of energy use since nonresidential buildings demand more operational energy than residential ones. But, when considering the operation of a community microgrid, it is important to have an appropriate mix of building types with complementary energy-use profiles in order to maintain a fairly consistent energy demand throughout the system. When a microgrid serves a range of complimentary energy users (for example, a mix of residential, school, and office buildings) a relatively constant energy demand is observed over a 24-h period. For a microgrid, this translates into consistency in power demand and economic stability of the system. For instance, when a commercial center with peak hours from 8 a.m. to 5 p.m. is part of the same microgrid serving a residential area with peak hours in the mornings and evenings, such cluster of users provide a combined daily demand profile that is steady throughout the day. Therefore, to develop a community microgrid with an optimal number of operating units or buildings, one has to first determine the combination of load types in the regional boundary of the community microgrid including the presence of any anchor loads.[n] Identifying the anchor energy users on a site is important because by knowing the pattern of their energy consumption, one can determine the number of complementary loads (such as residential and retail) needed to create a consistent energy demand in the community microgrid, given the amount of energy that is potentially produced on site.

Closure

Addressing energy issues at urban scale brings more complexity than at the building scale, mainly because of the larger number of stakeholders involved in urban-scale projects. With this comes extended and obscurant power relations making urban issues ill-defined and multifaceted, especially when it comes to energy-related issues and its inherently political nature. In an era when the causes and effects of climate change have been a topic of dispute among politicians and scientists, the goal of reaching low carbon and energy self-sufficient communities and cities has become more urgent than before (2011). Reaching a low carbon and energy self-sufficient community entails reducing fossil fuel consumption and combating greenhouse gas emissions by taking actions in pursuit of building resilient communities and cities which are less pollutant and less energy demanding. A main action item for reaching this goal is the development of community microgrids that support the local supply and demand of clean energy. To develop low carbon and energy self-sufficient community microgrids, this research was grounded on past studies and assessed the role that urban planning plays in the energy performance of these power-grid-independent territories. With this study, a new framework is introduced for understanding the significant effect that urban design can have on the energy dynamics of communities and effectively cities at large.

[n] Anchor energy users are those who are likely to be in that location for many years in the future, such as hospitals and universities.

Our contextual analysis shows that unlike common knowledge where it is expected that dense urban areas have higher temperatures than the surrounding rural areas (due to the effect of urban heat island), San Diego's downtown area is highly influenced by the westerly winds which help disperse the heat. That justifies why residential buildings in San Diego's urban areas do not have air-conditioning systems since the area typically experiences year-long mild and pleasant weather conditions. The other unexpected discovery from our analysis shows that in the presence of other indicators of urban form, community orientation has minimal impact on the net energy consumption of a community in San Diego. To summarize the discussed analyses, some general rules and principles for the spatial design of communities in San Diego that maximize the energy performance of their underlying solar microgrid can be outlined as follows:

- Dense and compact neighborhoods, where the distance between buildings is minimal, increase the rates of energy demand and decrease the potential for installing PV panels on building and land surfaces because of overshadowing by adjacent buildings. Specially in scenarios where building facades are used for mounting PV cells, it is important to have south-facing façades clear from any shadows from surrounding building to maximize the amount of produced solar energy. This is when the orientation of communities becomes important. Unlike community-scale energy consumption, community-scale PV energy production is highly dependent on the orientation of buildings.
- Larger building volumes demand more energy.
- For a fixed volume, buildings with smaller exterior surfaces require lesser energy for space heating and cooling.
- For lesser energy consumption, building spaces need to be approximately 12 m (or less) in depth, and if a space is deeper then shorter heights can reduce energy demand.
- More buildings or more operational units within a community result in more energy consumed by the community which, in turn, means the need for more PV energy to be produced in the community. Note that there is no universal rule for how many operational units need to be clustered as a community microgrid, as it is highly associated with their type of use in a microgrid context. A community microgrid with a consistent energy demand needs to have an appropriate mix of building types with complementary energy use profiles to maintain a consistent energy demand throughout the system.

The resulting combination of urban indices discussed above impacts the amount of energy demand in San Diego, with its specific urban form characteristics and climatic conditions. The results of this research cannot be generalized to any other city and/or climate. However, the introduced framework can be utilized to discover each region's specific combination of urban form indices that has the highest impact on community scale energy demand.

An important next step for this study is to include the effect of climate change on the overall energy behavior of communities. This study was undertaken with the assumption that the weather in San Diego would not change due to global warming in the future. However, this is not true as studies show that by 2080 climate change will extensively impact the weather in major cities, including San Diego (Wang and Chen, 2014). In this regard, future measures and principles of urban design and planning need to be considerate of changes of weather and climatic conditions in urban areas.

Acknowledgments

This study was financed in part by the Hamer center for Community Design and the Stuckeman Center for Design Computing at the Stuckeman School of Architecture and Landscape Architecture, The Pennsylvania State University, United States. The authors thank Guido Cervone for his assistance related to the selection of appropriate methods and interpretation of Machine Learning data.

References

Amado, M., Poggi, F., 2014. Solar urban planning: a parametric approach. Energy Procedia 48, 1539–1548.
Andreson, J., Bausch, C., 2006. Climate Change and Natural Disasters: Scientific Evidence of a Possible Relation between Recent Natural Disasters and Climate Change. Policy Department Economic and Scientific Policy, p. 2.
Baker, N., Hoch, D., Steemers, K., 1992. The LT Method, Version 1.2: An Energy Design Tool for Non Domestic Buildings. Commission of the European Communities.
Barnett, J., 1989. Redesigning the Metropolis—the case for a new approach. J. Am. Plann. Assoc. 55, 131–135.
Bastiononi, S., Pulselli, F., Tiezzi, E., 2004. The problem of assigning responsibility for greenhouse gas emissions. Ecol. Econ. 49, 253–257.
Bettencourt, L.M., et al., 2007. Growth, innovation, scaling, and the pace of life in cities. Proc. Natl. Acad. Sci. U. S. A. 104 (17), 7301–7306.
Bourdic, L., Salat, S., Nowacki, C., 2012. Assessing cities: a new system of cross-scale spatial indicators. Build. Res. Inf. 40, 592–605.
Bourgeois, T., et al., 2015. Community Microgrids: Smarter, Cleaner, Greener. Pace Energy and Climate Center.
Bradford, A., et al., 2019. Shining Cities 2019 - The top U.S. Cities for Solar Energy. Environment America Research & Policy Center.
Cajot, S., et al., 2017. Obstacles in energy planning at the urban scale. Sustain. Cities Soc. 30, 223–236.
Castañeda-Garza, G., Valerio-Ureña, G., Izumi, T., 2019. Visual narrative of the loss of energy after natural disasters. Climate 7 (10), 118.
Chatzidimitriou, A., Yannas, S., 2015. Microclimate development in open urban spaces: the influence of form and materials. Energ. Buildings 108, 156–174.
Chen, L., Sakaguchi, T., Frolick, M., 2000. Data mining methods, applications, and tools. Inf. Syst. Manag. 17, 67–68.
Compagnon, R., 2004. Solar and daylight availability in the urban. Energ. Buildings 36, 321–328.
Coseo, P., Larsen, L., 2014. How factors of land use/land cover, building configuration, and adjacent heat sources and sinks explain Urban Heat Islands in Chicago. Landsc. Urban Plan. 125, 117–129.
Dodman, D., 2009. Blaming cities for climate change? An analysis of urban greenhouse gas emissions inventories. Environ. Urban. 21, 185–201.
Ewing, R., Cervero, R., 2010. Travel and the built environment. A meta-analysis. J. Am. Plann. Assoc. 76 (3), 265–294.
Fayyad, U., Piatetsky-Shapiro, G., Smyth, P., 1996. From data mining to knowledge discovery in databases. AI Mag. 17 (3), 37.
Garson, D., 1991. Interpreting neural-network connection weights. AI Expert, 46–51.
Géron, A., 2017. Hands-on Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. O'Reilly Media.
Gil, J., et al., 2012. On the discovery of urban typologies: data mining the many dimensions of urban form. Urban Morphol. 16, 27–40.
Grubler, A., et al., 2012. Chapter 18: Urban Energy Systems. Cambridge University Press, pp. 1307–1400.
Güneralp, B., et al., 2017. Global scenarios of urban density and its impacts on building energy use through 2050. Proc. Natl. Acad. Sci. U. S. A. 114, 8945–8950.
Hemsath, T., 2016. Housing orientation's effect on energy use in suburban developments. Energ. Buildings 122, 98–106.
van den Hoek, J., 2008. The MXI (mixed-use index) as tool for urban planning and analysis. In: Corporations and Cities: Envisioning Corporate Real Estate in the Urban Future.
Höök, M., Tang, X., 2013. Depletion of fossil fuels and anthropogenic climate change-a review. Energy Policy 52, 797–809.
Jebaraj, S., Iniyan, S., 2006. A review of energy models. Renew. Sustain. Energy Rev. 10 (4), 281–311.

Jie, W., Yufeng, Z., Qinglin, M., 2013. Calculation method of sky view factor based on rhino-grasshopper platform. In: Proceedings of BS2013.
Joseph, A., 2019. Shapley Regressions: A Framework for Statistical Inference on Machine Learning Models. arXiv preprint arXiv:1903.04209.
Ko, Y., 2013. Urban form and residential energy use: a review of design principles and empirical findings. J. Plan. Lit. 28 (4), 327–351. CPL bibliography.
Lariviere, I., Lafrance, G., 1999. Modelling the electricity consumption of cities: effect of urban density. Energy Econ. 21, 53–66.
Lobaccaro, G., Frontini, F., 2014. Solar energy in urban environment: how urban densification affects existing buildings. Energy Procedia 48, 1559–1569.
Lundberg, S., Lee, S.-I., 2017. A Unified Approach to Interpreting Model Predictions.
Lundberg, S., et al., 2020. From local explanations to global understanding with explainable AI for trees. Nat. Mach. Intell. 2, 56–67.
Magoules, F., Zhao, H.-X., 2016. Data Mining and Machine Learning in Building Energy Analysis: Towards High Performance Computing. John Wiley & Sons.
Mirzaee, S., et al., 2018. Neighborhood-scale sky view factor variations with building density and height: a simulation approach and case study of Boston. Urban Clim. 26, 95–108.
Newman, P., Kenworthy, J., 1989. Gasoline consumption and cities: a comparison of US cities with a global survey. J. Am. Plann. Assoc. 55 (1), 24–37.
Owens, S., 1986. Energy, Planning, and Urban Form. Pion Limited.
Pont, M., Haupt, P., 2005. The Spacemate: density and the typomorphology of the urban fabric. Nord. J. Archit. Res., 55–68.
Powering a New Generation of Community Energy, 2015. New York State Energy Research and Development Authority. Available at: https://www.nyserda.ny.gov/All-Programs/Programs/NY-Prize.
Rahimian, M., Iulo, L., Duarte, J., 2018. A review of predictive software for the design of community microgrids. J. Eng. 2018, 1–13.
Rahimian, M., et al., 2020. A Machine Learning Approach for Mining the Multidimensional Impact of Urban Form on Community Scale Energy Consumption in Cities. Springer.
Ratti, C., Baker, N., Steemers, K., 2005. Energy consumption and urban texture. Energ. Buildings 37, 762–776.
Reinhert, C., et al., 2013. UMI—An Urban Simulation Environment for Building Energy Use, Daylighting and Walkability.
Robinson, D., et al., 2007. SUNtool—a new modelling paradigm for simulating and optimising urban sustainability. Sol. Energy 81, 1196–1211.
Samuel, A., 1959. Some studies in machine learning using the game of checkers. IBM J. Res. Dev., 210–229.
Santamouris, M., et al., 2001. On the impact of urban climate on the energy consumption of buildings. Sol. Energy 70, 201–216. Elsevier Science Ltd.
Sarralde, J., et al., 2015. Solar energy and urban morphology: scenarios for increasing the renewable energy potential of neighbourhoods in London. Renew. Energy 73, 10–17.
Seto, C.K., et al., 2014. Human Settlements, Infrastructure and Spatial Planning. Cambridge University Press.
Silva, M., Oliveira, V., Leal, V., 2017a. Urban form and energy demand: a review of energy-relevant urban attributes. J. Plan. Lit. 32, 0885412217706900.
Silva, M., et al., 2017b. A spatially-explicit methodological framework based on neural networks to assess the effect of urban form on energy demand. Appl. Energy 202, 386–398.
Steadman, P., Evans, S., Batty, M., 2009. Wall area, volume and plan depth in the building stock. Build. Res. Inf. 37, 455–467.
Štrumbelj, E., Kononenko, I., 2014. Explaining prediction models and individual predictions with feature contributions. Knowl. Inf. Syst. 41 (3), 647–665.
Taha, H., 1997. Urban climates and heat islands: albedo, evapotranspiration, and anthropogenic heat. Energ. Buildings 25, 99–103.
Tardiolli, G., et al., 2015. Data driven approaches for prediction of building energy consumption at urban level. Energy Procedia 78, 3378–3383.
The City of San Diego, 2015. City of San Diego Climate Action Plan. The City of San Diego.
Tsui, K., et al., 2006. Data mining methods and applications. In: Springer Handbook of Engineering Statistics. Springer, pp. 651–669.

Vaz Monteiro, M., et al., 2016. The impact of greenspace size on the extent of local nocturnal air temperature cooling in London. Urban For. Urban Green. 16, 160–169.

Villareal, C., Erickson, D., Zafar, M., 2014. Microgrids: A Regulatory Perspective. CPUC Policy & Planning Division.

Wang, H., Chen, Q., 2014. Impact of climate change heating and cooling energy use in buildings in the United States. Energ. Buildings 82, 428–436.

Wilson, B., 2013. Urban form and residential electricity consumption: evidence from Illinois, USA. Landsc. Urban Plan. 115, 62–71.

Further reading

The European Commission, 2011. A Roadmap for Moving to a Competitive Low Carbon Economy in 2050. EU COM, p. 112.

CHAPTER

9

The image of the city through the eyes of machine reasoning

Elcin Sari[a], *Cengiz Erbas*[b], *and Imdat As*[c]

[a]Middle East Technical University, Department of City and Regional Planning, Ankara, Turkey [b]TUBITAK International Fellow, Hacettepe University, Ankara, Turkey [c]TUBITAK International Fellow, Istanbul Technical University, Istanbul, Turkey

Introduction

According to the United Nations, more than 55% of the world's population currently resides in urban settlements (United Nations, 2018). They predict that 6.5 billion people, that is 66% of the world population will live in cities by the end of 2050. With the increase in population, city layouts are expanding day by day, and becoming increasingly more complex. Considering that urban design and planning need to deal with complex issues that affect the quality of life (QoL) and the performance of cities, such as traffic commute time, pollution, safety, climate, and the like, novel, and innovative tools can help planners and designers create new cities and reshape existing ones. Over decades, various methods of urban design have been explored, e.g., designing with patterns (Alexander et al., 1977; Salingaros, 2000) or codes (Blum et al., 2006), and many others. These methods dealt mostly with quantifiable characteristics of the city. However, recent developments in artificial intelligence (AI) provide the opportunity to explore qualitative issues as well. The integration of AI in the design processes can help us understand latent qualities of urban spaces that were impossible to quantify before. These latent qualities, therefore, were often neglected in design deliberations. There are a few AI-driven urban planning studies, such as the "Smart Design framework featuring urban design-decision-making reinforced by artificial intelligence-aided design (AIAD)" (Quan et al., 2019) or "AI for Earth Land Cover Mapping user-centric tool which helps urban planners make decisions," developed by the Ho Chi Minh City Planning Department in Vietnam (Traunmueller et al., 2021). Nevertheless, there has been no thorough attempt to learn latent qualities or patterns common in cities with high QoL. According to Forbes magazine, hundreds of new cities will be developed around the world in the near future. About 400 new

https://doi.org/10.1016/B978-0-12-823941-4.00003-2

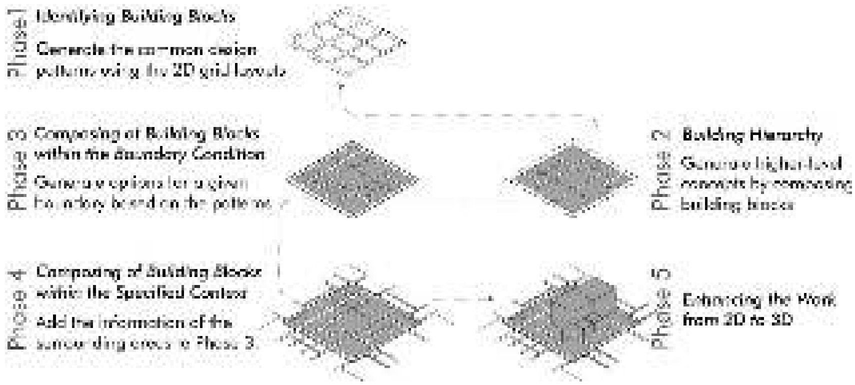


FIG. 9.1 Phases of the study. *No permission required.*

cities were built just in China since 2013 (Shepard, 2017). Therefore, some of the questions we want to address in this chapter are whether we can leverage AI to discover recurring urban patterns on a small number of cities, and whether these can be used to compose new city layouts.

We developed a machine reasoning (MR) tool that allows conventional machine learning to work with more structured and combinatorial data. The MR tool is able to learn the structure of underlying functions, grammars and relationships, within the city data. Our research work has five primary phases:

- Phase 1: Identifying common architectural patterns (base concepts) using two-dimensional grid maps of select cities.
- Phase 2: Generating higher-level concepts that correspond to higher-level architectural patterns, by building a hierarchy of the base concepts identified in Phase 1.
- Phase 3: Generating architectural options for a given region by composing urban patterns identified in Phases 1 and 2.
- Phase 4: Taking the wider context of the city into account, when generating architectural options.
- Phase 5: Expanding the research from two-dimensional city layouts to three-dimensional city form.

As illustrated in Fig. 9.1, Phases 1 and 2 focus on the discovery of latent patterns; whereas Phases 3 and 4 deal with the design and composition of new city layouts. In other words, in Phases 1 and 2, we are determining common design patterns of select cities, and in Phases 3 and 4, we will be composing new layouts within a defined boundary condition. Finally, in Phase 5, we will add three-dimensional space. The scope of the chapter, however, is limited to the work and results for Phases 1 and 2.

Background

Christopher Alexander set out the basic principles of computational design in his work "Notes on the Synthesis of Form" (Alexander, 1964). Nicholas Negroponte demonstrated that human-machine dialogue can be actively provided in the creation of space compositions with his “Architecture Machine” (Negroponte, 1970). Later, Alexander showed in “A Pattern Language” (Alexander et al., 1977) how computation can help to formalize the concept of design patterns. He proposed patterns as helpful conceptual tools to deal with complex design challenges. More recent projects in the area of computational design as it relates to urban planning and design include the “City Matrix” (Zhang, 2017) at MIT’s Media Lab, which leverages machine learning to generate multiple urban simulations within a given urban field. The simulation results are used to train a convolutional neural network (CNN) to predict traffic and solar performances of unprecedented city configurations; and, “City Induction,” which aims to develop an urban design machine for producing site plans (Duarte et al., 2012). Moreover, “City Scope,” another MIT Media Lab project, facilitates interaction between people and machines through 2D and 3D interfaces. It has set an example for similar studies in terms of combining computational and physical models (Alonso et al., 2018). Furthermore, “Urban Design Optimization,” examines computational optimization techniques at the urban design levels to optimize various performance criteria for the city, such as accessibility (Lima et al., 2021).

From an experiential point of view, Kevin Lynch in “The Image of the City” assesses environmental quality with the concepts of *legibility* and *imageability* (Lynch, 1960), to understand how people cognitively perceive a city. Lynch defines *legibility* as ‘the ease with which the city’s parts can be recognized and organized into a coherent pattern’ and *imageability* as, ‘that quality in an object which gives it a high probability of evoking a strong image in the observer’ (Lynch, 1960). Lynch conducted a study in which participants were asked to describe main aspects of their experiences in cities like Boston, Jersey City, and Los Angeles. The participants were asked to describe the main elements formed in their minds about their experiences in these cities. Lynch discovered that there are five main elements that organize the human experience in cities: *Paths*, *edges*, *districts*, *nodes*, and *landmarks* (Fig. 9.2). Lynch claims that these elements together form an environmental image that allows a satisfying city form to emerge in the minds of the observers.

Paths are the predominant city elements that guide people’s movement by supporting orientation in the city. People observe the environment and relate to environmental elements while moving on paths. Paths are characterized by continuity, directional quality, and gradients, e.g., main streets and boulevards. *Edges*, on the other hand, are linear elements that act as lateral references—not used or considered as paths. Urban barriers, e.g., shores, railroads, cuts, and walls may be *edges* of areas. *Districts* are relatively large parts of the city that have common characteristics like shape, texture, class, or ethnicity. These characteristics determine an endless variety of district types, e.g., neighborhoods or blocks with clear edges.

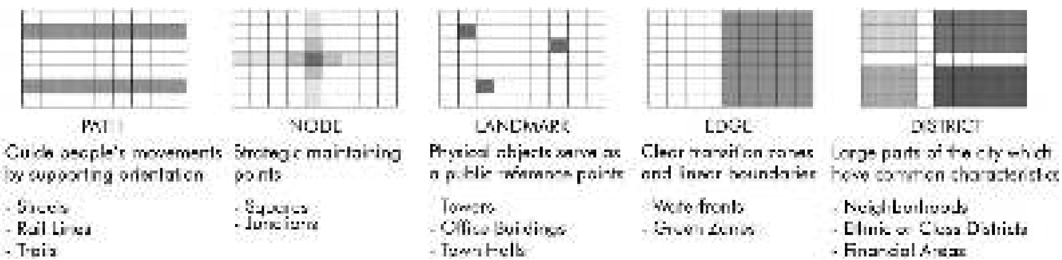


FIG. 9.2 Lynch’s five elements. *No permission required.*

Nodes are identified as the highest central focus point in the street network. They may be junctions, a crossing or convergence of *paths*, a central square, or park where more functions happen simultaneously. Finally, *landmarks* are physical objects which are identified by uniqueness, singularity, and specialization. *Landmarks* must be visible over long vistas and represent reference points within the city. Various important buildings, statues, monuments, minarets, church towers, etc., might constitute *landmarks* (Lynch, 1960). In this chapter, we illustrate a computational method—specifically, a machine reasoning (MR) tool—that automatically detects Lynch's five core elements on given city layouts.

Methods, tools, and techniques

Machine learning (ML), in particular deep neural networks (DNNs), form the backbone of the current phase of the AI revolution. ML techniques have proven successful in leveraging big data to answer questions narrowly posed around training datasets, in particular for applications using voice, image, and text data. However, architectural data for cities are more structured and combinatorial than these modalities (As et al., 2018). We can leverage DNNs to identify common design patterns in cities, but the lack of big data is also a bottleneck. The number of cities in the world are in the thousands and not in the millions, and we may have access to only a few of them to use as training sets. Therefore, a more promising approach is to learn from a small number of city samples, in order to discover and generate urban patterns.

The very nature of the research objectives of discovering design patterns from data requires the ability to make abstractions and generalizations. Even though there are some successes in transfer learning, deep learning has proven difficult to generalize beyond their initial set of training questions. Pushing the boundaries of AI toward a general-purpose tool that can model urban layouts, requires a new approach that can address the shortcomings of current-day machine learning techniques.

In this study, we used an MR engine to identify common design patterns in cities. Similar to ML, an MR engine can be used to train MR models in a supervised or unsupervised manner. Supervised training requires annotated data with class membership, and learns to identify which patterns differentiate one class from another. It can, for example, be used to reason about what characteristics make a city livable. Unsupervised training does not require annotations and is used to identify common patterns as intermediate vocabulary so that the data can be compressed without losing critical information. The discovery of Lynch's five design elements falls into this category.

MR models capture the underlying patterns that explain the training data, and the MR engine generates output from simple to more complex patterns, where each output corresponds to an MR model. The MR engine is configurable in that it can operate with different sets of hyperparameters. It can learn arbitrary concepts from a few examples, and can also discover higher-level cognitive relationships among them. The MR engine complements existing ML systems in three ways:

1. It does not require problem-specific model development.
2. It can be trained with small data.
3. It can identify cognitive relationships that are out of reach for ML tools and techniques.

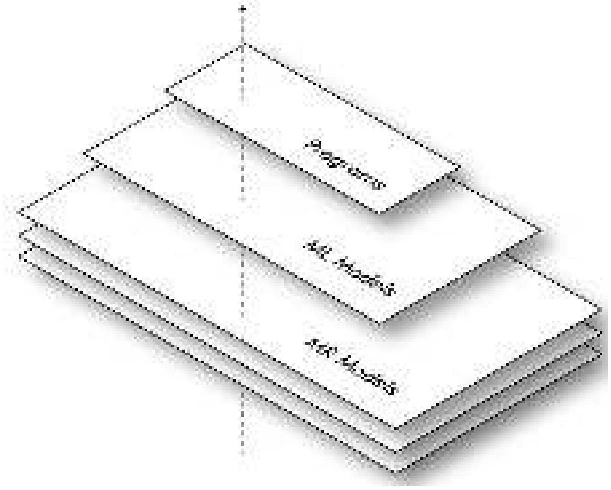


FIG. 9.3 Artificial intelligence (AI) framework. *No permission required.*

We can view the MR engine from the perspective of an AI framework. Fig. 9.3 illustrates our vision of how AI will be built based on the combination of ML and MR models and programs.

If we look at the figure from the top downwards, it encapsulates three different ways of building AI capabilities:

- In its simplest form, intelligent functions can be developed by coding them in the form of *programs*. Early work in AI (including expert systems) falls into this category.
- Alternatively, we can build *ML models* that demonstrate intelligence capabilities. ML models may use "features" that are extracted using programs as input to do classification. However, the output of the model is not within the space of the features. We cannot feed the output of a model to itself recursively to build a hierarchy of learned concepts.
- On the other hand, *MR models* do not have this limitation. They operate at the "concept" level. Both inputs and outputs of MR models are within the space of concepts. The output of an MR model can be fed into the same model recursively to build a hierarchy of learned concepts. They are also able to use ML models and other programs as input, leveraging existing AI systems.

An MR engine is also a step toward building more explainable AI systems. ML models are tensors—huge arrays of floating-point numbers—which do not lend themselves to easy interpretation. MR models, on the other hand, can be presented in a form that can be inspected by humans. We can debug the inference process of such models and see why certain test data are accepted or rejected. MR engine provides the following main functions: Observation, induction, deduction, hypothesis generation, concept discovery, tokenization, and abstraction. The details of how these main functions are used in our case study are given in the following section.

Case study

For our case study, we converted the downtown areas of select six cities into two-dimensional matrices. We populated the matrices with ten symbols representing various city programs, e.g., commercial, residential, etc. We considered Lynch's main five elements for environmental imageability in cities, and determined three policies, (a) frequency, (b) range, and (c) coverage policies, to discover them automatically. Fig. 9.4 illustrates our workflow.

Selecting cities and creating grid layouts

We based our selection of six cities on Numbeo's QoL index (Numbeo, 2021). Three of them were very highly ranked: Adelaide, Australia (1st), Wellington, New Zealand (3rd), and Raleigh, USA (4th) as illustrated in Fig. 9.5; and, the other three were at the bottom of the list: Nairobi, Kenya (230th), Ho Chi Minh, Vietnam (235th), and Manila, Philippines (240th) as illustrated in Fig. 9.6. In order to keep the samples uniform, we selected cities that were built on grid layouts, and picked an area of about 100 ha within their downtown areas.

Besides the Numbeo index, there are also various other indexes that evaluate cities, e.g., the Cities in Motion index, the Global Cities index, the Livability index, etc. We decided to use the Numbeo index, because their QoL index is more comprehensive and uses an empirical formula that takes into account purchasing power, pollution, house price to income ratio, cost of living, safety, health-care, traffic commute time, and climate (Numbeo, 2021).

$$QoL = Math.\max\left(0, 100 + \frac{ppi}{2.5} - (hpr \times 1.0) - \frac{cli}{10} + \frac{si}{2.0} + \frac{hi}{2.5} - \frac{tti}{2.0} - \frac{(pi \times 2.0)}{3.0} + \frac{ci}{3.0}\right)$$

where ppi = purchasingPowerInclRentIndex, hpr = housePriceToIncomeRatio, cli = costOfLivingIndex, si = safetyIndex, hi = healthIndex, tti = trafficTimeIndex, pi = pollutionIndex, and ci = climateIndex.

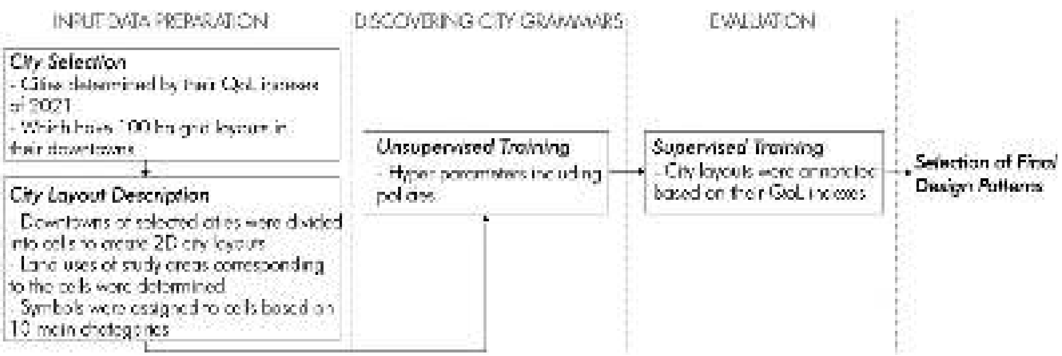


FIG. 9.4 Conceptual model workflow. *No permission required.*

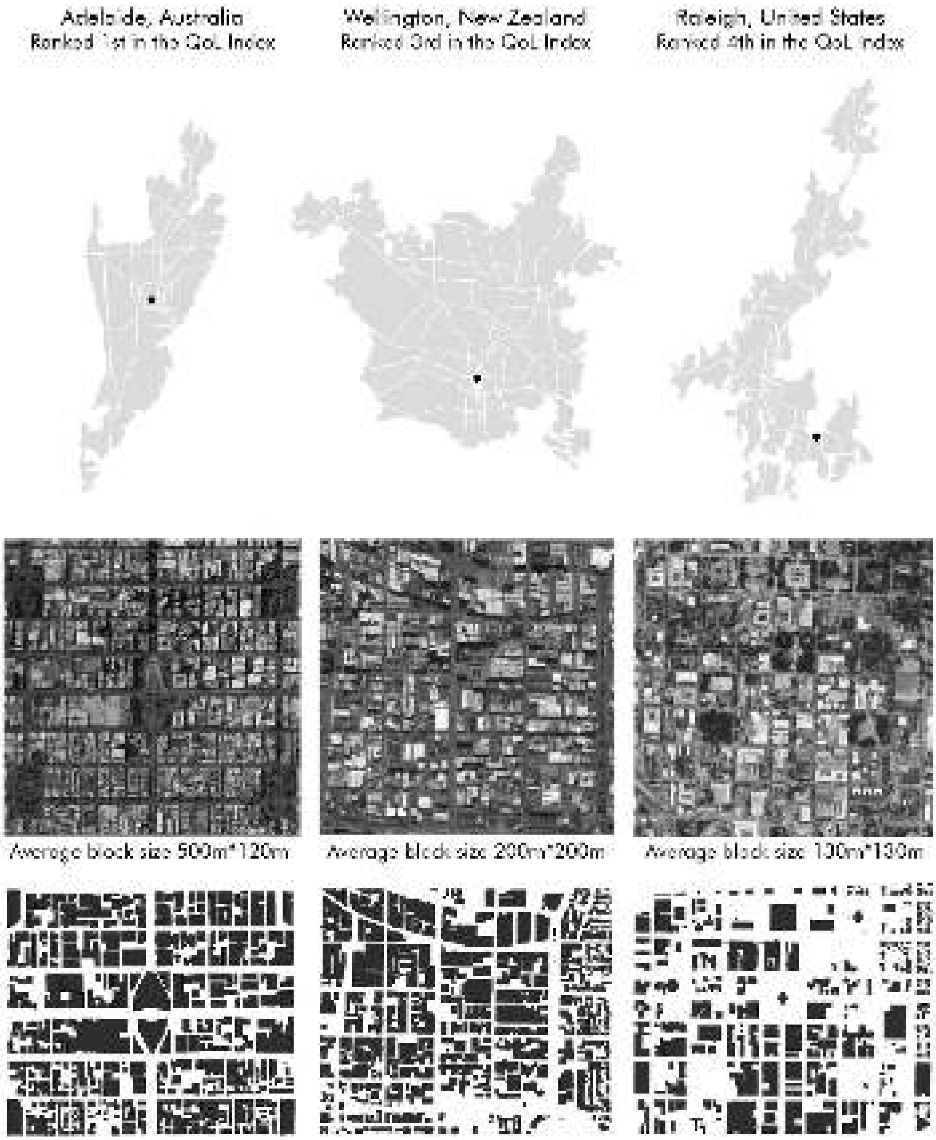


FIG. 9.5 City layouts with the highest quality of life indexes (prepared according to May 2021 QoL indexes on the Numbeo website). *No permission required.*

We divided the downtowns areas into 10 m × 10 m cells in order to convert them into two-dimensional matrices in a spreadsheet. Each cell has been denoted with a character that defined the function of that space, e.g., residential buildings, transportation, health centers, etc. We determined the city program in those cells, such as residential buildings, transportation, health centers, etc. We formed 96 subcategories for the six cities, and clustered them into ten

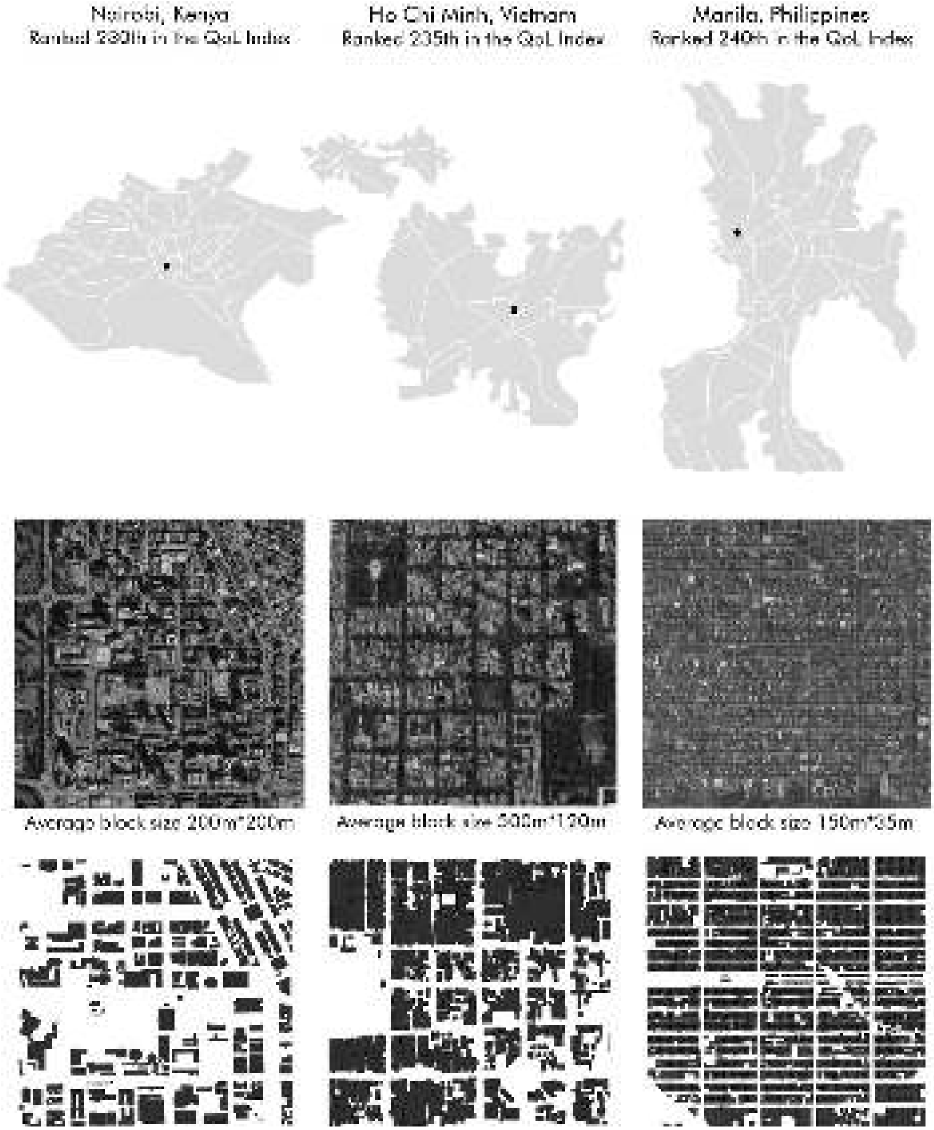


FIG. 9.6 City layouts with the lowest quality of life indexes (prepared according to May 2021 QoL indexes on the Numbeo website). *No permission required.*

main categories, e.g., M (mixed use), R (residential buildings), G (open areas), H (health centers), + (transportation), E (educational buildings), S (sociocultural buildings), P (public buildings), C (commercial buildings), and O (others). These symbols formed the base vocabulary of the matrix data. Within the scope of this study, we limited the top-level categories to these ten symbols.

Guiding policies to discover design patterns

As indicated by Lynch, there are common themes that help us grasp general physical characteristics of the city. *Singularity* or *figure-background clarity* are the qualities that make an element remarkable, noticeable, and recognizable; *form simplicity* allows us to easily incorporate these elements in our perception; *continuity* facilitates the perception of interrelated complexity; *dominance* is a quality that dominates one part over others; *clarity of joints* are the strategic points of structure that shows clear relation and interconnection; *directional differentiation* differentiates one end from another by means of asymmetries and gradients; *visual scope* increases the range and penetration of vision by using transparencies, overlaps, vistas, and panoramas; *motion awareness* provides an observer to reinforce and develop sensing form in motion; *time series* are sensed sequences; and *names and meanings* are the nonphysical characteristic qualities that may enhance the imageability of an element (Lynch, 1960).

Similarly, we introduced various policies that guide the MR engine, (a) frequency, (b) range, and (c) coverage policies. While determining these three policies, we considered the themes that Lynch mentioned as the common physical characteristics of cities, e.g., the frequency policy has similar features with the continuity quality; range and coverage policies have similar features with the dominance quality, etc.

1. The frequency policy counts each occurrence of candidate patterns and prioritizes the most frequent ones over the less frequent ones.
2. The range policy looks at the size of patterns. In this policy, regardless of whether the pattern repeats to other areas or not, the pattern that is associated with the largest area is prioritized over the others.
3. The coverage policy adds up the areas of every occurrence of a given pattern and prioritizes the ones which cover the largest area over the others (Fig. 9.7).

The MR engine goes through three steps to discover design patterns. First, it generates numerous pattern candidates, where each can be represented as a regular expression. Then, each candidate is evaluated and ranked based on available policies. Then, highly ranked candidates are evaluated further based on their fitness to contribute to the specification of the city grammar in a compressed manner. If a candidate pattern leads to a more concise representation of the grid data, then it is favored over the others.

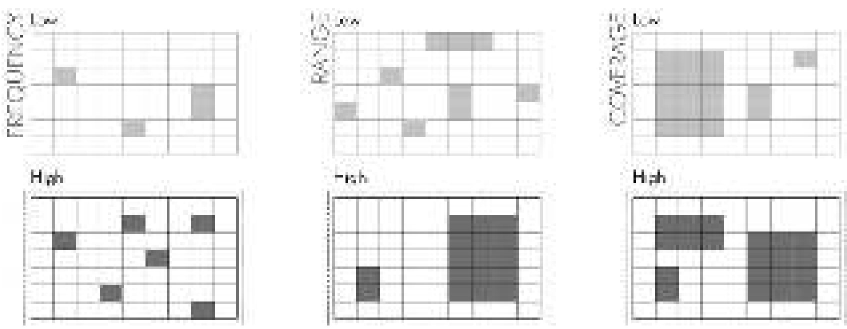


FIG. 9.7 Frequency, range, and coverage policies for identification of urban patterns. *No permission required.*

Discovering city grammars

When we train the MR engine with our city data, it will first try to identify the best *vocabulary* to represent the city layouts. The vocabulary consists of the base concepts (R, G, H, …, O) that appear in the city layout, plus the new concepts that we discover, to achieve a concise overall representation. Each new concept corresponds to a pattern that is expressed as a regular expression. The first level of vocabulary contains commonly used simple design patterns within the training data. It will then discover a hierarchy of more complex design patterns, using not only the base concepts but also the newly discovered ones, which will gradually build the *grammar* of city layouts, as shown in Fig. 9.8. For example, the tool may discover the concepts of residential areas (RA) as a function of *residential* buildings (R) and parks (P) and commercial areas (CA) as a function of commercial buildings (C) and schools. These two new concepts (RA and CA) then may serve as the building blocks of higher-level concepts, such as towns (TT), as follows:

$$RA = \boldsymbol{f}(R, P)$$

$$CA = \boldsymbol{g}(C, S)$$

$$TT = \boldsymbol{h}(RA, CA, *)$$

The MR engine can be trained in a supervised and unsupervised manner. Unsupervised training is used to detect common patterns from unlabeled data. Supervised training, on the other hand, requires annotated data. In this exercise, we explored whether the MR engine can discover Lynch's components for the imageability of a city; and, whether there is a difference in the frequency, range, and coverage of these components in cities with low and high QoL scores. The data samples from the above six cities are annotated based on membership to two layout categories. The first category contains cities with high QoL, and the second category contains cities with low QoL. The remaining data are unannotated. The aim here is to determine the basic features that distinguish the cities into two categories. The tool uses all data to capture commonly seen design patterns but uses only the annotated data to decide which patterns should be used and which ones to be avoided when generating new designs. The training produces a model, which describes high-performing layouts as a function of all the input, symbols plus the newly discovered concepts (Fig. 9.8). The tool also provides a utility, which generates an unbounded number of new designs using the high-performing layout models. The tool allows experimentation to see the impact of adding new layouts to the dataset.

Results

In this section, we provide a peek into the preliminary results in relation to our research objective of automatically discovering Lynch's design elements as *paths*, *edges*, *districts*, *nodes*, and *landmarks* using the MR engine. Fig. 9.9 is a summary of a typical training session using the MR engine.

Fig. 9.10 illustrates the command line interface of the training session performed to discover the city grammar for this research.

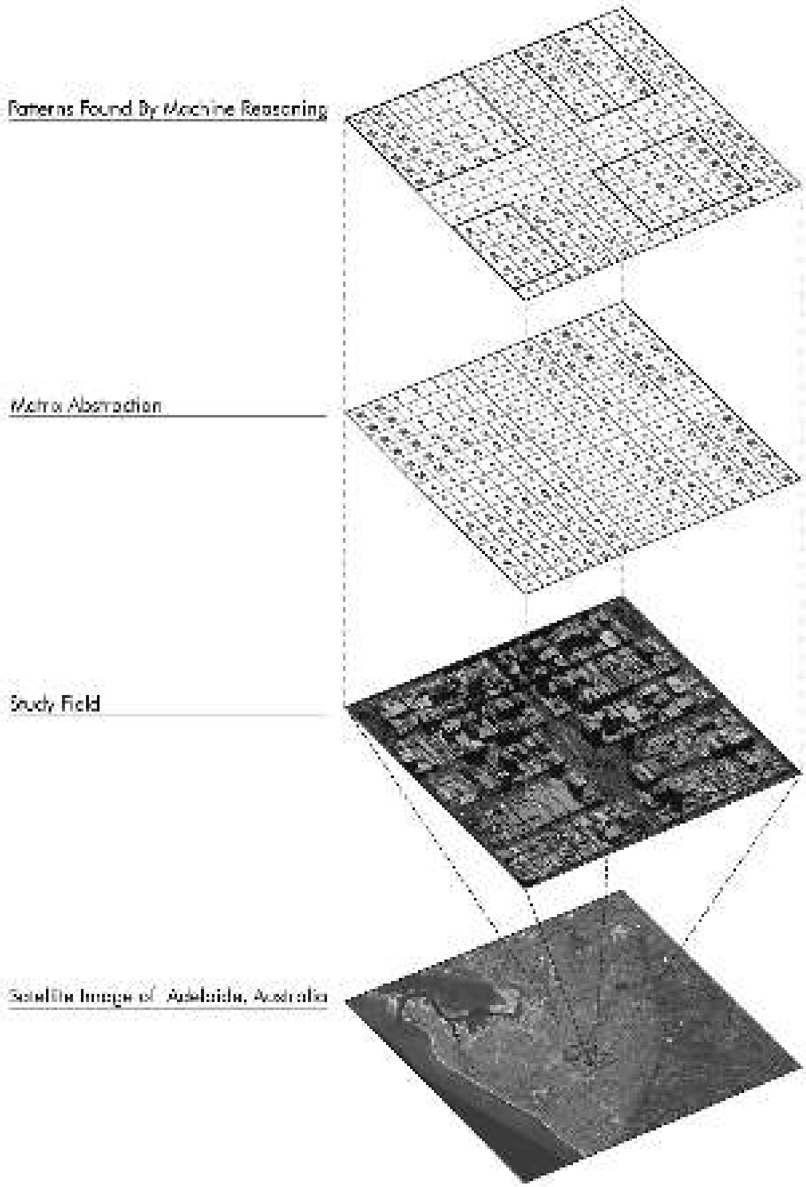


FIG. 9.8 From raw data to city grammar. *No permission required.*

Notice that training the MR Engine is as simple as introducing the data (L), setting hyperparameters, and successive rounds of discovering new concepts (X, Y, Z, and so on), and expressing L as a function of these new concepts. With these training sessions, the MR engine is able to identify Lynch's five design elements as illustrated in the Raleigh city and Manila city examples (Figs. 9.11 and 9.12).

```
Create a new concept A and introduce positive training samples
Introduce negative training samples
Repeat (i=1...n)
        Set the hyperparameters
        Discover a patterns X(i) within A
        Visualize X(i)
        Express A as a function of X(i)
Generate a theory to express A as a function of X(0), X(1),..., X(n)
Visualize A=f(X(0), X(1), ..., X(n))
```

FIG. 9.9 The pseudo code of a typical training session using our MR engine. Please see related script in Fig. 9.10. *No permission required.*

```
u L+ Adelaide.txt    /* Create a new concept L for "liveable cities" */
u L+ Wellington.txt  /* Introduce Adelaide, Wellington and Raleigh */
u L+ Raleigh.txt     /* as positive samples */

u L- Nairobi.txt     /* Introduce Nairobi, Ho Chi Minh and Manila */
u L- HoChiMinh.txt   /* as negative examples */
u L- Manila.txt

s L C                /* Set the hyperparameters */
n f X L              /* Discover a pattern X within L */
c X                  /* Visualize X */
u L< X               /* Express L as a function of X */
n f Y L              /* Discover a pattern Y within L */
c Y                  /* Visualize Y */
u L< Y               /* Express L as a function of Y */
n f Z L              /* Discover a pattern Z within L */
c Z                  /* Visualize Z */
u L< Z               /* Express L as a function of Z */
```

FIG. 9.10 Command line interface of the training session. *No permission required.*

The *Path* element is the first design pattern that the MR engine discovers. It specifies path as a function of "+" symbols distributed in 2D rectangular districts. The path elements work well for compositionality, for building the city grammar as it breaks the grid data into smaller modular districts. Fig. 9.11 illustrates the result of one such run for the grid data of Raleigh. Here, we can see the roads that appear horizontally and vertically in the grid. We can also see the nodes in Lynch's terminology that corresponds to the intersection of path elements. As can be seen in Fig. 9.11, the identified path elements divide the city map into rectangular areas and serve as the intermediary concepts in building the city grammar.

The rectangular areas that stay between these roads are the unprocessed portions of the data. Notice that Kevin Lynch's districts correspond to the rectangular regions separated by path elements. The MR engine does not immediately assign any symbol (concept) to these rectangular regions but treats them as raw data that can be taken into account for further concept discovery. In the next round, the MR engine identifies regions that have both commercial (C) and residential buildings (R) as a new concept, which is an example of a district. Notice

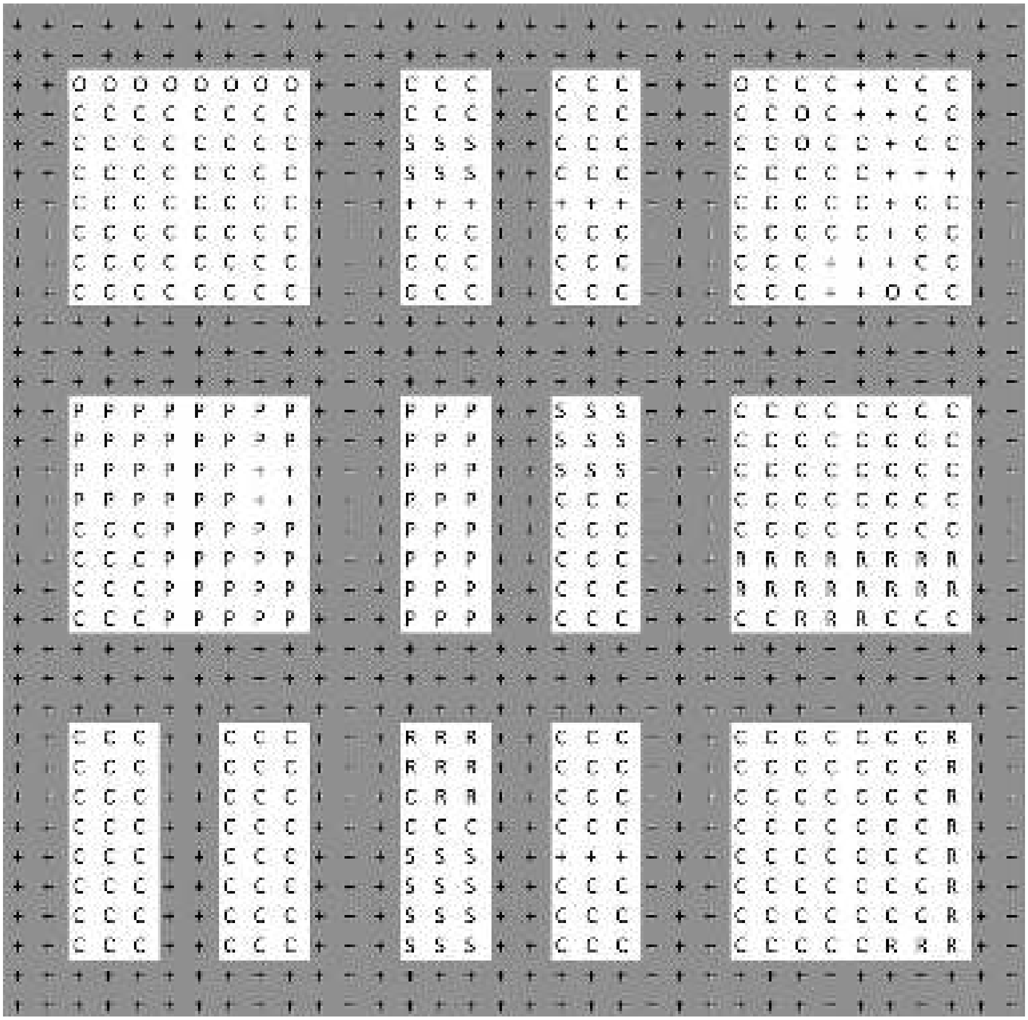


FIG. 9.11 Patterns discovered by MR engine in Raleigh's downtown. *No permission required.*

that there may be many different patterns for districts. The MR engine's discovery process works based on the discovery policy, and prioritizes the candidates that contribute to the most concise expressions.

The MR engine also generates patterns that correspond to Lynch's edge elements. As can be seen in Fig. 9.12, there are examples of edge elements, such as the border between the green areas and the rest of the rectangular region. Landmark elements have a special place from the perspective of this analysis in that they do not correspond to a pattern that appears in many places, but as a unique instance that appears just once. We use the input data to mark the landmark instances.

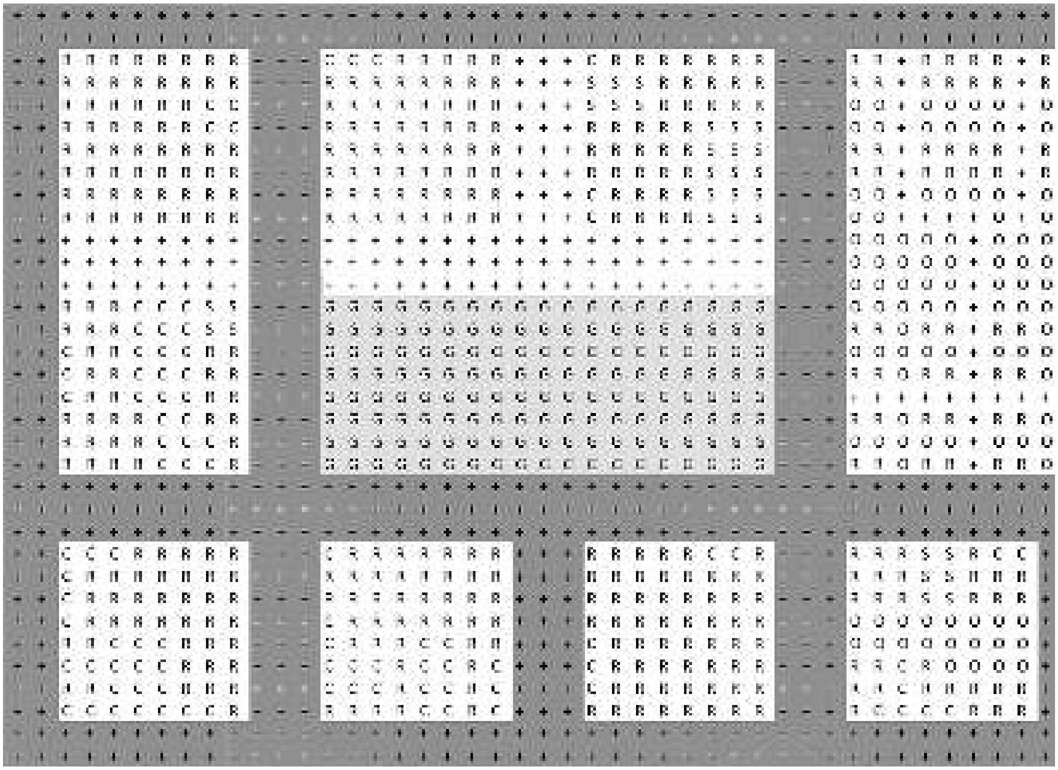


FIG. 9.12 Patterns discovered by MR engine in Manila's downtown. *No permission required.*

This outcome is not unique to a single city but can be witnessed in all the cities we selected. Fig. 9.13 illustrates samples of the design elements that we identified automatically for each of the six cities. While the MR engine is successful in identifying Lynch's city components, the results illustrate that there is no major difference in the frequency, range, and coverage of city components when comparing cities with low and high QoL. This could be due to the fact that there is not enough granularity to evaluate the cities, e.g., due to the absence of the third dimension. Indeed, in this chapter we only showcase the results for Phases 1 and 2, and once we take the study further, i.e., develop Phases 3, 4, and 5, we anticipate seeing more nuanced results that give further insights to compare and contrast the cities.

Conclusions

The urban design process has a crucial role in shaping our environment and cities. However, this process poses plenty of challenges in practice, and also traditional urban planning methods are failing to meet the needs of an ever-growing urban expansion around the globe. AI offers opportunities to learn what differentiates cities with a high QoL score from the ones with low QoL, and one may use this knowledge to grow cities in the future.

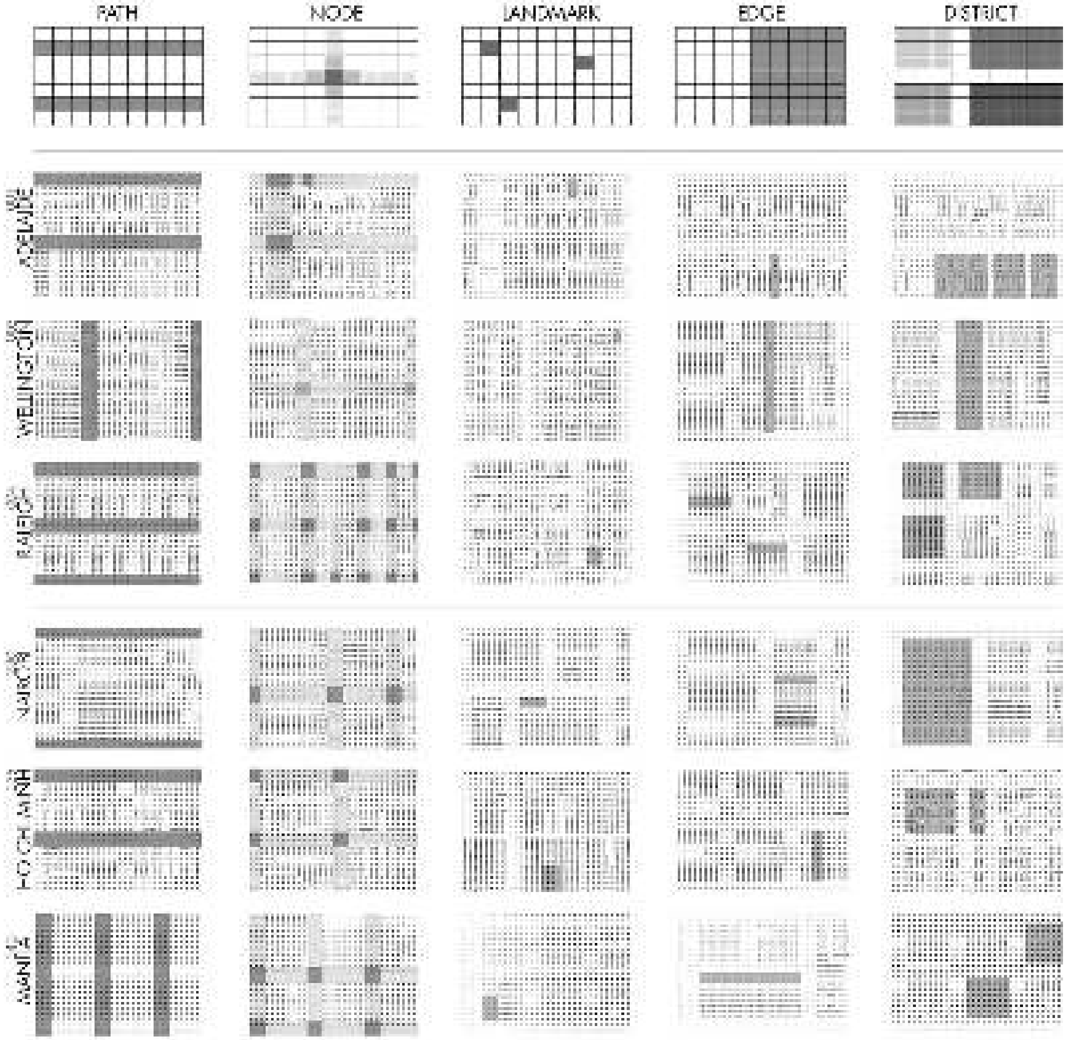


FIG. 9.13 Samples of Lynch's design elements were automatically discovered using the MR engine. *No permission required.*

We investigated whether AI can contribute to developing new languages by automating the discovery of common design patterns in cities from a small number of examples. We developed an MR engine that discovers common design patterns and we applied them to generate novel city layouts. The MR engine identified latent patterns within the city layouts using a set of policies, and generated a city vocabulary starting with the lower-level patterns that were directly observed, and then combined these hierarchically, to develop higher-level concepts corresponding to more complex design patterns. To create and analyze grid city layouts in 2D, we have selected six cities with high and low QoL indexes according to the data on the Numbeo website from May 2021. Unlike neural networks, which require big data, our approach was able to train MR models using data from only few cities and was able to detect core city elements in these cities.

Our research roadmap consists of five phases, and this chapter presented the preliminary results of the first two phases, where the focus was to discover design patterns from base concepts and build hierarchies expressing more complex patterns with the ultimate goal of discovering concise city grammar. We envision that such grammar will enable us to distinguish designs with high QoL scores from the ones with low QoL scores. In our future research, we intend to add more complexity to the study by considering other parameters, like the location of public buildings, services, amenities, and housing, and by considering the relation and adaptation of predicting design patterns by our MR engine to its environment. In Phase 3, we will use the city grammar discovered to generate unique designs for a given boundary conditions. In Phase 4, we will extend our approach to take into account the context of the city (in particular the neighboring areas) to produce designs that are also compatible with their larger environments. In Phase 5, we will enhance our approach from two-dimensional grid layouts to three-dimensional spatial forms.

Hundreds of new cities are built around the world, the fact that China has built more than 600 cities since 1949 is an indicator of this trend. The MR method has the potential to serve municipalities and government institutions to expand their urban areas and help the future growth of cities around the world.

Acknowledgment

We want to thank our interns Hulya Sacin and Seyit Semih Yigitarslan who have diligently worked on this porject. This publication has been produced benefiting from the 2232 International Fellowship for Outstanding Researchers Program of TÜBİTAK (Project No: 118C228 and 118C284). However, the entire responsibility of the publication belongs to the owner of the publication. The financial support received from TÜBİTAK does not mean that the content of the publication is approved in a scientific sense by TÜBİTAK.

References

Alexander, C.W., 1964. Notes on the Synthesis of Form. Harvard University Press, Cambridge, Massachusetts.

Alexander, C., et al., 1977. A Pattern Language: Towns, Buildings, Construction. Oxford University Press, New York.

Alonso, L., et al., 2018. CityScope: a data-driven interactive simulation tool for urban design. Use case volpe. In: Unifying Themes in Complex Systems IX. ICCS 2018. Springer, Cham, pp. 253–261, https://doi.org/10.1007/978-3-319-96661-8_27.

As, I., Pal, S., Basu, P., 2018. Artificial intelligence in architecture: generating conceptual design via deep learning. Int. J. Archit. Comput. 16 (4), 306–327. https://doi.org/10.1177/1478077118800982. United States: SAGE Publications Inc.

Blum, R., et al., 2006. Design Coding in Practice, An Evaluation. DCLG, England.

Duarte, J.P., et al., 2012. City induction: a model for formulating, generating, and evaluating urban designs. In: Arisona, S.M., et al. (Eds.), Communications in Computer and Information Science. Springer, Berlin, Heidelberg, Portugal, pp. 73–98, https://doi.org/10.1007/978-3-642-29758-8_5.

Lima, F., Brown, N., Duarte, J., 2021. Urban design optimization: generative approaches towards urban fabrics with improved transit accessibility and walkability. In: Projections—Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2021.

Hong Kong. 26th CAADRIA- International Conference of the Association for Computer-Aided Architectural Design Research in Asia.

Lynch, K., 1960. The Image of the City. The MIT Press.

Negroponte, N., 1970. The Architecture Machine: Toward a more Human Environment. The MIT Press.

Numbeo, 2021. Available at: https://www.numbeo.com/quality-of-life/. Accessed: May 2021.

Quan, S.J., et al., 2019. Artificial intelligence-aided design: smart design for sustainable city development. Environ. Plann. B Urban Anal. City Sci. 46 (8), 1581–1599. https://doi.org/10.1177/2399808319867946. South Korea: SAGE Publications Ltd.

Salingaros, N.A., 2000. The structure of pattern languages. Archit. Res. Q. 4 (2), 149–162. https://doi.org/10.1017/S1359135500002591. United States.

Shepard, W., 2017. Why Hundreds of Completely New Cities are Being Built Around the World. Available at: https://www.forbes.com/sites/wadeshepard/2017/12/12/why-hundreds-of-completely-new-cities-are-being-built-around-the-world/?sh=3839c7ac14bf.

Traunmueller, M., et al., 2021. In: Kaatz-Dubberke, T., et al. (Eds.), AI-Supported Approaches for Sustainable Urban Development: Analysis of Case Studies. Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH and Austrian Institute of Technology.

United Nations, 2018. The World's Cities in 2018, Statistical Papers—United Nations (Ser. A), Population and Vital Statistics Report., https://doi.org/10.18356/c93f4dc6-en.

Zhang, Y., 2017. City Matrix: An Urban Decision Support System Augmented by Artificial Intelligence. The MIT Press.

CHAPTER

10

Optimizing urban grid layouts using proximity metrics

Fernando Lima[a], *Nathan C. Brown*[b], *and Jose Pinto Duarte*[c]

[a]Department of Architecture, Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, The Pennsylvania State University, University Park, PA, United States [b]Department of Architectural Engineering, College of Engineering, The Pennsylvania State University, University Park, PA, United States [c]Stuckeman School of Architecture and Landscape Architecture, College of Arts and Architecture, The Pennsylvania State University, University Park, PA, United States

Introduction

Artificial intelligence (AI) relies on the idea of optimizing, simplifying, and extending the possibilities of operations in various tasks and areas of knowledge, from medical diagnosis to self-driving cars, from education to social media marketing. Although the term AI was coined in 1955 by the Dartmouth Summer Research Project members (Kaplan and Haenlein, 2019; McCarthy et al., 2006), it has become more popular due to big data, advanced algorithms, and recent computing power and storage improvements. In the urban design context, AI systems are widely accepted as a technology offering an alternative way to tackle complex and dynamic problems. Moreover, AI has a great potential to boost performance-based design approaches and improve decision-making processes by performing complex iterations and carrying out predictions with speed and accuracy.

Although AI has become largely equated with machine learning (ML) among the public in recent years, it includes other paradigms and methods, including rule-based systems and search and optimization, which are explored in this chapter. Computational optimization (CO) approaches are increasingly employed to address challenging design problems, even though CO applications at the urban design scale have been limited compared to architecture due to enhanced complexity and computation requirements. Multiobjective optimization (MOO), in turn, supports decision-making in the presence of trade-offs between two or more conflicting objectives. Thus, it enables the exploration of complex design spaces while

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00001-9

managing and prioritizing multiple objectives (Brown, 2016, 2019). While it has been utilized widely in fields such as the aerospace industry, mechanical engineering, and economics for decades (Marler and Arora, 2004), forms of multiobjective optimization have recently become more common in design (Coello and Romero, 2003; Evins et al., 2012; Brown, 2016, 2019; Lima et al., 2022; Cichocka et al., 2017). The works of Navarro-Mateu et al. (2018) and Makki et al. (2019) are among the first few to explore MOO approaches in the generation of urban fabrics.

Computational optimization systems require measurable design goals to drive the automated design process. Goals can be derived through urban metrics that describe positive aspects of cities. Throughout the evolution of cities, proximity has played a fundamental role in promoting urban dynamics, influencing urban morphology, and affecting the quality of life, whether creating areas of high population density or setting "ideal" boundaries for neighborhoods (Gehl, 2010). Moreover, increased proximity—as well as density—in urban areas is believed to promote environmental, social, and economic sustainability, since important urban features such as transit accessibility, density, land-use diversity, and walkability—crucial for easing traffic congestion and CO_2 emissions and improving public health—can be either assessed or explained by proximity indicators.

There are metrics of two natures for estimating the overall proximity of urban fabrics: physical (or dimensional) and topological. While physical proximity metrics consider distances in meters, yards, miles, or even time measures, topological metrics are more concerned with the connectivity, the number of turns in a specific path, or other syntactic features that arise from fabric configurations, like the relationships between spatial elements, such as street networks. The Space Syntax theory proposed by Hillier and Hanson (1984) describes the spatial relations of a given location through a set of syntactic measures, which make it possible to understand essential aspects of an urban fabric, such as accessibility and connectivity. Accordingly, an extensive body of research has addressed physical or topological metrics for assessing urban areas from various perspectives, from physical activities estimation to environmental and transit-oriented practices in urban planning (Brewster et al., 2009; Carr et al., 2011; Dogan et al., 2020; Feng and Peponis, 2021; Koohsari et al., 2016; Lima, 2017; Lima et al., 2016a, 2017; Nourian et al., 2015; Sevtsuk et al., 2016). Nonetheless, optimizing physical metrics does not necessarily mean optimizing topological metrics, often resulting in a trade-off that must be addressed.

This chapter explores computational optimization techniques in early urban design stages, aiming to improve the performance of urban grid layouts according to the physical and topological proximity metrics. To this end, this work addresses evolutionary multiobjective optimization to generate urban fabrics with improved proximity, analyzing the outcomes of different urban design rules toward the formulation of orthogonal and nonorthogonal grid typologies. Thus, computational tools specifically designed to measure the shortest physical distance between locations in a given urban fabric and assess syntactic measures (integration and connectivity) were coupled in a computational multioptimization framework to generate optimal urban grid layouts while comparing the benefits and drawbacks of four different fabric typologies: regular and orthogonal grid, irregular and orthogonal grid, an irregular displaced corners grid, and a Voronoi-shaped blocks grid. These typologies were chosen because they are easier to implement and represent several important fabric configurations around the globe, such as Manhattan, Chicago, Barcelona (both the Cerdá's plan and the old city), and several slums like the Brazilian and Indian ones. In the future, we intend to address other typologies like circular/radial grids like New Delhi and other more complex typologies.

This work is structured into sections that present materials and methods, consisting of a delineation of the research framework, a presentation of the addressed proximity metrics, and a brief discussion on multiobjective optimization; a description of our case study, in which four different fabric typologies were implemented and optimized through computational generative approaches; a presentation of the case study results, consisting of a performance analysis of the generated urban grids; and an overall discussion, addressing final remarks, limitations, and future developments of this research.

Materials and methods

Research framework

Sevtsuk et al. (2016) investigate how block sizes, plot dimensions, and street widths affect pedestrian accessibility (through a physical metric) in American and Australian regular grids. Lima et al. (2017) use a set of tools to assess physical (distance) and syntactic metrics. Zhao et al. (2019) concluded that urban areas with orthogonal street grids and high street density have good accessibility to reach destinations. Recently, Feng and Peponis (2020, 2021) have addressed grid performance from a topological or syntactic perspective.

In recent work, we have evaluated the performance of different optimization algorithms and addressed the generation of urban grid typologies that maximize transit accessibility, as estimated by the overall physical proximity of an urban area to its central transport station (Lima et al., 2022). We have also explored the suitability of a shape grammar-based optimization approach for solution finding in urban design, focusing on pedestrian accessibility, measured through physical proximity and infrastructure cost, as estimated by cumulative street length (Lima et al., 2022).

This paper builds on this research thread by implementing both physical and topological metrics in multiobjective optimization procedures that address different grid generation typologies. Our goal is to explore computational optimization techniques to assess urban grid layout performance according to the physical and topological proximity metrics. We utilize the generation of different grids in order to address the following questions: Do regular and orthogonal grids provide greater proximity than irregular and orthogonal ones? Do nonorthogonal grids (like Voronoi-shaped ones) provide greater topological proximity at the expense of lower physical proximity? Which of the addressed generative approaches performed better considering physical metrics? What happens when one considers syntactic measures? Is there a specific approach that better balances the two metrics?

Physical metrics: Physical proximity index

A significant body of research has addressed physical distances for estimating urban features such as the walkability or the transit accessibility of a given urban area. However, considering only algorithmic-parametric environments in the Rhinoceros/Grasshopper platform—the one adopted for this research—(Nourian et al., 2015) explored accessibility

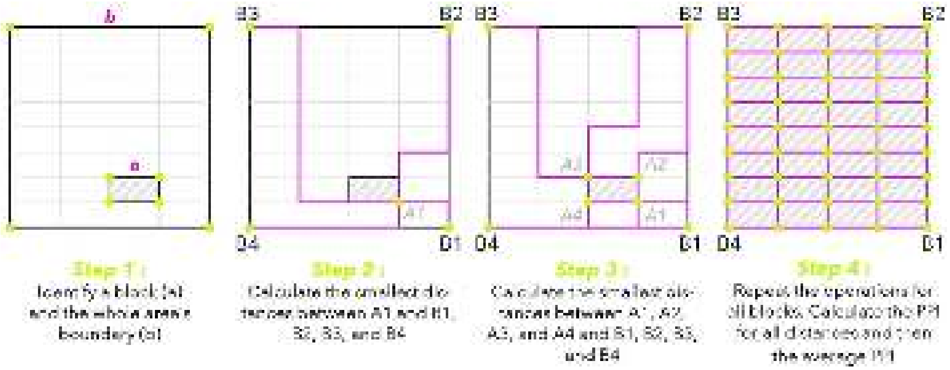


FIG. 10.1 Steps in the calculation of the Physical Proximity Index. *No permission required.*

measures through an "easiest path" algorithm toolkit that provides distances between locations. Dogan et al. (2020) introduced a computational toolbox to evaluate active transportation and assess pedestrian accessibility to public transport and urban amenities. In a comparable setting, Lima et al. (2017) presents the set of Grasshopper tools used in this research, which allows one to consider physical (distance) and topological metrics (e.g., connectivity and integration).

This research adopts the physical proximity calculator, a tool introduced by Lima et al. (2017) that can be used to assess physical distances to destinations within an urban area. The physical proximity calculator (PPC) computes the smallest distance for two or more destinations in a 0–1 scale index that considers the street network. For example, a distance of 400 m (5-min walk) or less between two points of interest returns a Physical Proximity Index (PPI) of 1, which decreases as the distance approaches 1600 m (20-min walk), equaling 0 when the distance becomes greater than 1600 m. In our studies, which seek to assess the overall proximity of a given fabric, we have set the PPC to compute the PPIs between each street intersection to its fabric boundary corners. We have successfully set the average PPI of an urban area as the fitness function in various previous studies (Lima et al., 2016a,b, 2017, 2022; Lima, 2017). Although it has different meanings for different grids, according to its size, geometry, and the number of destinations (corners), the average PPI helps drive optimization procedures toward solutions with greater proximities since small changes in PPI average values have meaningful results implications. For instance, when considering a Voronoi-shaped blocks typology, an average PPI improvement of 0.01 corresponds to a reduction of 457,600 m in the sum of all distances between all corners in our area of study. Fig. 10.1 describes how the PPI is calculated.

Topological metrics: Space syntax integration and connectivity

Space Syntax (SS) consists of a set of theories and methods introduced by Hillier and Hanson (1984) to model and analyze spatial configurations and understanding the social dynamics they involve. The main idea of SS is that spaces can be decomposed into components of a *system and then represented by maps and graphs that describe different attributes (or syntactic measures) related to these spaces. SS relies on three basic concepts of space: (a) convex space—an empty space that can be represented by a polygon or convex solid; (b) the axial space—that can be synthesized by one or more axial lines or segments, derived from the convex space, and; (c) an isovist—defined by a visibility polygon that represents the field of view from a specific location.

In the SS logic, the spatial structure of an urban area is understood as its urban configuration, which involves the totality of relationships between barriers and open areas that make up the physical structure of the city space. In this regard, several works (Feng and Peponis, 2021; Hillier, 2002; Hillier and Hanson, 1984; Penn et al., 1998; Peponis et al., 2007, 2008, 2015) have addressed the syntactic structure of urban grids, leading to an understanding that the urban spatial syntax plays an essential role in the circulation of pedestrians and vehicles and the distributions of commercial land use, for instance. However, due to several factors, including the complex and time-demanding nature of city evolution and the computational requirements needed to process multiple alternative fabrics configurations, studies often focus on urban configurations as an end product for assessment rather than exploring and assessing different possibilities for urban fabrics in design and planning processes.

This paper explores two syntactic measures as fitness functions in a multiobjective optimization procedure: integration and connectivity. Integration refers to how close one space is to everything else in the urban system, referring to the to-movement potential (Hillier, 2002; Hillier et al., 1993). In other words, integration is a normalized measure of distance from any point of origin to all others in a system, similarly to closeness centrality in network science (Wasserman and Faust, 1994). Hypothetically, it shows the cognitive complexity of reaching a street, allowing one to predict its pedestrian importance. Thus, in brief, integration captures how close one street segment is in relation to all others in a system. Connectivity, in turn, measures the number of direct links of a given space; that is, the connectivity of each space is given by the number of spaces that intersect it. We intend to verify how different fabric typologies perform considering these two syntactic measures. To do this, we set the average integration and connectivity measures as fitness functions to be maximized, seeking to find fabrics more connected and integrated. Fig. 10.2 explains the logic of these measures and illustrates integration and connectivity segment maps.

Multiobjective optimization: Physical and topological metrics trade-off

In a meaningful multiobjective optimization problem, a single solution cannot optimize each objective function simultaneously. Thus, a MOO optimal solution occurs when none of the objective functions can be enriched without worsening other objective values. This is called a Pareto optimal or nondominated solution, and without additional information or a post-Pareto analysis, all Pareto optimal solutions in an optimization problem are considered equally good.

In this context, our goal is to explore the performance of urban grid layouts by simultaneously optimizing physical and topological proximity metrics. This work thus addresses evolutionary multiobjective optimization techniques in the generation of urban fabrics with different morphologies while evaluating their Physical Proximity Index, integration, and

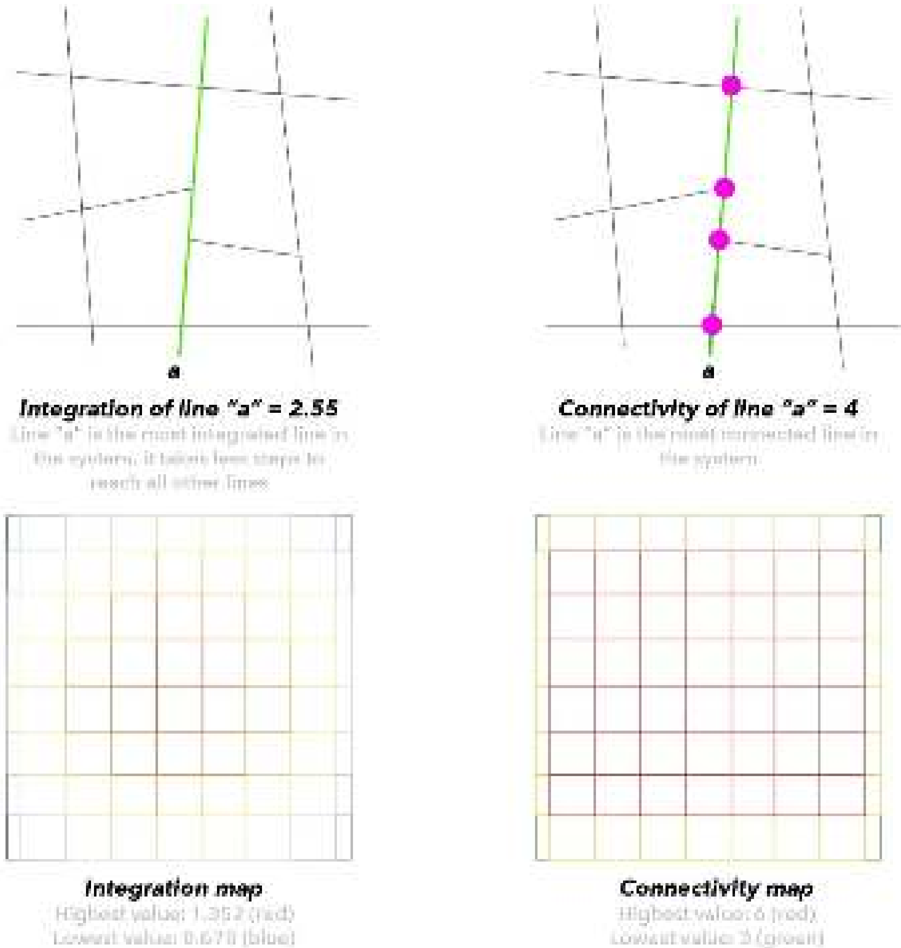


FIG. 10.2 The logic for measuring integration and connectivity (above), an integration color segment map (bottom-left), and a connectivity color segment map (bottom-right) of the same area. *No permission required.*

connectivity. For some grid situations, improving one of these metrics means decreasing the performance of the others. Therefore, we explore optimization as a tool to discover potentially enhanced designs or even directions for further modification, rather than as a deterministic approach for selecting a single, perfect solution.

Considering the software platform used for our work (Rhinoceros/Grasshopper), we have evaluated four multiobjective optimization add-ons for this research: Octopus, which employs Strength Pareto Evolutionary Algorithm 2 (SPEA-2) and fast hypervolume-based many-objective optimization algorithm (HypE) (ETH, 2018); Opossum, which utilizes Nondominated Sorting Genetic Algorithm II (NSGA-II) and Particle Swarm algorithms (Wortmann, 2017, 2019); and Design Space Exploration (Brown et al., 2020) and Wallacei X (Makki et al., 2020) that also employs NSGA-II.

We opted to use NSGA-II (Deb et al., 2000) because of three primary aspects: avoiding dependency on initial solutions to converge to optimal solutions, computational time, and preventing getting stuck to suboptimal solutions. Wallacei X was our final choice because it uses NSGA-II in a compatible way with our grid generation algorithms, which rely on the Gene Pool tool. Still, Wallacei interface and data accessing possibilities provided us with increased freedom of analysis.

Case study

Methodology

Our case study consists of four experiments exploring different grid generation approaches of increasing complexity in multiobjective optimization procedures that simultaneously use physical (Physical Proximity Index) and topological metrics (integration and connectivity) as objective functions. We have implemented a set of algorithms that generate different fabric layout typologies for a given area. A hypothetical square-shaped site of 1600 m on its side was addressed to run the tests, so that we could observe a regular and orthogonal shape sample while considering a walkable threshold. Thus, we intended to analyze the performance outcomes of the following grid typologies after optimization: (i) regular grid—an orthogonal fabric containing quadrilateral blocks with the same length and width; (ii) irregular grid—an orthogonal fabric containing quadrilateral blocks with varying dimensions; (iii) moving corners—an experimental fabric generation approach that consists of displacing the corners of an irregular grid input, in a nonorthogonal logic, and; (iv) - Voronoi-shaped blocks—an experimental nature-inspired grid shape.

All experiments were carried out in a Rhinoceros/Grasshopper software environment, using the Wallacei X add-on for multiobjective optimization procedures. An Intel Core i9-9900 $\times$ 3.5 GHz with 128 GB installed RAM computer was utilized to address a population size of 10,000 solutions (200 generations of 50 individuals) for each experiment, taking a total computation time of approximately 54 h, with different calculation times for each typology approach. Our goal was to find optimal grid layouts by maximizing the Physical Proximity Index and the integration and connectivity measures.

Regarding Physical Proximity, in orthogonal grid systems, as in experiments 1 and 2, the average distance between all block corners and the site corners is always the same, no matter the size of the blocks, as depicted in Fig. 10.3 (above). However, since PPI does not consider distances on a linear scale above and below the stated thresholds (less than 400 m and more than 1600 m), the average PPI of the entire neighborhood is slightly different from the average distance between the corners. Therefore, maximizing the PPI of an urban area means looking for arrangements that avoid distances larger than 1600 m (PPI = 0) while not further prioritizing distances smaller than 400 m (PPI = 1). Accordingly, maximizing PPI means obtaining more homogeneous proximity values, in this case, distances to the grid's corners and providing more balanced proximity values to more blocks and consequently more people.

The integration and connectivity measures, in turn, were calculated considering a segment map instead of an axial map due to the computational cost of automatically generating axial maps for assessing each solution during the optimization process. The major difference

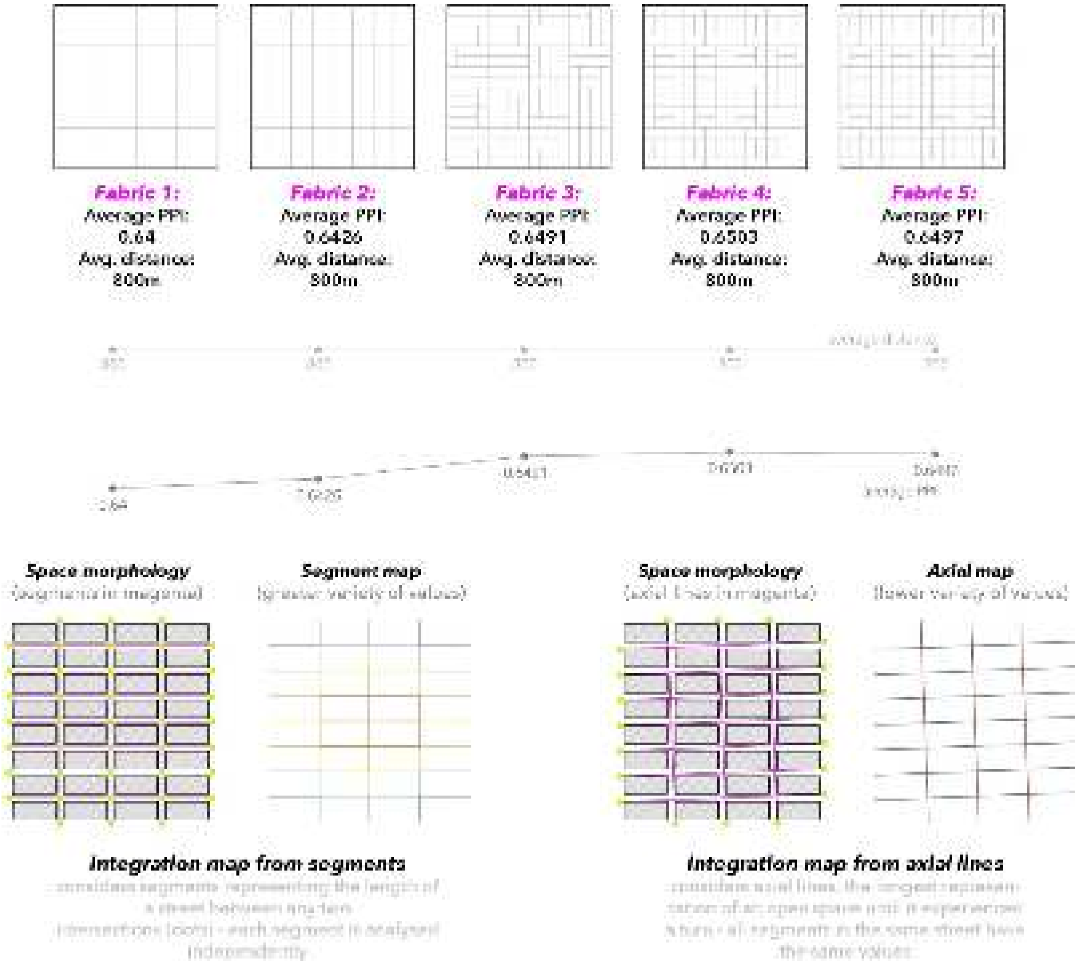


FIG. 10.3 Different orthogonal fabric arrangements—the average distance between all parcels corners and the grid corners is always the same, no matter the size of the urban blocks (above), and the difference of using segment maps or axial maps for calculating integration, given our addressed typologies (below). *No permission required.*

between a segment and an axial map is that the former considers segments representing the length of a street between any two intersections. In contrast, the latter considers axial lines, the longest representation of a street until it experiences a turn. Thus, addressing segment maps allowed us to verify and understand each part of a street separately, providing a more accurate analysis regarding integration, for instance, as depicted in Fig. 10.3 (below).

Experiment 1: Regular grid approach

The regular grid approach consisted of subdividing our study site into orthogonal blocks with the same width and length, a common situation in urban planning. So, the input

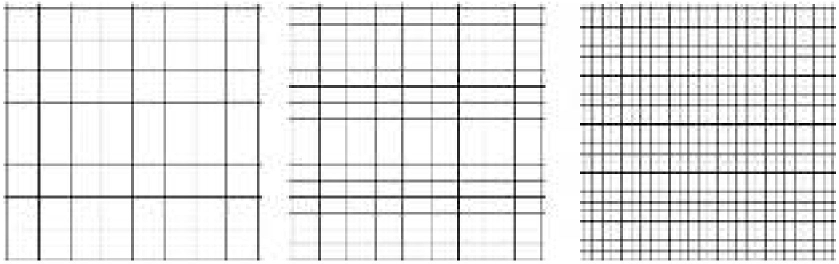


FIG. 10.4 Examples of regular grid approach generated fabrics: all the blocks have the same length and width. *No permission required.*

variables in this experiment were: the number of blocks along the X-axis and the Y-axis (ranging from 8 to 26, meaning block lengths and width with approximately 60–200 m), and street width (ranging from 12 to 20 m). These variable settings resulted in a design space size of 3200 solutions. Fig. 10.4 illustrates different examples of fabrics with a regular grid.

Experiment 2: Irregular grid approach

The irregular grid approach consisted of subdividing our study site into orthogonal blocks with different dimensions while keeping grid alignments. In this scenario, the number of input variables reached 43, increasing the problem's complexity and allowing us to compare the performance of different grid typologies. So, the input variables in this experiment were block length and width (ranging from 60 to 200 m in both cases) and street width (ranging from 12 to 20 m). These variable settings resulted in a design space size of 1.7e91 solutions. Fig. 10.5 illustrates different examples of fabrics within the irregular grid approach.

Experiment 3: Moving corners approach

The moving corners approach consisted of an experimental fabric generation approach aimed at verifying different proximity performance possibilities by displacing the corners of blocks in an irregular orthogonal grid, following a nonorthogonal logic. In this scenario, each corner in an input grid could be displaced −15 to 15 m along the X-axis and the

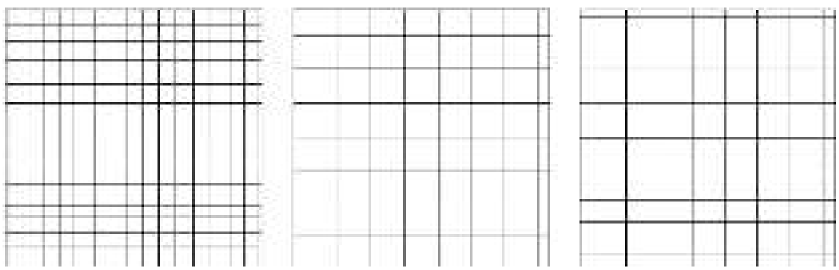


FIG. 10.5 Examples of irregular grid approach generated fabrics: block length and width vary while keeping grid alignments. *No permission required.*

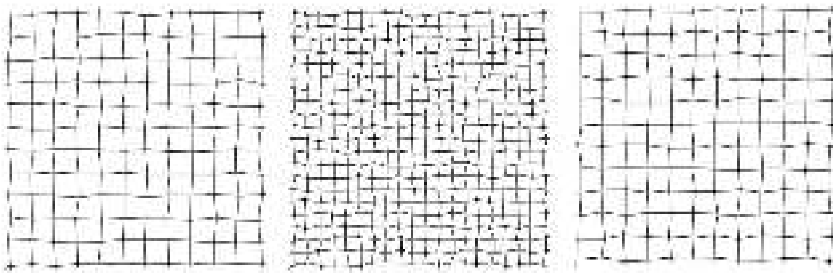


FIG. 10.6 Examples of moving corners approach generated fabrics: the intersections of the streets are moved in different arrangements. *No permission required.*

Y-axis. So, the input variables in this experiment were the number of blocks along the X-axis and the Y-axis (ranging from 10 to 20), the displacement of a corner along the X-axis, and along the Y-axis (ranging from −15 to 15 m on both cases, as mentioned above), and street width (ranging from 12 to 20 m). These variable settings resulted in a vast design space (*NaNeInfinity* solutions, according to Wallacei X). Fig. 10.6 illustrates different examples of fabrics within the irregular grid approach.

Experiment 4: Voronoi-shaped blocks approach

The Voronoi-shaped blocks approach consisted of a nature-inspired experimental fabric generation procedure that explores the Voronoi principle. This type of grid is obtained by scattering points randomly on a Euclidean plane. The plane is then divided up into cells or tessellating polygons around each point. A Voronoi cell is the region of the plane nearer to that respective point than any other. The input variables for this experiment were the number of scattered points (ranging from 100 to 400), the displacement of each of these points along the X-axis and along the Y-axis (ranging from −35 to 35 m in both cases), and street width (ranging from 12 to 20 m). These variable settings resulted in a vast design space (also *NaNeInfinity*, according to Wallacei X). Fig. 10.7 illustrates different examples of fabrics within the Voronoi-shaped blocks approach.

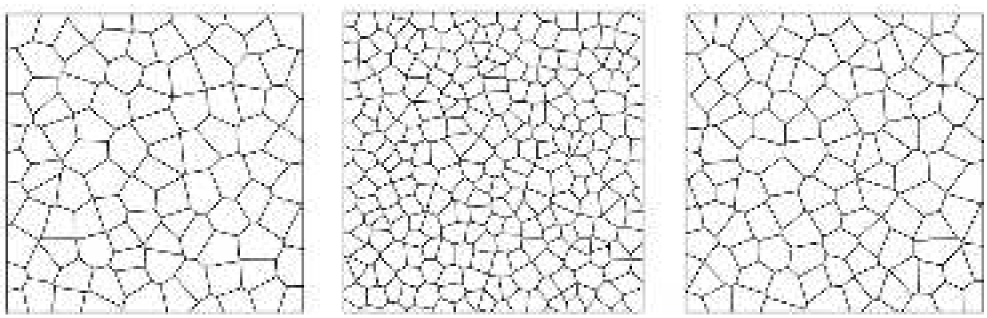


FIG. 10.7 Examples of Voronoi-shaped blocks approach generated fabrics: an experimental nature-inspired logic. *No permission required.*

Results

Experiment 1 results

After 19:56 h of calculation, experiment 1 led to 10,000 different solutions sorted into 428 clusters of designs with the same performance, depicted in Fig. 10.8. The obtained solutions provided Physical Proximity Indexes varying from 0.213 to 0.220, integration values varying from 0.473 to 0.953, and connectivity values varying from 5.400 to 5.786. In turn, the Experiment 1 Pareto frontier presented 50 nondominated solutions balancing the objective functions across 40 different performance outputs. The Pareto solutions provided Physical Proximity Indexes varying from 0.215 to 0.220, integration values varying from 0.473 to 0.953, and connectivity values varying from 5.400 to 5.786. The best solution for integration and the best solution for PPI presented slightly different layouts, seeking more spaced grids, while the best solution for connectivity maximized the number of lines and, consequently, intersections. Fig. 10.8 shows the solution space in Experiment 1, the Pareto frontier, and the layout of the best solutions according to each fitness function. Although we maximized all the fitness functions, our utopia point is at the origin of the design space because we minimized the negative fitness values, as Wallacei works in a classical optimization logic.

Experiment 2 results

Experiment 2 took 5:48 h of calculation, leading to 10,000 solutions sorted into 927 clusters of designs with the same performance, as shown in Fig. 10.9. The obtained solutions provided Physical Proximity Indexes varying from 0.220 to 0.258, integration values varying from 0.683 to 0.983, and connectivity values varying from 5.342 to 5.628. Experiment 2 Pareto frontier, in turn, presented 50 nondominated solutions balancing the objective functions across 30 different performance outputs. The Pareto solutions provided Physical Proximity Indexes varying from 0.236 to 0.258, integration values varying from 0.683 to 0.983, and connectivity values varying from 5.342 to 5.628. The best solution for integration consisted of a symmetrical layout with fewer streets. The best solution for PPI, in turn, "adapted" this solution by inserting some streets in the peripheral zone and increasing the connection to the boundary corners. In contrast, the best solution for connectivity resulted in a denser fabric, maximizing the number of lines and intersections. Fig. 10.9 illustrates the solution space in Experiment 2 and the Pareto frontier and the layout of the best solutions according to each fitness function.

Experiment 3 results

Experiment 3 calculations lasted 15:48 h, leading to 10,000 solutions sorted into 1642 clusters of designs with the same performance, as depicted in Fig. 10.10. This experiment yielded solutions with Physical Proximity Indexes varying from 0.238 to 0.270, integration values varying from 0.569 to 0.802, and connectivity values varying from 5.535 to 5.721. The Pareto frontier, in turn, presented 50 nondominated solutions balancing the objective functions across 20 different performance outputs. The Pareto solutions had Physical Proximity Indexes

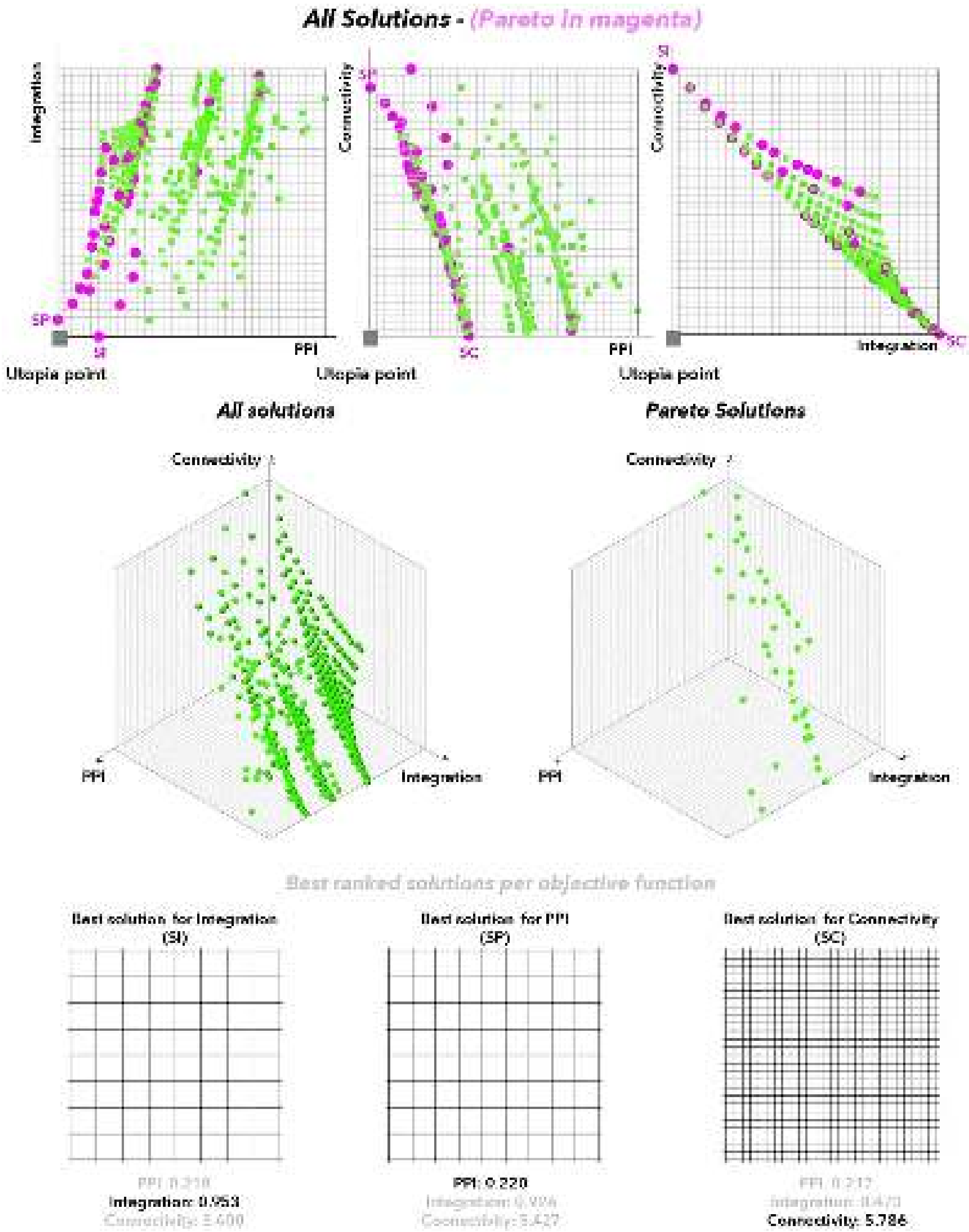


FIG. 10.8 Experiment 1 solution space, its Pareto frontier, and the layout of the best solutions according to each fitness function. *No permission required.*

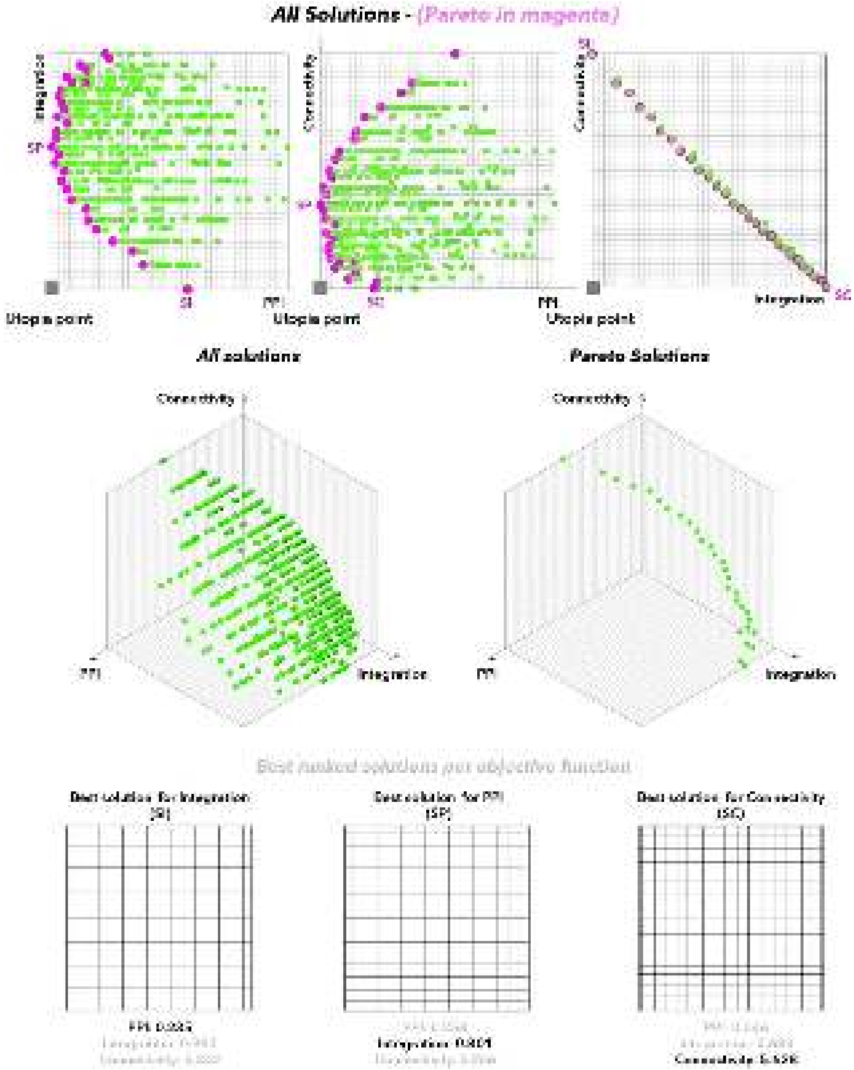


FIG. 10.9 Experiment 2 solution space, its Pareto frontier, and the layout of the best solutions according to each fitness function. *No permission required.*

varying from 0.262 to 0.270, integration values varying from 0.569 to 0.802, and connectivity values varying from 5.538 to 5.721. The best solutions for experiment 3 follow a pattern observed in experiment 1, with the best solution for integration and the best solution for PPI presenting slightly different layouts that seek more spaced grids and the best solution for connectivity maximizing the number of lines and intersections. Fig. 10.10 illustrates the solution space in Experiment 3 and the Pareto frontier and the layout of the best solutions for each fitness function.

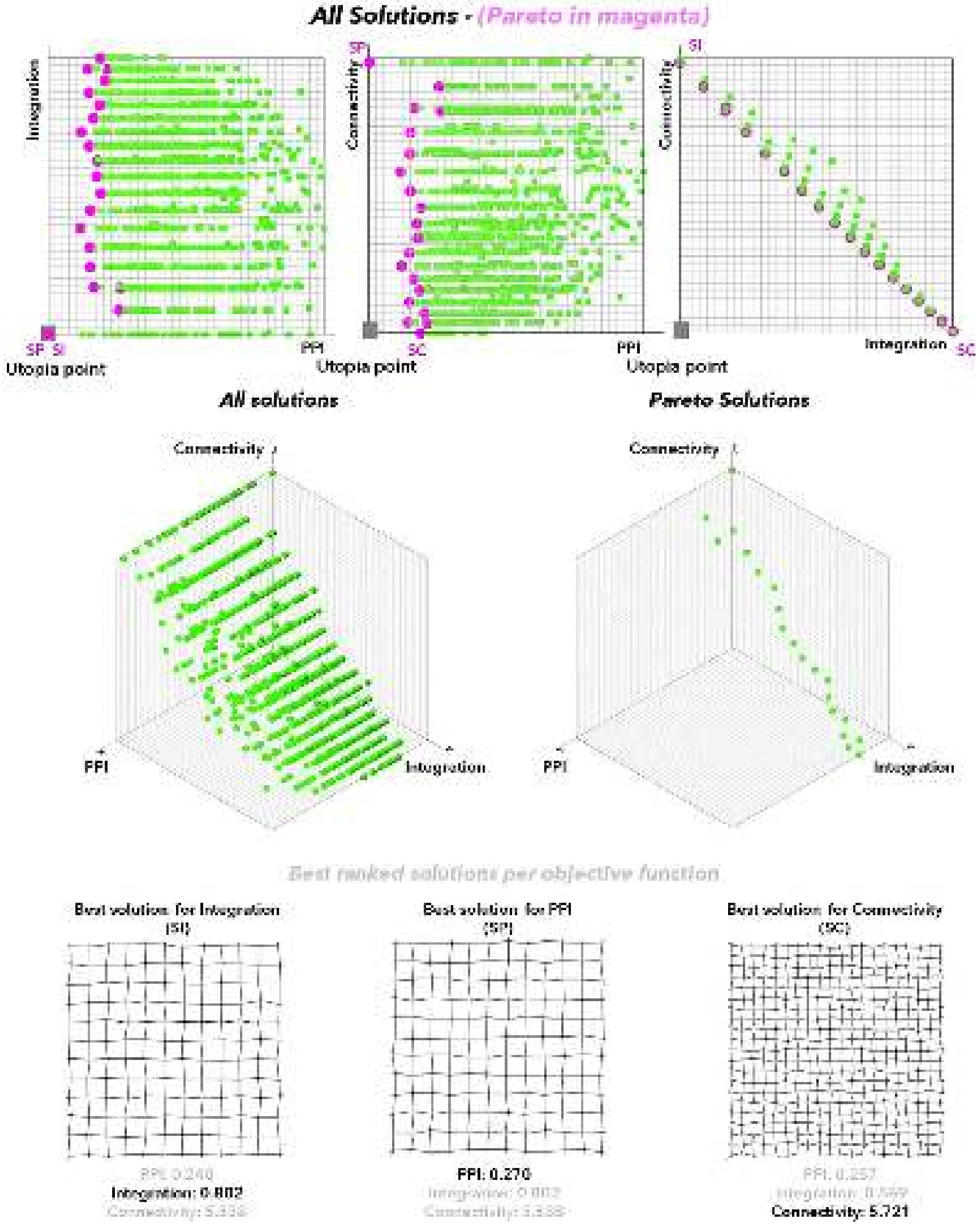


FIG. 10.10 Experiment 3 solution space, its Pareto frontier, and the layout of the best solutions according to each fitness function. *No permission required.*

Experiment 4 results

After 11:45 h of calculation, experiment 4 led to 10,000 solutions sorted into 1370 clusters of designs with the same performance, as depicted in Fig. 10.11. Experiment 4 solutions provided Physical Proximity Indexes varying from 0.266 to 0.285, integration values varying from 0.423 to 0.665, and connectivity values varying from 3.973 to 4.005. In turn, experiment 4 Pareto frontier presented 50 nondominated solutions balancing the objective functions across 46 different performance alternatives. This experiment's Pareto solutions provided Physical Proximity Indexes varying from 0.272 to 0.285, integration values varying from 0.473 to 0.665, and connectivity values varying from 3.973 to 4.005. Once again, the best solution for connectivity maximized the number of lines and intersections while the best solutions for PPI and integration looked more alike. Fig. 10.11 illustrates the solution space in Experiment 4 and the Pareto frontier and the layout of the best solutions according to each fitness function.

Overall comparison results per fitness function

The Physical Proximity performance of all Pareto solutions presents a clear upward trend that follows the complexity of the typologies, as can be seen in Fig. 10.12. Accordingly, the PPIs of all Experiment 4 solutions, which range from 0.272 to 0.285, are better than those of all Experiment 3 solutions (from 0.262 to 0.270), which, in turn, are better than those of all Experiment 2 solutions (from 0.236 to 0.258), and so on. Moreover, Experiment 2 solutions provided the broadest range of PPI values (from 0.236 to 0.258). In this sense, our results suggest that the regular grid is the least recommended typology for urban fabrics when considering Physical Proximity, while Voronoi-shaped fabrics are the most recommended.

Regarding integration, the irregular grid typology provided the best solutions (0.983), performing slightly better than the best regular grid solution (0.953), as shown in Fig. 10.11. However, Experiment 1 provided the broadest range of values (from 0.473, one of the worst overall, to 0.953), suggesting higher flexibility within this context. The moving corners and Voronoi-shaped solutions did not perform well considering this objective function (from 0.569 to 0.802 and 0.473 to 0.665, respectively). Therefore, our results suggest that orthogonal typologies (Experiments 1 and 2) tend to provide higher integration values.

Relationships between objectives are also notable. Integration and connectivity have a nearly linear trade-off across the case studies, with Experiment 2 producing an entirely linear set in these two dimensions. From viewing the best overall designs, these two objectives seem to largely depend on the size of the block cell, with increasing density leading to better connectivity. While the best results for PPI and integration tend to be similar, suggesting the two metrics could be condensed into one in some instances, their relationship across the design spaces changes. Some of the experiments show a clear edge curve in the biobjective plot between PPI and integration, pointing to exactly where the other objectives typically are when optimizing one, while others do not.

Finally, our results show that the regular grid typology provided the best connectivity solution (5.786) and the broadest range of values (from 5.400 to 5.786). Furthermore, it is important to highlight that Experiments 1, 2, and 3 provided solutions with similar performance (from 5.400 to 5.786, 5.342 to 5.628, and 5.538 to 5.721, respectively), while Experiment 4 solutions performed significantly worse considering this measure (from 3.973 to 4.005), as can also be seen in Fig. 10.12.

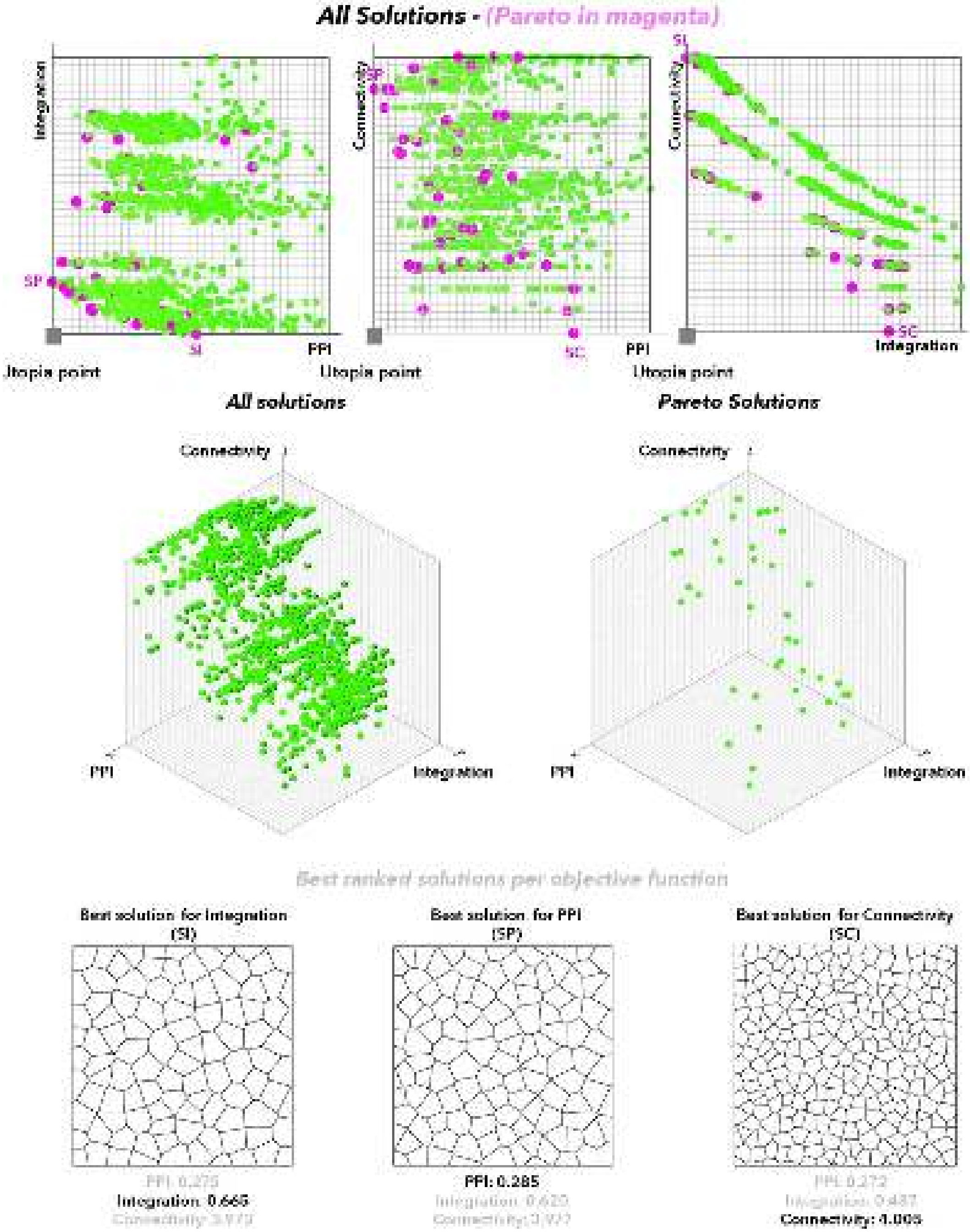


FIG. 10.11 Experiment 4 solution space, its Pareto frontier, and the layout of the best solutions according to each fitness function. *No permission required.*

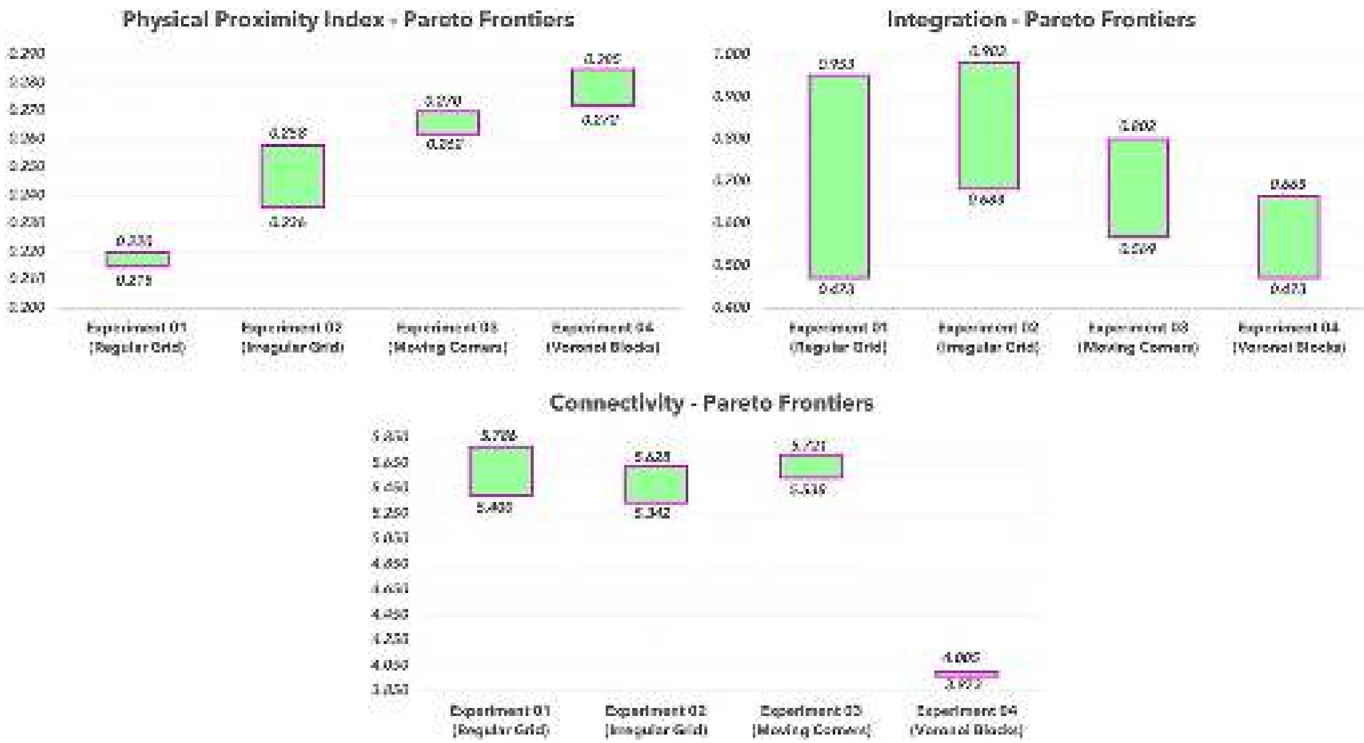


FIG. 10.12 Candlestick graphs comparing the performance of solutions according to the various fitness functions in all the experiments. *No permission required.*

Discussion

This work addresses the use of physical and topological proximity metrics in multiobjective optimization procedures, aiming at exploring and assessing the performance possibilities of different grid typologies (regular orthogonal grid, irregular orthogonal grid, irregular nonorthogonal grid, and Voronoi-shaped grid) while considering physical proximity and syntactic measures (integration and connectivity). Our goal is to identify some advantages and drawbacks of each one of the studied typologies. We assessed 40,000 grids using optimization, 10,000 from each typology while comparing each metric's three-dimensional (3D) Pareto fronts and best designs.

Our study points to several meaningful findings regarding different possibilities for urban fabric evaluation and design. First, our approach allowed us to compare the performance of the various typologies after filtering them through multiobjective optimization procedures, meaning that we evaluated Pareto-optimal grids within the addressed trade-off, rather than evaluating just single objective solutions. Second, in some situations, our approach resulted in clusters of optimal potential solutions with the same performance, providing great flexibility for decision-making. Third, our results suggest that orthogonal grid solutions tend to perform better than nonorthogonal ones when considering the topological metrics. In this sense, if topological measures prioritize orientation while physical proximity prioritizes how much one walks within a fabric, it is reasonable to conjecture that orthogonal grids are more appropriate for car-oriented cities, while nonorthogonal ones are more suitable for walkable areas. Finally, the Voronoi-shaped grids presented a significantly better performance considering physical proximity, but at the expense of substantially worse syntactic (both in terms of integration and connectivity) performances. In other words, people would be able to walk considerably less in Voronoi-shaped fabrics, but only if they avoided getting lost in those maze-like fabrics (like it happens in medieval European cities and Brazilian slums, for instance). On the other hand, despite being commonly adopted in cities worldwide, the regular orthogonal typology presented a considerably worse performance in terms of physical distance.

Despite achieving meaningful findings, this study reveals some limitations. More typologies such as organic, triangular, and radial grids should be addressed in order to achieve more comprehensive findings. The implementation of shape grammars in the generation of different typologies can be helpful in this sense. Still, other topological metrics should be explored as objective functions. For instance, the angular integration, which measures how close each segment is to all the others in terms of the sum of angular changes on each route, should be considered. Therefore, for the future work, there is a broad spectrum of possibilities for exploration. We intend to incorporate more objective functions, addressing other topological metrics; increase model complexity by considering topographic constraints; address other trade-offs related to proximity; and explore different shape grammars capable of generating more complex urban grids. Still, since there are metrics that seem to correlate with one another in a linear trade-off, we can study the possibilities of collapsing some objective functions to get more decipherable results.

In summary, this work aimed to contribute to urban fabric design by exploiting the potential of coupling both physical and topological metrics in multiobjective optimization procedures to tackle trade-offs in early stages of urban design. Since our study provided us with an overall view of the performance of urban fabrics with different typologies while exploring metrics of different natures, it can be considered as an initial step toward more rigorous design and evaluation of urban fabrics considering proximity-related issues.

Acknowledgments

This study was financed in part by the Stuckeman Center for Design Computing, the Department of Architecture, and the Stuckeman School of Architecture and Landscape Architecture, at The Pennsylvania State University, United States, and by the Brazilian Coordination of Superior Level Staff Improvement—Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES) Finance Code 001.

References

Brewster, M., et al., 2009. Walkscore.Com: a new methodology to explore associations between neighborhood resources, race, and health. In: 137st APHA Annual Meeting and Exposition 2009.
Brown, N.C., 2016. Multi-Objective Optimization for the Conceptual Design of Structures. Massachusetts Institute of Technology. Available at https://dspace.mit.edu/handle/1721.1/106367.
Brown, N.C., 2019. Early Building Design Using Multi-Objective Data Approaches. Massachusetts Intitute of Technology, Cambridge. Thesis. Available at https://dspace.mit.edu/handle/1721.1/123573.
Brown, N.C., Jusiega, V., Muller, C., 2020. Implementing data-driven parametric building design with a flexible toolbox. Autom. Constr. 118, 1–16. https://doi.org/10.1016/j.autcon.2020.103252.
Carr, L.J., Dunsiger, S.I., Marcus, B.H., 2011. Validation of walk score for estimating access to walkable amenities. Br. J. Sports Med. 45 (14), 1144–1148. https://doi.org/10.1136/bjsm.2009.069609.
Cichocka, J.M., et al., 2017. SILVEREYE—the implementation of particle swarm optimization algorithm in a design optimization tool. In: Çağdaş, G., et al. (Eds.), Communications in Computer and Information Science Book Series. Springer, pp. 151–169. Available at https://link.springer.com/chapter/10.1007/978-981-10-5197-5_9.
Coello, C.A., Romero, C.E., 2003. Evolutionary algorithms and multiple objective optimization. In: Ehrgott, M., Gandibleux, X. (Eds.), International Series in Operations Research & Management Science. Springer US, Boston, MA, pp. 277–331, https://doi.org/10.1007/0-306-48107-3_6.
Deb, K., et al., 2000. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: Schoenauer, M., et al. (Eds.), Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 849–858, https://doi.org/10.1007/3-540-45356-3_83.
Dogan, T., et al., 2020. Urbano: a tool to promote active mobility modeling and amenity analysis in urban design. Technol. Archit. Des. 4 (1), 92–105. https://doi.org/10.1080/24751448.2020.1705716.
ETH, 2018. PISA—A Platform and Programming Language Independent Interface for Search Algorithms. Available at: https://sop.tik.ee.ethz.ch/pisa/. Accessed: September 19, 2021.
Evins, R., et al., 2012. Multi-objective design optimisation: getting more for less. Proc. Inst. Civ. Eng. Civ. Eng. https://doi.org/10.1680/cien.11.00014.
Feng, C., Peponis, J., 2020. The definition of syntactic types: the generation, analysis, and sorting of universes of superblock designs. Environ. Plann. B Urban Anal. City Sci. 47 (6), 1031–1046. https://doi.org/10.1177/2399808318813576.
Feng, C., Peponis, J., 2021. Pathways to creating differentiated grids: types, benefits and costs. Environ. Plann. B Urban Anal. City Sci. https://doi.org/10.1177/23998083211013818.
Gehl, J., 2010. Cities for People. Island Press, Washington, DC. Washington DC: Island Press. Available at https://islandpress.org/books/cities-people.
Hillier, B., 2002. A theory of the city as object: or, how spatial laws mediate the social construction of urban space. Urban Des. Int. 7 (3–4), 153–179. Available at https://discovery.ucl.ac.uk/id/eprint/1029/.
Hillier, B., Hanson, J., 1984. The Social Logic of Space. Cambridge University Press, Cambridge, https://doi.org/10.1017/CBO9780511597237.
Hillier, B., et al., 1993. Natural movement: or, configuration and attraction in urban pedestrian movement. Environ. Plann. B. Plann. Des. 20 (1), 29–66. Available at https://discovery.ucl.ac.uk/id/eprint/1398/.
Kaplan, A., Haenlein, M., 2019. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004.

Koohsari, M.J., et al., 2016. Street network measures and adults' walking for transport: application of space syntax. Health Place 38, 89–95. https://doi.org/10.1016/j.healthplace.2015.12.009.

Lima, F., 2017. Urban Metrics: (Para)Metric System for Analysis and Optimization of Urban Configurations. Federal University of Rio de Janeiro, Rio de Janeiro, Brazil. PhD Thesis.

Lima, F., Paraízo, R.C., Kós, J.R., 2016a. In: Amoruso, G. (Ed.), Algorithms-Aided Sustainable Urban Design: Geometric and Parametric Tools for Transit-Oriented Development. IGI Global, Hershey, pp. 875–897.

Lima, F., Paraízo, R.C., Kós, J.R., 2016b. Algorithmic approach towards transit-oriented development neighborhoods: (Para)metric tools for evaluating and proposing rapid transit-based districts. Int. J. Archit. Comput. 14 (2), 131–146. https://doi.org/10.1177/1478077116638925.

Lima, F., et al., 2017. Urbanmetrics: an algorithmic-(Para)metric methodology for analysis and optimization of urban configurations. In: Geertman, S., et al. (Eds.), Lecture Notes in Geoinformation and Cartography. Springer International Publishing, Cham, https://doi.org/10.1007/978-3-319-57819-4_3.

Lima, F., Brown, N.C., Duarte, J.P., 2022. A grammar-based optimization approach for walkable urban fabrics considering pedestrian accessibility and infrastructure cost. Environ. Plann. B Urban Anal. City Sci. https://doi.org/10.1177/23998083211048496.

Makki, M., et al., 2019. Evolutionary algorithms for generating urban morphology: variations and multiple objectives. Int. J. Archit. Comput. 17 (1), 5–35. https://doi.org/10.1177/1478077118777236.

Makki, M., Weinstock, M., Showkatbajhsh, M., 2020. Wallacei. Available at: http://www.wallacei.com. Accessed: September 20, 2021.

Marler, R.T., Arora, J.S., 2004. Survey of multi-objective optimization methods for engineering. Struct. Multidiscip. Optim. 26, 369–395. https://doi.org/10.1007/s00158-003-0368-6.

McCarthy, J., et al., 2006. A proposal for the dartmouth summer research project on artificial intelligence, August 31, 1955. AI Mag. 27 (4), 12. Available at https://doi.org/10.1609/aimag.v27i4.1904. http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html.

Navarro-Mateu, D., Makki, M., Cocho-Bermejo, A., 2018. Urban-tissue optimization through evolutionary computation. Mathematics 6 (10), 89. https://doi.org/10.3390/math6100189.

Nourian, P., et al., 2015. Configurbanist: urban configuration analysis for walking and cycling via easiest paths. In: Towards Smarter Cities. Towards Smarter Cities, eCAADe 2015 33rd Annual Conference 16–18 Sept. 2015.

Penn, A., et al., 1998. Configurational modelling of urban movement networks. Environ. Plann. B. Plan. Des. 25 (1), 59–84. https://doi.org/10.1068/b250059.

Peponis, J., et al., 2007. Measuring the configuration of street networks. In: Proceedings of the Sixth International Space Syntax Symposium.

Peponis, J., Bafna, S., Zhang, Z., 2008. The connectivity of streets: reach and directional distance. Environ. Plann. B. Plann. Des. 35 (5), 881–901. https://doi.org/10.1068/b33088.

Peponis, J., et al., 2015. Syntax and parametric analysis of superblock patterns. J. Space Syntax 6 (1), 109–141. Art and Design Faculty Publications. Available at https://scholarworks.gsu.edu/art_design_facpub/.

Sevtsuk, A., Kalvo, R., Ekmekci, O., 2016. Pedestrian accessibility in grid layouts: the role of block, plot and street dimensions. Urban Morphol. 20, 89–106. Available at https://urbanism.uchicago.edu/content/pedestrian-accessibility-grid-layouts-role-block-plot-and-street-dimensions.

Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications, Structural Analysis in the Social Sciences. Cambridge University Press, Cambridge, UK, https://doi.org/10.1017/CBO9780511815478.

Wortmann, T., 2017. Opossum: introducing and evaluating a model-based optimization tool for grasshopper. In: Janssen, P., et al. (Eds.), Protocols, Flows and Glitches 22nd International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2017. The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hong Kong.

Wortmann, T., 2019. Genetic evolution vs. function approximation: benchmarking algorithms for Architectural design optimization. J. Comput. Des. Eng. 6 (3), 414–428. https://doi.org/10.1016/j.jcde.2018.09.001.

Zhao, P., et al., 2019. Analysis of urban drivable and walkable street networks of the ASEAN smart cities network. ISPRS Int. J. Geo Inf. 8 (10), 459. https://doi.org/10.3390/ijgi8100459.

PART 4

Case studies in urban design and planning

This page intentionally left blank

CHAPTER

11

Image analytics for urban planning: The case of the Barcelona Superblock

Aldo Sollazzo

IAAC, Barcelona, Spain; Noumena, Barcelona, Spain

The urgency for a new urbanism

Environmental pollution is set to redefine all ecosystems.

The geological era of the Anthropocene is the ultimate cause of a new shift in weather patterns affecting climate, biodiversity, geomorphology, and consequently our cities and built environments.

Rising levels of air contamination are dictating urgent actions by administrators and urban planners, facing the need to adapt urban organisms to this invisible enemy lingering over our parks, schools, offices, and houses, ultimately deteriorating the well-being of the entire population.

Air pollution has been associated with congenital anomalies in numerous studies, mostly linked to exposure to traffic-related gasses (Schembari et al., 2014).

In this regard, the Air Quality Index (AQI) categorizes the risks associated with air pollutants based on different scales. Warnings begin at 51–100, and levels at 201–300 indicate 'significant increase in respiratory effects.' Between 301 and 500, it is possible to detect 'serious aggravation of heart or lung disease, and premature mortality.'

In 2013, China reached a peak of the Air Quality Index of 993. That year, smog was responsible for 1.37 million deaths in the country (Liu et al., 2016).

To face this unprecedented threat, cities need to reshape their urban patterns, reprogram mobility, public spaces, and urban infrastructures toward safer, healthier, and ecological solutions.

The plan for the 'extension' of the city of Barcelona, proposed by Ildefonso Cerdà, was originally designed reframing built and natural environments into a hybrid urban pattern balancing lighting, ventilation, public spaces, greenery, and mobility.

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00020-2

Nonetheless, Barcelona is today ranked among the most polluted cities in Europe (Cyrys et al., 2012; Eeftens et al., 2012). This is partly attributable to its geography; high traffic density (Ajuntament de Barcelona, 2007), which is four times higher than that for London; and large proportion of diesel-powered vehicles, currently 50% (Reche et al., 2011).

To reverse this trend, in 2016, Barcelona introduced a new urban planning model, called the Superblock. It aims to reclaim public space for people, reduce motorized transportation, promote sustainable mobility and active lifestyles, provide urban greening, and mitigate effects of climate change (Mueller et al., 2020). This planning approach threatens the urban fabric as a programmable surface, regulating the access to cars and vehicles in public streets while enabling the extension of walkable areas and cycling paths.

Concurrent to the development of new urban strategies, novel data-driven instruments have been emerging, providing different approaches to inform spatial planning.

This chapter will highlight several techniques, triggered by computer vision and machine learning algorithms, to analyze image-based data, extracting meaningful metrics to inform spatial transformations and estimate CO_2 emissions in an urban environment.

Different methodologies for image analytics will be compared and evaluated to determine the most efficient algorithms for the correct analysis and interpretation of spatial dynamics.

From the applications of those instruments will be generated maps and visual representations of spatial occupancy, clustering and classifying the spatial associations among the different actors operating in the urban environment.

Consequently, pollution levels will be estimated upon detected objects, calculating the carbon footprint for each agent populating the scenes analyzed.

In conclusion, this approach can provide a deeper understanding of urban dynamics, adopting image-based information for clustering and classifying the spatial dynamics produced by multiple actors operating in the urban environment, and finally calculating their environmental footprint.

This methodology can enrich the emergent approaches of urban planning, such as the Superblock, with a novel set of metrics and criteria based on real-time spatial usage and carbon footprints to guide and orient future urban transformations, ultimately improving the implementation of more resilient, ecological, and sustainable urban models.

Toward spatial analytics

As technology improves and extends its capabilities, it becomes all the more relevant to establish decision-making protocols toward more resilient, participatory, responsive public spaces, in which urban configurations might be defined and redefined by a city's inhabitants (Ho et al., 2012).

With the growth of multimedia data generation and consumption, image-based data analytics plays an increasingly important role in big data systems. Those approaches become relevant to offer a clearer interpretation of spatial dynamics, beyond already established TPA datasets based on GPS and mobile data.

Everyday movements of millions of individuals through the city leave discernible digital traces, leveraging location awareness to a new, prominent role in urban experience.

Although Geographic Information Systems (GIS) dates from the late 1960s, it was not until the Clinton directive authorized wider availability of **GPS data** for civilian use, in May 2000, that a wave of experimentation with new devices was triggered (Fast et al., 2017).

Providing accessibility to GPS data triggered an infinite number of applications shaping a new hybrid environment, influenced by digital and physical traces affecting social, economic, and spatial behaviors.

The spread of positioning sensor systems triggered the shift toward a new definition of the urban city plan toward a living programmable surface, converting whoever carries a device into a live cursor potentially affecting the urban spatial identity. GPS data has been influencing traffic and mobility infrastructure management; it is used to improve the operational planning of transport operators (Laranjeiro et al., 2019), risk assessment, and public safety exploiting spatiotemporal dependency (Hoang et al., 2016).

Today, at the city scale, the emergence of novel technologies is providing a variety of datasets and solutions to monitor and evaluate urban phenomena, opening a new range of opportunities to determine metrics and transformation of urban spaces. In this context, **Big Data** becomes the reference domain representing a wide spectrum of observational or informal data produced through transactional, operational, planning, and social activities. In the urban environment, these datasets establish a new operational area called **Urban Informatics**, focused on the exploration and understanding of urban systems by leveraging novel sources of data.

The major potential of Urban Informatics research and applications is in four areas: (1) improved strategies for dynamic urban resource management, (2) theoretical insights and knowledge discovery of urban patterns and processes, (3) strategies for urban engagement and civic participation, and (4) innovations in urban management, and planning and policy analysis (Thakuriah et al., 2017).

These four areas depend on data sources that can be classified according to two main domains: **structured** and **unstructured data**. Structured data can be defined as all data inputs adhering to a predefined data model, organized within a specific format and length and therefore straightforward to analyze; on the contrary, unstructured data, referring to all data inputs not related to an existing structure, results in a content hard to segment, search, sort, and classify.

The vast majority of unstructured data refers to all text, printable files, digital visual media, such as images and videos, which, by their nature, are hard to label and organize according to their content. As claimed by existing studies, those datasets are estimated to represent more than 80% of total data produced nowadays, having reached around 40 zettabyte in 2020 (Eberendu, 2016).

As stated already, unstructured data cannot be sorted, searched, visualized, or analyzed in the same way as structured data; therefore new tools and processes are required to extract intelligence, share information, and deliver value (Hänig et al., 2010).

Conventional data scientists will have to acquire new skills and knowledge to define protocols and methodologies for the interpretation of unstructured datasets.

With the growth of **multimedia data** generation and consumption, image-based data analytics plays an increasingly important role in big data analytics systems. For image analytics, machine learning and computer vision algorithms provide a foundation for a variety of image-based applications (Chang et al., 2015).

In recent years, **image analytics** emerged as a disruptive technology to sense, capture, and describe complex **spatial dynamics**.

In fact, today's most popular methods for spatial dynamics' representation relies on a few and generic data sources. Data stored by mobile devices represent a limiting source when it is about providing deeper insight into spatial dynamics. Those datasets present positioning inaccuracies due to incorrect GPS signals, and can not provide useful insights regarding transportation means or most articulated individual behaviors.

Image analytics sensing technologies can introduce new workflows informing design solutions through spatial-sensing data. Information-rich descriptions of behavior can support the development of **design and visualization tools,** enabling the development of architecture with consideration for the interactions between occupants and space, based on factual observations of existing and similar interactions (Jørgensen et al., 2020).

In the following section, this chapter will describe emerging solutions generating datasets from video frames, by means of computer vision and machine learning, introducing convolutional neural networks to determine and classify video and image contents, providing useful insights into spatial dynamics.

Deep learning and spatial analytics

The increasing quantity of publicly available labeled data, and the appearance of GPU computing, boosted deep learning algorithms, improving the performance and efficiency of neural network applications.

Substantial breakthroughs in deep learning architecture date back to 2006, when Hilton et al. introduced unsupervised training logic. These improvements paved the way for many computer vision applications implemented for object detection, image recognition, motion tracking, pose estimation, and semantic segmentation among other algorithms. Guiding the training of intermediate levels of representation using unsupervised learning, performed locally at each level, was the main principle behind a series of developments that brought about the past decade's surge in deep architectures and deep learning algorithms (Voulodimos et al., 2018).

With regard to spatial analytics, deep learning algorithms are finding a widespread application, adopting image data for behavioral analysis of crowded scenes such as Crowd Management, implemented for management strategies, avoiding crowd-related disasters, and ensure public safety; Public Space Design, providing indicators and metrics to inform spatial solutions; Virtual Environments, to validate and improve the performance of digital representations and simulations of digital crowds; Visual Surveillance, for automatic detection of anomalies and alarms; all culminating into Intelligent Environments: to reorganize flows and crowd distribution in given environments (Silveira Jacques Junior et al., 2010).

In the Superblock framework, analyzing mobility and patterns of spatial occupancy becomes a crucial parameter to calibrate instruments necessary for the activation of areas with restricted accessibilities for cars and heavy vehicles.

There is a need to develop a model of mobility and a more sustainable public space, in order to guarantee a more accessible, comfortable, safe, and multifunctional public space where people can be citizens and exercise in the public space the rights to interchange, culture, leisure, expression, and demonstration, besides the right to move (Rueda, 2018).

Through these technologies it is possible to introduce a responsive approach to adapt, reconfigure, and extend public spaces, regulating mobility based on data-driven criteria of intervention.

Novel methods for image analytics

Operational setup

Image analytics allows rendering spatial dynamics, by detecting locations and movements of different objects in space.

Existing methods based on image analytics can be distinguished according to two main categories: computer vision and machine learning approaches. Several algorithms have been deployed in computer vision-based processes, such as optical flow, background subtraction, edge detection, etc. (Kam Ho et al., 2012). While these approaches are able to detect motions of different objects, they lack individual discrimination as well as robustness in different lighting conditions, such as weather changes.

Machine learning methods can compensate for these issues, improving the accuracy of detections as well as more robustness in different light conditions. Some of the existing machine learning methods in image analytics include image classification, image segmentation, and object detection.

This section will focus on a comparative evaluation of recent algorithms for object detection to determine and calibrate the most accurate available solution to describe spatial dynamics, describing mobility and pedestrian's behavior in a public space.

The experiment will be run using video frames recorded from street intersections in the city of Barcelona. This context can serve as a unique proving ground to determine spatial dynamics evaluating detection algorithm performances, measure time capabilities, class identifications, calibrate image data sources and, finally, output spatial resolution for mapping transposition (Fig. 11.1).

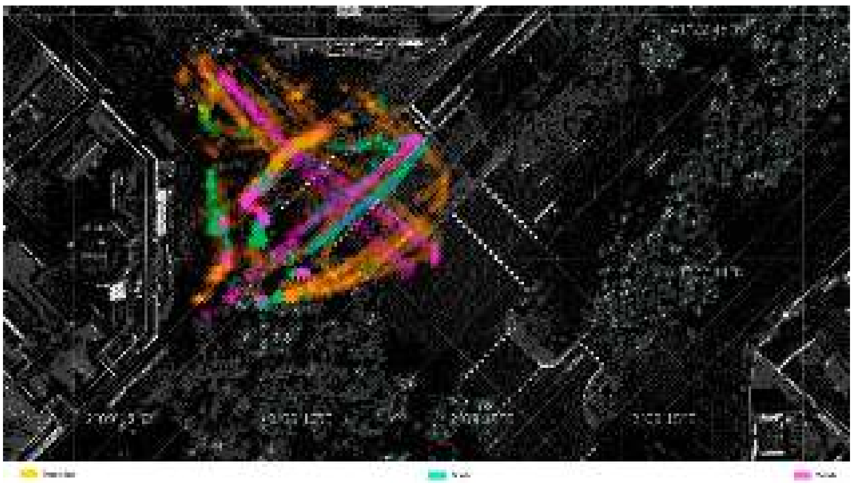


FIG. 11.1 Mapping pedestrian occupation in Piazza Campo de Fiori in Rome. *Source: Noumena.*

Object detection algorithms

Deep learning technology has been widely used in object detection.

Although deep learning technology greatly improves the accuracy of object detection, we also have the challenge of a high computational time (Lu et al., 2019).

These kinds of algorithms can be categorized according to two main characteristics.

One type refers to single-stage detectors, such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), which threatens object detection as a simple regression problem by taking an input image and predicting the class probabilities and bounding-box coordinates.

A second category refers to two-stage detectors, such as Faster R-CNN or Mask R-CNN, that use an RPN (Region Proposal Network) to generate regions of interests in the first stage and send the region proposals down the pipeline for object classification and bounding-box regression.

Two-stage detectors provide regions of the segmented object compared to bounding boxes from single-stage detectors; however, these algorithms also require more computation time compared to single-stage detectors.

In this chapter, we will focus on single-stage detectors since we are prioritizing real-time capability to ensure responsive spatial solutions.

Main algorithms to focus our comparative analysis will be the following:

- YOLOv4 (You Only Look Once)

  A clever convolutional neural network (CNN) for object detection in real-time. The algorithm applies a single neural network to the full image (Bochkovskiy et al., 2020).
- MobileNet v2—SSD (Single Shot MultiBox Detector)

  Single Shot MultiBox Detector (SSD), set to recognize objects in a scene starting with a set of default prediction boxes. It uses several feature maps of different scales (i.e., several grids of different sizes like 4×4, 8×8, etc.) and a fixed set of default boxes of different aspect ratios per cell in each of those grids/feature maps. For each default box, the model computes the "offsets" along with the class probabilities. (Hoang et al., 2016; Howard et al., 2017).
- FairMOT (MOT17)

  On the Fairness of Detection and ReIdentification in Multiple Object Tracking.

  FairMOT is a one-shot multiobject tracker (MOT). It combines and performs Object Detection and Tracking tasks.

  Tracking is the task of taking an initial set of object detections, creating a unique ID for each of the initial detections, and then tracking each of the objects as they move around frames in a video, maintaining the ID assignment (Zhang et al., 2021).

Comparison: Intersection over union

To estimate which algorithm performs better, a comparative method, known as Intersection Over Union (IoU), has been adopted to evaluate detection results from different algorithms. IoU is also known as the Jaccard Index, a statistic used for gauging the similarity and diversity of sample sets that evaluates the overlap between two bounding boxes. It requires a ground truth bounding box and a predicted bounding box. By applying the IoU, we can tell if a detection is valid or not (Padilla et al., 2021).

Different single-stage detector algorithms such as YOLO, MobileNet SSD, and FairMot are compared in terms of accuracy and speed based on our dataset. Both YOLO and MobileNet SSD used in this comparison are pretrained on the MS COCO dataset; thus, they can detect up to 80 different classes, whereas the pretrained FairMOT model used here can only detect pedestrians (Fig. 11.2).

To evaluate the accuracy of each model, the Average Precision (AP) is calculated for each detection class. The AP is a score between 0 and 1 (that can also be given in %), which combines two other scores: the precision score and the recall score. The precision score (valid detections/all detections) evaluates the ability of the model to detect only relevant objects, while the recall score (valid detections/all ground truths) evaluates the ability of the model to detect all relevant objects. Valid detections are defined as detections having an IoU with a ground truth object higher than the IoU threshold (here set to 0.3).

MobileNet SSD's input resolution is fixed at 300×300p. For FairMOT the original resolution of our dataset frames is used, i.e., 640×320p. In the case of YOLO, the input resolution of the network can be configured; so, both 640p and 320p input resolutions are used for better comparison with the other models (Fig. 11.3).

The evaluation results show that in most cases, if the resolution increases the Average Precision is improved. Comparing the three models, FairMOT has the best Average Precision (AP) with a 0.39 AP score. YOLO-640 also has a good result, having an AP of 0.35 (Fig. 11.4).

Another aspect of comparison is the Frame Per Second (FPS) rate, based on the average time needed by a model to perform all the detections on a single frame. This rate depends on the hardware used. MobileNet shows to be the fastest model having a rate of 76 FPS. FairMOT also has a better result than YOLOv4-640, with 18 FPS against 8 FPS for YOLOv4-640 (Fig. 11.5).

As a conclusion, the experiments described in this chapter point toward FairMOT algorithms as more accurate instruments to determine spatial dynamics, producing better levels of detection and tracking accuracy, outperforming YOLO and Mobilenet SSD models.

Fairmot's limitation lies on a pretrained architecture focused purely on pedestrian detection. Nonetheless, custom training is made possible and properly documented in the project repository, in which are described four steps pointing to the generation of JavaScript Object Notation (Json) files containing labels for custom training.

YOLO is a good option relying on a wider range of pretrained models and having a relevant capacity of detection accuracy.

In future iterations, custom training will be tested for FairMot models and evaluated on classes which were not compared in the calculations described in this chapter.

Carbon footprint calculation

According to studies performed by ISGlobal CREAL over an area of 56 municipalities, including Barcelona, air pollution has been appointed responsible for 3500 premature deaths per year, 1800 hospitalizations for cardiovascular reasons, 5100 cases of chronic bronchitis

FIG. 11.2 Comparison of different detection methods: (A) The scene that the detection was performed on. (B) Ground Truth, manually labeled bounding boxes. (C) Ground Truth, manually labeled bounding boxes for different categories of objects. (D) Detection result from YOLOv4-640 with an accuracy of 66%. (E) Detection result from YOLOv4-320 with an accuracy of 56%. (F) Detection result from FairMOT algorithm with an accuracy of 72%. (G) Detection result from MobileNet SSD with an accuracy of 68%. *Source: Noumena.*

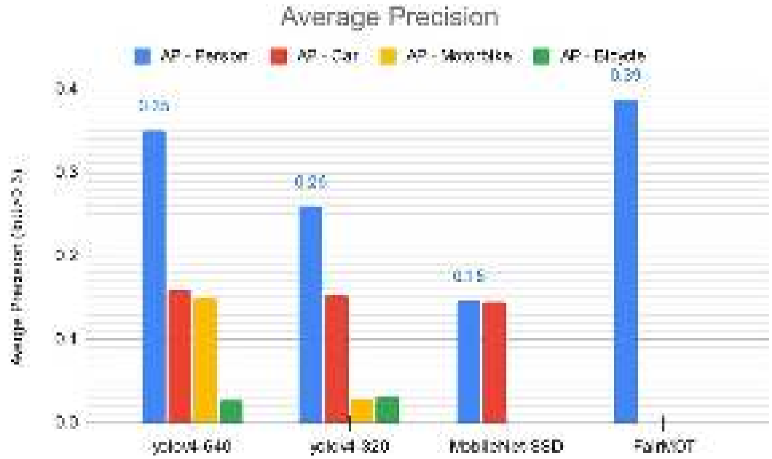


FIG. 11.3 Comparison of (AP) Average Precision from different detection algorithms. *Source: Noumena.*

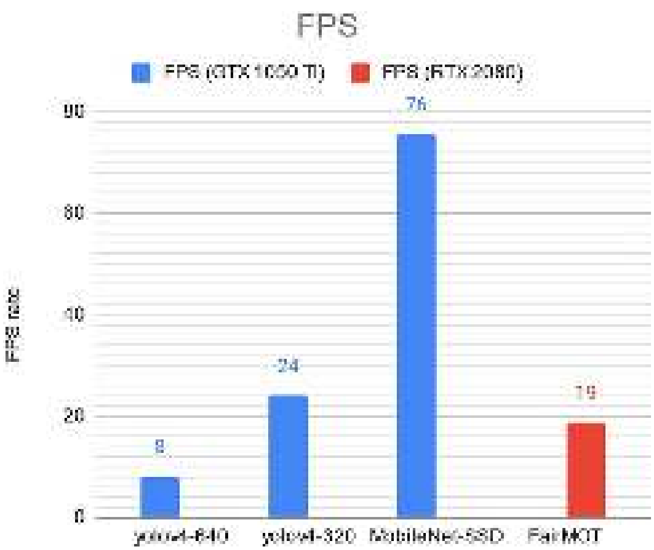


FIG. 11.4 Comparison of (FPS) Frames Per Second from different detection algorithms. *Source: Noumena.*

in adults, 31,100 cases of children bronchitis, and 54,000 asthma attacks among children and adults (Künzli and Pérez, 2007).

The impacts of air pollution on health are today the main problem to solve out of all the problems caused by the current model of mobility.

Having developed a robust method for object detection, our system introduces a computational method to define and estimate carbon dioxide emissions provoked by the different actors populating the urban scene.

Multiple classes have been detected for the most accurate calculation of CO_2, according to which the following estimations are made (Annamalai et al., 2018) emissions:

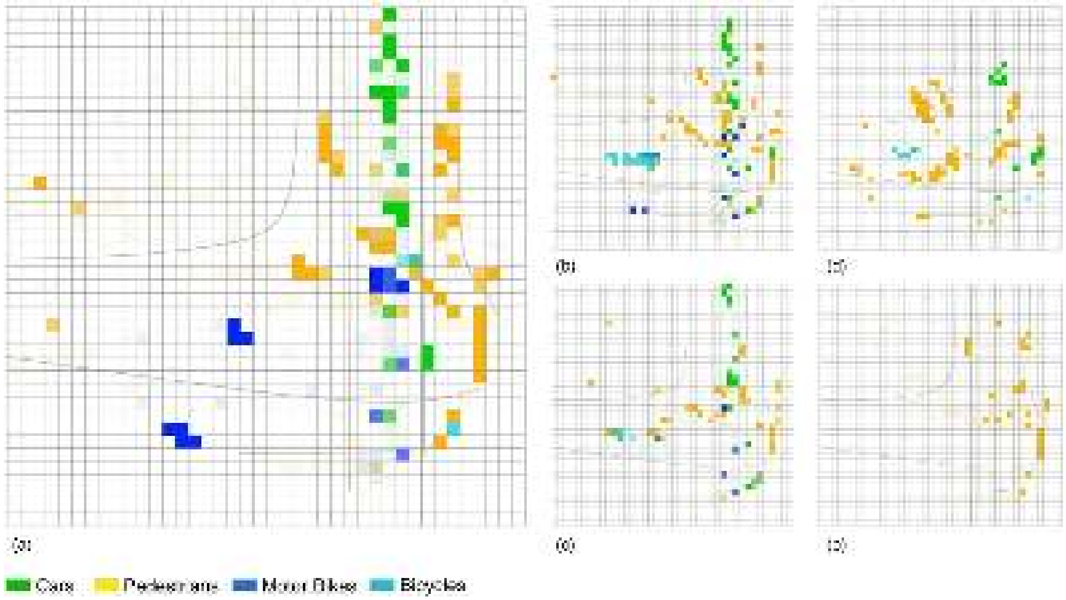


FIG. 11.5 Results of heat maps created from different detection algorithms. (A) Ground Truth: manually labeled detections, (B) YOLOv4-640, (C) YOLOv4-320, (D) MobileNet SSD, (E) FairMOT algorithm. *Source: Noumena.*

Human walking

For the calculation of CO_2 emissions for human walking,

Standard speed of 5km/h.

Metabolic rate is 70kg and 80W at rest.

It is shown that the respiratory quotient (RQ) is defined as the ratio of moles of CO_2 exhausted per mole of O_2 consumed in the organism, RQ = moles of CO_2/moles of O_2 consumed in the oxidation process. It consumes a total of 6mol of CO_2 and 6mol of O_2. So the result is RQ = 1.

As mentioned above, knowing the metabolic rate and the energy released per minute (Y), which is 0.0048MJ, the following formula is applied:

$$\text{CO2 in g} = G = 100 \times RQ \times Y = 100 \times 1 \times 0.48 = 0.48\,\text{g}$$

With a standard pace of 5km/h, the energy consumed EC is 280W, applying the following formula we obtain the CO_2 emission in g/s

$$Human\ walking = \left(\frac{EC}{ER}\right) \times G \times s^{-1} = \left(\frac{280}{80}\right) \times 0.48 \times 60^{-1} = 0.028\,\text{g/s}$$

Human cycling

With the same standard values of the metabolic rate, and knowing that the energy consumed when cycling at a speed of 13–18km/h is 400W, applying the same formula, we calculate the value of emission per second by a bicycle.

$$Human\ cycling = \left(\frac{EC}{ER}\right) \times G \times s^{-1} = \left(\frac{400}{80}\right) \times 0.48 \times 60^{-1} = 0.04\,\text{g/s}$$

Car

A car has an approximate average spending of 5 L per 100 km with a total of 2640 g of CO_2/L. That last parameter is the same for the following vehicles.

So the following formula remains:

$$\frac{L \times X \times V}{K \times S}$$

where L = liters; X = g/L; V = speed in km/h; k = kilometers; s = seconds.

The final result is that it consumes a total of 1833 g/s per car.

Motorcycle

In the case of motorcycles, the above formula is applied with a consumption of 50.4 g CO_2/km.

Therefore, the total consumption for each is approximately 0.7 g/s.

Bus/truck

With the same formula that has been applied in the last two classes, it is used also with the bus/truck, although with an average consumption of 218 g of CO_2 per kilometer, with a final result of 3.023 g/s per bus/truck.

Conclusions

Urban models evolve as the Superblock is defining a novel approach to city planning, driven by ecological methods targeting healthier and safer habitats.

In such a context of increasing complexity, it becomes necessary to adopt novel instruments for decision making.

This chapter serves as an operational ground, promoting machine learning techniques to evaluate the implementation of urban models such as the Superblock, establishing data-driven criteria of activation, based on actual observations performed in public spaces.

In fact, AI-driven techniques can provide a deeper understanding of spatial dynamics, offering extensive insights related to spatial occupancy and carbon emissions. Nonetheless, in a panorama of rapidly evolving technologies, it becomes increasingly necessary to adopt comparable approaches to estimate more performative solutions, introducing methods as the one described.

Furthermore, as technology paves the way for novel applications, it becomes necessary to calibrate such instruments within a legal and administrative framework, to guarantee privacy, ethical coherency, and citizen participation.

As a result, it becomes crucial to evaluate opportunities and implications derived from the application of these instruments, establishing a critical approach to measure novel methodologies, and operational strategies.

Even more, parallel to technological improvement, it will be necessary to ensure the coherency of its applications compared to human norms and values. Evaluating and calibrating these models represents today a substantial portion of the research around machine learning. The alignment problem represents the beginning of a new challenge to ensure that machine learning models will capture our norms and values.

The looming threat of a climate crisis elevates our decisions, improving awareness regarding dependencies and implications of the actions we perform to manipulate our habitats.

There is a new challenge to reshape cities toward responsive and resilient solutions.

Acknowledgment

The following are acknowledged: The author gratefully acknowledges the contributions of Soroush Garivani (IAAC, Noumena), Oriol Arroyo (Noumena), Cosme Pommier (Noumena), Maria Espina (Noumena), Salvador Calgua (Noumena).

References

Ajuntament de Barcelona, 2007. Barcelona, a City Committed to the Environment. Barcelona City Council, Barcelona.

Annamalai, K., Thanapal, S.S., Ranjan, D., 2018. Ranking renewable and fossil fuels on global warming potential using respiratory quotient concept. J. Combust. 2018. https://doi.org/10.1155/2018/1270708. United States: Hindawi Limited.

Bochkovskiy, A., Wang, C.-Y., Liao, H.-Y.M., 2020. Yolov4: Optimal Speed and Accuracy of Object Detection. ArXiv:2004.10934 [Cs, Eess]. http://arxiv.org/abs/2004.10934.

Chang, H.-Y., et al., 2015. Feature detection for image analytics via FPGA acceleration. IBM J. Res. Dev. 59 (2–3), 8:1–8:10. https://doi.org/10.1147/JRD.2015.2398631. IBM.

Cyrys, J., Eeftens, M., Heinrich, J., Ampe, C., Armengaud, A., Beelen, R., Bellander, T., Beregszaszi, T., Birk, M., Cesaroni, G., Cirach, M., de Hoogh, K., De Nazelle, A., de Vocht, F., Declercq, C., Dėdelė, A., Dimakopoulou, K., Eriksen, K., Galassi, C., et al., 2012. Variation of NO2 and NOx concentrations between and within 36 European study areas: results from the ESCAPE study. Atmos. Environ. 62, 374–390. https://doi.org/10.1016/j.atmosenv.2012.07.080.

Eberendu, A.C., 2016. Unstructured data: an overview of the data of big data. Int. J. Comput. Trends Technol., 46–50. https://doi.org/10.14445/22312803/IJCTT-V38P109. Seventh Sense Research Group Journals.

Eeftens, M., Tsai, M.-Y., Ampe, C., Anwander, B., Beelen, R., Bellander, T., Cesaroni, G., Cirach, M., Cyrys, J., de Hoogh, K., De Nazelle, A., de Vocht, F., Declercq, C., Dėdelė, A., Eriksen, K., Galassi, C., Gražulevičienė, R., Grivas, G., Heinrich, J., et al., 2012. Spatial variation of PM2.5, PM10, PM2.5 absorbance and PMcoarse concentrations between and within 20 European study areas and the relationship with NO2—results of the ESCAPE project. Atmos. Environ. 62, 303–317. https://doi.org/10.1016/j.atmosenv.2012.08.038.

Fast, K., Jansson, A., Lindell, J., Bengtsson, L.R., Tesfahuney, M., 2017. Geomedia: Networked Cities and the Future of Public Space. Wiley/Routledge. https://www.wiley.com/en-es/Geomedia%3A+Networked+Cities+and+the+Future+of+Public+Space-p-9780745660769.

Hänig, C., Schierle, M., Trabold, D., 2010. Comparison of Structured vs. Unstructured Data for Industrial Quality Analysis. Undefined. https://www.semanticscholar.org/paper/Comparison-of-Structured-vs.-Unstructured-Data-for-H%C3%A4nig-Schierle/31e03c431e93fd246e1871ba932cbd761eb4770c.

Ho, T.K., Matthews, K., O'Gorman, L., Steck, H., 2012. Public space behavior modeling with video and sensor analytics. Bell Labs Techn. J. 16 (4), 203–217. https://doi.org/10.1002/bltj.20542.

Hoang, M.X., Zheng, Y., Singh, A.K., 2016. FCCF: forecasting citywide crowd flows based on big data. In: GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems. Association for Computing Machinery, United States, https://doi.org/10.1145/2996913.2996934.

Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., Adam, H., 2017. Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications. ArXiv:1704.04861 [Cs]. http://arxiv.org/abs/1704.04861.

Jørgensen, J., Tamke, M., Poulsgaard, K., 2020. Occupancy-Informed: Introducing a Method or Flexible Behavioural Mapping in Architecture using Machine Vision.

Kam Ho, T., Matthews, K., O'Gorman, L., Steck, H., 2012. Public space behavior modeling with video and sensor analytics. Bell Labs Techn. J. 16 (4), 203–217. https://doi.org/10.1002/bltj.20542.

Künzli, N., Pérez, L., 2007. The Public Health Benefits of Reducing Air Pollution in the Barcelona Metropolitan Area. Undefined. https://www.semanticscholar.org/paper/The-public-health-benefits-of-reducing-air-in-the-K%C3%BCnzli-P%C3%A9rez/58f8e45158eca9b2634483244b1da24a96fb939e.

Laranjeiro, P.F., et al., 2019. Using GPS data to explore speed patterns and temporal fluctuations in urban logistics: the case of São Paulo, Brazil. J. Transp. Geogr. 76, 114–129. https://doi.org/10.1016/j.jtrangeo.2019.03.003. Brazil: Elsevier Ltd.

Liu, J., et al., 2016. Estimating adult mortality attributable to PM2.5 exposure in China with assimilated PM2.5 concentrations based on a ground monitoring network. Sci. Total Environ. 568, 1253–1262. https://doi.org/10.1016/j.scitotenv.2016.05.165. China: Elsevier B.V.

Lu, S., et al., 2019. A real-time object detection algorithm for video. Comput. Electr. Eng. 77, 398–408. https://doi.org/10.1016/j.compeleceng.2019.05.009. China: Elsevier Ltd.

Mueller, N., et al., 2020. Changing the urban design of cities for health: the superblock model. Environ. Int. 134, 105132. https://doi.org/10.1016/j.envint.2019.105132. Elsevier BV.

Padilla, R., et al., 2021. A comparative analysis of object detection metrics with a companion open-source toolkit. Electronics (Switzerland) 10 (3), 1–28. https://doi.org/10.3390/electronics10030279. Brazil: MDPI AG.

Reche, C., Querol, X., Alastuey, A., Viana, M., Pey, J., Moreno, T., Rodriguez, S., González Ramos, Y., Fernandez-Camacho, R., Verdona, A.M., de la Rosa, J.D., Dallósto, M., Prevot, A., Hueglin, C., Harrison, R., Quincey, P., 2011. New considerations for PM, black carbon and particle number concentration for air quality monitoring across different european cities. Atmos. Chem. Phys. 11, 6207–6227. https://doi.org/10.5194/acp-11-6207-2011.

Rueda, S., 2018. Superblocks for the design of new cities and renovation of existing ones: Barcelona's case. In: Integrating Human Health into Urban and Transport Planning: A Framework. Springer International Publishing, Spain, pp. 135–153, https://doi.org/10.1007/978-3-319-74983-9_8.

Schembari, A., et al., 2014. Traffic-related air pollution and congenital anomalies in Barcelona. Environ. Health Perspect. 122 (3), 317–323. https://doi.org/10.1289/ehp.1306802. Spain: Public Health Services, US Dept of Health and Human Services.

Silveira Jacques Junior, J., Musse, S., Jung, C., 2010. Crowd analysis using computer vision techniques. IEEE Signal Process. Mag., 5562657. https://doi.org/10.1109/MSP.2010.937394.

Thakuriah, P., Tilahun, N.Y., Zellner, M., 2017. Big data and urban informatics: innovations and challenges to urban planning and knowledge discovery. In: Springer Geography. Springer, United Kingdom, pp. 11–45, https://doi.org/10.1007/978-3-319-40902-3_2.

Voulodimos, A., et al., 2018. Deep learning for computer vision: a brief review. Comput. Intell. Neurosci. 2018. https://doi.org/10.1155/2018/7068349. Greece: Hindawi Limited.

Zhang, Y., et al., 2021. FairMOT: on the fairness of detection and re-identification in multiple object tracking. Int. J. Comput. Vis. https://doi.org/10.1007/s11263-021-01513-4. Springer Science and Business Media LLC.

This page intentionally left blank

CHAPTER

12

Complexity science-based spatial performance analyses of UNStudio/DP Architects' SUTD Campus and WOHA's Kampung Admiralty

Anjanaa Devi Sinthalapadi Srikanth[a], *Benny Chin Wei Chien*[a], *Roland Bouffanais*[b], *and Thomas Schroepfer*[a]

[a]**Singapore University of Technology and Design, Singapore, Singapore** [b]**University of Ottawa, Ottawa, ON, Canada**

Introduction

Singapore is a city-state in maritime Southeast Asia. It is located one degree of latitude north of the Equator off the southern tip of the Malay Peninsula and covers an area of about 728 km^2. It currently has a population of about 5.7 million with a population density of about 7810 per km^2. Singapore's high population density leads to its urban development to become more spatially efficient and convenient to improve the quality of life of the residents. This creates a demand for using advanced technology to improve urban planning and design.

In Singapore, the approach to the use of AI in urban planning and design is fivefold: transport, home and environment, business productivity, health and enabled aging, and public-sector services (Kong and Woods, 2018). In the city-state's urban planning, particularly in the transportation domain, the use of AI is currently explored in areas such as the study of mobility patterns, traffic flows, devising active learning and sensing algorithms, developing decision models for real-time data, and enhanced automated systems for safety (Varakantham et al., 2017). The development of Virtual Singapore, a semantic 3D-model that virtually replicates Singapore and inputs real-time data including on demographics, climate, and traffic, signals the country's vision for an AI-enabled future (Liceras, 2019).

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00019-6

Singapore's land scarcity and increasing urban density require innovative approaches to the further intensification of land use, which has resulted in urban planners and designers experimenting with increasingly complex and often vertically integrated building types. These often combine residential, civic, and commercial programs with public and common spaces on elevated levels such as sky bridges, parks, terraces, and roof gardens, producing "vertical cities" (Schröpfer, 2020).

Analyses of two vertically integrated spatial networks

The following examples are part of a larger ongoing Complex Systems Studies project funded by the Singapore Government under its Urban and Complexity Science for Urban Solutions Research Program. Of the two case studies, we present, in this chapter, Kampung Admiralty (KA) and the Singapore University of Technology and Design (SUTD) Campus, the former is conducted in collaboration with the Urban Redevelopment Authority Digital Planning Laboratory, the Ministry of National Development, the Ministry of National Development Center for Liveable Cities, and the Housing & Development Board Singapore. The latter is part of the cities: Urban Science and Design for Density research thrust at SUTD. The basic statistics of the two case studies are shown in Table 12.1.

Located in the northern part of Singapore and adjacent to the Mass Rapid Transit (MRT) hub Admiralty Station, KA, designed by Singapore-based architecture firm WOHA, is Singapore's first integrated public development that brings together a mix of public facilities, shops, open and green spaces, and residences in a vertical arrangement . Conceptualized as a "vertical kampung" ("kampung" means "village" in Malay) and completed in 2017, it is a building prototype that addresses two key issues in Singapore, the city-state's land scarcity and rapidly aging population. The project was awarded the World Architecture Festival "Building of the Year" Prize in 2018.

TABLE 12.1 Information on the two studies, including Plot Area, Gross Floor Area (GFA), number of floors, number of types of space, number of spaces (nodes, N), number of vertical street (and the percentage to N, VP), number of adjacent links, number of 50 m reachable links and the corresponding network density (ND) in brackets.

Index	KA	SUTD
Plot area (m^2)	8981	Approx. 83,000
Gross floor area (GFA) (m^2)	32,332	106,000
Floors	13	8
Different types of space	7	8
Number of spaces (nodes)	124	271
Number of "vertical streets" (VP)	69 (55.7%)	133 (49.1%)
Number of adjacent links (ND)	396 (5.2%)	560 (1.5%)
Number of reachable links (ND)	1566 (20.5%)	2319 (6.3%)

Network density is calculated as the number of links divided by the maximum possible links (pair of nodes). Vertical streets include stairs and lift lobbies.

SUTD, established in collaboration with the Massachusetts Institute of Technology (MIT) in 2009, is the fourth autonomous university in Singapore. The SUTD Campus, completed in 2015, was designed by the dutch architecture firm UNStudio together with Singapore-based DP Architects., The campus encourages cross-disciplinary interaction between faculty, students, and professionals by incorporating informal meeting and working spaces in an adaptable, flexible layout. SUTD's Campus Center serves as a flexible space for exhibitions and events, while the faculties and various campus programs are spatially distributed with a focus on connectivity. Lecture halls, classrooms, laboratories, and meeting rooms are located in currently three of the originally planned four main blocks that are connected vertically and horizontally through various circulation systems (UNStudio, 2019).

Responding to the tropical climate and the natural landscape of Singapore, natural ventilation and cooling principles with covered walkways and louvred facades were provided together with facade planters, green roof terraces, and sky gardens that use native trees and flowering plants. The campus design achieved the Singapore Platinum Green Mark rating with buildings that are 30% more energy efficient than typical institutional buildings (Mark, 2016).

Methodology and research phases

In both case studies, our research had two main phases. Phase 1 included an urban and architectural network mapping that was informed by a review of the planning and design concepts and intentions, a mapping of the resulting spatial networks, and a superimposition of node attributes such as Euclidean distance on the spatial network. Phase 2 comprised an empirical on-site sensing of human mobility with people counters and Bluetooth beacons. ML algorithms were used to classify activity ML to inform the analysis of the collected actual space use data. The two phases allowed for a systematic review of the effectiveness of KA and SUTD (Figs. 12.1–12.5) in terms of their intended space use.

Phase 1: Architectural network mapping

Phase 1 included a mapping of the nodes and linkages of the buildings' circulation and function of spaces, based on information provided by the respective architects. These included architectural diagrams and drawings that illustrate spatial distributions, e.g., intended circulation and flow, collaborative zones, connections in, between, and across the buildings, as well as lateral and vertical program distributions.

KA: The architects designed and integrated programs vertically to comprise KA's public spaces that include a community plaza and a hawker center located on the lower levels, a medical and childcare center as well as an active aging hub (that includes senior care) on the intermediate, and a community park for the residents on the upper levels (Figs. 12.6 and 12.7). KA includes two 11-story residential towers with 104 apartments to house elderly singles and couples (Gopalakrishnan et al., 2021).

SUTD: In the case of the campus, the concepts of "circulation" and "interaction" (Schroepfer, 2017) served the architects as their two main conceptual guides—with

FIG. 12.1 Point cloud image of the Kampung Admiralty Level 1 Atrium. (Point cloud data was collected with FARO Focus 330D and visualized with FARO SCENE). *SUTD Cities: Urban Science and Design for Density.*

FIG. 12.2 Point cloud image of the Kampung Admiralty Level 4 Sky Garden. (Point cloud data was collected with FARO Focus 330D and visualized with FARO SCENE). *No permission required.*

horizontal, vertical, and diagonal flows connecting the various spaces of the four buildings (Figs. 12.8 and 12.9). UNStudio, the design architect of SUTD, designated two axes of circulation, the “Learning Spine” and the “Living Spine” with a large plaza at the center.

For our analysis, we extracted the nodes from the main program areas in both cases. Edges were defined by connecting each one of the nodes to other nodes which are spatially adjacent and connected, e.g., via doorways and corridors. We calculated the Euclidean distance between the nodes from their corresponding links. We then joined elevator cores and stair lobbies as

FIG. 12.3 Point cloud image of the SUTD Campus Center. (Point cloud data is collected with FARO Focus 330D and visualized with FARO SCENE). *SUTD Cities: Urban Science and Design for Density.*

FIG. 12.4 Point cloud image of the SUTD Level 3 Sky Garden. (Point cloud data is collected with FARO Focus 330D and visualized with FARO SCENE). *SUTD Cities: Urban Science and Design for Density.*

"vertical street lobby" nodes and connected them directly and to all other vertically adjacent elevator core and stair lobby nodes, considering elevator and stair cores as "vertical streets." Various network centrality measures, including Degree, Closeness, and Betweenness Centrality were calculated from the spatial networks. Fig. 12.10 shows the adjacent and 50-m reachable networks of the two case studies. The node colors correspond to different floor levels.

We mapped the spatial network analysis measures in a digital model to visualize the relative significance of each space in terms of its connectivity and accessibility within the overall

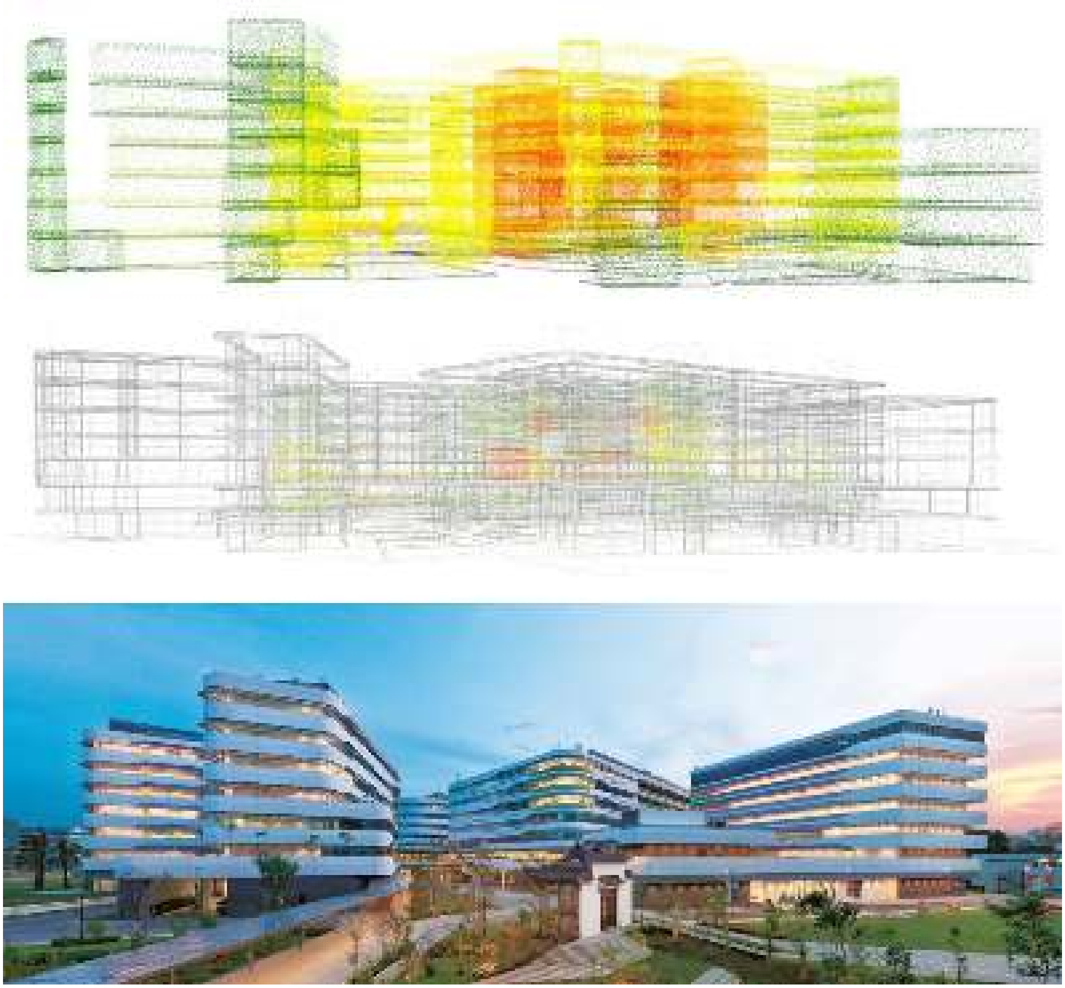


FIG. 12.5 From building to spatial metrics. Network centrality measures: Closeness and Betweenness diagrams, visualized in Rhinoceros Grasshopper, and actual SUTD Campus seen from the northeast. *Photograph by Daniel Swee.*

spatial network. Figs. 12.11 and 12.12 show the most central space of KA. From there, all other spaces can be reached within a travel distance of 50 m. Figs. 12.13 and 12.14 show the relative connectivity strength of all the spaces, illustrated through the varying sizes of the node measure.

Phase 2: Empirical on-site sensing

Tracking via smartphone app with BLE beacons

As part of our research, we developed a low-energy Bluetooth (BLE) tracking and localization method that we used in KA and SUTD to track and localize study participants (Figs. 12.15 and 12.16). These included residents, employees, and frequent visitors in KA and

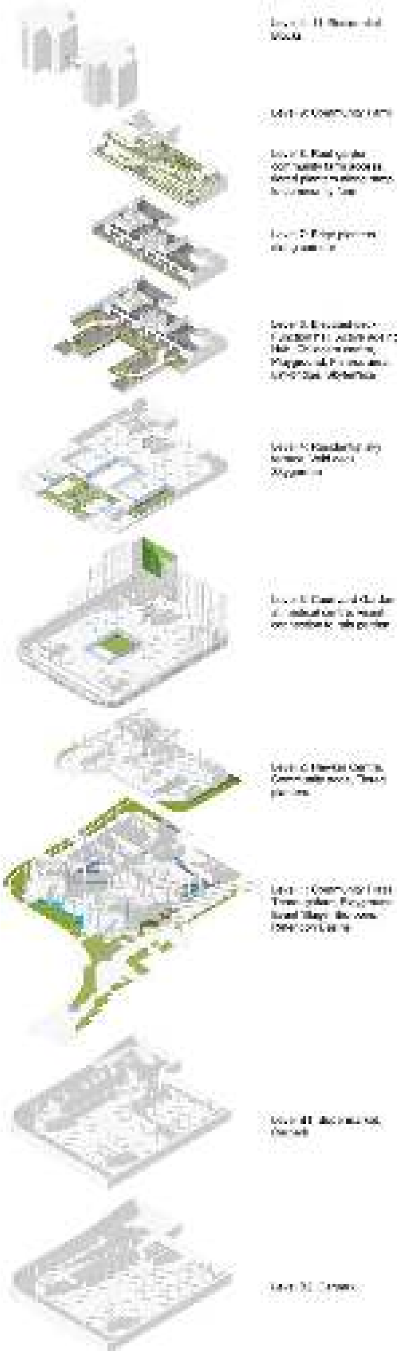
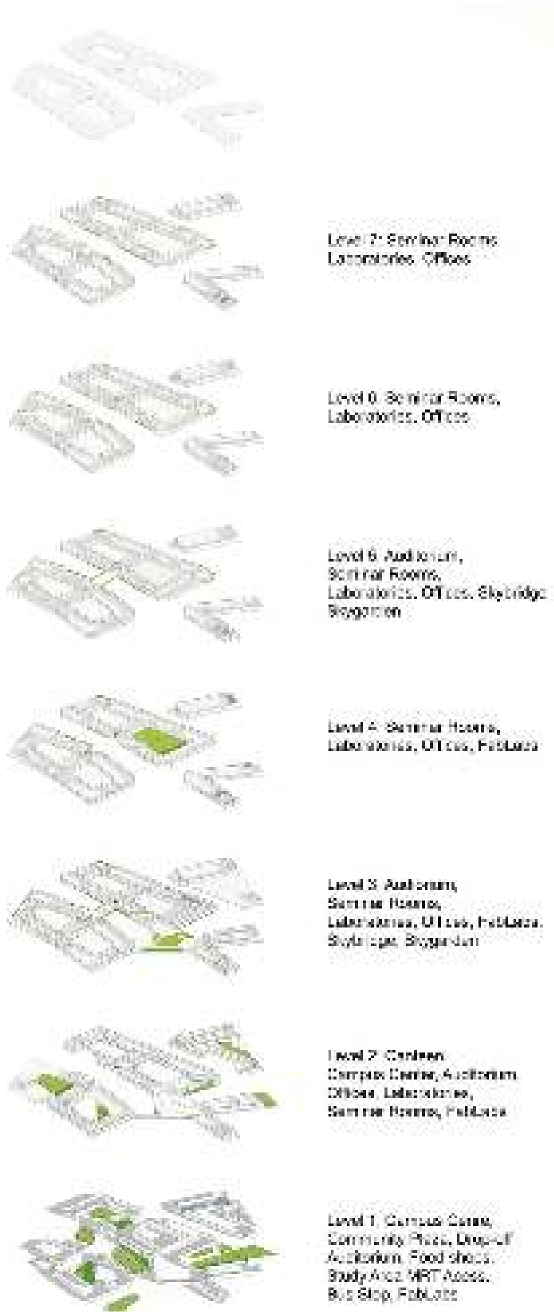


FIG. 12.6 Exploded isometric of KA showing the development's various programs. *Gopalakrishnan, S. et al., 2021. Mapping Emergent Patterns of Movement and Space Use in Vertically Integrated Urban Developments.*

FIG. 12.7 Exploded isometric of SUTD showing the development's various programs. *SUTD Cities: Urban Science and Design for Density*.



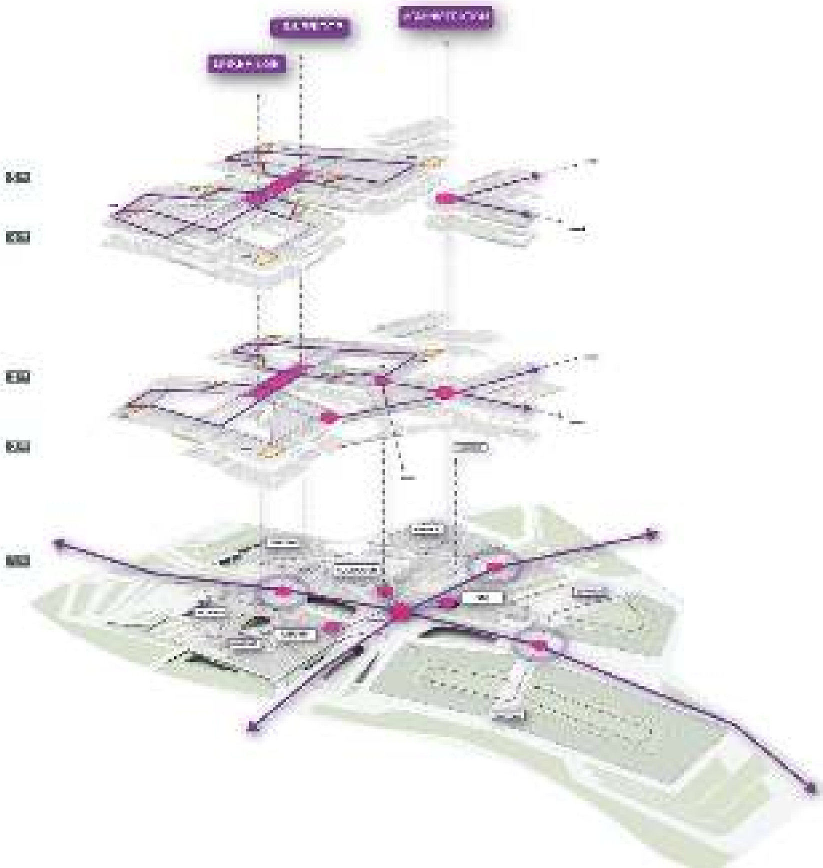


FIG. 12.8 UNStudio, SUTD, Singapore, 2014. Horizontal and vertical circulation, collaborative zones. *Source: UNStudio.*

faculty, students, staff, and vendors in SUTD. The Bluetooth localization consisted of four components, (1) stationary low-energy Bluetooth beacons placed around the study sites, (2) a mobile app that scanned for beacons when participants moved around the area, (3) a cloud server that recorded the data collected using the mobile app, and (4) processed the data for analysis. This approach is referred to as a "peer-to-environment" sensing system. The smartphone devices allowed for the mobile users to receive the data sent by beacons. The received data contained information about the transmitting beacon such as unique ID, time, telemetry (temperature, light, etc.) and the transmitting distance (indicating the stationary beacon's reach from the mobile app). Smartphones constituted the peer component of the system. A custom app installed on smartphones running iOS or Android worked in the background and scanned for Bluetooth data from the BLE beacons. It stored relevant data temporarily and then transmitted the information to our cloud server. The data

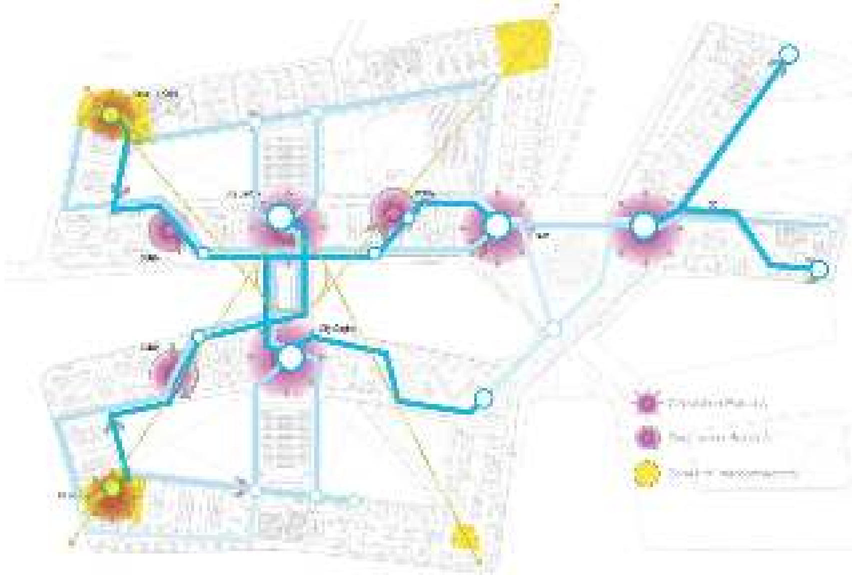


FIG. 12.9 UNStudio, SUTD, Singapore, 2014. Conceptual diagram of nodes of interactivity connected by circulation paths. *Source: UNStudio.*

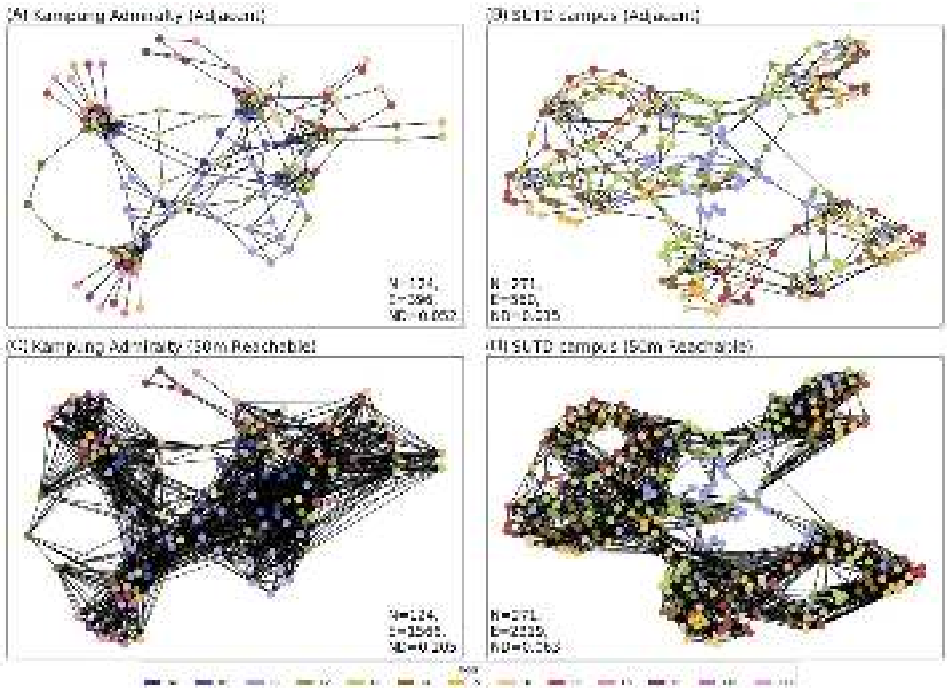


FIG. 12.10 The adjacency networks for (A) KA and (B) SUTD, and the corresponding walking distance (50 m reachable) networks [respectively (C) and (D)]. The numbers at the corner indicate the (N) number of nodes, (E) number of links, and (ND) network density. *SUTD Cities: Urban Science and Design for Density.*

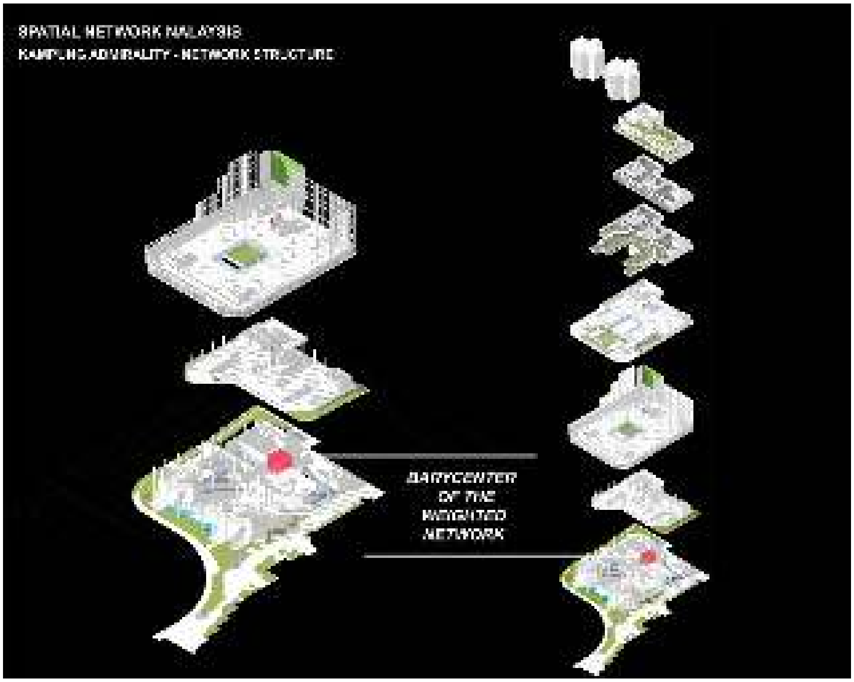


FIG. 12.11 Optimal location in KA. All other locations fall within the shortest travel distance of 50 m. *SUTD Cities: Urban Science and Design for Density.*

collected from the participants' Bluetooth devices was plotted on the spatial network to map their movement routines over the research period. We then deduced the experimental data measurements from the spatial network analyses and subsequently validated them with the real-world data, with the correlations between the designed and actual space use providing the basis for the performance assessment of KA and SUTD.

For the on-site experiment, we recruited a total of 73 participants in KA to track and record movement patterns. The BLE beacon scanning recorded a total of 42.6 million sensor data points which included beacon, accelerometer, barometer, and Bluetooth data (the SUTD study is still ongoing at the time of writing this chapter).

We used the collected BLE-localized movement data to construct socio-spatial networks and analyzed the dynamic network processes of mobility and occupancy as well as the correlations between network topologies, spatial configurations, and the network processes.

In addition, we constructed copresence networks constructed from the BLE-localized mobility patterns. In complexity science, when two or more people are in close proximity, they are said to be in copresence. Copresence is a necessary but not sufficient condition for interactions. A copresence network is a social network of friends and strangers that can help to analyze social relationships as a dynamic process. In our case studies of KA and SUTD, the participating users formed the nodes and the time spent in each other's proximity constituted the edges. Copresence networks are temporal networks, since their edges appear and disappear. Over time, a copresence network emerges that displays strong and weak ties. Persistent encounters between users indicate homophily (strong ties), while brief and chance encounters indicate

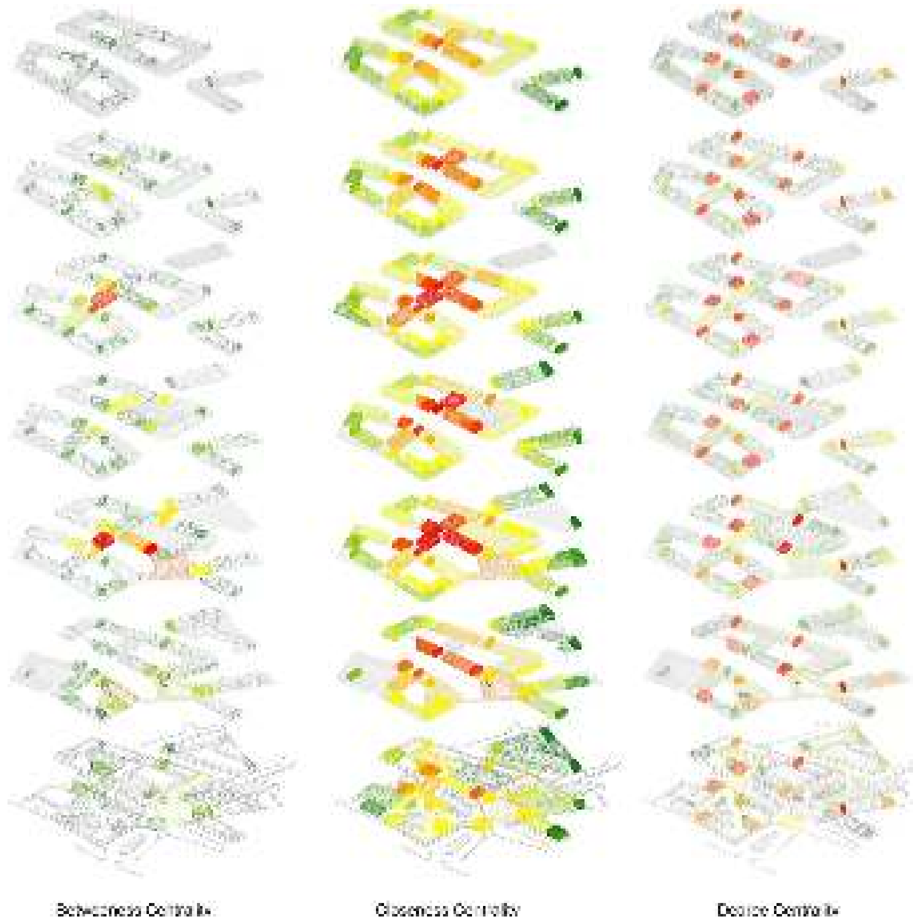


FIG. 12.12 Optimal location in SUTD. All other locations fall within the shortest travel distance of 50 m. *SUTD Cities: Urban Science and Design for Density.*

heterophily (weak ties). Stronger ties influence social behavior while weaker ties complete the connectivity within the network. When mapped onto the spatial layout of a building, the socio-spatial network reveals the patterns of user interaction and their relative strength over time. The aggregated network also shows the connectivity of different social spaces that enable homophily (active social interactions) and the areas that allow for more opportunities for chance encounters based on high movement flows. These results can provide important insights for the future planning and design of buildings and urban environments.

Measured mobility and occupation data of spatial nodes

Figs. 12.17 and 12.18 show the socio-spatial mobility analysis of KA by floor level and location type. Different types of users exhibited different mobility patterns. Residents and employees of KA showed a higher mobility "footprint" on the median than frequent visitors. Spaces with high connectivity like the Level 1 Community Plaza, elevated sky gardens, and vertical streets saw high pedestrian flow volumes.

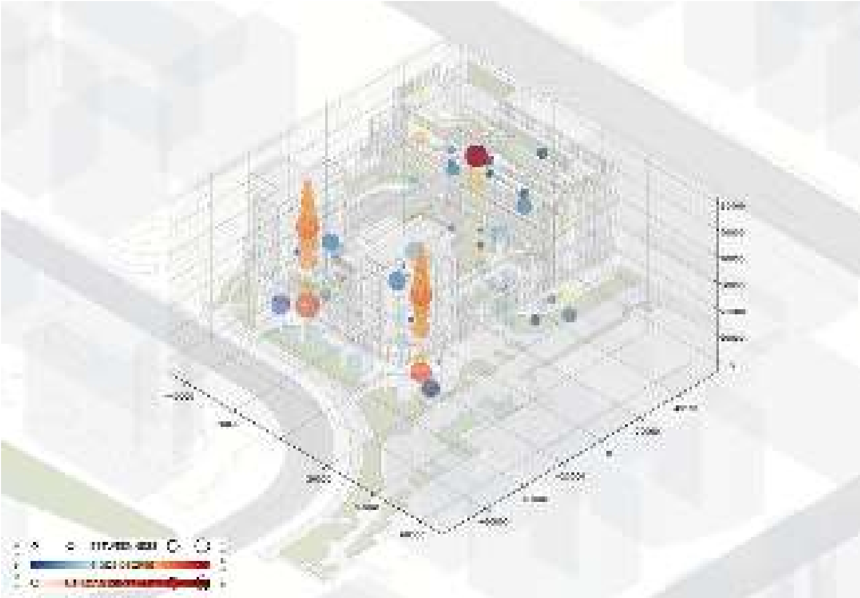


FIG. 12.13 Centrality measures visualized within the KA spatial model; the size of the circles indicates the significance of the space as a key connector within the network (Betweenness Centrality) and the color indicates the number of spaces each node is immediately connected to (Degree Centrality). *SUTD Cities: Urban Science and Design for Density*.

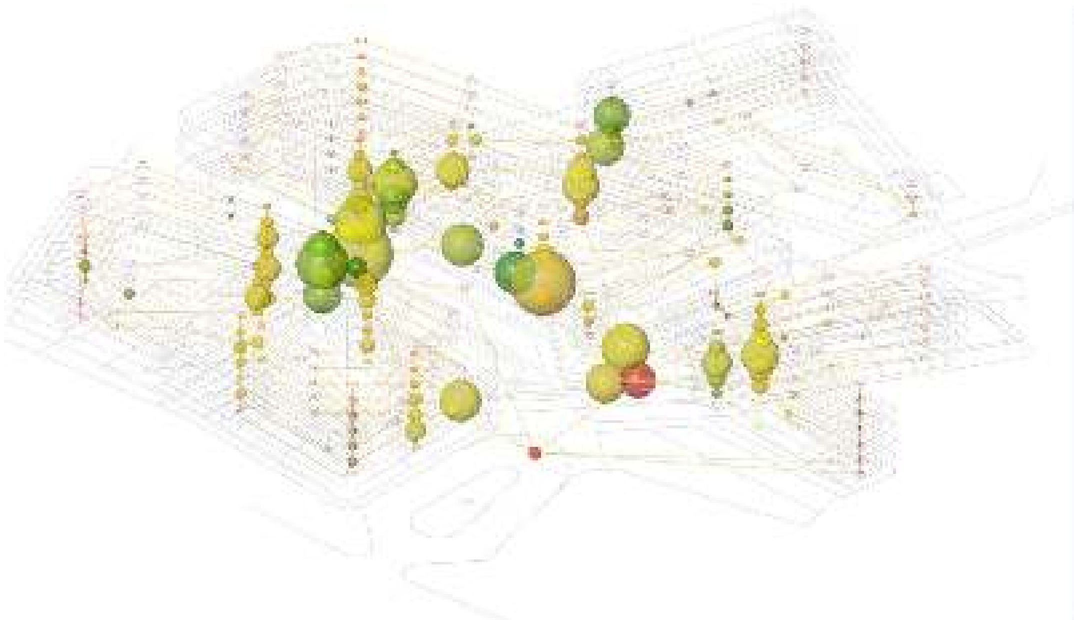


FIG. 12.14 Centrality measures visualized within the SUTD spatial model; the size of the circles indicates the significance of the space as a key connector within the network (Betweenness Centrality) and the color indicates the number of spaces each node is immediately connected to (Degree Centrality). *SUTD Cities: Urban Science and Design for Density.*

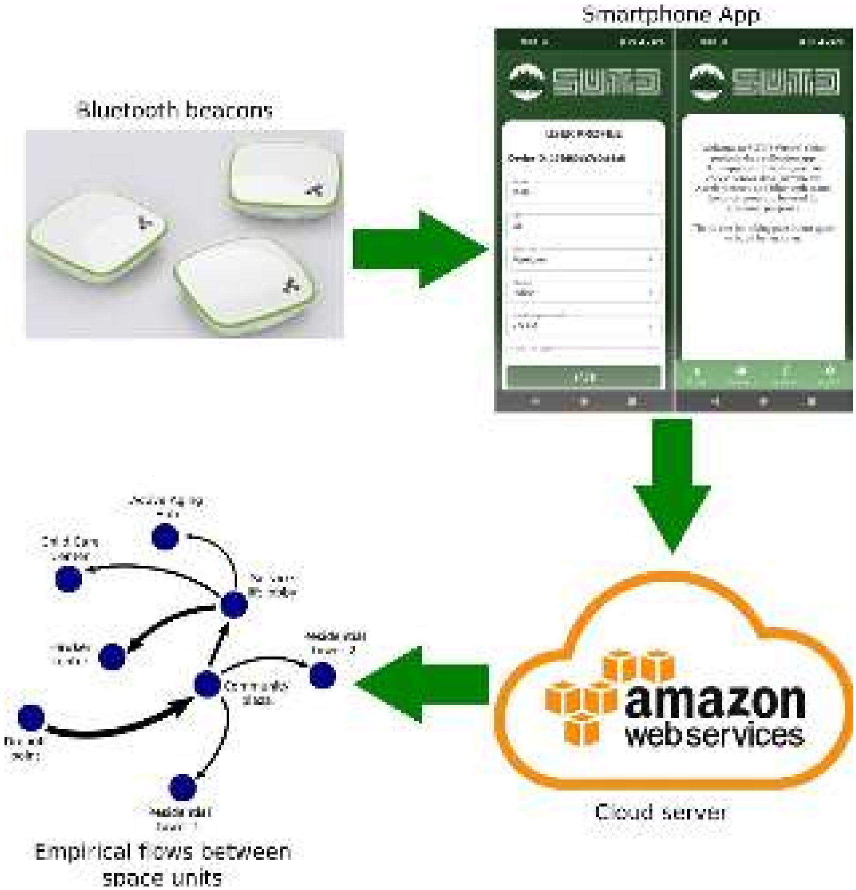


FIG. 12.15 Bluetooth (BLE) localization and tracking consisting of low-energy Bluetooth beacons, mobile app, and cloud server. *SUTD Cities: Urban Science and Design for Density.*

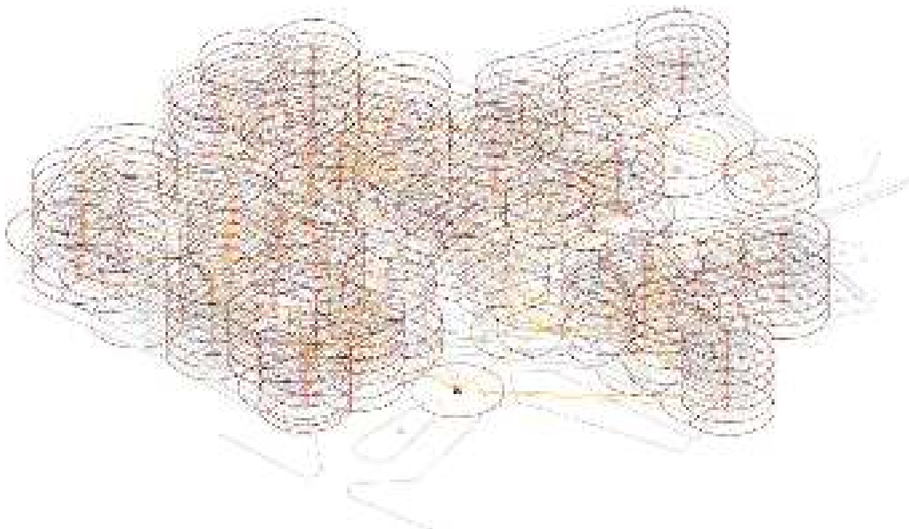


FIG. 12.16 20 m BLE detection radii in SUTD. *SUTD Cities: Urban Science and Design for Density.*

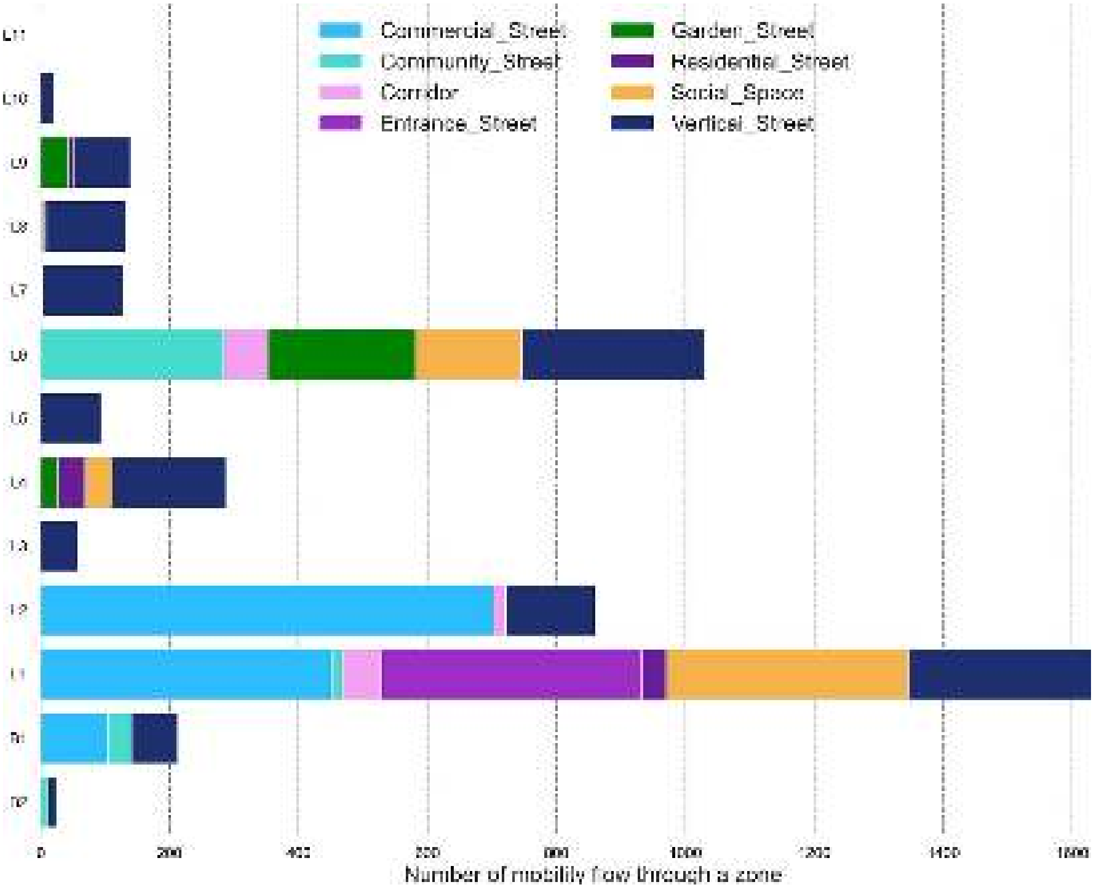


FIG. 12.17 Total distance traveled in KA public spaces per day per study participant. (A) Overall, (B) by gender, (C) by age group, (D) by KA user type. *SUTD Cities: Urban Science and Design for Density*.

The occupancy analysis shows the time spent in different KA spaces. The total time spent in the development by floor level and location type over time is shown in Figs. 12.19 and 12.20. We studied the occupancy patterns of different users to understand the effective use of spaces, e.g., users spent significant amounts of time in the social areas at ground and the elevated levels. Activity destinations like community gardens showed the longest occupancy compared to the other areas.

The beacon data points were visualized in a spatial model allowing for comparisons across different nodes within the architectural space and the timing of activities. Fig. 12.21 shows the spatial distribution of the daily aggregated beacons reading heat maps by the day of the week (from Monday to Sunday). Clear activity patterns at different locations and during different times were visible with consistent peaks and lows throughout the week, thus revealing the effective patterns of movement and space use.

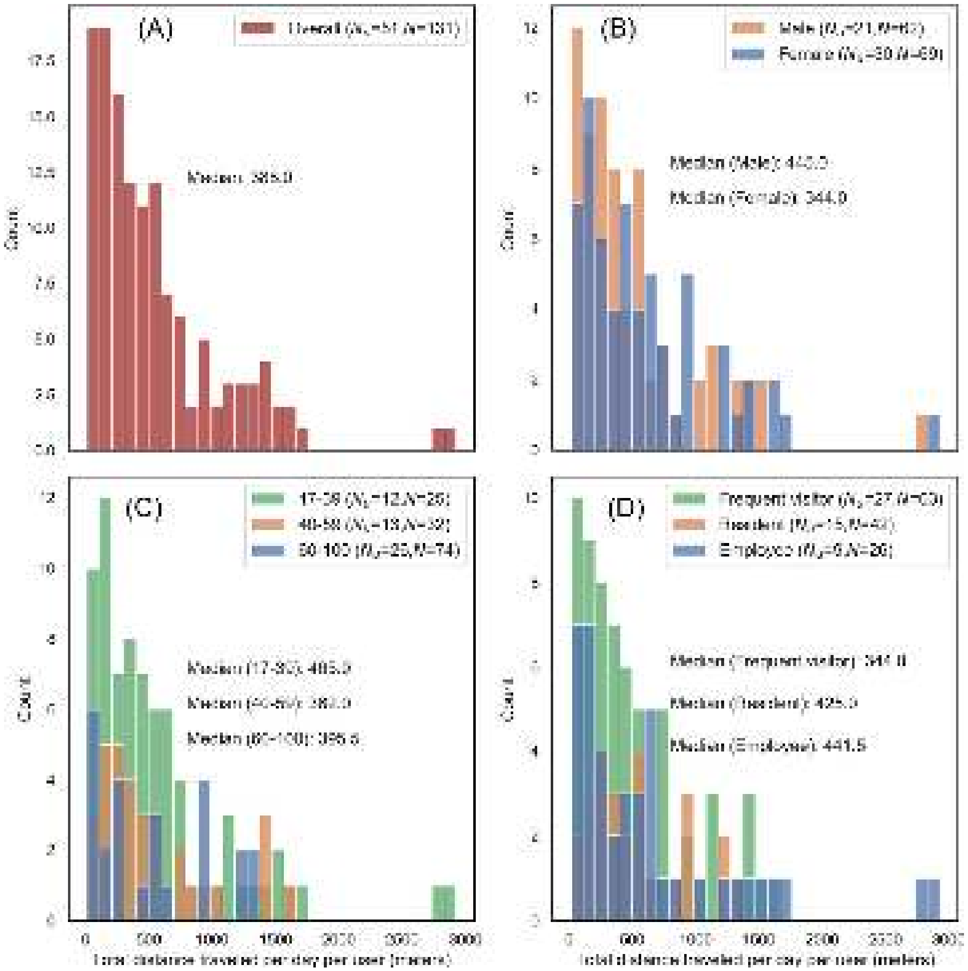


FIG. 12.18 Number of mobility inflows through KA public spaces per floor and location type. *SUTD Cities: Urban Science and Design for Density.*

Tracking with radar and infrared-based bidirectional people counters

Our mobility mappings included tracking and recording of pedestrian movement in significant public and common spaces and key collaborative zones at the ground and elevated levels in both of our case studies. We recorded the frequency and intensity of actual space use using radar- and infrared-based bidirectional people counter sensors. People counters measure the volume and the time of human traffic flows across predefined points and zones. The devices were installed at key access points to the nodes that we identified in Phase 1 of our research to collect data of inflow and outflow volumes at different times of the day. The collected data provided us with the total volume of users circulating through the selected spaces. The variations in usage volumes allowed us to identify micro- and macro-patterns over hours, days, and weeks, providing a measure of actual space use and performance. Photographs of the people-counter devices and an illustration of the results are shown in Figs. 12.22 and 12.23.

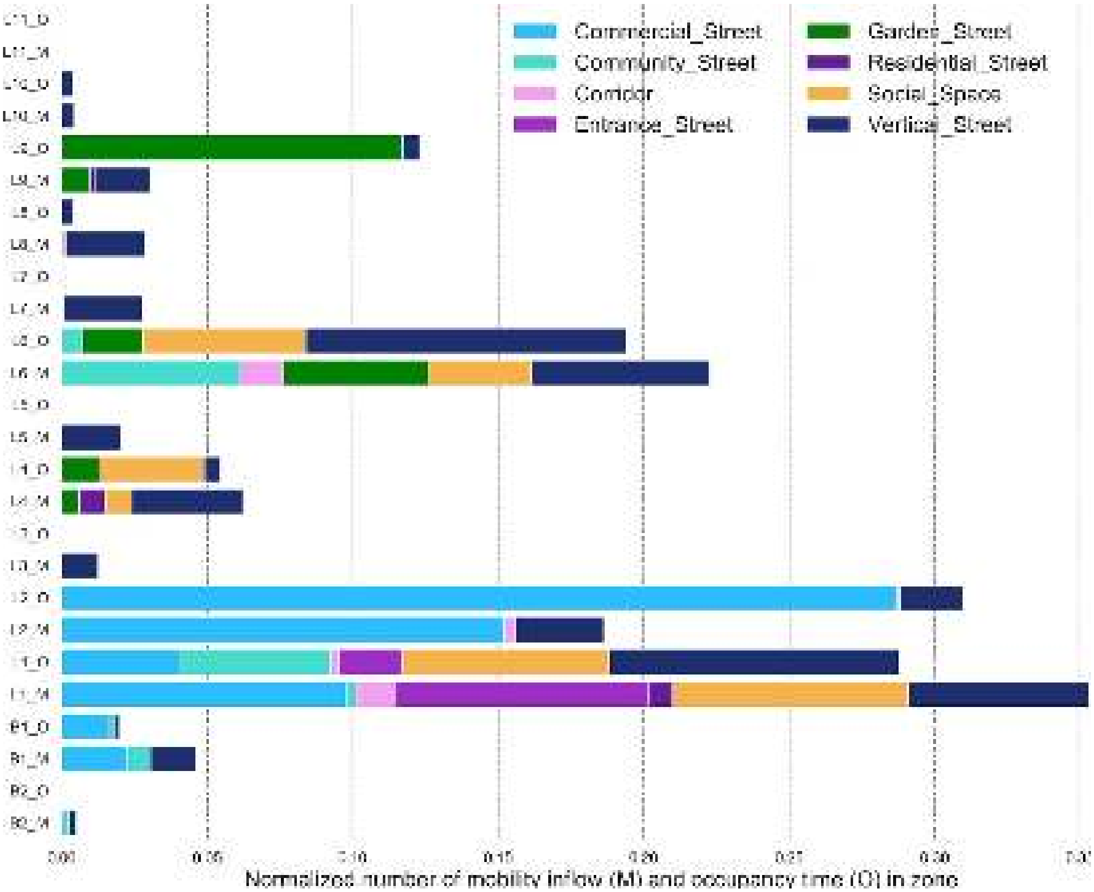


FIG. 12.19 The graph shows the interplay between mobility and occupancy in KA's public spaces per floor and location type. X-axis values also represent relative scaling for location types. *SUTD Cities: Urban Science and Design for Density.*

We analyzed the people counter data in terms of temporal patterns of movement and space use at key social spaces. Fig. 12.24 shows the hourly aggregated use of garden spaces and community facilities at KA. Garden spaces were regularly used during daytimes with fewer visits in the evenings, while the community facilities were used more frequently on weekdays compared to weekends.

In the following paragraphs, we present a comparison between the movement flows in two important SUTD spaces. Area 1 includes the Level 1 Campus Center and the Level 3 Sky Gardens directly above it. Area 2 refers to the L1 Community Plaza, and the Levels 3 and 5 Sky Bridges directly above.

Fig. 12.25 illustrates the flow on weekdays and weekends across four different time periods (0000–0559, 0600–1159, 1200–1759, 1800–2359), showing peaks in the afternoon both on weekdays and weekends, albeit significantly lower weekend traffic across all time periods. The peaks occur at lunch and dinner times, with a significant rise and drop in overall use before 0800 and after 1900 h. Also, the afternoons generally show greater volume of movement than the mornings (Fig. 12.26).

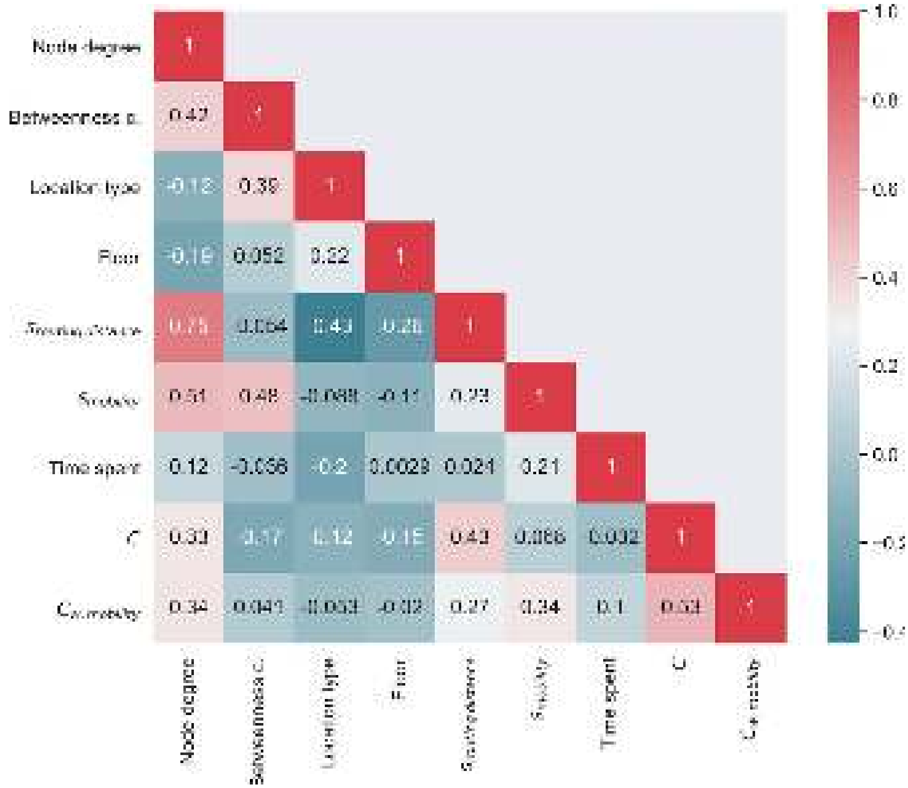


FIG. 12.20 Correlation matrix between network topology, space, and network processes of KA. *SUTD Cities: Urban Science and Design for Density.*

Figs. 12.27 and 12.28 show the comparative proportion of flows per node; we can see that nodes generally have a mid-week peak followed by a drastic drop in use on weekends, except in the Level 1 Community Plaza/Study Area (Area 2) which had a larger proportion of flow despite the overall dipping trend.

On weekends, the elevated links on Level 3 and Level 5 all show significantly lower use than the ground nodes. This suggests a bias or preference toward ground level space use. The Level 3 Skybridge (Area 2) shows a greater flow of use than the other elevated links. There are small daily fluctuations in flow volumes on weekdays for the elevated links and ground nodes, with the Level 1 Campus Center (Area 1) showing the most variation.

Importance of space levels in the KA and SUTD networks

We calculated the Degree Centrality, Closeness Centrality, Betweenness Centrality, PageRank, and Geographical PageRank for the 50 m reachable networks. Fig. 12.29 shows the distribution of these network metrics according to floor levels and location types. In the left column, almost all boxes (showing 25–75 percentile) of the same cases overlap, indicating that floor levels had weak effects on the nodes' importance levels. One exception exists

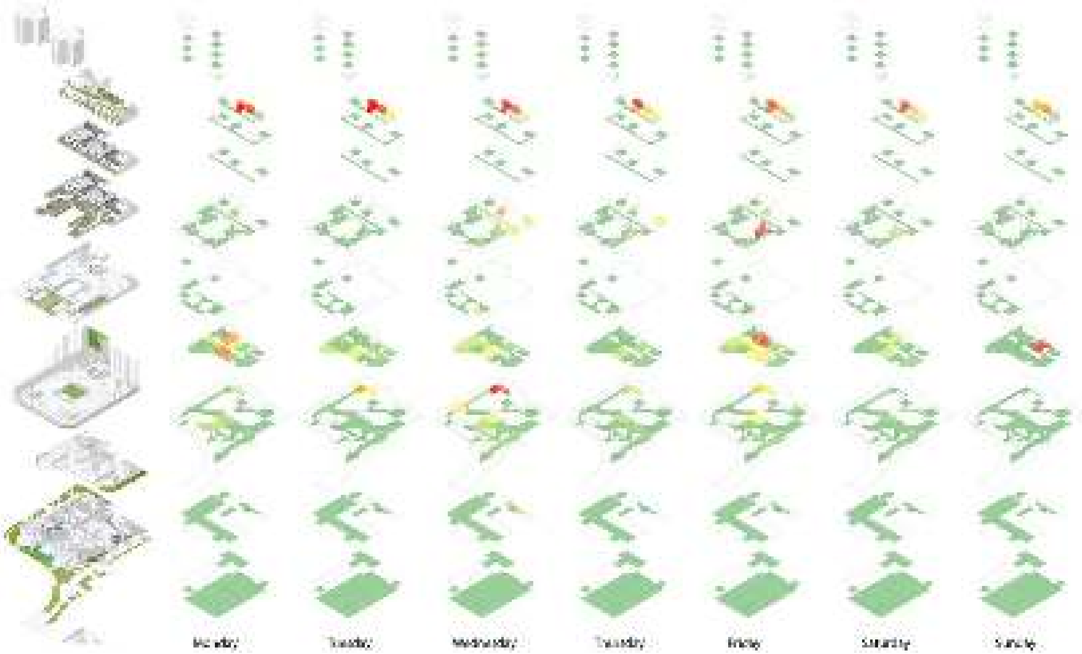


FIG. 12.21 Visualization of daily beacon activity heatmap, aggregated by the day of the week: (from left to right) from Monday to Sunday. *SUTD Cities: Urban Science and Design for Density.*

in the result for Betweenness. Boxes are low at lower floors and higher floors, i.e., Basements 1 and 2 and Level 11 for KA, and Levels 1 and 7 for SUTD. In the right column, we aggregated metrics according to five major location types and other groups, including main (residential for KA and education for SUTD), vertical street (Ver), community facilities (Fac), social spaces (Soc), and commercial spaces (Com). In the KA network, vertical streets, social spaces, and commercial spaces have slightly higher Degree Centrality, Betweenness Centrality, and PageRank. In the SUTD network, the patterns are slightly different. Commercial spaces have lower Degree, Betweenness, and PageRank. The vertical streets and social spaces have higher Betweenness Centrality in both networks, indicating that these locations might be used more than others. The Closeness Centrality result is similar to the left column. Most of the boxes are covering each other. The geographical PageRank result shows that the vertical street's scores are higher than the four other groups in both networks.

One interesting observation is about the vertical streets. In buildings, the spaces on each level are typically connected and form clusters of nodes (communities) and the vertical circulation or "streets," including stairs, escalators, and lifts, connect the different levels. Thus, we expected the vertical streets to act as "bridges" between floors. However, we found that these vertical streets (especially the lift lobbies) not only have higher Betweenness, but also higher Degree PageRank and Geographical PageRank. This indicated that the vertical streets also act as hubs in the two networks. Looking more closely at the KA network structure result, the connected lift lobbies form the cores of densely connected communities, while other spaces (e.g., residential units and community facilities) connect to the lift lobbies core nodes.

FIG. 12.22 Placement of Sensmax people counter in SUTD. *SUTD Cities: Urban Science and Design for Density.*

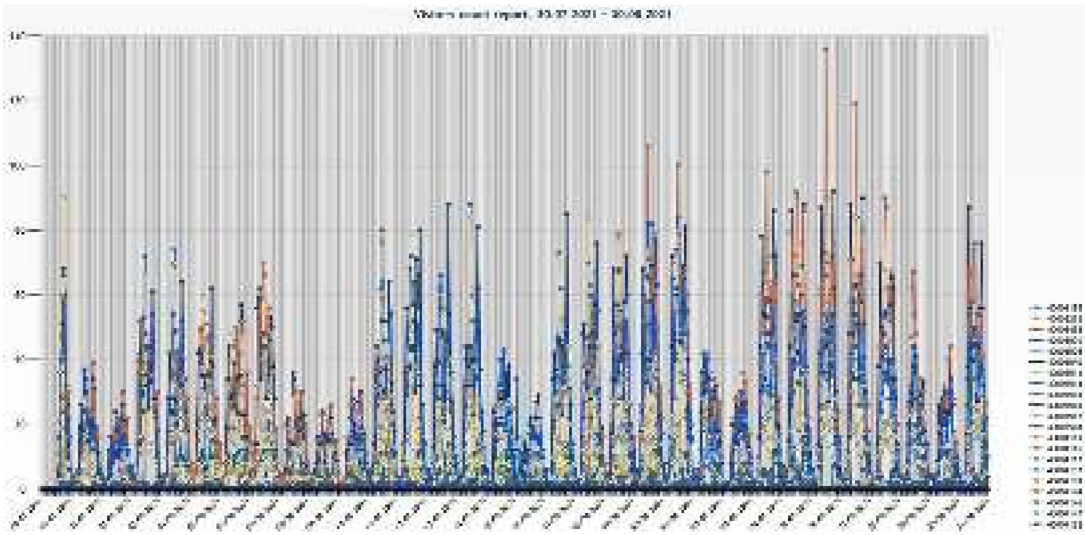


FIG. 12.23 Visitor count report over 7 weeks (July 30 to September 16, 2021). *SUTD Cities: Urban Science and Design for Density.*

This observation also highlighted the uniqueness of a vertical urban network in which hub-like bridge nodes exist.

When comparing the Network Centrality measure patterns with actual movement flow data in KA and SUTD, we see that the results indicate the use of vertical streets (lifts and staircases) as dominant connecting nodes between clusters of levels. However, it is also worth important to note that several vertically elevated nodes that serve as horizontal connectors or bridges between buildings also stand out, showing substantial movement flows. In KA, these include the Level 6 skygardens which serve as a bridge between the residential program clusters and commercial/social programs. In SUTD, they include the Level 3 and 5 skybridges between Buildings 1 and 2, as well as the Level 3 Skygarden that connects the Campus Center with the Library in Building 1.

The shared features of the buildings—vertical integration with social and landscaped spatial programs located at ground and elevated levels—result in shared characteristics in terms of vertical streets that connect clusters. This is despite of the fact that the two developments are different building types, one with a mixed-use and the other with an institutional program. This points to a possible correlation of space use in vertically integrated buildings in general.

In conclusion, the comparison of the predicted space use and movement patterns with the actual user-space interactions provided us with important insights into the performance of social spaces. We were able to identify critical factors that influence the performance of the public spaces in KA and SUTD by studying network metrics, node configurations, attributes, adjacencies, and topologies within the respective networks. The analysis of the various socio-spatial network measures provided us with important insights regarding the

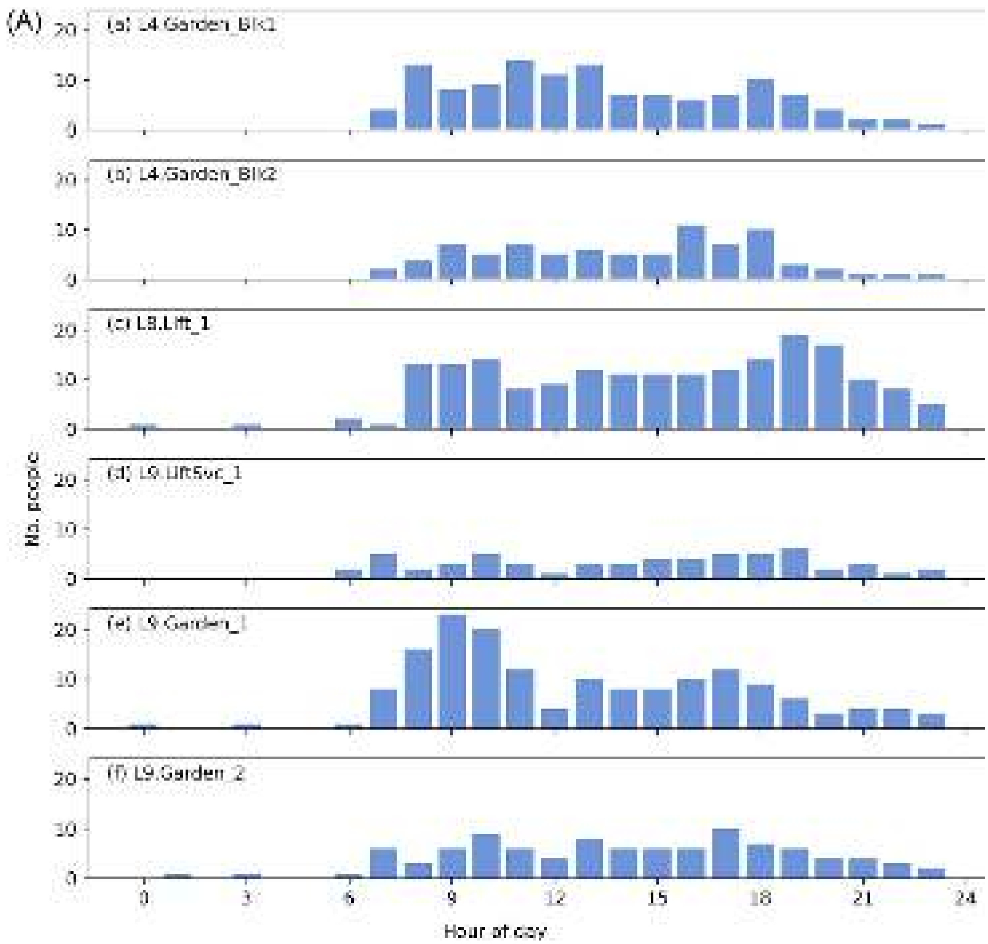


FIG. 12.24 The people counter data aggregated to show the hourly use of gardens (A) and the hourly aggregated use of all community facilities (B). *SUTD Cities: Urban Science and Design for Density.*

(Continued)

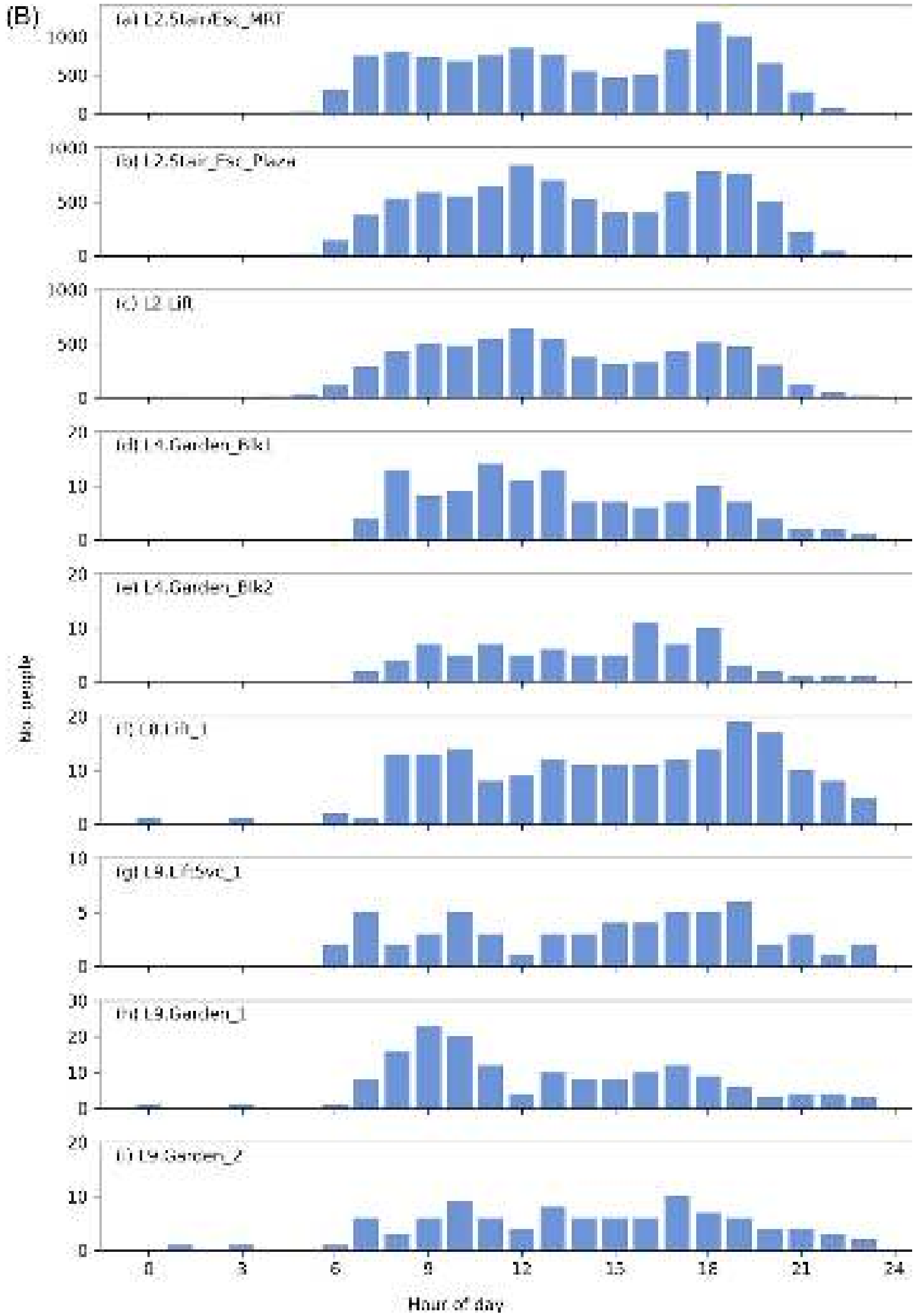


FIG. 12.24, CONT'D

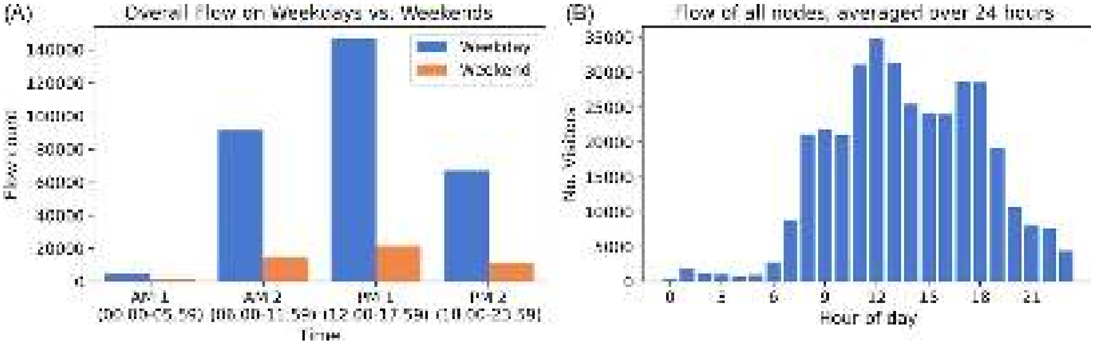


FIG. 12.25 Graph of overall flow on weekdays vs weekends (A) and flow of all nodes in Area 1 & 2, averaged over 24 h (B). *No permission required.*

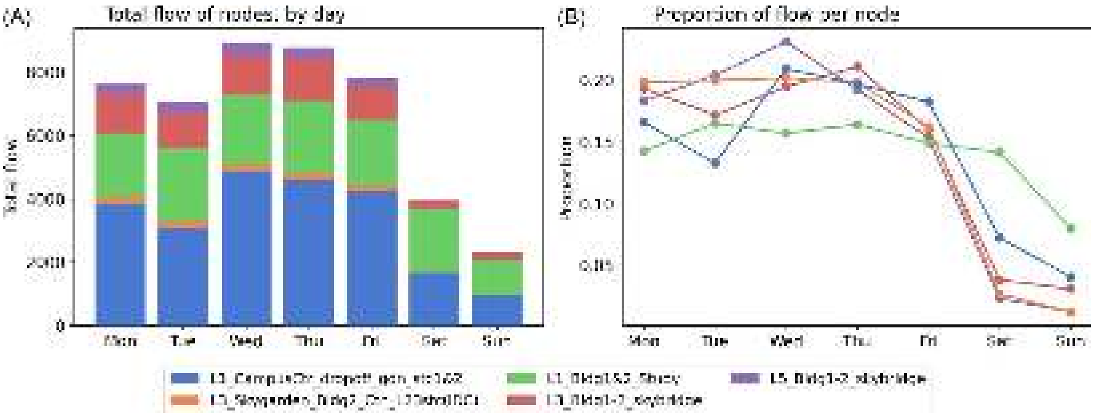


FIG. 12.26 Graphs of Total Flows of Nodes by Day (A), and Proportion of Flow per Node, divided by the total of the same location (B). *No permission required.*

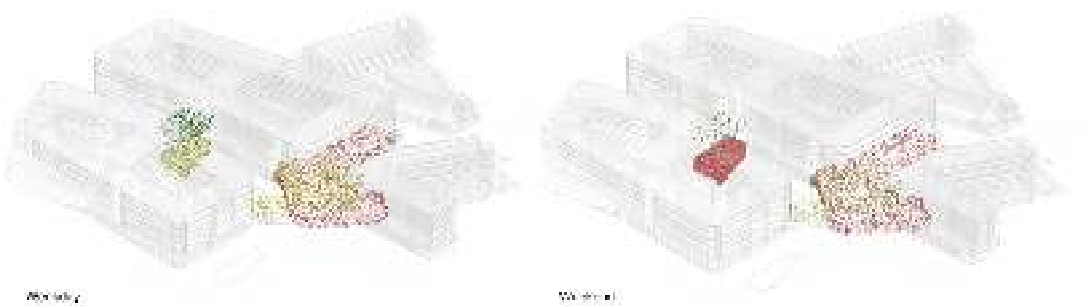


FIG. 12.27 Comparison of weekday and weekend relative flow. *No permission required.*

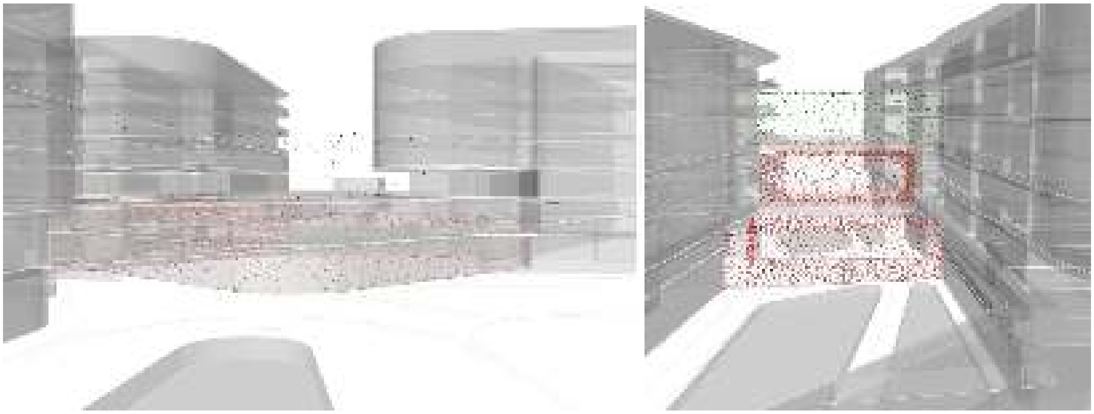


FIG. 12.28 Comparison of overall relative flow between ground and elevated areas in Areas 1(left) and 2(right). *SUTD Cities: Urban Science and Design for Density.*

parameters that should be considered in the further development of complexity science-based predictive planning and design methodologies.

Limitations of research and future plans

At the time of writing, our data collection in the SUTD study is still underway. Continuing our research, we plan to capture seasonal events such as term breaks as well. The analyses of the additional data will allow for a better understanding of longer-term space use patterns. Once available, we will process the additional Bluetooth-based tracking data with machine learning algorithms. This will allow for a finer granularity in terms of findings and therefore for a more detailed comparison of network measures with actual space use.

Our findings presented in this chapter are based on data collection that took place in 2020–2021 in a situation that was affected by the COVID-19 pandemic (Fig. 12.30). The population of Singapore was advised to stay at home as much as possible, to reduce outdoor activities and gatherings, to work and study from home, and to generally reduce physical interactions as much as possible. Although most human activities resumed to a certain degree after Singapore's "Circuit Breakers" (lockdown measures that started in April and ended in June 2020), the human movement patterns discussed here should be assumed as being irregular. For example, the circulation on the upper levels of SUTD was limited as access was only possible through the University's Campus Center. This situation led to an increase in the measurements of actual space use of the Campus Center and other main access points. Similarly, in the case of KA, social distancing was practiced and affected the activities (particularly, community gathering, various events that used to be held in the public space at Level 1, activities used to be held by the active aging hubs for elderly people, etc.) in the community facilities.

Further detailed analysis of the collected empirical flow data, flow network, and copresent network analysis should be conducted. In addition, through the analysis of the distribution of

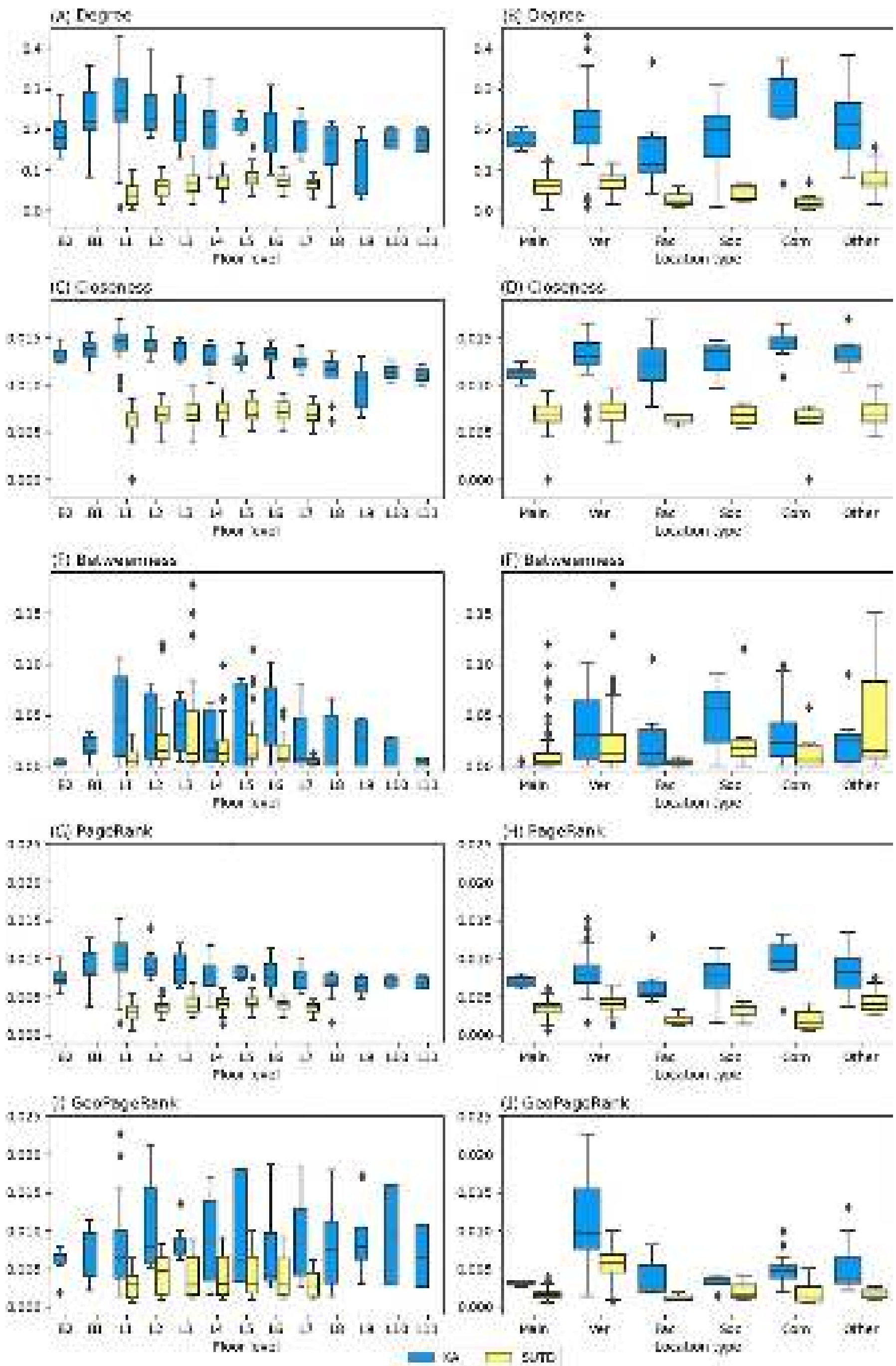


FIG. 12.29 Boxplots showing the distribution of the five network indexes for nodes on (left column) different levels and nodes in (right column) different location types for KA and SUTD. The box indicates the first and third quartile and the whiskers indicate the interquartile range (IQR). Note that the location type "Main" in the right column indicates the main program of the two networks, i.e., residential for KA and education for SUTD. *SUTD Cities: Urban Science and Design for Density.*

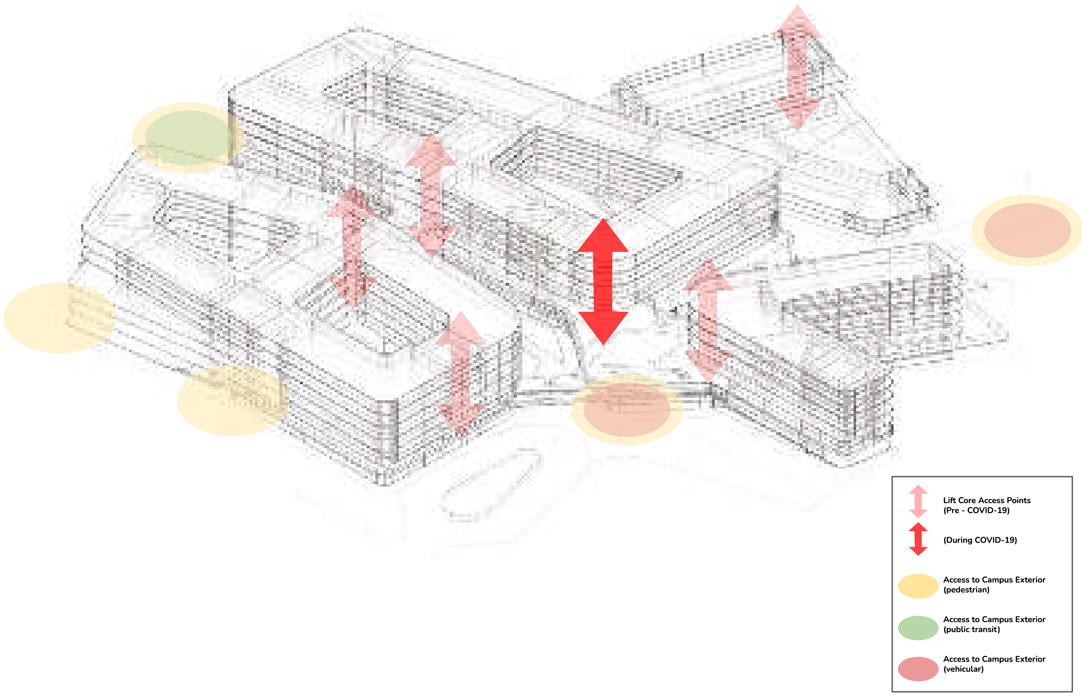


FIG. 12.30 COVID-19-related vertical circulation constraints in SUTD. *SUTD Cities: Urban Science and Design for Density.*

the flow data, appropriate distribution parameters should be obtained. This would allow for future agent-based simulations and large-scale scenario-testing analyses, such as: What would be the magnitude of the affected population if some movement policies (i.e., different stages of lockdown measures, such as movement control according to age groups or household sizes, or movement restriction according to distance) are applied.

Lastly, as mobile apps, social media, and governmental COVID-tracking health programs already capture proprietary movement ostensibly used in activity pattern analysis, compliance with ethical standards was paramount to our approach. Much debate and discussion around these issues in contact tracing apps such as Australia's COVIDSafe and Singapore's TraceTogether programs have taken place over the past months. Anonymization and opt-out options are therefore crucial and need to be implemented.

Conclusions

The research discussed in this chapter is based on both complexity science and AI. It enables us to study everyday space uses on a scientific basis. The scalability of the methodology allows for new ways of analyzing and evaluating multiple measures of space performanceand therefore future planning and design. In providing an empirical model of the socio-spatiality of an urban environment, it can help us to better understand its actual performance.

Our research methodology harnesses the ubiquity of smart devices and uses AI techniques to cluster emergent patterns of user activities that are subsequently embedded in the specific dimensions and spatial parameters of the built environment. The further use of AI tools and techniques that we are currently developing for activity classification will allow us to understand better how human flows and space uses form emergent clusters and patterns that correlate with spatial nodes and their properties. This will ultimately result in more complete spatial analyses that include temporal and copresence patterns and factors that can help us comprehend the correlation of planning and design intent and the actual performance of built environments.

Until now, complexity science-based approaches to urban planning and design have been mainly applied at large scales, using statistics to understand emergent patterns and flows of resources, e.g., urban metabolism (Kennedy et al., 2011) or scaling effects of wealth, innovation, and crime (Bettencourt et al., 2010). AI-aided approaches to the study of mobility have mainly been used to provide commercial services such as geolocation for advertising on the Web and social media-based platforms, traffic management and sensing systems such as autonomous vehicles, and transportation intelligence, e.g., in ride sharing systems and urban mobility mapping, but not to analyze buildings and their relationships to the urban contexts they are part of. Our approach aims to fill this gap to inform planning and design decision-making processes more holistically. The comparison of intent with results of spatial network analyses and actual on-site measurements can provide important insights regarding spatial performance. This includes, but is not limited to, the placement of important social urban and architectural spaces at locations that correlate with high Degree Centrality, elevated connections at node points with high Closeness and Between Centrality measures, and the provision of programs that support the function of nodes. Such insights into spatial performance suggest show the potential of applications of complexity science and AI for future urban planning and design processes.

Acknowledgment

The authors would like to thank Srilalitha Gopalakrishnan, Chirag Hablani, and Daniel Kin Heng Wong for their contributions to this chapter.

References

Bettencourt, L.M.A., et al., 2010. Urban scaling and its deviations: revealing the structure of wealth, innovation and crime across cities. PLoS One 5 (11). https://doi.org/10.1371/journal.pone.0013541. United States.

Gopalakrishnan, S., et al., 2021. Mapping Emergent Patterns of Movement and Space Use in Vertically Integrated Urban Developments.

Kennedy, C., Pincetl, S., Bunje, P., 2011. The study of urban metabolism and its applications to urban planning and design. Environ. Pollut. 159 (8–9), 1965–1973. https://doi.org/10.1016/j.envpol.2010.10.022. Canada.

Kong, L., Woods, O., 2018. The ideological alignment of smart urbanism in Singapore: critical reflections on a political paradox. Urban Stud. 55 (4), 679–701. https://doi.org/10.1177/0042098017746528. Singapore: SAGE Publications Ltd.

Liceras, P., 2019. Singapore and Its Digital Twin, an Exact Virtual Copy. Available at: https://www.smartcitylab.com/blog/digital-transformation/singapore-experiments-with-its-digital-twin-to-improve-city-life. Accessed: January 6, 2021.

Mark, S., 2016. SG MARK GOLD. Singapore University of Technology and Design. Singapore Good Design Awards. Available at: https://sgmark.org/blog/winners/singapore-university-of-technology-and-design/. Accessed: January 26, 2021.

Schroepfer, T., 2017. Singapore University of Technology and Design: Crossing Disciplines by Design. vol. 287 Singapore Architect, pp. 76–86.

Schröpfer, T., 2020. Dense + Green Cities: Architecture as Urban Ecosystem. Birkhäuser, Basel.

UNStudio, 2019. Singapore University of Technology and Design, 2010–2015. United Network Studio. Available at https://www.unstudio.com/en/page/12103. Accessed: January 260, 2021.

Varakantham, P., et al., 2017. Artificial intelligence research in Singapore: assisting the development of a smart nation. AI Mag. 38 (3), 102–105. https://doi.org/10.1609/aimag.v38i3.2749. Singapore: AI Access Foundation.

CHAPTER

13

Understanding urban leisure walking behavior: Correlations between neighborhood features and fitness tracking data

Özgün Balaban

Chair of Design Informatics, Faculty of Architecture and the Built Environment, Delft University of Technology, Delft, The Netherlands

Introduction

The impact of form, design, and amenities of cities on the health of residents was acknowledged in the 18th century when urban planning became a means of enhancing public health (Koohsari et al., 2013). This link between urban planning and public health has been mostly neglected during the 20th century. However, many researchers are recently restating the importance of public health in urban planning (Boarnet and Takahashi, 2011; Frank and Kavage, 2008; Giles-Corti and Whitzman, 2012; Hoehner et al., 2003) as there is mounting evidence on suburban sprawl, inadequate public green spaces, and bad infrastructure causing physical inactivity, obesity, and poorer mental health (WHO, 2010). Physical inactivity is the fourth leading cause of death globally and causes 3.2 million deaths each year (WHO, 2009). Therefore, increasing regular physical activity became a priority for many governmental agencies (Beaglehole et al., 2011).

Of the many physical activities, walking is the most popular (Ball et al., 2001; Booth et al., 1997). Much attention is given by the research community to walking for transportation or utilitarian purposes and forms the foundation of walkability studies. Walkability studies aim to increase the use of walking in daily interactions of a neighborhood by creating diverse, well-designed, safe, and dense neighborhoods with plenty of destinations within walking distance. Influential urban designers (Gehl, 2011; Jacobs, 1961; Speck, 2012) stress the value of walkable neighborhoods.

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00014-7

Walking for leisure is an easy way to increase physical activity levels. However, the environment built around the people can be a potential facilitator or barrier for leisure walking (Handy et al., 2002). Physical activity and active living can be promoted in a well-designed urban environment that provides access to the natural environment (Edwards and Tsouros, 2006). The availability of sidewalks, shaded pathways, or adequate lighting can provide a comfortable experience, whereas overcrowding, bad design, traffic, and pollution decrease the willingness to engage in a leisure walk.

Urban planning and design are complex processes that are highly dependent on information and knowledge that come from many different sources such as experience, professional knowledge, new data collection, and interactions with other decision-makers (Krizek et al., 2009). When urban planners and designers make design decisions, they need to use this information and knowledge and complement it with "assumptions about users and use cases" (You and Tuncer, 2017). To create these assumptions, planners rely on evidence from existing places to have insights from existing situations or draw upon new visions for new planning projects. However, having evidence alone does not guarantee a successful planning outcome, since design is a complicated process with many factors influencing decision-making. Nevertheless, quantitative evidence supports the planner by grounding assumptions about use cases and by providing straightforward measures of performance.

Initial studies on pedestrian movement depended on expertise and anecdotal knowledge yet lacked actual data of these movements. For example, Jane Jacobs, in *The Death and Life of Great American Cities*, relied on her anecdotes along with some interviews and third-party sources, which lead to some critics accusing her of being unscientific (Jacobs, 1961; Marshall, 2012). Today, increased use of smartphones and fitness trackers has resulted in large volumes of publicly accessible data about people's leisure walking activities. This data is substantially different from traditional methods, both temporally (longitudinally over time) and spatially (any place in the world) (Ballagas et al., 2006). Moreover, since data from smart devices are collected passively, users carry on their usual way of living, resulting in more realistic data.

There are many different definitions of walkability, focusing on different aspects of the concept. Forsyth (2015) groups these different definitions along with three themes: "means or conditions" that are necessary for walkability, "outcomes or performance" that walkable environments bring, and walkable environments as a "proxy for better urban places". In this chapter, we aim to find out which urban environmental features bring a positive outcome for leisure walks.

With the availability of data from fitness tracking applications (FTAs), we aim to use these data to identify urban features that affect leisure walking activity. After identifying the indicators of leisure walking activity, a machine learning model was developed to predict the levels of activity in a specific location.

This chapter focuses on Singapore. Most of the walkability studies are written from European and American perspectives. This chapter offers a different interpretation, with Singapore being an Asian, well-planned, active, tropical, and "garden-city" state (Briffett et al., 2004; Tan, 2006; Urban Redevelopment Authority, 2007). These features are not common in previous studies, which predominantly focus on Western, nontropical contexts.

This chapter is organized as follows:

- In "Leisure walk" section, we discuss the urban features affecting leisure walking behavior.

- "Methodology and data" section introduces data and methodology to verify the effect of these features.
- "Results" section provides the results of the study.
- "Destinations" section involves a discussion of urban features with respect to the obtained results.
- Finally, in "Conclusion and future work" section we conclude and present future opportunities.

Leisure walk

A "leisure walk" is defined as a walk that is not utilitarian, meaning it is not performed to fulfill a task such as shopping or commuting to work. The reasons for leisure walks can be for exercise, to relax, or to socialize, all of which will benefit the general well-being of the person. For this work, a leisure walk is any walking activity that is tracked with a sports tracker, and it includes running, walking, fitness walking, hiking, and jogging.

A leisure walk in the built environment follows very similar associations with the urban setting as utilitarian walking. However, there are some unique considerations for leisure walk activity. First, in leisure walking, the person does not generally have a fixed destination. Second, leisure walkers tend to choose a route that makes them feel more comfortable (Choi, 2013), therefore, by checking the routes of urban residents, it is possible to see which spaces are preferable for walking activity. There is evidence that people become involved in physical activity in a setting supporting it.

In the literature, six topics of indicators are validated to be tested in this work: destination and diversity, naturalness, street typology, perception, population density, and amenities.

Destination and diversity ensure there are plenty of locations to walk to and from, which increases the possibility of walks occurring. Cervero and Kockelman (1997) mention the effects of density, design, and diversity (3D's) on walkability, and Ewing and Cervero (2010) added destinations and distance over the original 3D's. There is a substantial amount of research done showing balanced land use increasing walkability levels both for utilitarian walking and recreational walking (Brown et al., 2009; Van Dyck et al., 2010; Yamada et al., 2012). In this study, we focused mainly on two types of spaces, residential and recreational, to find out how the mix of two spaces affects leisure walking activity.

Humans have evolved to have an affection for nature and living things as stated in the Biophilia hypothesis by biologist Edward O. Wilson (Wilson, 1984). Therefore, it is not surprising that one of the most accepted indicators that are agreed to increase walkability levels is the naturalness of the surrounding environment. In the work of Ode Sang et al. (2016), high perceived naturalness generated more activities, higher aesthetic values, and well-being of residents in the vicinity of urban green spaces. The concept of naturalness is used interchangeably with green spaces in urban studies. However, there might be other elements, such as water elements, that make a person perceive naturalness in an area.

Street types strongly affect leisure walking as some street configurations do not allow for comfortable running. For example, highways have fast-flowing traffic and might be dangerous, whereas service roads, generally, lack comfortable sidewalks and might be crowded with delivery trucks during the day. In Singapore, park connectors are roads that are often used for leisure activities.

Although the physical features of the streets play an essential role in making streets more conducive to walking, the perception of the features by pedestrians is just as crucial. To measure perception is a difficult task as it generally involves many different factors. This phenomenon was examined by Ewing and Handy (2009), where they checked how objective features are perceived by the people, which in turn affects their walking behavior.

One crucial indicator for a walkable neighborhood is sufficient population density. For a neighborhood to be walkable, there needs to be a certain amount of people to interact with. Although it depends on the urban form, a population density in the range of 5000–10,000 people per square kilometer is required (Alexander, 1965).

Finally, amenities such as means of transportation to an area, the availability of water fountains, and light sources for the walks at night increase the willingness of the residents to engage in a leisure activity in an area. These six indicators will be investigated with the data to find correlations between them and leisure walk activity.

Methodology and data

Data

In this study, the dependent variable is the number of leisure walks that occurred in a specific area. FTA data is the primary source of data for determining the number of leisure walks in an area. FTAs work by recording the movements of a person during an activity. After users finish their workout, their devices automatically upload data regarding their workout to a database. Workouts are recorded in a sequence globally. Therefore, it is possible to make a script that loops through workout numbers and scrapes this data into a file. Workouts are only accessible if the user chooses to store them publicly. FTA data can be collected using mobile phones, smartwatches, or pedometers. These devices can collect data from various sports activities, along with the GPS track of the person during the activity (provided that the activity is done outdoors or that the user's device has GPS capability). From these activities, only fitness walking, hiking, running, trail running, and walking are considered as leisure walking in the context of this work.

Any study using an external data source has some inherent error or limitation on the representation of the whole population. This study uses a sample of people: those using Endomondo as a personal FTA and listed as living in Singapore (on Endomondo). This sample will have some degree of bias; there are several factors such as ownership of a smartphone, interest in recording workouts, or willingness to share data publicly using Endomondo that influence the overall results. Additionally, the number of workouts gathered for this study does not qualify as big data. However, the amount of data is enough to make inferences regarding the leisure walking activity in Singapore. In the future, we could gather more data in Singapore by developing a better scraper algorithm. We only scraped workouts from Endomondo users listed as living in Singapore, as scraping all Endomondo data and checking for workout location proved too data-heavy at that time. It is probable that many Endomondo users (including Singaporean users) do not set their location in the user settings. The gathered data is first anonymized for the protection of the identity of the users and then cleaned of erroneous data.

The independent variables are aggregated into 400×400 m grid cells that covers the city of Singapore. Different cell sizes ranging from 100×100, 200×200, 400×400, and 800×800 m were tried for the study, and the best results are acquired when using 400×400 m for the cell sizes.

To consider the effect of six indicators of leisure walking, we collected data from various sources. First, to check the effect of destination and diversity, we collected land use data from data.gov.sg, which is the open data portal of the Singapore government. The land use types of plots are gathered in five categories: residential, recreational, business, commercial, and others. We used two different types of entropy index: land use mix and recreational land use mix, ranging from 0 (homogenous use) to 1 (equally distributed use). A normalized Shannon score is used to represent the land use mix, calculated by Eq. (13.1):

$$LUM = -\sum_{i=1}^{k} \frac{P_i \times \ln(P_i)}{\ln(k)} \tag{13.1}$$

where k refers to the number of land use categories and P_i is the ratio of each land use category in a grid cell (Frank et al., 2004). In the land use mix, we considered four different land use categories, whereas in the recreational land use mix, we considered only recreational and residential land use to focus on how varied use of green space in a residential area affects leisure walking behavior.

An often-used method to quantify the ratio of vegetation in an area is a vegetation index. It was created to monitor the differences in vegetation levels with climate changes using satellite remote sensors. Normalized Difference Vegetation Index (NDVI) works with the principle of light reflection. Plants reflect a different spectrum of light than manmade objects. Satellite images capturing reflected light from an area can be used to measure the amount of the near-infrared light to indicate the amount of vegetation on that area (Weier and Herring, 2000).

The results of NDVI measurement can range from −1 to 1. A negative value indicates that a body of water is present in the location. The value becomes less as the body of water becomes deeper. Positive values indicate land. Very low positive values (0.1 and below) mean rock, sand, or manmade structures like buildings. Values in the range of 0.2–0.3 indicate grassland and shrubs, 0.3–0.5 indicate forests, and 0.6–0.8 indicate temperate and tropical rain forests. We took images from the Landsat 8 satellite (USGS, n.d.).

To investigate the effects of street types on leisure walk activity, streets should be separated by type. Instead of Singapore's Land Transport Authority's (LTA) road classification, since we are using OpenStreetMap (OSM) data for urban street networks, we used OSM highway tags (Table 13.1). An additional benefit of using OSM road types is that it is possible to compare any other city with Singapore by using the same road types in the future. The roads are tagged with road types as listed in the table.

To quantify the perceived urban environment, images from GSV were collected and the features of that point were extracted using machine learning tools. First, we divided the whole public space network of Singapore according to its typologies as defined in OSM. Some of these typologies are only human accessible. Some of them, like service roads, have many segments, but they receive fewer walks, therefore, to keep the model within a reasonable number of points, we did not include them. We selected four typologies to inspect with GSV images: residential, primary, secondary, and tertiary.

TABLE 13.1 Road types tagged in highway field in OSM.

Road class	Road type
Principal tags (listed from most to least important)	Motorway
	Trunk
	Primary
	Secondary
	Tertiary
	Unclassified
	Residential
	Service
Link roads	Motorway link
	Trunk link
	Primary link
	Secondary link
	Tertiary link
Special roads	Living street
	Pedestrian
	Track
	Bus guideway
	Escape
	Raceway
	Road
Paths	Footway
	Bridleway
	Steps
	Path

The next phase is to extract features from the images saved during the previous phase. For this purpose, we used Tensorflow, a deep learning framework developed by Google (Abadi et al., 2016). Deep learning starts with the training of the algorithm. A labeled dataset is needed for training and to evaluate the training. Creating a dataset for training a deep learning algorithm requires the annotation of many images taken from the same context. This task needs human processing time. On the other hand, there are ready datasets that include labeled data, and we used Cityscapes as our dataset as it holds more labeled data taken from different European cities at different times of the day. Ideally, the deep learning algorithm should be trained with images from the actual network. However, this requires manual labeling of hundreds of images. The use of images from European cities gave an accuracy of around 0.9, which proved sufficient in successfully identifying areas.

Cityscapes has 29 different labels for different features that can be found in a GSV image. Some of the features are rarely present in GSV images, such as caravan, which represents caravan-type vehicles; therefore, they are not included in the model. On the other hand, some features like car, human, etc. depend on the time the photos are accessed, so they cannot be used in the model. After initial trials, we included road, sidewalk, building, vegetation, terrain, and sky in the model. Vegetation represents trees in the images. Terrain represents open grounds, generally with grass.

All the GSV images that are prepared for feature extraction are loaded into the Tensorflow model trained with the labeled data. This model extracts the mentioned features from the images. An example of extracted features can be seen in Fig. 13.1. After extraction, a Python script calculates the percentage of the pixel classes for each image. In the end, for all the grid cells, we take the mean of all percentages of different features and come up with a score for each feature for each grid cell.

FIG. 13.1 Google Street View image. GSV image in the background; the foreground colors is the classified image with the labels. *No permission required.*

Spatial regression

To explore the effects of each indicator on leisure walking behavior, we developed a regression model. However, an ordinary regression model will not work; as in a grid setup, the values of neighboring cells correlate to the values of their neighbors since areal features have a continuity (Arbia, 2014) and their values are like their neighbors'. There are different methods to include spatial information of neighboring cells. And finally, if the residuals of a cell affect the residuals in a neighboring cell, this case is named spatial autocorrelation. In this case, the equation is:

$$\gamma = \sum_{k=1}^{n} \beta_k X + u$$

$$u = \lambda W u + \varepsilon$$

where y is the number of leisure walks that occurred in the grid cell, which is also the dependent variable; k is the regression coefficient for each independent variable X; u is the spatially lagged error; W is the weight matrix; λ is the spatial error coefficient; and ε is the uncorrelated error. We used queen-type spatial correlation, which means all the neighboring grid cells are included in the weight matrix, provided there is a leisure activity (Arbia, 2014). Therefore, all regression models that are defined in a spatial configuration must be checked for the effect of spatial relationships. To check spatial dependency, models are checked against a hypothetically randomly distributed model of the same size. This check is Moran's I (Anselin, 2013). In Moran's I, a value of one indicates values are clustered spatially, zero indicates randomness, and minus one means dispersed values. Our model has a high positive value, meaning they are spatially dependent.

Neural networks

We used a machine learning model to predict the level of leisure walking activity in a selected grid cell, given the values of parameters studied in the analysis part. Neural networks (NN) are used as the machine learning model, which simulates the working mechanism of a biological neuron. NNs have three layers: the input layer, the hidden layers, and the output layer. NNs work by manipulating input variables with mathematical operations in the hidden layer to successfully estimate the value of the output layer.

Results

The dataset used in this chapter consists of 30,853 leisure walks collected from an FTA called *Endomondo* (Fig. 13.2). These are leisure walks with a speed slower than 30 km/h, distance longer than 1 km, but shorter than 50 km as classified as one of the activities we consider leisure walking. The data reports 613 users. The user with the maximum number of leisure walk activities has 2150 activities. However, 566 users have less than 200 leisure activities.

In the Spatial Durbin Model, the rho value is 0.736 (Table 13.2). This implies that, when observing a particular cell, if its neighboring cells have an average number of runs of, for

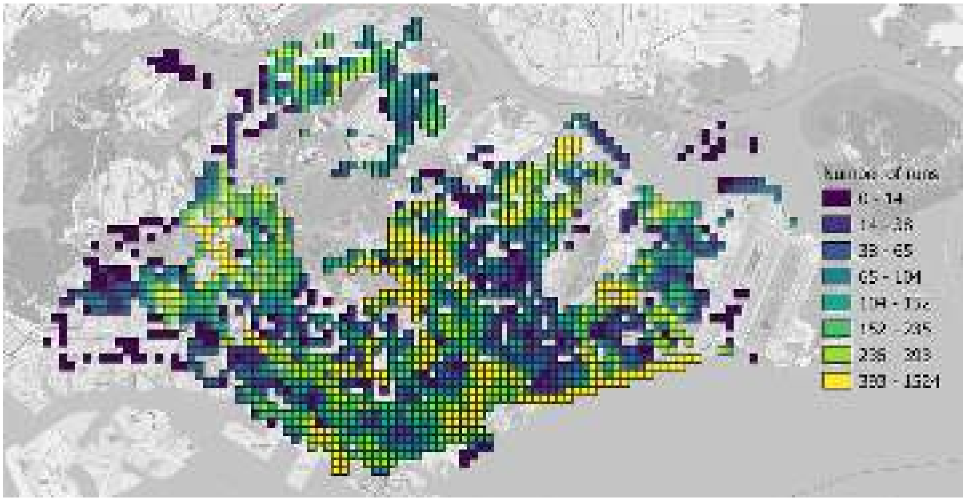


FIG. 13.2 Leisure walk—grid 400. Leisure walk activity in a 400 m × 400 m grid. *No permission required.*

TABLE 13.2 Spatial Durbin model of the leisure walk behavior for 400 m × 400 m grid cells

Variable	β	Sign.	θ	Sign.
Land use				
Recreational ratio	0.2643	0.1063	−0.08146	0.77654
Residential ratio	−0.0307	NA	0.02439	NA
Business ratio	0.2442	0.10512	−0.59889	0.00532
Recreational land use mix (entropy)	0.3556	2.919E−07	0.04656	0.67903
Street				
Traffic lights	0.0029	0.03499	−0.00498	0.08200
Bus stops	0.1048	1.437E−13	−0.04730	0.12469
Amount of road type				
Motorway	−0.00020	0.01579	−0.00023	0.11605
Primary	0.00025	2.693E−06	−0.00027	0.00545
Unclassified	−0.00016	0.04986	−0.000009231	NA
Residential	−0.00016	0.00018	0.000018	NA
Cycleway	0.00121	<2.2E−16	−0.00060	0.00036

Continued

TABLE 13.2 Spatial Durbin model of the leisure walk behavior for 400 m × 400 m grid cells—cont'd

Variable	β	Sign.	θ	Sign.
Footway	0.00018	6.393E−06	0.00004	0.54462
Path	−0.00009	0.25115	0.00022	0.14556
Amenities				
Street lights	0.00483	4.349E−06	−0.00178	−0.45561
Trees on streets	0.00043	0.0303	−0.00018	0.75433
Densities				
Greenness	0.42535	0.35899	−0.74773	0.32751
Water feature	−0.00049	0.19979	0.00027	NA
Population density	−0.00023	NA	0.00031	NA
Intercept	0.6724	7.199E−07		
Rho	0.73672			
AIC	8102.6			
Pseudo *R*-squared	0.60803			

No permission required.

example, 100, it is expected that around 73 leisure walks will happen in the observed cell without the effect of any parameter. In other words, regardless of the qualities of an observed cell, 73% of the runs occurring in its neighbors will also take part in the observed cell.

Next, the impacts table shows the direct (local effect), indirect (effect of the neighboring cells), and the total of both effects for a unit change in each variable (Table 13.3).

TABLE 13.3 Direct (local) and indirect (spill-over from neighboring cells) and total effect of a unit change in each of the predictor variables

Variable	Direct	Indirect	Total
Land use			
Recreational ratio	2.88E−01	0.40587	6.94E−01
Residential ratio	−3.03E−02	0.00642	−2.39E−02
Business ratio	1.55E−01	−1.50122	−1.35
Recreational land use mix (entropy)	4.21E−01	1.10560	1.53
Street			
Traffic lights	2.32E−03	−0.01013	−7.81E−03
Bus stops	1.11E−01	0.10725	2.18E−01
Amount of road type			
Motorway	−2.84E−04	−0.00135	−1.63E−03

TABLE 13.3 Direct (local) and indirect (spill-over from neighboring cells) and total effect of a unit change in each of the predictor variables—cont'd

Variable	Direct	Indirect	Total
Primary	2.35E−04	−0.00031	−7.37E−05
Unclassified	−1.91E−04	−0.00046	−6.57E−04
Residential	−1.834E−04	−0.00036	−5.44E−04
Cycleway	1.28E−03	0.00106	2.34E−03
Footway	2.20E−04	0.00062	8.39E−04
Path	−6.85E−05	0.00052	4.56E−04
Amenities			
Street lights	5.21E−03	0.00638	1.16E−02
Trees on streets	4.67E−04	0.00051	9.80E−04
Densities			
Greenness	3.33E−01	−1.55625	−1.22
Water feature	−5.15E−04	−0.00032	−8.40E−04
Population density	−2.07E−04	0.00049	2.90E−04

Destinations

The influence of destinations and land use recreational areas positively affect the number of leisure walks. For example, a 10% change in recreational area ratio increases the number of leisure walks by 6.9%. This is expected, as most leisure walks occur in recreational areas. On the other hand, residential and business areas negatively affect leisure walking activity; a 10% increase of the residential and the business are ratio decreases the number of walks by 0.23% and 13.5%, respectively. There is a strong decrease in the number of leisure walks in areas designated as business. In the case of Singapore, this can be because business areas are often in peripheral locations, or there are external conditions in those areas such as traffic, pollution, and noise. Like previous models, the strongest connection occurs in the case of recreational land use mix; a 10% change increases the number of leisure walks by around 15%.

Walkability studies focus heavily on destinations (Cervero and Kockelman, 1997). The effect of destinations in leisure walks is assumed to be simpler. To examine the dependence on destinations, we included different land use in the models. Recreational land use has a significant effect in all the models. The rest of the land uses, business, commercial, and residential, have no significant effect. Also, from the recorded 202 million meters of leisure walks, 87 million meters of the walks occurred in land plotted and allocated for recreation. This high percentage and our finding of a significant positive correlation of recreational areas on leisure walks in the grid-based analysis confirms the importance of recreational areas as destinations for leisure walks. On the other hand, different from utilitarian walking, we did not observe any influence of the other land use areas.

The lack of effect of the commercial and business land use areas also undermined the land use mix, which is widely used in walkability. In our models, we did not observe any positive effect land use mix. However, the modified land use mix value, which includes only residential and recreational areas in the entropy value and excludes other land uses, provided much better results in the model. The significance of recreational land use mix points out an area that consists of entirely recreational land plot is probably out of human reach, whereas an area that is entirely residential offers too little space for activity. The balance between these two land use areas accommodates better use for leisure walks.

Naturalness has a more complicated relationship with leisure walks. The amount of trees does not have an effect on leisure walks. However, NDVI greenness value has a strong negative relationship, a 10% increase on NDVI greenness score decreases the number of leisure walks by 12%. This negative effect might be caused by the fact that areas with higher NDVI scores are empty plots far from residential centers.

Naturalness is an important feature for recreational activities. However, generating a score for naturalness is not an easy task. We tried three different ways to inspect the effect of naturalness on leisure walks. Satellite-based greenness value was used and found to be significantly positive in correlation. Additionally, water features were positively correlated in the bigger grid cells. Water features are generally located in big parks and in canals next to the park connectors. Therefore, this is expected to have a positive effect.

Road typology affects leisure runs in two ways. Unsurprisingly, roads that are higher in hierarchy receive fewer leisure walks, as they are noisy, less secure, and less comfortable. Most of the leisure walks happen on roads that are only accessible by pedestrians and bicycles. The amount of primary, unclassified, and residential motorways decreases leisure walks, whereas cycleways, footways, and paths increase it.

Certain typologies receive more leisure walks than others. The most prominent feature is the cycleway road type. Cycleways in Singapore include park connectors; therefore, it is not unexpected to find a big beta value for cycleways. The data in hand confirms that the goal of covering Singapore with parks and connecting them to the dense residential areas with park connectors is positively influencing residents by encouraging them to use these for leisure walks.

In our models, higher tier road types had differing effects on leisure walks. Mostly, they do not affect leisure walk behavior. However, especially in longer walks, trunk and primary roads are observed to have a positive effect on the leisure walk.

Signalized intersections do not have much effect on the overall amount of leisure walk activity. Increasing the amount of traffic signals by 10% decreases the amount of leisure walks slightly by 0.08%. Inspecting the coefficients, it is possible to observe that the local effect is positive for traffic lights, which might indicate roads with better connections and safety from traffic.

The number of bus stops has a profound effect on the leisure walk activity. The model shows a 10% increase in the number of bus stops increases the amount of leisure walks by 2.2%. This confirms the previous analyses and is a good indication of the effect of transportation availability on leisure walks.

The number of streetlights has a slightly positive effect; with a 10% change in the number of streetlights, the amount of leisure walks increases by 0.11%. This effect is stronger in activities performed at nighttime.

Lastly, population density has a slight positive total influence on the amount of leisure walks. Inspecting its localized effect, there is a negative influence probably because fewer leisure walks happen in crowded areas. However, population density of neighboring cells positively influence leisure walking activity as some humans need to have some leisure walking activity.

Finally, all the features are scaled to show which features have more effect on the leisure walking behavior. According to the scaled Spatial Durbin model (Table 13.4), the amount of cycleway-type roads has the highest impact on the amount of leisure walking. It is followed

TABLE 13.4 Scaled Spatial Durbin model of the leisure walk behavior for 400 m × 400 m grid cells.

Variable	β	Sign.	θ	Sign.
Land use				
Recreational ratio	0.058	0.0066111	−0.020	0.4091902
Residential ratio	−0.0001	0.5543044	−0.002	NA
Business ratio	0.035	0.0480567	−0.083	0.0013434
Recreational land use mix (entropy)	0.086	2.050E−08	0.010	NA
Street				
Traffic lights	0.035	0.0223404	−0.060	0.0124655
Bus stops	0.118	1.201E−13	−0.054	0.0891218
Amount of road type				
Motorway	−0.034	0.0186063	−0.039	0.1031357
Primary	0.067	1.931E−06	−0.073	0.0025256
Unclassified	−0.024	0.8521	−0.002	0.6234093
Residential	−0.064	0.0001922	0.007	NA
Cycleway	0.168	<2.2E−16	−0.083	0.0006416
Footway	0.068	3.842E−06	0.014	0.5703057
Path	−0.016	0.2121247	0.036	0.2129856
Amenities				
Streetlights	0.111	5.548E−08	−0.041	0.1885274
Trees on streets	0.053	0.0039382	−0.022	0.5053441
Densities				
Greenness	0.022	0.2983943	−0.043	0.1344342
Water feature	−0.012	NA	0.006	NA
Population density	−0.009	NA	0.012	NA
Intercept	−0.017	0.1317712		
Rho	0.73667			
AIC	5468.1			
Pseudo *R*-squared	0.60605			

by bus stops, streetlamps, recreational land use mix, amount of footway, and primary type of roads. It is negatively affected by the amount of residential type of roads. These results confirm the previous models.

Transport availability is an important feature for walkability. For leisure walks, in the grid-based model, bus stops were positively correlated for leisure walks. However, MRT stations did not have a significant effect. Average distance from start of the walks to the nearest bus stop was 157 m; similarly, the average distance from the ending points of the walks to the nearest bus stop was 166 m. Although it is expected that some of the leisure walkers arrive at recreational areas by public transportation, it is hard to read this information from the data. Also, the reason of the positive effect of bus stops might be because they are located in well-connected locations.

In this study, the results we obtained are specific to Singapore. Especially residents' preference of different road types for leisure walk is different in different cities. Every city has its organization of different typologies of roads. Unsurprisingly, in Singapore, most of the leisure walks happen over Park Connectors that are tagged as Cycleways in OSM. As mentioned previously, in Singapore, these roads are explicitly planned for leisure activities and active transportation. From the results, we can conclude, in Singapore, urban planners were successful in including Park Connectors for their residents to be more active. Notably, there are future plans to extend the park connector network.

Similarly, extensive coverage of well-maintained parks in Singapore showed up in the results as the primary destination of leisure walks. However, some locations received more leisure walks than others. This phenomenon is partly explained by recreational land use mix value, which is higher for areas that have a good mixture of recreational and residential areas. Some parks can be reached from dense residential areas while others cannot.

Conclusion and future work

Understanding how residents use public spaces during leisure walking is fundamental to create a network of spaces that will increase the willingness of residents to engage in more walks. Increased levels of walking will enhance the life quality of residents by improving their health and mental state. This understanding needs "well-validated, durable criteria for successful outcomes" (Talen and Koschinsky, 2013). In this chapter, we aimed to use FTA data to quantify the effect of some physical features on leisure walking. This study also examined if indicators of utilitarian walkability hold for leisure walks, and we showed some of these indicators apply for leisure walks, whereas some of them have no significant effect. In this section, as a closing discussion, we gathered the results and discussed how they affect urban planners' understanding of space requirements for leisure walking.

Most importantly, this research focuses on Singapore. Most of the walkability studies are written from European and American perspectives. This study offers a different interpretation with Singapore being an Asian, well-planned, active, tropical, and "garden-city" city-state. These features of Singapore are not common in previous studies, and for this reason, this study brings novelty into the literature.

First, the methodology devised in this study provides a novel approach to utilize data sourced from a multitude of sources. Referring to the discussion of evidence sources for urban planning studies, this study used big data as a source of evidence, which provided the potential advantage of capturing more leisure walks and in a larger area. Scraping data from the web eliminates the need for finding volunteers for a study, which can be costly and hence debilitating for the breadth of scale. In this study, we used FTA data as the source of traces of leisure walks. However, scraping of the web can be used for creating data out of many different sources such as social media or GSV images.

The investigation of leisure walks over a public space network aimed to find out how the configurations of roads enabled leisure walking. Additionally, a more precise investigation was conducted of the amenities and the perception of streetscapes by using GSV images.

This research confirmed the effect of recreational areas as destinations, recreational land use mix, naturalness, and certain road types on leisure walks and disproved some widely discussed features such as urban configurations. This research offered a possibility of offering some inferences on the movements of the residents of Singapore. However, these results are not causal. The reasons for residents taking cycleways, for example, are not captured in this research. To confirm the validity of the results and deepen the understanding of leisure walking behavior, the movement traces of residents should be supplemented with interviews.

Although this research captures some insights into the behavior of urban residents during their leisure walks, it is not always possible to create a positive environment for certain behaviors. For example, in Singapore, space is often the limiting factor. Although park connectors have a strong effect on leisure walks, it is not possible to offer each neighborhood a park connector. However, even small changes can offer an increased rate of leisure walks, which can improve the overall healthiness of cities.

Concomitant to the increased use of smart devices in the daily life of residents, it is now possible to collect data to assess the use of urban spaces by residents on a much broader scale, which was never possible before. This will allow urban planners and designers to understand how residents use certain places for leisure walks.

At the time this study started, fitness tracking apps were used to track the data of workouts, which the user specifically wanted to record. Some other daily activities were not being recorded. Because of this, the collected data has many gaps. In a short time, devices that continuously collect data from movements of the residents become popular. Today, these devices are widely used by many that offers an almost unlimited amount of evidence for planners. Although the big data approach offers an almost unlimited data source in capturing peoples' movements, we needed to limit our study with a reasonable number of observations of leisure walks. The reasons for this limit were the lack of computational power and lack of time and resources. With more resources, it is possible to repeat the study with more data, which will offer better resolutions.

We can further improve this study by making comparisons with different cities. Singapore is a city-state that offers a well-designed environment for active people. Comparisons with cities that are older, less centrally controlled, less active, and with different climates will point toward different features being more fundamental for leisure walk activity. For example, in a city where safety is an issue, residents might avoid parks, especially during nighttime (Doran and Burgess, 2011).

Last and most importantly, in this study, the results are associative but not causal for the relationship between the features and leisure walk activity. For example, in the results, the effect of greenness is found to be complicated. It is not possible to know how greenness affects leisure walking from the data; it can be due to its aesthetic appeal or calming of the environment. If residents prefer green areas for aesthetic qualities, then the density of green areas will be less relevant. To include causality, we need to have null-conditions to evaluate the complicated relationship of the features for leisure walking, which is hard to have in urban studies. However, through time and by performing cross studies that involve many different cities and by including user feedback, urban planners will become more informed about the effect of urban features over leisure walks.

References

Abadi, M., et al., 2016. Tensorflow: a system for large-scale machine learning. In: 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16).

Alexander, C., 1965. The city ls not a tree. In: Arrlritectuml Forum I.

Anselin, L., 2013. Spatial Econometrics: Methods and Models. Springer Science & Business Media.

Arbia, G., 2014. A Primer for Spatial Econometrics: With Applications in R. Springer.

Ball, K., et al., 2001. Perceived environmental aesthetics and convenience and company are associated with walking for exercise among Australian adults. Prev. Med. 33 (5), 434–440. Elsevier.

Ballagas, R., et al., 2006. The smart phone: a ubiquitous input device. IEEE Pervasive Comput. (1), 70–77. IEEE.

Beaglehole, R., et al., 2011. Priority actions for the non-communicable disease crisis. Lancet 377 (9775), 1438–1447. Elsevier.

Boarnet, M.C., Takahashi, L.M., 2011. Interactions between public health and urban design. In: Companion to Urban Design. Routledge, London and New York, pp. 198–207.

Booth, M.L., et al., 1997. Physical activity preferences, preferred sources of assistance, and perceived barriers to increased activity among physically inactive Australians. Prev. Med. 26 (1), 131–137. https://doi.org/10.1006/pmed.1996.9982.

Briffett, C., et al., 2004. Green corridors and the quality of urban life in Singapore. In: Proceedings 4th International Urban Wildlife Symposium.

Brown, B.B., et al., 2009. Mixed land use and walkability: variations in land use measures and relationships with BMI, overweight, and obesity. Health Place 15 (4), 1130–1141. https://doi.org/10.1016/j.healthplace.2009.06.008.Mixed.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. Part D: Transp. Environ. 2 (3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6.

Choi, E., 2013. Understanding walkability: dealing with the complexity behind pedestrian behavior. In: Proceedings of the Ninth International Space Syntax Symposium, p. 14. Available at: http://www.diva-portal.org/smash/record.jsf?pid=diva2:677835.

Doran, B.J., Burgess, M.B., 2011. Putting Fear of Crime on the Map: Investigating Perceptions of Crime Using Geographic Information Systems. Springer Science & Business Media.

Edwards, P., Tsouros, A., 2006. FACTS Promoting Physical Activity and Active Living in Urban. World Health, p. 66. Available at http://www.euro.who.int/document/e89498.pdf.

Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76 (3), 265–294. https://doi.org/10.1080/01944361003766766. Routledge.

Ewing, R., Handy, S., 2009. Measuring the unmeasurable: urban design qualities related to walkability. J. Urban Des. 14 (1), 65–84. https://doi.org/10.1080/13574800802451155.

Forsyth, A., 2015. What is a walkable place? The walkability debate in urban design. Urban Des. Int. 20 (4), 274–292. Springer.

Frank, L.D., Andresen, M.A., Schmid, T.L., 2004. Obesity relationships with community design, physical activity, and time spent in cars. Am. J. Prev. Med. 27 (2), 87–96. https://doi.org/10.1016/j.amepre.2004.04.011.

Frank, L.D., Kavage, S., 2008. Urban planning and public health: a story of separation and reconnection. J. Public Health Manag. Pract. 14 (3), 214–220. LWW.

Gehl, J., 2011. Life Between Buildings: Using Public Space. Island Press.

Giles-Corti, B., Whitzman, C., 2012. Active living research: partnerships that count. Health Place 18 (1), 118–120. Elsevier.

Handy, S.L., et al., 2002. How the built environment affects physical activity: views from urban planning. Am. J. Prev. Med. 23 (02), 64–73. https://doi.org/10.1016/S0749-3797(02)00475-0.

Hoehner, C.M., et al., 2003. Opportunities for integrating public health and urban planning approaches to promote active community environments. Am. J. Health Promot. 18 (1), 14–20. SAGE Publications Sage CA: Los Angeles, CA.

Jacobs, J., 1961. The Death and Life of Great American Cities. Random House.

Koohsari, M.J., Badland, H., Giles-Corti, B., 2013. (Re)Designing the built environment to support physical activity: bringing public health back into urban design and planning. Cities 35, 294–298. https://doi.org/10.1016/j.cities.2013.07.001. Elsevier Ltd.

Krizek, K., Forysth, A., Slotterback, C.S., 2009. Is there a role for evidence-based practice in urban planning and policy? Plan. Theory Pract. 10 (4), 459–478. Taylor & Francis.

Marshall, S., 2012. Science, pseudo-science and urban design. Urban Des. Int. 17 (4), 257–271. Springer.

Ode Sang, Å., et al., 2016. The effects of naturalness, gender, and age on how urban green space is perceived and used. Urban For. Urban Green. 18, 268–276. https://doi.org/10.1016/j.ufug.2016.06.008. Elsevier GmbH.

Speck, J., 2012. Walkable City: How Downtown Can Save America, One Step at a Time. Farrar, Straus and Giroux.

Talen, E., Koschinsky, J., 2013. The walkable neighborhood: a literature review. Int. J. Sustain. Land Use Urban Plann. 1 (1), 42–63. https://doi.org/10.24102/ijslup.v1i1.211.

Tan, K.W., 2006. A greenway network for Singapore. Landsc. Urban Plan. 76 (1–4), 45–66. https://doi.org/10.1016/j.landurbplan.2004.09.040.

Urban Redevelopment Authority, 2007. Annual Report 2006–2007. Available at: https://www.ura.gov.sg/-/media/Corporate/Resources/Publications/Annual-Reports/PDFs/AnnualReport_2006-2007.pdf.

USGS, n.d. Earthexplorer. Available at: https://earthexplorer.usgs.gov/.

Van Dyck, D., et al., 2010. Neighborhood SES and walkability are related to physical activity behavior in Belgian adults. Prev. Med. 50 (Suppl), 74–79. https://doi.org/10.1016/j.ypmed.2009.07.027.

Weier, J., Herring, D., 2000. Measuring Vegetation (NVDI & EVI). NASA Earth Observatory, Washington, DC.

WHO, 2009. Global health risks: mortality and burden of disease attributable to selected major risks. Bull. World Health Organ. 87, 646. https://doi.org/10.2471/BLT.09.070565.

WHO, 2010. Global Forum on Urbanization and Health. Available at: http://www.gfuh.org/docs/WHO_UrbanForumReport_web.pdf.

Wilson, E.O., 1984. Biophilia. Harvard University Press, Cambridge, MA.

Yamada, I., et al., 2012. Mixed land use and obesity: an empirical comparison of alternative land use measures and geographic scales. Prof. Geogr. 64 (2), 157–177. https://doi.org/10.1080/00330124.2011.583592.

You, L., Tuncer, B., 2017. Informed design platform: interpreting 'big data' to adaptive place designs. In: IEEE International Conference on Data Mining Workshops, ICDMW, pp. 1332–1335, https://doi.org/10.1109/ICDMW.2016.0197.

This page intentionally left blank

CHAPTER

14

Spacemaker.Ai: Using AI in developing urban block variations

Jeffrey Landes

Autodesk Spacemaker.ai, Cambridge, MA, United States

It has always been the nature of technology to prioritize speed and efficiency. The spinning jenny, an invention emblematic of the Industrial Revolution, mechanized mass production of the cotton industry, allowing cloth workers to work up to eight times faster. More recently the progression of Moore's law—which observes the doubling of transistors in a dense microchip every 2 years—has computers working at an ever-increasing speed thereby allowing for such technologies as streaming and digital cameras to become ever more pervasive.

What, then, are the implications when technology and artificial intelligence collide with design, specifically architectural and urban design? After all, design requires careful, deliberate consideration and applies numerous fields within a single domain. Furthermore, the architecture, engineering, and construction (AEC) space is so complex that speed in and of itself is not enough to mechanize an industry in which abstract reasoning dominates. These concerns influence many conversations and applications in generative design, wherein machines—including artificial intelligence systems—produce designs (Fig. 14.1).

Over the past decade, the design world has seen a proliferation in approaches and applications of generative design. While it is clear what has allowed this change to happen—advances in computing power and artificial intelligence—there is by no means one accepted approach to generative design. In this article, I will discuss some of the past and present methods of machine-driven design before using a case study to detail the tools driving Spacemaker's generative design engine.

Generative design

There are generally three advantages to leveraging a generative design tool in a design workflow. First and foremost, a generative design engine allows designers to observe considerably more options than ever before. Imagine the time it would take for a human to

https://doi.org/10.1016/B978-0-12-823941-4.00010-X

FIG. 14.1 Real proposal generated with Spacemaker. A project proposal by AART architects in Norway designed with the help of Spacemaker's generative design tool. *From Widing, G. (2018) Skal utvikle 70.000 kvadratmeter i Ski. Available at: https://www.estatenyheter.no/skal-utvikle-70000-kvadratmeter-i-ski/240478 (Accessed: July 9, 2021).*

draw thousands of options of a chair. A machine has no such time limitation. Another benefit of generative design involves the explicit maintenance of certain parameters. In the space of architectural design, this may include explicitly limiting building heights to accommodate for local regulations, ensuring adequate separation between buildings, or guaranteeing that a site has enough parking spaces for the number of potential inhabitants. In a traditional design workflow, it is tedious to consider all of these factors. The worst-case scenario involves a designer creating a wonderful site before finding out that it does not comply with certain regulations. The final benefit of generative design relates to the first in terms of the speed and variety it gives users: by understanding what works and what does not, designers may combine the best of different proposals to achieve more than what was originally possible.

Methods of generative design

While there are many methods for building a generative design tool—including the increasing use of neural networks—the most successful are rule-based and parametric designs.

Rule-based systems/design

Rule-based systems are computational tools in which user-curated rules define a system. Any design that conflicts with the set of rules is invalid. The generative design engine in this system will output proposals according to these rules. Accordingly the production of the rules can be finicky—a rule that mandates that a certain amount of sunlight reaches the interior of a building may limit the options considerably. On the other hand, a rule that simply requires that a building have fewer than eight stories does little to constrain the engine and may result in unvaried options.

At its conception, Spacemaker pursued a common rule-based generative design approach, which generated thousands of proposals with the press of a button. The rules included regulatory requirements and user-specified objectives. While there remain some success stories including the project shown at the top of this article, initial feedback found that it was difficult for designers to interact with this type of engine—they simply acted as critics without contributing their originality. Additionally, they were often losing their favorite part of the job: the chance to design something from scratch and materialize concepts of the mind. Finally, while some of the generated proposals did indeed perform quite well, many of them were visually unappealing or infeasible.

Parametric design

Parametric design defines a system composed of interdependent elements. These elements (or parameters) are combined with rules that govern how they interact with one another. As such, by manipulating certain elements—either manually or by injecting randomness into a system—one achieves a generative workflow that can produce a number of designs that is exponential relative to the number of parameters in the system.

A fascinating application of parametric design comes from the Spanish architect Antoni Gaudí (1852–1926) who designed the (as yet unfinished) Church of Colònia Güell by weighting interconnected strings with bullets. By altering the shape or location of a given arch in the church, the interconnected strings would influence the shape and location of surrounding arches.

While the application of parametric design has surely resulted in several beautiful buildings across the world, the interaction between components does little to prioritize the conditions of a space and may constrain the output too much by reliance on the initial parameters.

Generative design in early-phase architectural design

It is worthwhile to note that the alternative approaches to generative design produce different benefits based on the associated content: designing a chair is different from designing a building, and designing a building is different than designing a collection of buildings. What, then, does design mean at Spacemaker? Since Spacemaker's core offering focuses on early-phase design for residential building complexes, their design space involves multi-building layouts. More specifically, this includes where buildings are located, their height, and their technical feasibility in terms of associated apartment layouts and construction in the given terrain. Due to the high complexity of early-phase residential design—the developers are building many structures, not all of which are interconnected—there have not been many successful attempts at generative design in this space.

When creating a machine that can deliver realistic designs, it is generally accepted that the designer still plays a pivotal role in the final output: their architectural intuition encompasses hundreds of latent factors that contribute to a design's utility. With respect to architectural design, these factors may include perceiving how a site interacts with its surroundings, how people interact with the site, and, importantly, what the site may look like over time.

Introducing generative design tools into user workflows can be a delicate process. Specifically, there's a lot that can go wrong with a traditional one-shot approach in which users are shown only the best-performing designs. Imagine letting a machine do its magic; yet, the design that performs the best based on certain criteria does not perform well with respect to any number of intangible factors—dare I say, it's visually unappealing. Conversely imagine a designer going through thousands of generated designs before picking the best one. Is time really being saved? More importantly, are the creative impulses and skills of the designer being leveraged in an optimal way?

We will reconsider these questions when examining Spacemaker's generative design tool, but first let us consider the complementary tools that define Spacemaker's core product.

Tools at Spacemaker

Spacemaker offers many tools, which allow users to understand more about the context of their site and the quality of their designs. The software allows users to easily fetch data at a site level and draw buildings at a low level of detail. Users may then quickly understand the performance of a given design with respect to various living qualities and area statistics.

Analytical tools

The full list of analytical tools at the core of Spacemaker's product is:

Wind

The wind analysis tool measures wind velocity for a given direction and speed at the ground level of a site. Additionally, each combination of direction and speed, coupled with the pair's probability in a given region, gives a single "wind comfort" analysis across the site.

Noise

Given data regarding local traffic levels and train locations, the noise analysis will calculate noise levels across the ground of the site, as well as for each facade. This is a particularly important analysis for markets such as Norway, in which there are strict regulatory requirements regarding noise levels in new building areas.

Sunlight

The sunlight analysis measures the number of hours of sunlight reaching points along the ground and facades of a site, for a given day of the year.

Daylight

The Vertical Sky Component (VSC) analysis indicates daylight potential for points along facades. Specifically, it measures how much light from the sky reaches the facades, relative to available light on a horizontal unobstructed surface. The maximum VSC score is close to 40%.

View to area

When setting up a site, users may specify attractions, which are desirable for inhabitants to be able to view from their apartments, such as the Eiffel Tower or a specific fjord. This analysis identifies the facades within the site, which can view the given attraction(s).

View distance

This tool measures the average distance one can see from a given point along a facade.

Area statistics

Collectively, the suite of area statistics within Spacemaker's analysis tool gives information regarding how much area can be built upon or sold within a given site.

Outdoor area

This tool measures the total square meters of outdoor area (i.e., area not covered by buildings) on a site. Additionally, users may analyze the qualities of this outdoor area for many of the above analyses.

Collectively, these analytical tools (with more to come) allow users to understand the performance of a given design, which makes Spacemaker's software suitable to a generative design engine as proposals may be effectively compared to one another.

Explore—Spacemaker's generative design tool

The difficulties in Spacemaker's initial approach, described in the previous section, combined with careful consideration of the benefits of generative design, led to the reinvention of its engine toward one that focuses on user engagement and variety. Spacemaker has explored a process in which the designer still has control, yet may use the generative design tool at any point during the design process. This gives judgment to the user in order to leverage the computing power of the machine with the intuition and experience of the designer to create optimal proposals.

Spacemaker's generative design tool—named Explore—offers hundreds of proposals that a user may select and iteratively improve at their convenience. During the initial stages of the design process, users may utilize the engine to generate a variety of realistic proposals, while toward the end they may leverage the iterative improvement capabilities of the tool.

A common problem with generative design is the complexity of the design space. Even in a two-dimensional space in which we are simply devising building layouts, there are an infinite number of conceivable proposals. Many of these proposals are infeasible or excessively similar to one another. It is therefore an important consideration when designing a generative design engine to reduce the size of the design space while advancing sufficiently relevant and variant proposals. Fig. 14.2 shows a schema of Explore's workflow, which attempts to achieve the goal of variant proposals by automatically splitting a site into buildable sections that interact with one another. The split considers qualitative principles such as spatial layout and connectivity; the engine ensures adequate space between buildings and comfortable spatial interactions. Generally, the site divisions are roughly equivalent in size yet differ in shape and buildable space.

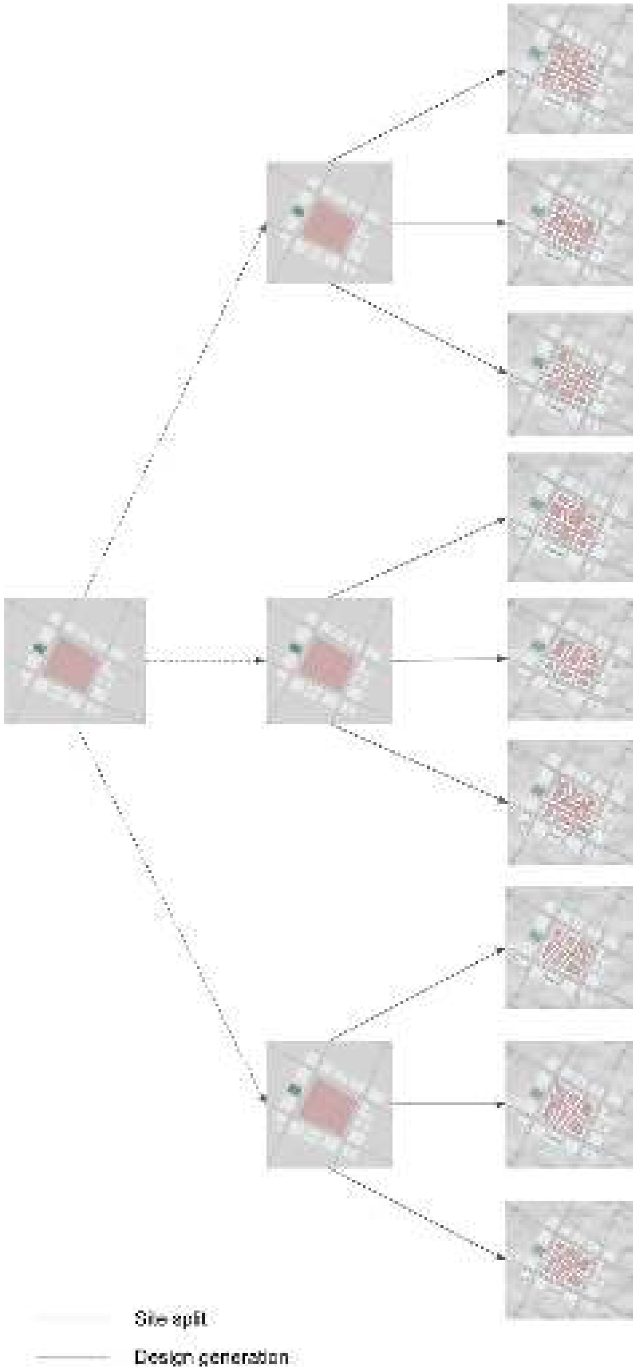


FIG. 14.2 The Explore tree. Spacemaker's generative design engine works by splitting the site in different ways before generating proposals based on layout types for each of the site splits. *No permission required.*

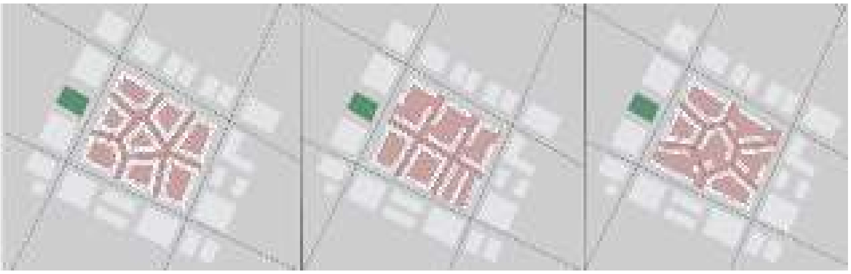


FIG. 14.3 Three different generated proposals. Each generated proposal has a different site division and correspondingly different building layouts. *No permission required.*

Fig. 14.3 shows the section splits as slightly darker lines. It is important to note the variation in section split: this variation promotes demonstrably differing site layouts, even as the building typology remains constant. Therefore, when a user considers the generated proposals, the features of negative space—that is, the undeveloped space of the site—plays equally an important role relative to the building layout. Spacemaker seeks to give designers the flexibility to incorporate design choices into the output of the generative engine by allowing users to split the site themselves.

In addition to site divisions, the Explore engine allows users to input building features such as width and height as well as the accepted distance between buildings. Finally, a user may select which layout types they wish to allow the generative design tool to output (see Fig. 14.4). This could be important if the user wants the layout to fit in with the surrounding area, say a newly developed area with ubiquitous city blocks. Alternatively, the rebellious designer may choose to limit the generated options to line buildings. Fig. 14.5 shows generated proposals with the city block layout specification.

In the remainder of this article, I will detail Spacemaker's generative design engine through a case study.

Case study

This case study considers a future city project developed by the City Development through the Design Intelligence (CIDDI) Lab, a research team exploring the development of future cities. The project (Fig. 14.6) envisages a sustainable, accessible, and smart city in the Esenler district in Istanbul, Turkey. CIDDI's team, together with the Turkish Ministry of Industry and Technology and the Ministry of Environment and Urban Planning, seek to design the district in such a way that it meets the needs of the city of the future while providing settlement for the densely populated surrounding region today.

In order to create compatible site planning for the project area, a grid distortion (Fig. 14.7) has been applied to the site area, creating a collection of nine-block superblocks. Each superblock internally prioritizes pedestrians while the collective program optimizes for connection and transportation.

For the purpose of this case study, we imagine an assemblage of developed superblocks surrounding an undeveloped superblock (in red, Fig. 14.7) in which developers plan to

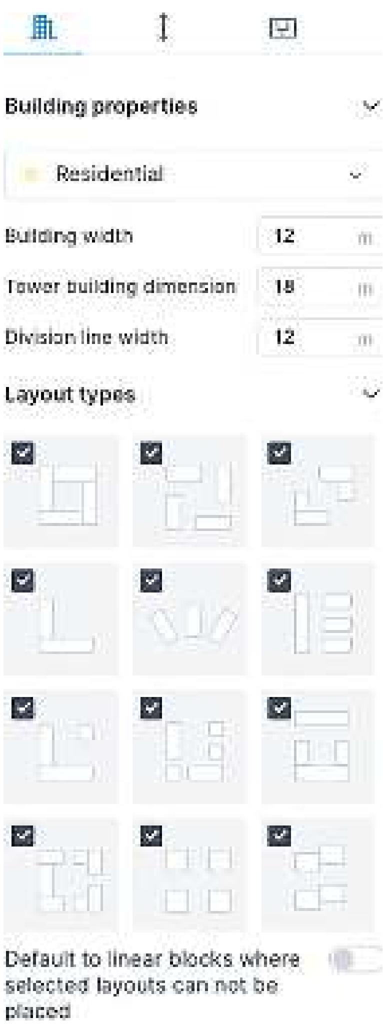


FIG. 14.4 Generative design input parameters. The user interface for inputs to the generative design engine. *No permission required.*

develop residential housing. The superblock has a total construction area of 59,281 m^2 on which to develop.

As in most cases, the designer in this scenario wishes to please both the building developer that they work with and the future inhabitants of the buildings. More concretely, they aspire to produce a design that includes a large number of sell-able apartments (for the developer) while maintaining great living qualities, in the form of excellent daylight qualities (for the inhabitants). Let us imagine, for the sake of tangibility, that there is a daylight requirement that she wishes to meet, described in depth. (The daylight analysis used by Spacemaker calculates the Vertical Sky Component (VSC) for points along the facades. This directly measures how much light from the sky reaches the facades, relative to available light on a horizontal

FIG. 14.5 Generated city block proposals. Fifteen generated proposals, which are restricted to output city block layouts. *No permission required.*

unobstructed surface. The maximum VSC score is around 40%, and desirable scores are above 27%. The daylight requirement in this scenario, then, specifies that 80% of the facades must have a score of 27% or above.) Let us see how we can use Explore to achieve an optimal site.

Explore at work

We begin this case study by defining a section split that behaves similarly to the surrounding super-blocks—a collection of blocks defined as a three-by-three grid. Additionally, we will exclude the middle section from generation, such that it may serve as a public space (Fig. 14.8). Now that we have specified the buildable area and split up the site, we are ready to let the machine do some work.

A few minutes after pressing a big blue Generate button, dozens of cloud-based proposals will begin to populate a user's screen as in Fig. 14.9. The options will be sorted on statistics

FIG. 14.6 CIDDI Project in Istanbul, Turkey. A satellite map of the planned location for the smart city in the Esenler district in Istanbul. *No permission required.*

such as gross floor area. As they sift through these proposals, users may save sites that they like, analyzing them further at their leisure. Should they want to update the parameters of the buildings or divisions of the site, they may easily compare their favorite proposals across studies. Finally, the more fastidious designers may continue to generate additional proposals if they feel uncertain about their current options.

It is worthwhile to note that designers may choose to work with Explore for various reasons at this stage in the design process. Perhaps they are exploring the generated designs to get inspiration before they themselves start drawing. Alternatively, they are hoping to define the building layouts that function well in a given space. Let us assume for the sake of this case study that the designer is using Explore to generate proposals that they would like to seriously pursue for their site. In this example, we have found three designs that, for different reasons, we like the best. Featured in Fig. 14.10 are these three proposals, with the corresponding area statistics showing the first proposal outperforming the others.

The three images (Figs. 14.11–14.13) show each of the generated designs with the surrounding site context and more granular building details. While understanding the area statistics is undoubtedly important (especially for the developer), our overall knowledge regarding the performance of these designs remains incomplete. Specifically, we wish to study the conditions of daylight on facades in order to reach our lofty objective.

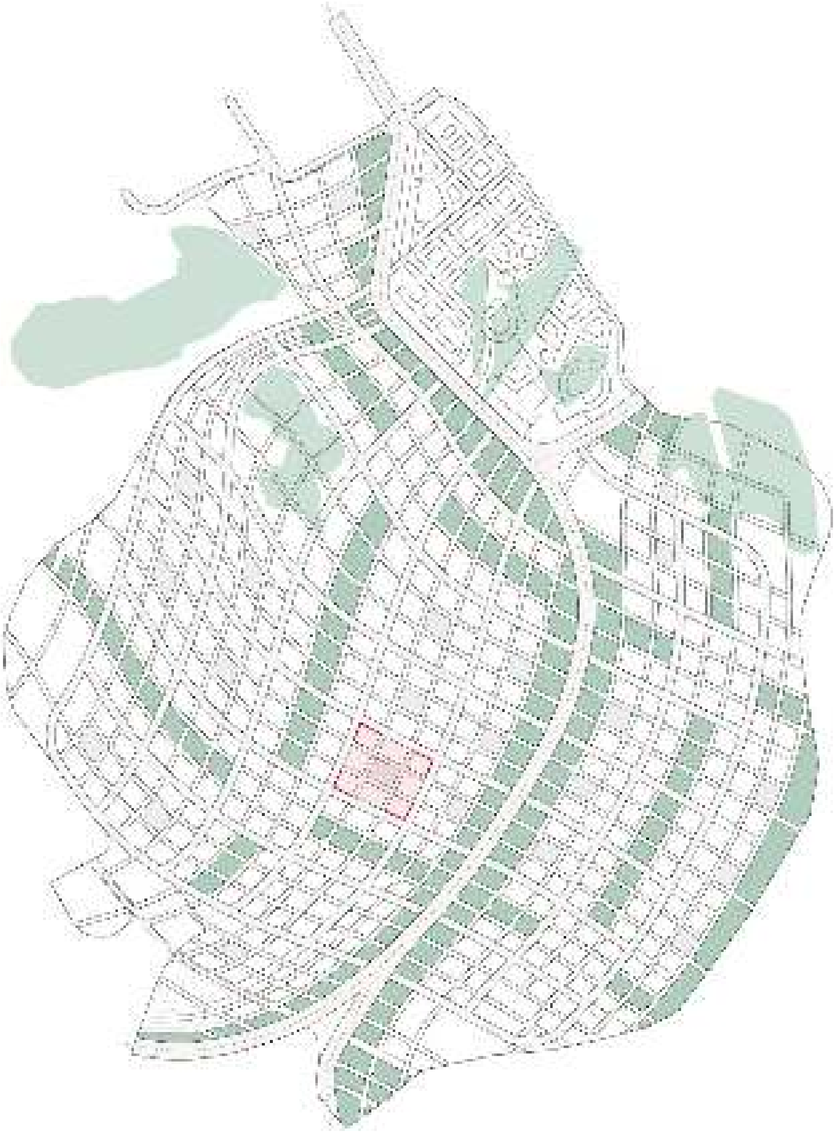


FIG. 14.7 Superblock structure of the case study project. A map showing the masterplan of the NAR innovation district in Istanbul, which consists of 40 superblocks. A complete superblock is made of 9 individual blocks. *No permission required.*

Pairing generative design with analysis

Generative design is little without a precise methodology to compare proposals. While design intuition goes a long way, there are certain aspects that cannot be deduced simply by studying or evaluating a site. Part of Spacemaker's core offering is the ability to analyze

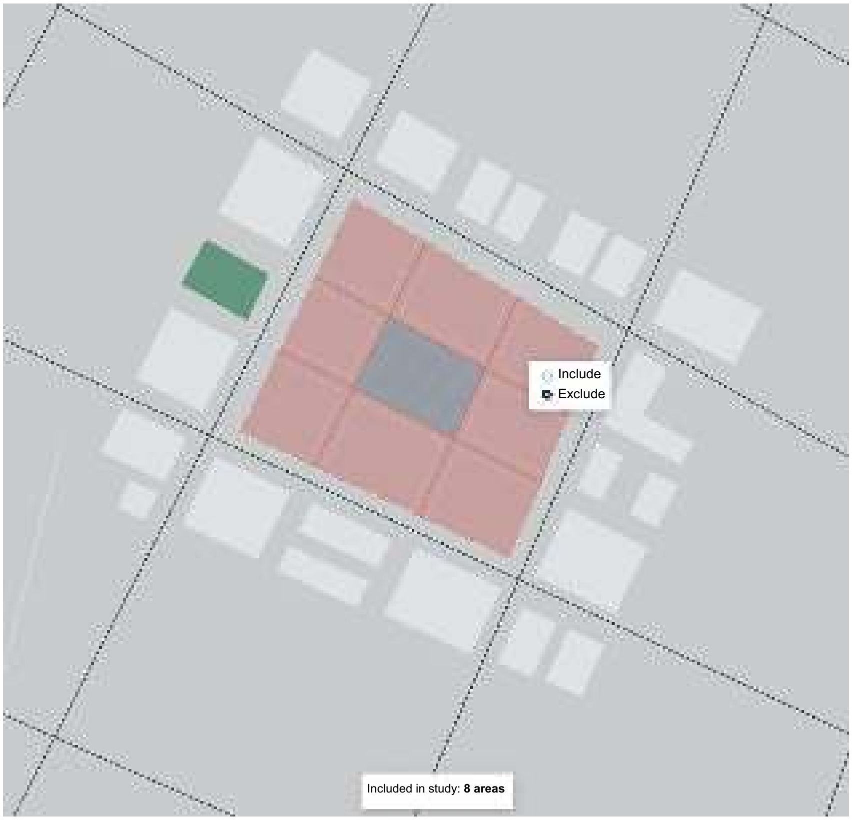


FIG. 14.8 Case study generative design configuration. We wish to exclude the middle section of the site from generation. *No permission required.*

early-phase designs for various factors. These include view distance, view to area, sunlight, daylight, outdoor area, noise, and wind. In this way, users may quantitatively compare favorite proposals in a multiobjective fashion. It is also often the case that government regulations will require a certain performance for a given analysis. For example, Norway (Spacemaker's home base) mandates that facades in new buildings have specific noise limitations.

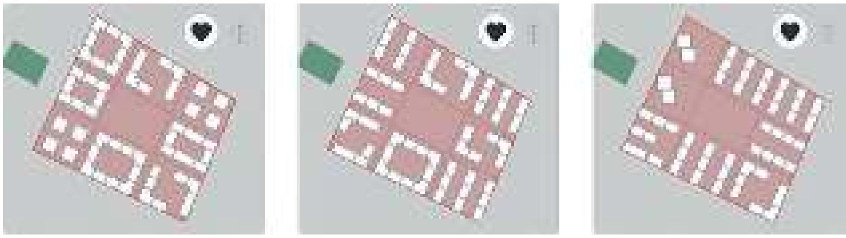
In this case, we are seeking to optimize for sell-able area and daylight on the facades. While Explore offers the ability to easily compare area statistics among the generated proposals, the other analyses must be explicitly ordered for each proposal. We therefore save our three favorite proposals from the previous section and start analyzing!

Once we have collected the desired analyses for the site, we are able to more rigorously compare proposals in Spacemaker.

View distance

Figs. 14.14–14.16 show the view distance from facades for each of the three proposals.

FIG. 14.9 Generated proposals. Fifteen of the proposals generated for the case study. *No permission required.*



BC	38 %	14,792 m^2	BC	36 %	13,828 m^2	BC	31 %	12,106 m^2
GIA	137 %	53,253 m^2	GIA	128 %	49,781 m^2	GIA	112 %	43,582 m^2
GFA	152 %	59,170 m^2	GFA	142 %	55,312 m^2	GFA	124 %	48,424 m^2

FIG. 14.10 Three favorite generated proposals. Our three favorite generated proposals, which we wish to analyze further. *No permission required.*

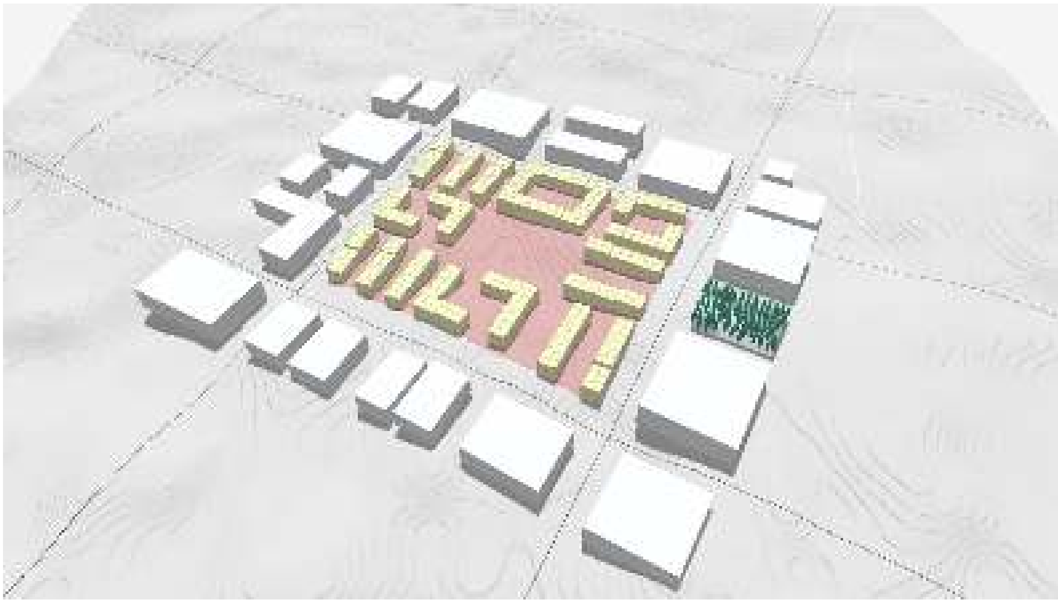


FIG. 14.11 Second generated proposal with surroundings. *No permission required.*

Sun

Figs. 14.17–14.19 show the sun on the ground and facades for each of the three proposals.

Daylight

Figs. 14.20–14.22 show the daylight conditions for each of the three proposals.

Included are images from the view distance, sun, and daylight analyses collected for each of the three sites. While these images are helpful when considering how a single site is performing—and where it can be improved—it is a difficult and time-consuming process

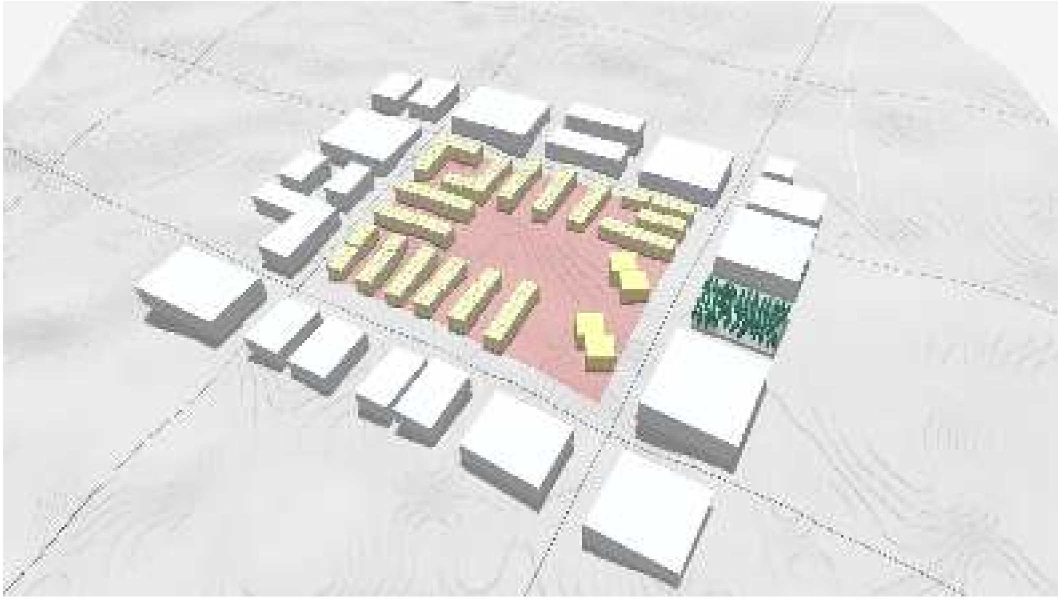


FIG. 14.12 Third generated proposal with surroundings. *No permission required.*

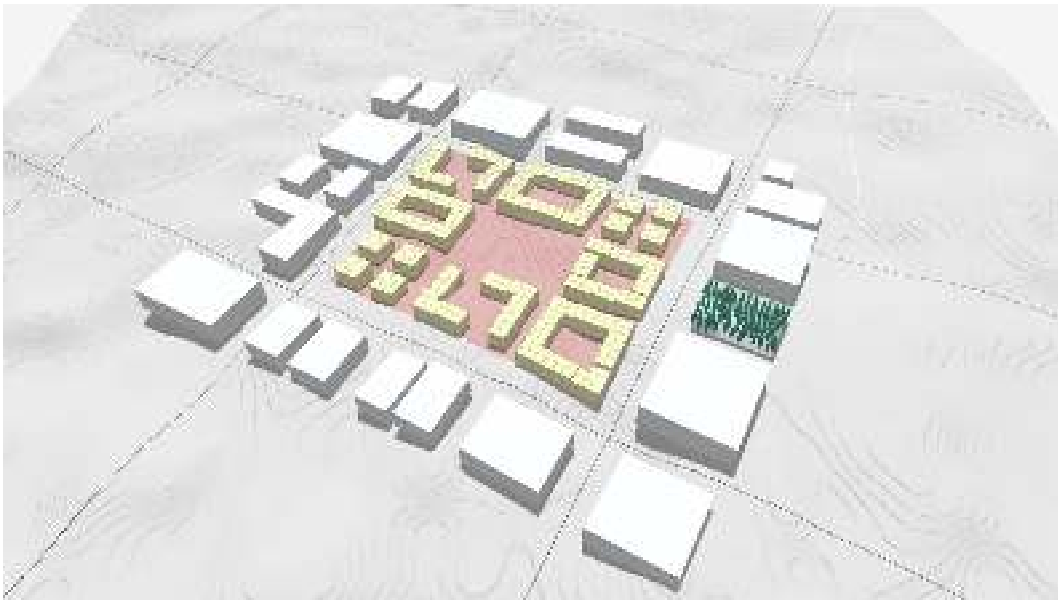


FIG. 14.13 First generated proposal with surroundings. *No permission required.*

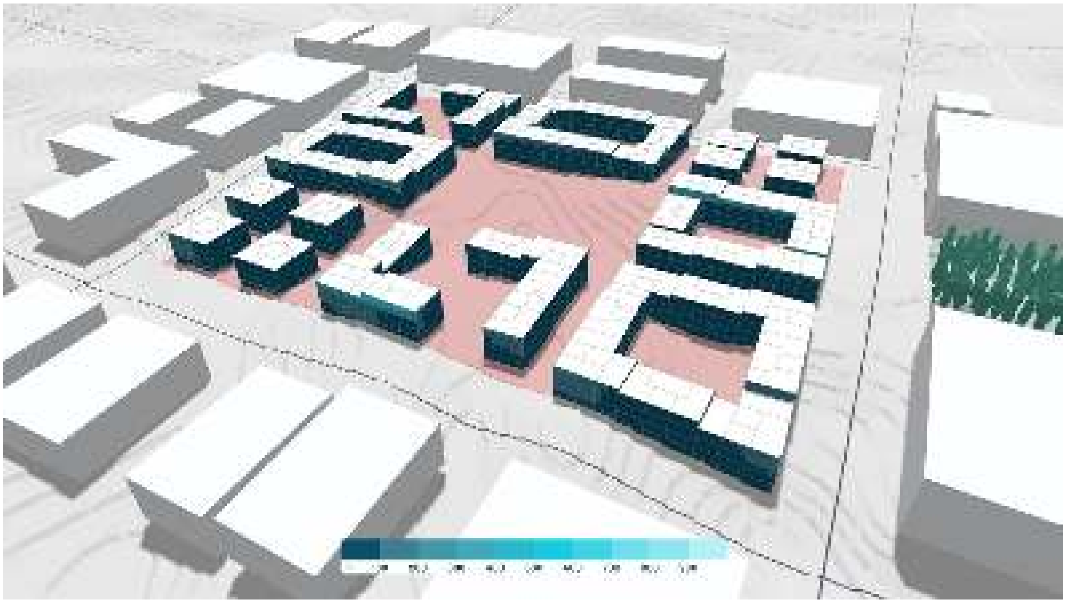


FIG. 14.14 View distance for the first proposal. Darker areas show less view distance, whereas lighter areas show deeper view distance. The scale from dark to light is 0–1000 m. *No permission required.*

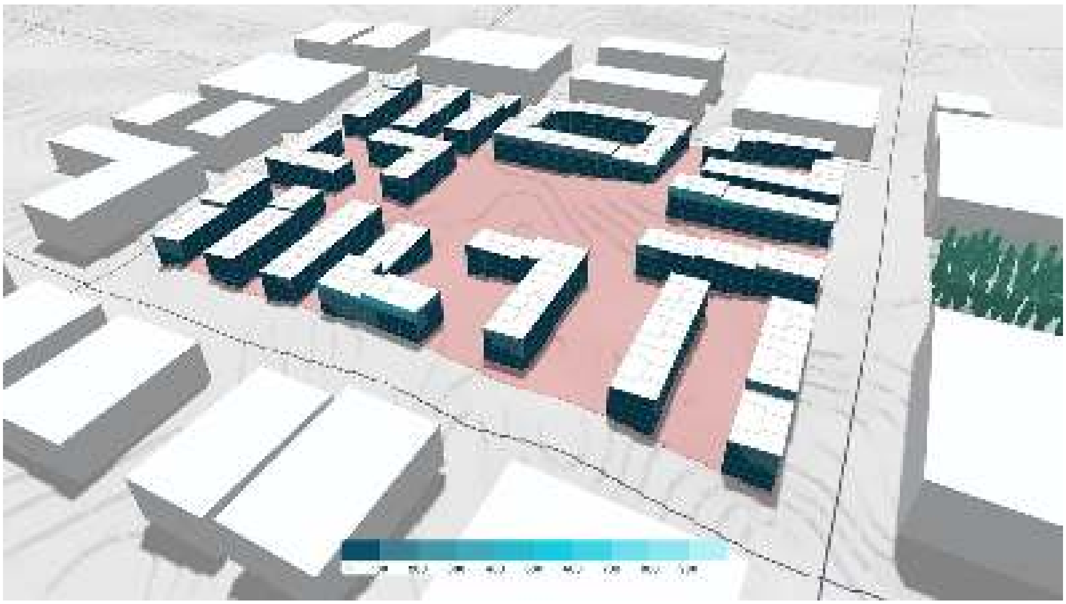


FIG. 14.15 View distance for the second proposal. Darker areas show less view distance, whereas lighter areas show deeper view distance. The scale from dark to light is 0–1000 m. *No permission required.*

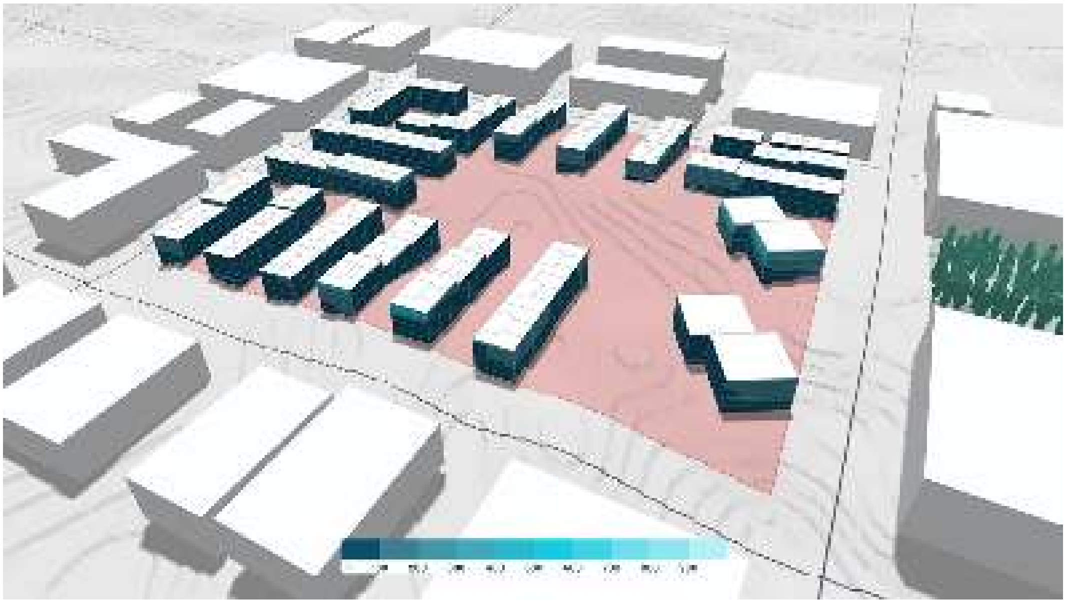


FIG. 14.16 View distance for the third proposal. Darker areas show less view distance, whereas lighter areas show deeper view distance. The scale from dark to light is 0–1000 m. *No permission required.*

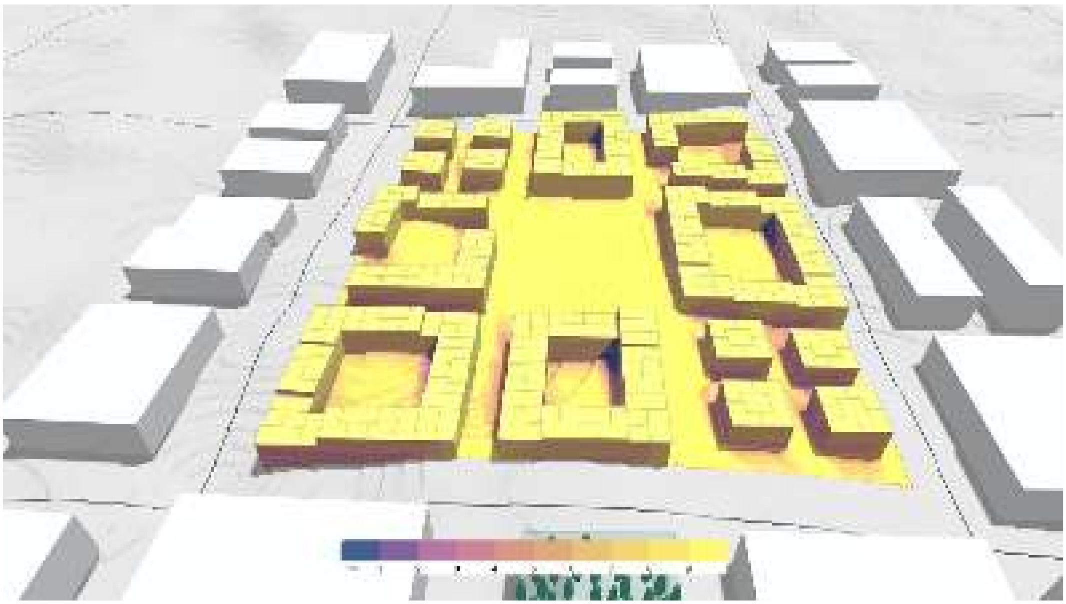


FIG. 14.17 Sun for the first proposal. Darker areas show less exposure to sun, whereas lighter areas show longer exposures to sun on facades. The scale from dark to light is 0–10 h. *No permission required.*

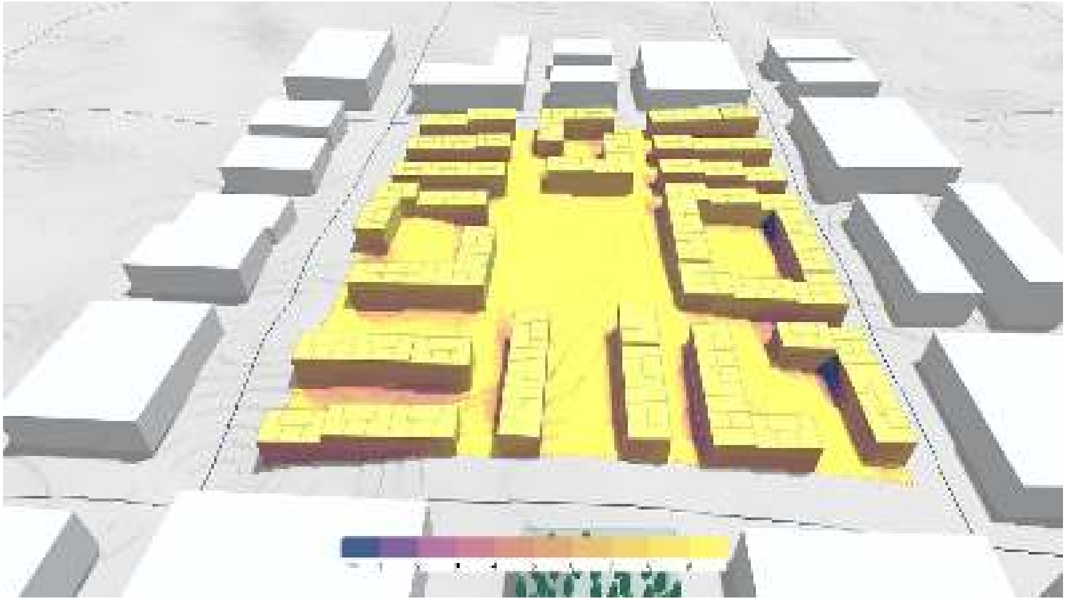


FIG. 14.18 Sun for the second proposal. Darker areas show less exposure to sun, whereas lighter areas show longer exposures to sun on facades. The scale from dark to light is 0–10 h. *No permission required.*

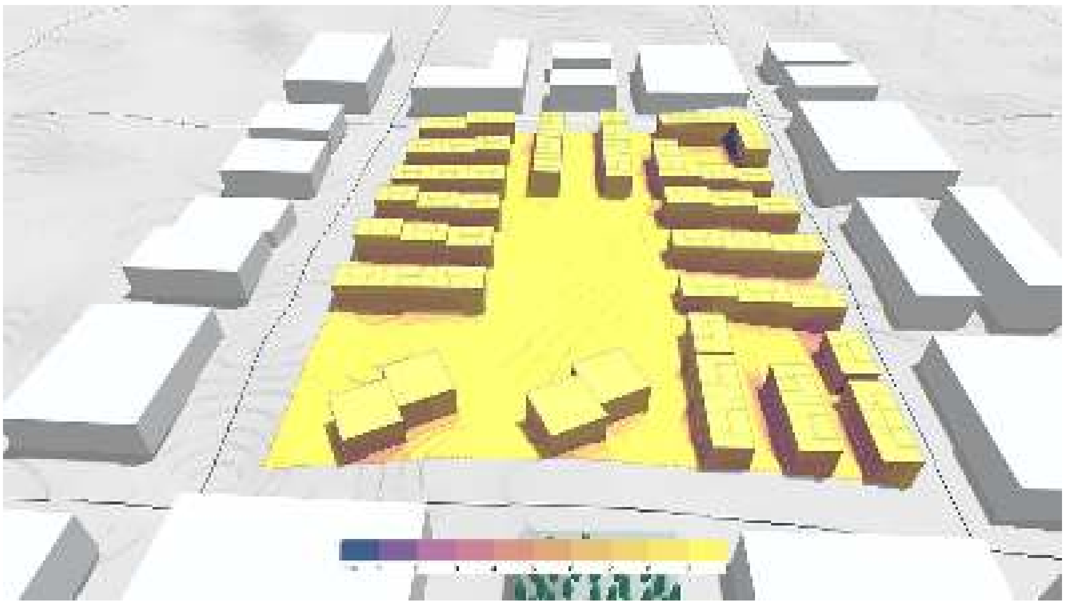


FIG. 14.19 Sun for the third proposal. Darker areas show less exposure to sun, whereas lighter areas show longer exposures to sun on facades. The scale from dark to light is 0–10 h. *No permission required.*

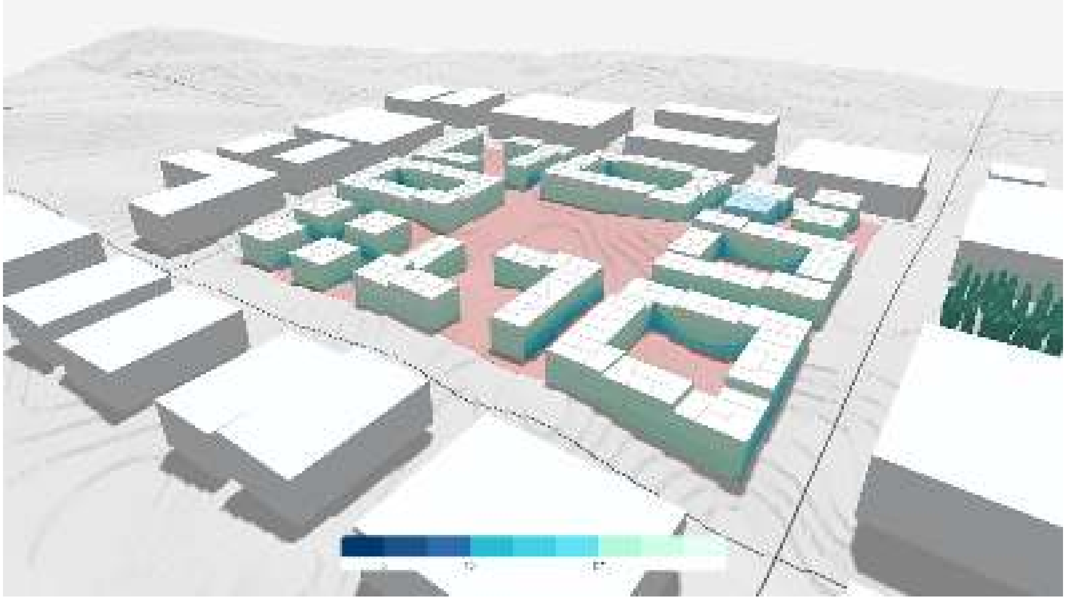


FIG. 14.20 Daylight for the first proposal. Darker areas show less exposure to daylight, whereas lighter areas show more exposure to daylight. *No permission required.*

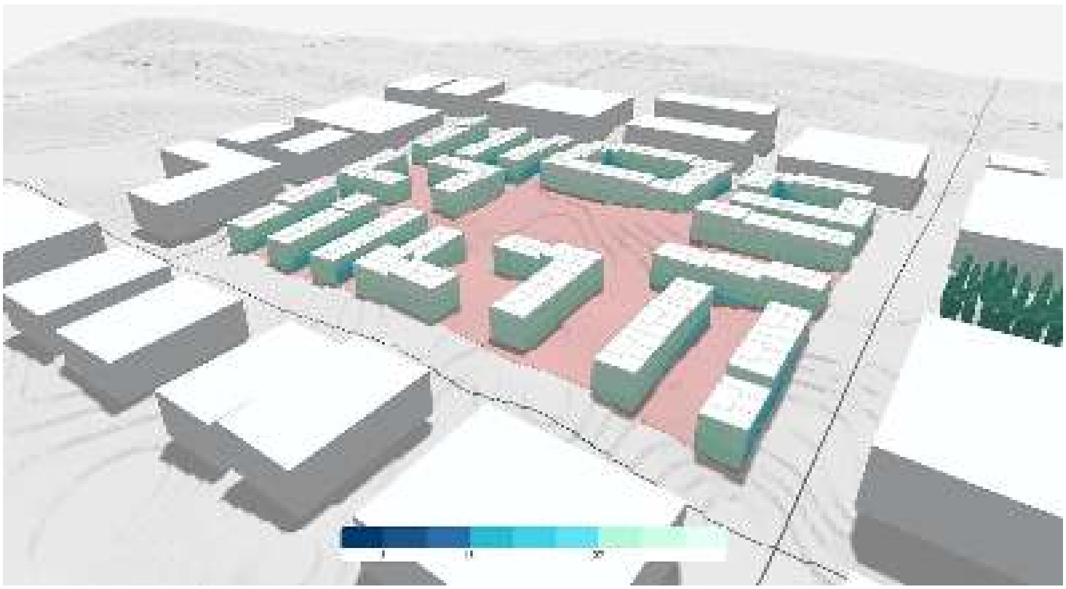


FIG. 14.21 Daylight for the second proposal. Darker areas show less exposure to daylight, whereas lighter areas show more exposure to daylight. *No permission required.*

FIG. 14.22 Daylight for the third proposal. Darker areas show less exposure to daylight, whereas lighter areas show more exposure to daylight. *No permission required.*

to decipher how proposals measure up to one another. Instead, we will use Spacemaker's Compare app, which contrasts overall statistics between the different designs.

Fig. 14.23 compares area statistics between designs. When generating the proposals, we have already seen that the first proposal outperformed the others in gross floor area.

In Fig. 14.24, we see that the first proposal also has better sun conditions on the facades relative to the other proposals. Specifically, in the first proposal 38% of facades have more than 7h of sunlight (on June 21st), compared to 36% of facades in the other two proposals.

Finally in terms of daylight, the analysis we seek to optimize, we see the first proposal underperforming (Fig. 14.25). While the other two proposals observe 80% of their facades meeting the desired vertical sky component score of 27%—thereby meeting the regulatory requirement mentioned in the definition of this case study—the first proposal falls short, with just 76% of its facades achieving the score.

The critical question at this juncture: where do we go from here? We have been unfortunate in that the best-performing proposal for one coveted factor is the worst-performing proposal for the other. Unfortunately, this is an incredibly common problem in the AEC industry and therefore the space of generative design: a multiobjective optimization problem with no clear winner. To address this complication, Spacemaker gives users the option of continuous iteration.

Localized improvement

The final stage of Spacemaker's generative design engine allows users to improve parts of the site that are either not to their liking, or else performing poorly with respect to any of the analyses. This highlights a divergence from a typical one-shot approach in which all of the generated proposals are analyzed and only the top performers are advanced. To understand the motivation underlying this decision, consider a scenario in which a site does not perform

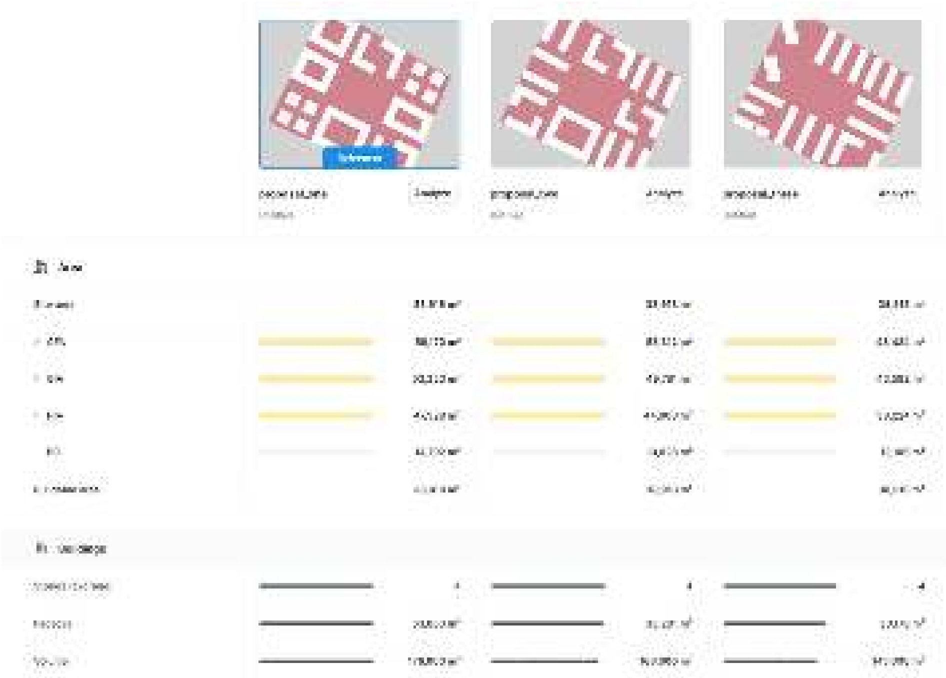


FIG. 14.23 Comparing the area statistics for each of our three generated proposals. *No permission required.*

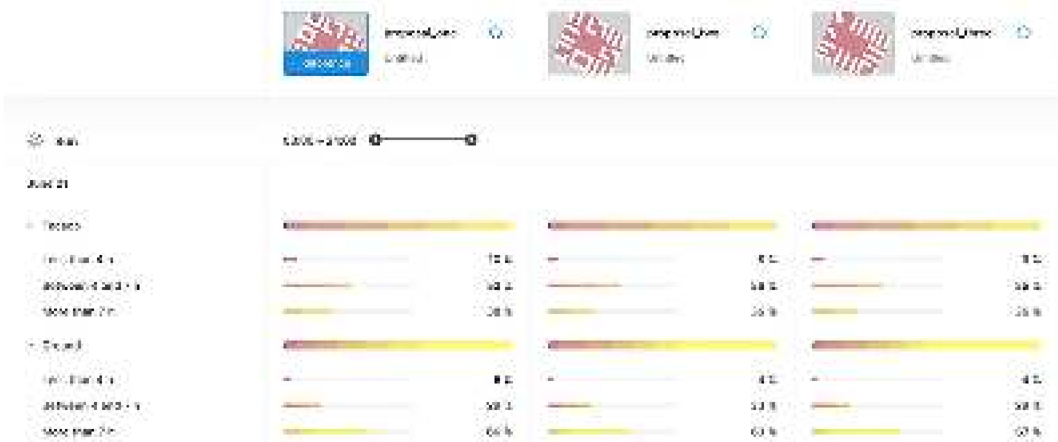


FIG. 14.24 Comparing the sun conditions for each of our three generated proposals. *No permission required.*

FIG. 14.25 Comparing the daylight conditions for each of our three generated proposals. *No permission required.*

well overall due to a single portion having poor view distances, while the rest of the site excels. By giving users the option to pick and choose parts of the generated proposals that they would like to keep, the door is open to iterative and localized improvement.

This improvement may happen in a few ways. A user may manually update the proposal to their liking, a flexible choice that may fail to capture the benefits of generative design described at the beginning of this article. Another option is the use of Spacemaker's generative design engine to alter the heights of prespecified buildings in order to optimize for certain analyses. This constricts users to keep the building layouts consistent and is accordingly most suitable for the end of the early-phase design process. Lastly, users may continue to use the building layout generative engine, optionally "freezing" certain sections of the site.

In this study, we will use the latter two options to optimize our site. Picking up where we left off, we saw that the first proposal—which achieved the optimal gross floor area—had the lowest percentage of facades with an appropriate amount of daylight. For the sake of this case study, let us choose to pursue this proposal, with the objective of leveraging the generative design engine in such a way that the proposal eventually outperforms its competition with respect to daylight conditions.

At this stage of the design process, we rely on the architectural intuition of our users to better understand where and why a site may be underperforming. Upon closer visual inspection of the daylight analysis, we find that the bottom left and middle left sections of the site reflect poor conditions. We therefore exclude the other divisions from further generation and open the door to new and better proposals.

Fig. 14.26 shows some of the new generated proposals:

Fig. 14.27 shows the new favorites.

We can now analyze these updated proposals to see if daylight has improved within the more disappointing sections of the site.

Recall that 76% of the facades in the original proposal had optimal daylight conditions. We see here in Fig. 14.28 that the newly generated proposals improve this percentage slightly, while maintaining a competitive edge against the other proposals in terms of sell-able area. Unfortunately, even the best-performing sites still have less than 80% of their facades achieving favorable daylight conditions.

In order to reach our goal, we now consider an aspect of early-phase design that, up until now, has been intentionally omitted: building height. Spacemaker's height optimization tool has the ability to optimize for one of three factors: daylight, sun on facades, and view to area. Included in Fig. 14.29 is the user interface, which parametrizes the number of stories that a building section may deviate from its original height. Additionally, users may specify the bounds of the change in building area, which we will exploit in this case to ensure that our proposal maintains a competitive edge in this space.

Shown in Fig. 14.30 are five options that deviate from the original design with improved daylight conditions. Importantly, all five achieve the regulatory requirement. In this case, we will pick the final one as it also increases gross floor area. In Fig. 14.31, you can see the sections of the buildings that have increased in height (see darker shade) contrasted with those that have decreased in height (see lighter shade). It is an interesting exercise to consider different trends resulting from height optimization, such as the consistent shortening of buildings in the bottom left. Insights from this exercise may in turn lead to continuous iterations on site division and building layout.

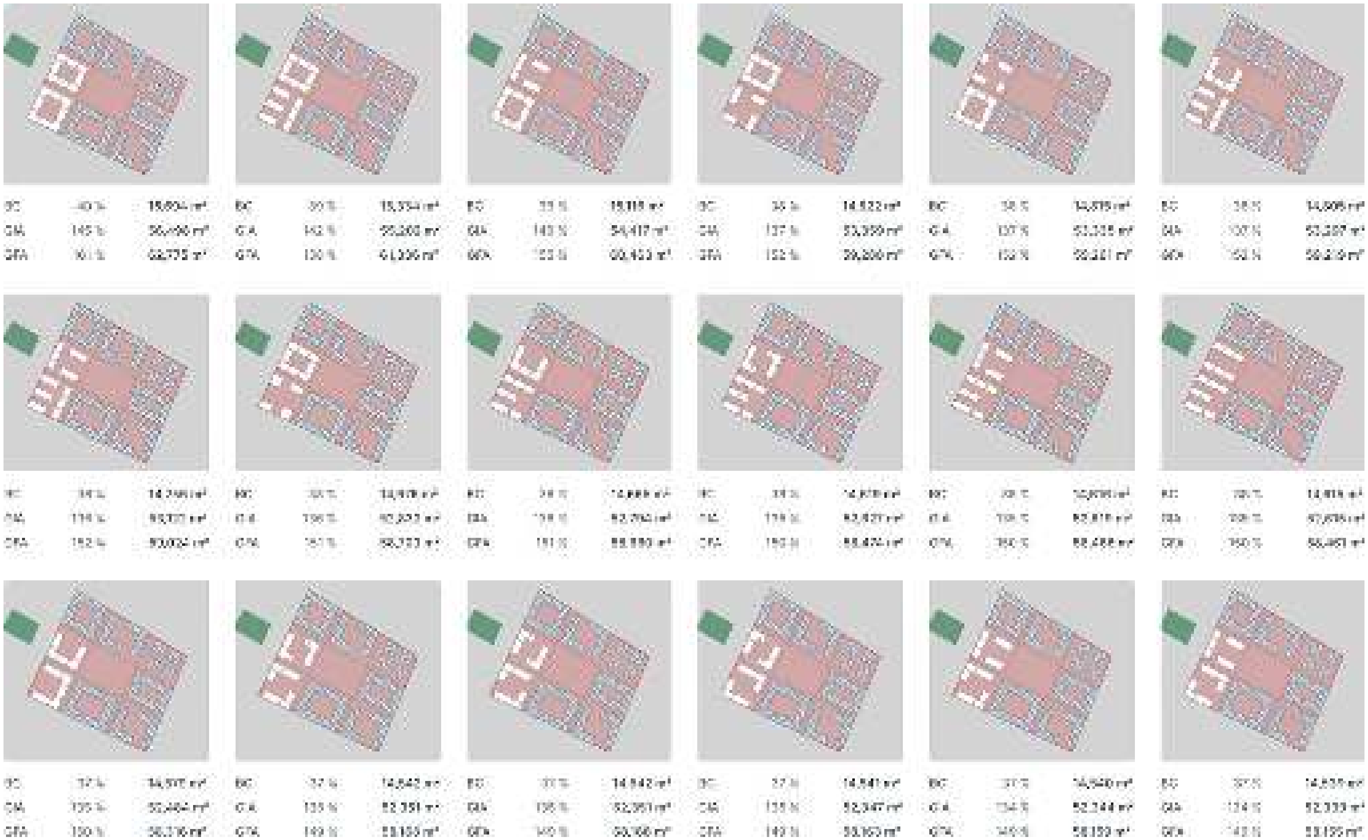


FIG. 14.26 Fifteen newly generated proposals with most of the site excluded from generation. *No permission required.*

FIG. 14.27 Our three favorite newly generated proposals. *No permission required.*

In Fig. 14.32, we see the final daylight qualities of the site, with 81% of facades having favorable conditions.

Conclusion

Our final proposal: Fig. 14.33.

At the beginning of this article, I questioned the consequences underlying the collision of technology and design. The former industry is built for speed and advancement while the latter enjoys scrupulous attention to detail and constantly reflects upon itself. What I would like to acknowledge now are the shared values within both industries that allow for harmonious synergy.

Technology and design, more than most other fields, crave originality and evolution. While this yearning certainly manifests itself in different ways, consider that the duty of the designer and the technologist is to create. In the current circumstance, the designer creates buildings while the technologist creates software or generative algorithms.

A more controversial claim is that technology and design strive for egalitarianism. While this is surely not true in all circumstances, consider the following. First, observe that the most important technological innovation of our time, the Internet, is a system that comprises billions of devices which, taken together, connect almost everyone in the world. Consider also that many of the most esteemed architectural structures in the world are shared public spaces or else open to many members of the public.

It is my contention that the synthesis between artificial intelligence and architecture, when working harmoniously, upholds these values. That is to say that a symbiotic relationship between the two industries creates ample space for innovation while designing for everyone.

Consider the case study included in this article. A designer, working together with a machine, was able to explore dozens of valid and varied design proposals within minutes. This gave the designer a more comprehensive understanding of the potential of a project than previously possible. Perhaps the designer considers details that they may have ordinarily overlooked; perhaps the designer better understands how building placement interacts within a given space before going to the drawing board. If this is true as we believe it to be, then Spacemaker's generative design engine (and machine-driven design more broadly)

FIG. 14.28 Newly generated daylight conditions. This shows the daylight conditions for the original proposal compared with the newly generated proposals, all of which outperform the original. *No permission required.*

FIG. 14.29 The inputs to height optimization in Spacemaker. *No permission required.*

is not limiting expressions of originality; rather, the saved time allows for designers to focus on parts of the process in which their design intuition contributes the most. Furthermore, when paired with an appropriate analytical tool, the generative design workflow operates on behalf of the public. Designers may leverage their understanding of the surrounding environment together with a generative design engine to make a positive impact on the living conditions of future inhabitants.

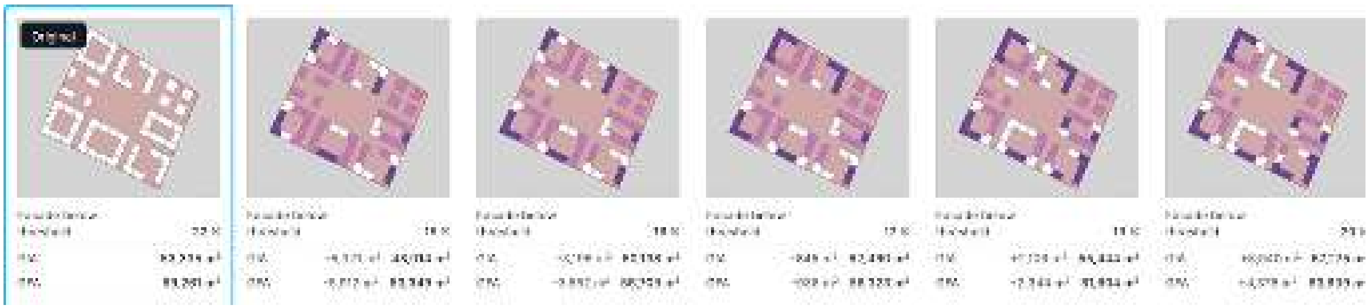


FIG. 14.30 Different height proposals. The far left shows the statistics for the original proposal with five proposals showing improved daylight conditions. *No permission required.*

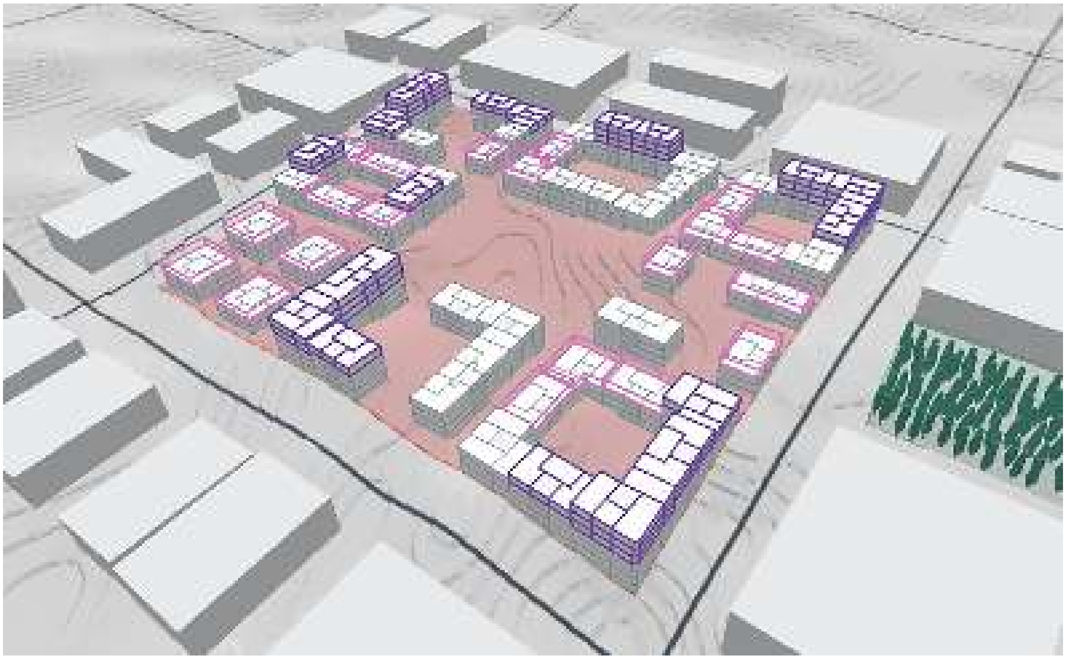


FIG. 14.31 Height optimization at work. Height optimization on our favorite proposal shows where height has been added and limited across the site. *No permission required.*

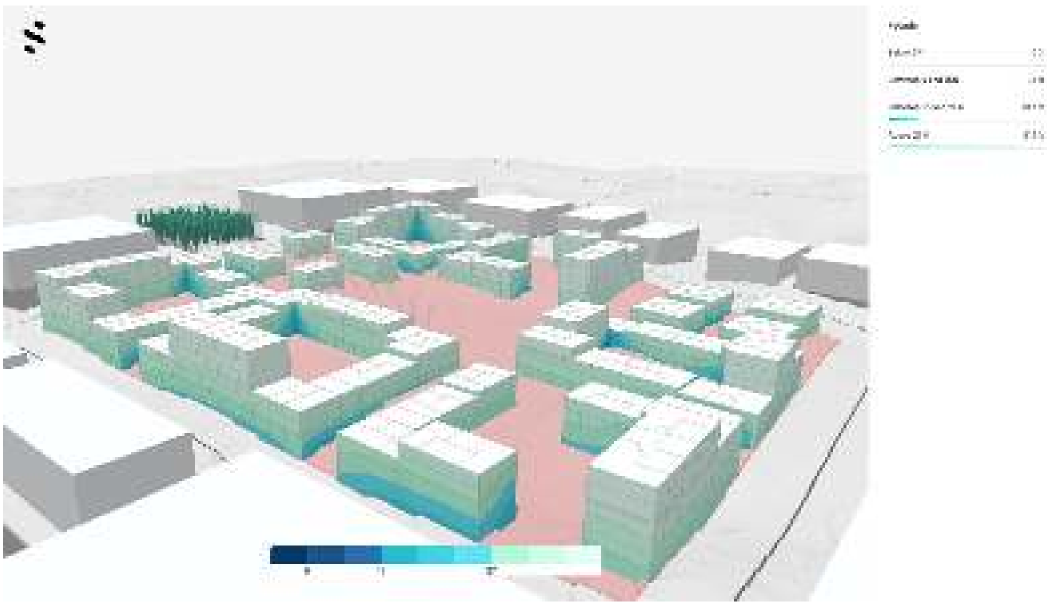


FIG. 14.32 Final daylight results in our optimized proposal. *No permission required.*

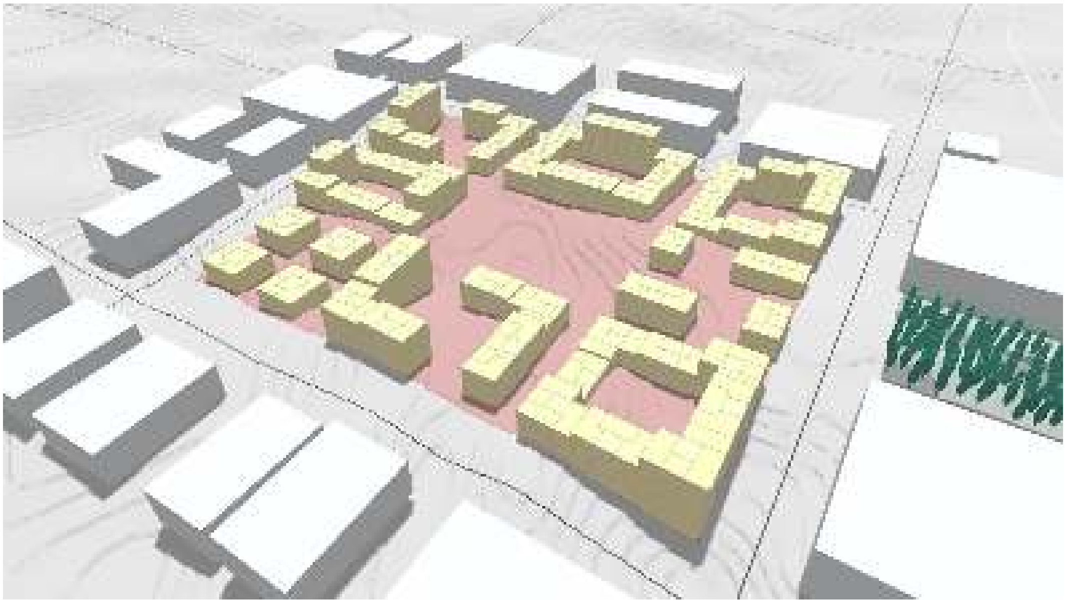


FIG. 14.33 The final proposal. The optimal result of Spacemaker's generative design engine. *No permission required.*

Just as technology and design are ever-changing, Spacemaker's generative design engine will continue to evolve in order to meet the needs of users and provide value to the beneficiaries of its software. While it is impossible to anticipate the trajectory of this evolution, it suffices to say that it will sufficiently embody Spacemaker's mantra regarding artificial intelligence and urban design; that is, the most valuable AI in a field that encompasses dozens of others, is the one that you have in your pocket.

This page intentionally left blank

CHAPTER

15

Möbius evolver: Competitive exploration of urban massing strategies

Patrick Janssen, Tung Do Phuong Bui, and Likai Wang

Department of Architecture, National University of Singapore, Singapore

Introduction

Since the 1990s, researchers have been investigating how evolutionary algorithms can be used to support performance-based design exploration and optimization. The approach typically requires the designer to define a generative procedure and an evaluative procedure. The generative procedure generates design variants, usually in the form of 3D models. The evaluative procedure calculates a fitness score by analyzing certain performance criteria. This procedure is often referred to as the *fitness function*. The evolutionary algorithm is then used to evolve a population of designs, with the aim of finding the parameter values which result in design variants with high fitness scores.

Over the last two decades, a range of user-friendly parametric modeling tools has been developed (Woodbury, 2010; Janssen and Stouffs, 2015). These tools allow designers to define generative and evaluative procedures using visual programming. Based on these tools, various design optimization systems have been built, including Galapagos (Rutten, 2013) and Octopus (Vierlinger, 2013).

The results of the previous research have been promising. In research labs, evolutionary algorithms have been successfully applied at varying scales, from building components to whole urban districts (Evins, 2013; Frazer, 1995; Radford and Gero, 1980; Bentley, 1999; Bentley and Corne, 2002). However, despite these significant achievements, the uptake of design optimization methods in practice has been very limited.

Several researchers have investigated the potential challenges and opportunities of design optimization. Attia et al. (2013) conducted interviews with 28 practitioners, focusing on optimization for the design of net-zero energy buildings. Although the study focuses on energy optimization, the general conclusions are applicable more broadly to other areas of design

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00015-9

optimization. The paper reflects positively on the use of evolutionary algorithms for supporting design exploration but highlights key limitations, including a steep learning curve and long computation times.

With regard to the computation time, the paper notes that several platforms support parallel execution, thereby greatly accelerating the overall computation time of the algorithm (GenOpt, 2021; Mode Fontier, 2021; Phoenix Integration, 2021). However, for most designers, these platforms remain inaccessible. First, they require access to large-scale parallel computing or grid-computing infrastructures. Second, installing and using the requisite software remains a complex task. We note that the results from the Attia et al. (2013) study were based on interviews with academics or researchers who nearly all had an engineering or other technical background. For architects and other designers in practice, the steep learning curve would likely be exacerbated.

Competing strategies

This paper focuses on the exploration of urban massing configurations in the early stages of the design process. Such massing configurations can be optimized for various objectives, relating to sunlight, daylight, energy, views, and so forth. Several previous studies have focused on using evolutionary optimization of urban massing (Chen et al., 2018; Harding and Shepherd, 2017; Lin and Gerber, 2014; Martins et al., 2014; Nault et al., 2018; Granadeiro et al., 2013). However, these all suffer from the steep learning curve and the slow computation times.

Over the past two decades, the authors have developed several design optimization systems aiming to tackle similar issues. Janssen (2013, 2015) developed the *Dexen* system, tackling the slow computation times by parallelizing the execution in the cloud (Janssen, 2015). Wang et al. (2019) and Wang et al. (2020a) developed the *EvoMass* system, tackling the steep learning curve by creating generic procedures applicable to many design scenarios.

In addition to the steep learning curve and the slow computation times, designers also report that the existing systems are not flexible enough to support early-stage design exploration of wicked problems that are fundamentally ill-defined and ill-structured (Rittel and Webber, 1973).

In the early stages of design exploration, a common approach is to develop alternative strategies for tackling a design scenario. Each strategy consists of a set of design rules and design goals, also referred to as a "design schema" (Janssen, 2004) or a "primary generator" (Darke, 1979). The rules demarcate a space of possibilities and the goals define a way of assessing those possibilities. The designer then tests these strategies to discover which result in the most promising designs. As they interrogate the strategies, the feedback they get will lead to modified strategies that may also warrant further investigation. What results is a complex and often messy iterative process of exploration and modification of competing design strategies. Through this process, one strategy will survive and a set of promising designs will then gradually emerge.

We aim to develop an evolutionary search system that can support this type of exploratory design process. We envision a system that allows the designer to competitively explore multiple design strategies in an iterative and fluid way, without breaking their design flow. To achieve this, we focus on three main requirements:

- *Iterative Exploration*: The ability to continuously question and challenge the results of the search process, by modifying design strategies.
- *Competitive Evolution*: The ability to evolve heterogeneous populations of design variants based on competing design strategies.
- *Fast Execution*: The ability to leverage cloud computing so that the evolutionary search process can be executed in parallel in the time it takes to have a coffee break.

The paper proposes a design approach that aims to fulfill these three requirements, which we will refer to as competitive evolutionary design exploration (CEDE).

The section "CEDE method" will give an overview of the CEDE design method, the CEDE evolutionary algorithm, and a set of web applications that enable designers to apply CEDE in practice. The section "CEDE web applications" will present a demonstration showing how the CEDE web application can be used to explore urban massing options. Finally, "Discussion" and "Conclusions" will discuss the results and draws conclusions.

Competitive evolutionary design exploration

A design method is proposed for competitive evolutionary design exploration (CEDE). The CEDE method aims to amplify the intelligence of the designer, through a cyclical exchange between the human and the computer. In this exchange, each actor has a specific task to perform.

- The task for the designer is to develop design strategies and to encode these as generative and evaluative scripts.
- The task of the computer is to take the generative and evaluative scripts and to search for high-performing design variants.

A cyclical process emerges, where the designer and the computer take turns to perform their respective tasks. The designer will start by uploading an initial set of scripts. The computer will then execute the search process and return a population of optimized designs. The designer will then reflect on the optimized designs and will most likely see certain deficiencies. They may then update their strategies and pass the updated scripts back to the computer. The computer will execute a new search process, thereby producing more optimized designs. This can continue until the designer is satisfied that they have developed a reasonable understanding of the space of design possibilities (Chen et al., 2021; Wang et al., 2019; Kaushik and Janssen, 2013).

The proposed cyclical process is based on the concept of double-loop learning, developed by Argyris and Schon (1978). Double-loop learning recognizes that the way a problem is defined and solved can be a source of the problem. In our case, the inner loop is the search process executed by the computer, while the outer loop is the definition of strategies controlled by the designer. This type of cyclical process is also sometimes referred to as a "human-in-the-loop" approach (Koenig et al., 2020; Scott et al., 2002). However, we find that this phrase inverts the power structure—we prefer "computer-in-the-loop."

The main aim of such design explorations is not to discover a single "optimal" design. The concept of optimality is easily challenged since the performance criteria being optimized only represent a tiny fraction of a complex web of factors influencing the quality of a design. Rather than optimality, the aim of evolutionary design exploration is to get a better understanding of the space of possibilities. For example Attia et al. (2013) state that "the notion of trying to find an optimum is nonsense... optimization is not so much about finding the 'best' solution, but as much about exploring the design space for alternative solutions." Similarly, Bradner et al. (2014) conducted a study interviewing architects and design professionals using optimization, discovering that "the computed optimum was often used as the starting point for design exploration, not the end product."

CEDE method

With the CEDE method, groups of design strategies are developed that compete with one another. To be able to compete, the design rules can differ but the design goals must be the same. The designer then encodes these strategies as a set of computational scripts. For each strategy, the design rules are encoded as a generative script. For the group as a whole, the design goals are encoded as a single evaluative script. The generative scripts create design models. The evaluative script processes these models and calculates fitness scores. The evaluative script should be able to process any design model, irrespective of the generative script used to create it. This ensures that comparable fitness scores can be calculated, which in turn allows the design strategies to compete with one another.

The scripts are then used to evolve a heterogeneous population of design variants. The success of a design strategy is based on the performance of its design variants relative to the other strategies. A strong design strategy produces design variants that outperform those produced by competing strategies. These design variants will have a higher chance of surviving and reproducing, and as a result the strategy may gradually start to dominate the population. In contrast, a weak strategy will produce design variants that have a lower chance of surviving and reproducing. For such strategies, their share of the population will gradually decrease and may eventually become extinct.

In the CEDE method, we are using a single-objective optimization approach. With this approach, the evaluation script needs to calculate a single fitness score for each design model. It should be noted that the evaluation script may still calculate scores for multiple performance criteria. However, the script then needs to combine these scores into a final fitness score, possibly using a weighted sum or weighted products (Wortmann and Fischer, 2020).

An alternative is to allow for a multiobjective optimization approach (Deb, 2005). In that case, multiple objectives are defined, and design models are then ranked using Goldberg's nondominated Pareto ranking method (Goldberg, 1989). The advantages and disadvantages of single versus multiobjective optimization are an ongoing area of research. Wortmann and Fischer (2020) have argued that for design optimization problems, multiobjective approaches come with many drawbacks. Our own experiences developing multiobjective optimization systems (Janssen, 2015) have led us to similar conclusions. We found that search efficiency can be significantly reduced. In addition, the final population can often contain large numbers of Pareto-optimal solutions, which can be overwhelming for the designer. We therefore decided to start with single-objective optimization and see how we got along.

CEDE algorithm

To support the CEDE method, a novel type of EP algorithm has been developed that supports evolving heterogeneous populations of design variants based on competing design strategies.

The four major evolutionary algorithm paradigms are genetic algorithms (GA) (Goldberg, 1989), evolution strategies (ES) (Beyer and Schwefel, 2002), evolutionary programming (EP) (Fogel et al., 1966), and genetic programming (GP) (Koza, 1992). These algorithms are all broadly similar, evolving a population of solutions through a cyclical process of selection and variation. The selection process emulates the mechanisms of natural selection (or "survival of the fittest"), by which solutions with higher fitness have higher chances of surviving and reproducing. The variation process emulates the mechanisms of reproduction, by which offspring solutions are generated from parent solutions, inheriting traits from their parents.

The variation process creates offspring through the application of two main types of operators: "recombination" and "mutation." The recombination operator creates offspring by stochastically combining information from two or more parents. (An example is the crossover operator typically used in GAs.) The mutation operator creates offspring by stochastically modifying certain pieces of information from a parent (Eiben and Smith, 2015).

The fact that the reproduction operator requires multiple parents means that the population needs to be homogeneous, with all design variants sharing the same representation. For the mutation operator, this is not the case since it only requires one parent. The mutation operator copies the parent information and then modifies certain pieces of this information to form a new offspring. This still means that the parent and offspring must both share the same representation. But there is no reason why the population could not be heterogeneous, consisting of solutions using different representations.

In contrast to the other types of evolutionary algorithms, in EP the variation process does not use any recombination operator. Instead, each parent generates exactly one offspring using only the mutation operator. This makes the EP algorithm particularly well suited for our competitive evolutionary approach.

The CEDE algorithm is based on the standard EP algorithm (Fogel, 1995, 1999). The key difference is that a heterogeneous population of design variants needs to be maintained. This requires the fitness function to be split into two subfunctions: one to generate design models and another to evaluate design models. These subfunctions are the generative and evaluative scripts defined by the designer.

Each generative script represents a different design strategy, with its own distinct representation. Within the population, subpopulations of design variants are created, based on the different generative scripts. As evolution progresses, these subpopulations can dynamically grow and shrink, based on the survival rate of the design variants in the population. When all the design variants in the subpopulation die, then that design strategy goes extinct.

The pseudocode for the main loop in the algorithm is as follows:

```
1: Define one or more generative scripts (GS1, GS2)
2: Define one evaluative script (ES)
3: Set search settings:
maximum number of generations (e.g., max=10)
```

```
population size (e.g., ps=50) tournament size (e.g., ts=10)
mutation standard deviation (e.g.; c=0.1)
initial number of design variants for each GS (e.g., gs1=40, gs2=40)
4: Set generation number to 0 (t=0)
5: Create the initial randomized population, P(t)
6: While t<max, Do
7: t=t+1
8: Create a new population, P(t), from the previous population, P(t-1)
9: End While
```

The algorithm starts with the designer specifying the generative and evaluative scripts to be used for the evolutionary search (lines 1 and 2). In addition, the designer also sets several settings for the evolutionary search process (line 3 of the pseudocode). The scripts and settings are summarized in Table 15.1.

An initial population is created (line 5), after which the search then progresses by repeatedly creating new populations (lines 6–9). These steps will be described in more detail below.

Creating an initial population

In line 5, an initial population of design variants is generated. As part of the initial setting for the search, the designer specifies the number of design variants to be generated for each generative script. This defines the size of an initial pool of design variants.

For each design variant in the initial pool, randomized parameter values are defined, a design model is generated, and a fitness score is calculated. If the initial pool is greater than the population size, then survivors are selected using round-robin tournament selection (described below). Survivors are added to the initial population until the population size is reached.

The process of randomly setting parameter values is based on three settings associated with each parameter: the minimum value, the maximum value, and the step size. These settings define a list of permissible values. Parameter values are then set by random selection from the list of permissible values.

TABLE 15.1 Settings for the evolutionary algorithm.

Setting	Description
Generative scripts	One or more scripts for generating design models.
Evaluation script	The script for evaluating design models.
Number of generations	The number of generations in the evolutionary search.
Population size	The number of live design variants each generation.
Initial subpopulation sizes	The size of the subpopulations for each generative script.
Tournament size	The size of the pool used for tournament selection.
Mutation standard deviation	The standard deviation used for mutating parameter values.

Creating a new population

In line 8, a new population of design variants is created from an existing population.

The first step is to create an offspring population. All design variants in the existing population are treated as parents. For each parent, one new offspring is created, inheriting the same generative script as the parent. The parameter values for the offspring are defined by mutating the parent parameters. For each mutated design variant, a design model is then generated and a fitness score is calculated. The parent and offspring populations are then merged into a single pool from which survivors are selected using round-robin tournament selection (described below). Survivors are added to the new population until the population size is reached.

The mutation process will create a new set of parameter values by perturbing the parameter values for the parent design variant. Perturbation of the parameter values is performed using a Gaussian function. This ensures that small perturbations have a higher probability than large perturbations. The width of the Gaussian "bell" is controlled by the standard deviation. The mutation standard deviation is a user-defined search setting, with a range between 0.01 and 1. When it is set to a low value, most perturbations will be small, but there is nevertheless a nonzero probability of a large perturbation since the tail of the distribution never reaches zero (Eiben and Smith, 2015). When it is set to a high value, perturbations will be more equally distributed, resulting in a high probability for large perturbations.

Maintaining diversity

For the designer, diversity must be maintained in the population. Having many design variants that are either identical or almost identical would not be useful (Wang et al., 2020b). The aim is therefore to ensure that design variants have parameters that differ significantly from one another.

The use of a discrete set of permissible parameter values based on the step size can be effective in preserving such diversity. It ensures that parameter values must differ by at least one step from one another. However, the use of discrete parameter values does increase the chance that multiple design variants in the population may end up having the same values. An additional step is therefore introduced when creating offspring. After having mutated the parameter values of a parent, the system will check if a design variant with the same parameter values already exists in the subpopulation. If a duplicate is found, then all mutated parameter values are discarded, and the mutation process is repeated. This is repeated up to a maximum of 20 times.

Tournament selection

Tournament selection is a method of selecting design variants from a population (Blickle and Thiele, 1995). In EP, round-robin tournament selection is commonly used as a survivor selection method (Eiben and Smith, 2015). The method works by holding pairwise tournament competitions, where each design variant is evaluated against a pool of other design variants randomly chosen from the merged parent and offspring populations. No distinction is made between the design variants from different design strategies.

The tournament size is one of the search settings that can be set by the designer. If the tournament size is small, weak design variants have a higher chance of surviving, which results in a lower selection pressure. Increasing the tournament size will increase the selection pressure. However, if selection pressure becomes too high, then there is a higher chance of the search process prematurely converging on local optima. The survival of weak design variants allows for a more divergent search process, which can help to escape from local optima. This is critical for design search spaces, which are typically large and complex.

CEDE web applications

The CEDE method is supported by two open-source web applications, called the Möbius Modeler and the Möbius Evolver. These web applications aim to make the CEDE method accessible to designers (Mobius, 2021).

The Möbius Modeler enables designers with limited programming skills to create their own generative and evaluative scripts (Mobius Modeller, 2021). The Möbius Evolver implements the CEDE algorithm and aims to support the three requirements stated in the introduction: iterative exploration, competitive evolution, and fast execution (Mobius Evolver, 2021).

Möbius modeler

The Möbius Modeler is a web application for creating 3D parametric models (Janssen et al., 2016). Fig. 15.1 shows the latest Möbius Modeler user interface. The Möbius Modeler runs as a client-side web application, without any requirements for server-side resources. The only requirement for using the Möbius Modeler is a Chromium-based browser.

The app allows designers to create generative and evaluative scripts using a visual programming approach. This requires the designers to define a flowchart that structures their overall script. For each node in the flowchart, a computational procedure is then created using "click and fill in the blanks" coding. When scripts are executed, the resulting 3D models are visible in integrated 3D viewers. Many other features are provided to support the coding process, including automated error checking and debugging.

Möbius evolver

The Möbius Evolver is a web app for optimizing parametric models created using the Möbius Modeler. Once the designer has completed the generative and evaluative scripts, they upload them using the Möbius Evolver application. After setting the search settings, the designer can execute the search process.

The Möbius Evolver provides a user interface with graphs and charts for viewing the evolutionary progress. The progress plot is a line graph showing the best, worst, and average fitness scores for each generation. The score plot is a bar chart showing a separate bar for each design variant in the population, with the height of the bar representing the fitness and the color of the bar representing the design strategy. Hovering over a bar will display a pop-up box showing an image of the model while clicking the bar will load the 3D model into an interactive 3D viewer embedded in the Möbius Evolver app. The designer can then interact

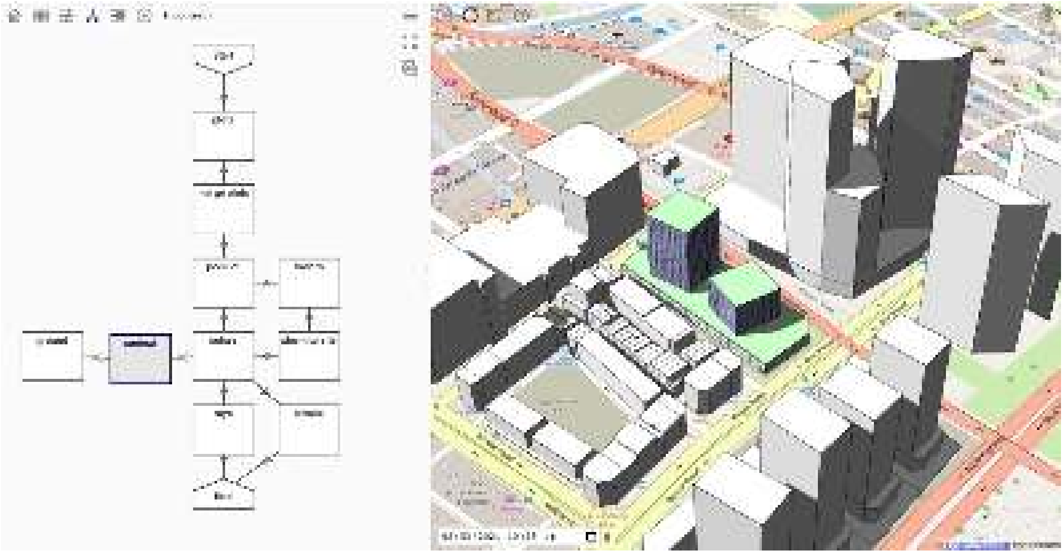


FIG. 15.1 The Möbius Modeler user interface showing a flowchart and the resulting 3D model within a geospatially located context model. *No permission required.*

with the selected 3D model. Finally, when the execution of the search process has completed, the designer can modify the settings and resume the search.

The Möbius Evolver application runs on the Amazon AWS Clouding Computing platform (Amazon AWS, 2021). The client-side provides the user interface and data visualization components. The server-side performs all the main computational tasks using AWS Lambda Functions, including executing the evolutionary algorithm and all the scripts. The data from the evolutionary search process is stored in an AWS DynamoDB database, while files, including design models and design images, are stored in AWS S3 object storage.

An important goal with the Möbius Evolver is to ensure that the computing infrastructure is accessible to all designers. We have developed the application using the "infrastructure as code" approach. This makes it very easy for designers to install a copy of the Möbius Evolver application on their own AWS account. This installation process installs both the front-end components and the whole of the back-end infrastructure. AWS provides all users with a significant quota of free computing resources. For the evolutionary process, the main resource that is required is the execution of the Lambda functions. The free quota provided means that any designer with access to the Internet can run large numbers of evolutionary searchers every month at minimal cost.

Parallelization efficiency

As stated previously, one of the key requirements for the CEDE method is fast execution. The evolutionary search process must be fast enough to not disrupt the design process. Preferably a single search is completed in under 5 min, which we consider to be the time it takes to have a coffee break.

For the evolutionary algorithm, the execution of generative and evaluative scripts can be easily parallelized. Each generation, new offspring design variants are created, requiring a design model to be generated and a fitness score to be calculated. Processing these new offspring in parallel can result in a significant reduction in execution time. The maximum theoretical speedup is equal to the population size. However, the actual speedup that is achievable will be less, due to the time taken to execute the serial portion of the code and due to the additional overheads resulting from the parallel execution.

The parallelization efficiency can be calculated as the ratio of the actual speedup to the theoretical speedup. To calculate the parallelization efficiency achieved by the Möbius Evolver, a series of test searches were executed where the total number of design variants was kept constant but where the population size was varied. The parallelization efficiency was then calculated by comparing the search execution time with a population size of 1 (no parallelization) to execution times with populations ranging between 10 and 100. Based on these tests, the parallelization efficiency varied between 80% and 90%. This means that doubling the population size will result in a reduction in execution time of between 40% and 45%. Note that increasing the population also reduces the number of generations in the search. A very low number of generations can negatively impact the search results.

Demonstration

The demonstration aims to show how the CEDE method can allow a designer to explore alternative design strategies by running a series of iterative evolutionary searches. The design scenario focuses on the exploration of urban massing options for a site in Singapore. The site is in the center of the city next to Bugis MRT station, with an area of 2.3 Ha. The building typology being explored is an office complex composed of a podium and one or more towers. This is a common type of building typology throughout Asia.

The podium has a fixed floor plan (defined by the site boundary), but the number of floors can vary. The towers on top of the podium can vary in number, shape, orientation, and height. The floor heights are predefined at 5 m for podium floors and 3 m for tower floors.

The following three constraints are applied:

- Plot Ratio constraint: The plot ratio (or floor area ratio) of the site is set to 7. This results in a total maximum floor area of 160,000 m^2.
- Setback constraint: The towers must have a minimum setback from the edge of the podium of 6 m.
- Spacing constraint: If there are multiple towers, then the minimum distance between the towers must be 20 m or more.

We imagine that the designer has chosen to focus on optimizing the facades of the office towers, to minimize solar radiation and improve views. Singapore is a hot and humid climate throughout the year. Minimizing solar radiation can have a significant impact on the energy consumption of the building (Givoni, 1994). Improving views can make the office spaces more desirable and can improve the well-being of the people in the offices.

We will describe below three iterations of evolutionary searches. In the first iteration, two strategies are explored. Based on the results of this first iteration, a second search is then performed with two new strategies. Finally, based on the results of this second search, a third strategy is defined. In this case, the second search is resumed. All searches use the same evaluation script.

The complexity of the design scenario is limited. We are intentionally keeping this scenario relatively simple for the sake of clarity. However, the general approach that we describe here can be applied to design scenarios of much greater complexity, involving more performance criteria, design strategies, and search iterations.

Evaluation script

The evaluation script analyzes the facades of the towers on top of the podium, calculating three performance indicators: solar exposure, unobstructed view, and river views. (Note that the facades of the podium block are not included in the fitness calculation.) Fig. 15.2 shows the location and orientation of the site.

For this demonstration, a set of simplified performance indicators will be used. These indicators can be calculated directly from the geometric model. All the indicators are calculated using ray tracing. We describe below in more detail how these performance indicators are calculated. However, it should be noted that for the designer creating the evaluation scripts, predefined functions are provided for calculating these indicators. This means that designers do not need to implement the detailed algorithms described below. The functions make it relatively straightforward for designers to define their own customized evaluation scripts.

Each façade is split into a grid of polygons. In the vertical direction, the polygons have a height of 3 m, aligning with the floor heights. In the horizontal direction, the façade is divided so that the polygons have a maximum length of 8 m. For each polygon, the three performance indicators are calculated by analyzing the center point of the polygon. For each indicator, rays are fired from the polygon centroid toward certain target points in the model using a raycasting approach, and any intersection with obstructions in the model is calculated.

Solar exposure indicator and river view Indicator

Solar exposure and river view are both calculated similarly. For solar exposure, the target points are equally distributed points on the solar sky-dome. The solar sky-dome is defined as the slice of the sky-dome between the June solstice and December solstice, as shown in Fig. 15.3.

For the river view, the target points are equally distributed along a section of the Singapore River. The accuracy of the indicator can be controlled by varying the number of target points. For this demonstration, solar exposure used 99 target points and river view used 20 target points.

In both cases, the score is calculated in the same way. First, the rays that hit any obstructions are filtered out so that only rays that reach the target points remain. The contribution of each ray is then cosine weighted, based on the angle between the ray and the polygon normal. This ensures that rays that are perpendicular to the polygon have a greater impact than oblique rays. The final performance indicator score for the façade polygon is calculated by

FIG. 15.2 Location and orientation of the site. *No permission required.*

summing up all the ray weights and dividing by the maximum possible value for the sum of ray weights. The latter is calculated by running several test models. The formula is as follows:

$$p = \left(\sum_{i=0}^{n} \cos\left(a_i\right)\right)\frac{1}{m} \tag{15.1}$$

where p is the performance indicator (either solar exposure or river view), a_i is the angle for ray i, n is the total number of rays that do not hit any obstructions, and m is the maximum possible sum of ray weights.

Unobstructed view indicator

Unobstructed view is calculated by firing rays from the façade polygon centroid toward target points arranged in a horizontal fan pattern, representing the view out of the window. The fan has a view angle and a maximum depth. The accuracy can be controlled by varying the number of points in the fan pattern. For the demonstration, the fan angle was set to 90°, the

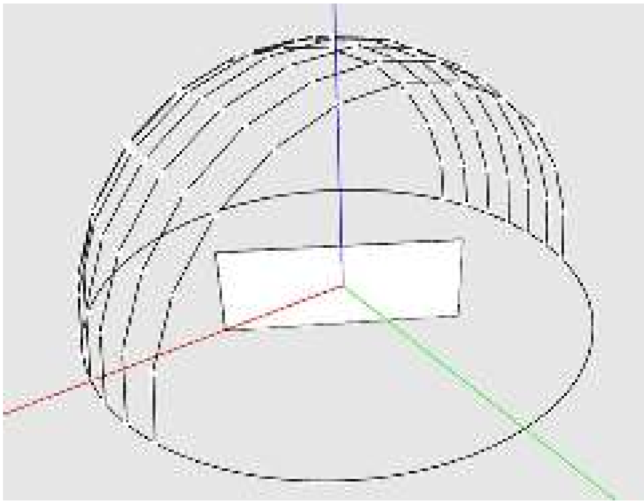


FIG. 15.3 Points on the sky-dome, distributed equally between the June solstice and December solstice. The rectangle at the center represents a vertical façade polygon being analyzed. *No permission required.*

depth was set to 200m, and the number of rays was set to 12. The length of each ray is then calculated. For rays that do not hit any obstructions, the length will be equal to the depth, 200m in this case. For rays that hit obstructions, the length is the distance from the centroid to the point of intersection. The final unobstructed view score for the façade polygon is then calculated by summing up all the ray lengths and dividing by the maximum possible sum of ray lengths. The latter is equal to the depth multiplied by the number of rays. The formula is as follows:

$$u = \left(\sum_{i=0}^{n} len(r_i)\right)\frac{1}{m} \tag{15.2}$$

where u is the unobstructed view score, r_i is ray i, n is the total number of rays, and m is the maximum possible sum of ray lengths.

Fitness score

The evolutionary algorithm uses a single objective optimization process. An overall fitness score therefore needs to be calculated for each design model. This is performed in two steps. First, an aggregated score is calculated for each façade polygon. Second, the final fitness for the whole design model is then calculated based on the scores for all façade polygons.

The three performance indicator scores all have values that range between 0 and 1. This simplifies the aggregation process. Each performance score is assigned a weight, and the sum of the weighted scores is then multiplied by the area of the polygon. The weights are assigned by the designer, depending on the importance they assign to each performance criterion. In the demonstration, the weights were set to 0.5 for solar exposure, 0.2 for the river view, and 0.3 for the unobstructed view.

$$p = (0.5s + 0.2r + 0.3u).a \tag{15.3}$$

where p is the aggregated score for the polygon, s is the solar exposure score, r is the river view score, u is the unobstructed view score, and a is the area of the polygon.

The fitness score is then calculated by summing up the aggregated scores for all façade polygons and dividing by the total area of the façade.

$$f = \left(\sum_{i=0}^{n} p_i \right) \frac{1}{t} \tag{15.4}$$

where f is the fitness of the design model, n is the total number of façade polygons, p_i is the aggregated score for polygon i, and t is the total area of the façade.

Evolutionary iteration 1

In iteration 1, two different strategies were defined, and for each strategy a generative script was implemented. Both generative scrips adhere to the constraints defined above. All design variants that are generated will have a plot ratio close to 7.

The generative scripts start by creating the podium. The shape of the podium is kept constant, based on the site boundary. The number of podium floors is defined by a parameter, varying between 0 and 5 floors.

All scripts then create polygons on the podium roof, representing the footprints of the towers. The towers are then generated by extruding footprints by the required number of floors. A brief description will be given of each script.

In the first strategy, two square towers were placed on the podium. The script parameters are shown in Table 15.2. Three design variants with randomly generated parameter values are shown in Fig. 15.4.

For creating the two towers, the generative script performs the following steps:

1. Two square footprints are created. The footprints are initially placed at either side of the center of the podium.
2. The footprints are moved, based on the "distance" parameter. The parameter specifies the distance between the centroids of the two footprints. The minimum distance is calibrated so that the spacing constraint is never violated.
3. The footprints are rotated and scaled. The footprints are each rotated around their centroids, based on the two "rotation" parameters. After rotation, each footprint is then scaled around its centroid to be as large as possible without violating the 6-m setback constraint.

TABLE 15.2 The parameters for two-tower generative script.

Description	Number of params	Minimum	Maximum	Step
Number of podium floors	1 Parameter	0	4	1
Rotation of tower 1 and 2	2 Parameters	−45	45	1
Percentage area of tower 1	1 Parameter	0	100	1
Distance between towers	1 Parameter	60	100	1

FIG. 15.4 Randomly generated models for the two-tower strategy. *No permission required.*

TABLE 15.3 The parameters for three-tower generative script.

Description	Number of params	Minimum	Maximum	Step
Number of podium floors	1 Parameter	0	4	1
Relative area of tower 1, 2 and 3	3 Parameters	0	100	1
Rotation of all three towers	1 Parameter	−45	45	1

4. The required number of floors for each of the two towers is then calculated. First, the combined floor area of the two towers is calculated. This area is then divided between the two towers based on the "percentage area tower 1" parameter. The floor areas are then used to calculate the number of floors for each tower.

In the second strategy, three towers are placed on the podium. The script parameters are shown in Table 15.3 and three randomly generated design variants in Fig. 15.5.

For creating the three towers, the generative script performs the following steps:

1. Three square footprints are created. The footprints are placed along the length of the podium. Note that in this case the distance between the three towers is fixed and has been calibrated to ensure that the spacing constraint is never violated.
2. The footprints are rotated and scaled. The footprints are each rotated by the same angle around their centroids, based on a single "rotation" parameter. After rotation, each footprint is then scaled around its centroid, like script 1.
3. The required number of floors for each of the three towers is then calculated. First, the combined floor area of the three towers is calculated. This area is then divided between the three towers based on the "relative area" parameters. The floor areas are then used to calculate the number of floors for each tower.

Results for search 1

For the first iteration, Table 15.4 shows the settings used. The total execution time was 2 min and 57 s. That works out at 177 ms per design.

Fig. 15.6 shows the progress plot. The horizontal axis indicates the generation number. The plotlines indicate the maximum, average, and minimum fitness values for each generation. The plotlines are associated with the left vertical axis, which is the score. The bars indicate how the population is divided between the different strategies. The bars are associated with the right vertical menu, ranging from 0 to 1. The plot shows that the three-tower strategy was significantly weaker and became extinct in generation 9. The two-tower strategy resulted in design variants with the highest fitness.

Fig. 15.7 shows the score plot. Each line in this plot represents one design variant. The height of the line shows the score. The color of the line shows the generative script to which it belongs, as well as whether it is alive or dead. Hovering with the mouse over on any line will show an image of the design variant and clicking the line will load the model into the model viewer (Fig. 15.8).

From the two-tower strategy, the design variants with high fitness all had a similar configuration. The design variant with the highest fitness had a score of 57.5%. It had a tower

FIG. 15.5 Randomly generated models for the three towers strategy. *No permission required.*

TABLE 15.4 Settings for search 1.

Number of generations	10
Population size	100
Tournament size	10
Initial subpopulation sizes	GS1: 100, GS2: 100
Mutation standard deviation	0.1

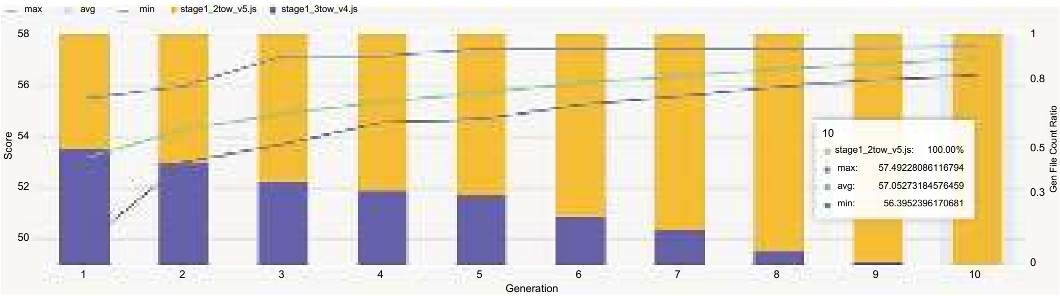


FIG. 15.6 Progress plot for search 1. *No permission required.*

at the north end of the podium with 27 floors, rotated at approximately −40°. The tower at the south end had zero floors. The design variant is shown in Fig. 15.8.

Evolutionary iteration 2a

The results from search 1 indicate that the best performance can be achieved with a podium of 3–4 floors and a single tower positioned at the north end of the podium. The two-tower strategy from search 1 was constrained to only produce square towers. Reflecting on the results, the designer might therefore wonder if it is possible to achieve better performance with towers located at the north end, but where the tower floor plate was not constrained to be square.

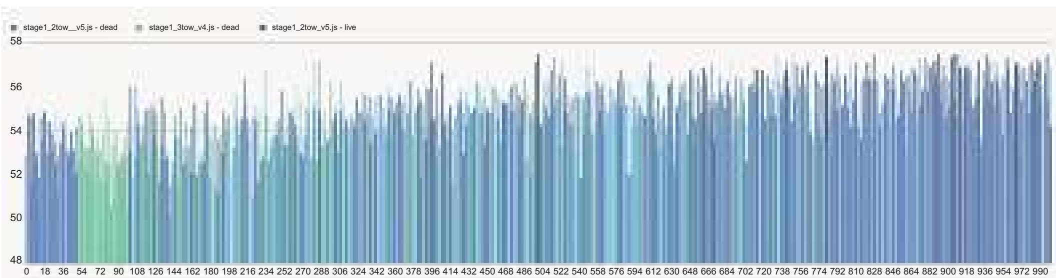


FIG. 15.7 Score plot for search 1. *No permission required.*

FIG. 15.8 The design variant with the highest fitness from search 1. *No permission required.*

To explore this possibility, two new strategies were created for towers with plans that vary in shape. The third strategy is for towers with plans that are regular polygons, and the fourth strategy is for towers with rectangular plans.

Apart from the difference in the shape of the footprint, the two new scripts are similar. A podium is generated with a fixed height of three floors. A tower footprint is created and then rotated and scaled. Finally, a tower is generated by extruding the footprint by the required number of floors.

Both scripts have a “position” parameter, a “rotation” parameter, and one additional parameter related to the shape of the footprint. For the polygonal strategy, Table 15.5 shows the parameters and Fig. 15.9 shows randomly generated examples.

For the rectangular strategy, Table 15.6 shows the parameters and Fig. 15.10 shows randomly generated examples.

Results for search 2a

For search 2a, the same search settings were used. The total execution time was 2 min and 26 s. Of the two strategies, the rectangular strategy resulted in design variants with the highest fitness. The polygonal strategy became extinct in generation 10.

From the rectangular strategy, the design variant with the highest fitness is shown in Fig. 15.11, a slender tall tower, orientated to minimize solar radiation and maximize views.

TABLE 15.5 Parameters for the polygonal tower generative script.

Description	Number of params	Minimum	Maximum	Step
Tower position	1 parameter	0	100	1
Tower rotation	1 parameter	0	180	1
Tower number of sides	1 parameter	3	9	1

FIG. 15.9 Randomly generated models for the polygonal tower strategy. *No permission required.*

TABLE 15.6 Parameters for rectangular tower generative script.

Description	Number of params	Minimum	Maximum	Step
Tower position	1 parameter	0	100	1
Tower rotation	1 parameter	0	180	1
Tower length-width ratio	1 parameter	0.4	1.6	0.01

Evolutionary iteration 2b

The results from search 2a indicate that the best performance can be achieved with a rectangular tower positioned at the north end of the podium. Reflecting on the results, the designer might be interested to investigate towers that are similar in form, but that are not necessarily perfect rectangles.

To explore this possibility, one new strategy was created for a tower with chamfered corners. The script is similar to the previous two scripts. As before, the script creates a polygon footprint on the podium roof and then rotates and scales the footprint. However, this time the resulting footprint may still violate the setback constraint. In such cases, the footprint polygon is trimmed by a Boolean operation that removes the parts of the polygon that extend beyond the setback. This results in a tower block with chamfered corners.

The script has a "position" parameter, a "rotation" parameter, and one additional parameter that sets the width of the tower. For the chamfered strategy, Table 15.7 shows the parameters and Fig. 15.12 shows randomly generated examples.

Results for search 2b

For search 2b, it was decided to let the chamfered strategy directly compete with the rectangular strategy. The previous search was therefore resumed and design variants for the chamfered generative script were added to the population.

The same search settings were used, except that the number of generations was increased to 20 and an additional generative script was added. The total execution time for the extra 10 generations (1000 designs) was 2 min and 17 s.

Fig. 15.13 shows the progress plot of all 20 generations from both search 2a and 2b. Search 2a consisted of generations 1–10, and search 2b of generations 11–20. The plot shows that in search 2a, the polygonal and rectangular strategies started off equally balanced, but the rectangular strategy quickly started to dominate. By generation 6, the polygonal strategy became extinct. Then in generation 11, the chamfered strategy was introduced. Gradually, this new strategy started winning over the rectangular strategy, which became extinct in generation 19.

From the chamfered strategy, the design variants with high fitness were again all similar. The tower with the highest fitness is shown in Fig. 15.14. It has a rotation of −40°, a position of 80%, and a width of 23 m. This configuration results in a tower that is aligned with the sun path, with the larger facades facing north and south. At Singapore's latitude, this results in the lowest solar radiation. In addition, the orientation results in both these facades having good unobstructed views. The east façade is largely overshadowed by a tall neighboring tower, reducing its solar radiation. For the west façade, the neighboring buildings are lower, resulting in some areas with high solar radiation. However, these areas are relatively small. For the

FIG. 15.10 Randomly generated models for the rectangular strategy. *No permission required.*

FIG. 15.11 The design variant with the highest fitness from search 2a. *No permission required.*

TABLE 15.7 Parameters for chamfered tower generative script.

Description	Number of params	Minimum	Maximum	Step
Rotation of tower	1 Parameter	−50	50	1
Position of tower	1 Parameter	0	100	1
Width of tower	1 Parameter	20	40	1

river view, the whole of the south façade scores reasonably well. The three performance indicators are aggregated using the weight-sum method previously described, to give the final overall score for each façade polygon.

The parallel plot is another type of graph that is incorporated into the Möbius Evolver. Fig. 15.15 shows the parallel plot for the 100 design variants in the final generation of search 2b. In the parallel plot, each line represents one design variant. In this case, the design variants all belong to the chamfered strategy, since those were the only ones surviving in generation 20. The first three vertical axes represent the three parameters of the generative script for the chamfered strategy. The last vertical axis represents the fitness score.

From the parallel plot, it can be seen that all design variants had a similar fitness score, between 61% and 62%. For the three parameters, the rotation and width parameters both have narrow ranges, while the position parameter has a wide range. From this, the designer can conclude that the rotation and width parameters are strongly correlated to the fitness, while the position parameter is weakly correlated.

Discussion

The demonstration has shown how the Möbius Modeler and the Möbius Evolver can enable designers to explore alternative design strategies by running iterative evolutionary

FIG. 15.12 Randomly generated models for the chamfered tower strategy. *No permission required.*

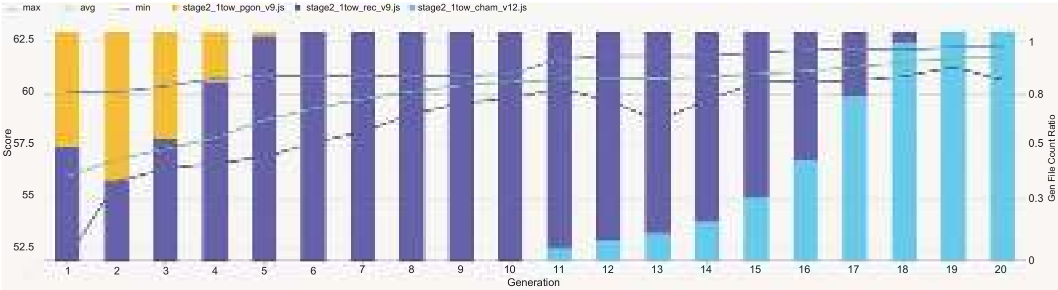


FIG. 15.13 Progress plot for search 2a and 2b. *No permission required.*

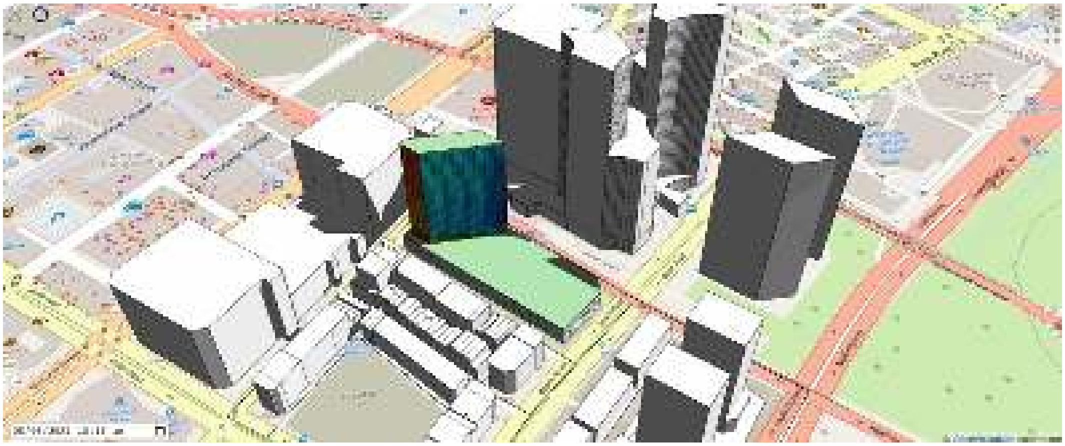


FIG. 15.14 The design variant with the highest fitness from search 2b. *No permission required.*

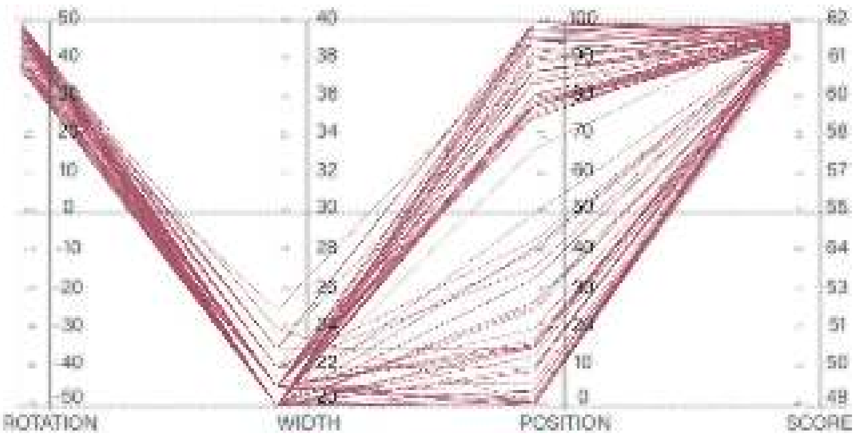


FIG. 15.15 The parallel plot of generation 20. *No permission required.*

searches with heterogeneous populations of design variants. For each search, relatively simple scripts were created for generating and evaluating design variants. The generative scripts created simple massing models, consisting of a podium with office towers. The evaluative script calculated three different performance indicators related to the facades of the office towers: minimizing solar irradiation, maximizing unobstructed views, and maximizing river views.

This example demonstrates the feasibility of the CEDE approach. However, we note that in most real-world design scenarios, three searches would not suffice. In a real design process, a designer might run many different searches, with a wide range of typologies and with different types of evaluation scripts. Through this process, the designer would gradually develop a deep understanding of the space of possibilities embedded in the design scenario.

The ambition behind this research is that the CEDE approach will allow designers to get a deeper understanding of the interrelationships between the design scenario and the competing design strategies. Furthermore, we believe that designers will be able to discover solutions that would have been difficult to find without intelligence amplification. To strengthen this hypothesis, many more examples and case studies need to be done, tackling a wider range of design scenarios.

In addition, for the CEDE algorithm, two key areas have been identified for further research. First, we will investigate the possibility of using multiobjective optimization by allowing more than one evaluation script to be used. Second, we will investigate the possibility of using self-adaption of the mutation standard deviation setting (Fogel, 1992, 1995). In both cases, we are interested in improving the double-loop learning process (Argyris and Schon, 1978).

Conclusions

The CEDE approach seeks to amplify the intelligence of the designer, through a cyclical exchange between the human and the computer. In this exchange, the task of the designer is to develop competing design strategies and the task of the computer is to search for high-performing design variants. Linking these two tasks together is a set of generative and evaluative scripts created by the designer.

The Möbius Modeler and Möbius Evolver web applications allow designers to apply the CEDE approach in practice. The Möbius Modeler allows designers with limited programming skills to develop their own generative and evaluative scripts. The Möbius Evolver allows heterogeneous populations of design variants to be evolved in the cloud, using parallel computing.

The cloud computing platform used by the Möbius Evolver allows searches generating thousands of designs to be completed in just a few minutes. This contrasts dramatically with many previous evolutionary design examples from the research, where evolutionary optimization can take many hours or even days to complete, even when using parallelization (Janssen, 2015; Nguyen et al., 2014).

The Möbius Evolver has been developed to make it easy for any designer to install it on their own private AWS account so that they can leverage the significant amount of free computing quotas that are provided. As such, the CEDE method and Möbius web applications can be used by any designer in the world with access to the Internet, at minimal cost.

Acknowledgment

This research was supported by the National Research Foundation, Singapore, under its AI Singapore Program (AISG Award No: AISG-RPKS-2019-004).

References

Amazon AWS, 2021. Available at: https://aws.amazon.com/. (Accessed 1 June 2021).

Argyris, C., Schon, D., 1978. Organizational Learning: A Theory of Action Perspective. Addison-Wesley.

Attia, S., et al., 2013. Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design. Energ. Buildings 60, 110–124. https://doi.org/10.1016/j.enbuild.2013.01.016. Elsevier BV.

Bentley, P.J. (Ed.), 1999. Evolutionary Design by Computers. Morgan Kaufmann.

Bentley, P.J., Corne, D. (Eds.), 2002. Creative Evolutionary Systems. Morgan Kaufmann, San Francisco.

Beyer, H.-G., Schwefel, H.-P., 2002. Natural Computing. Springer Nature, pp. 3–52, https://doi.org/10.1023/A:1015059928466.

Blickle, T., Thiele, L., 1995. A comparison of selection schemes used in evolutionary algorithms. Evol. Comput. 4 (4), 361–394.

Bradner, E., Iorio, F., Davis, M., 2014. Parameters tell the design story: ideation and abstraction in design optimization. In: SimAUD 2014: Symposium on Simulation for Architecture and Urban Design.

Chen, K.W., Janssen, P., Schlueter, A., 2018. Multi-objective optimisation of building form, envelope and cooling system for improved building energy performance. Autom. Constr. 94, 449–457. https://doi.org/10.1016/j.autcon.2018.07.002. Singapore: Elsevier B.V.

Chen, Y., et al., 2021. From separation to incorporation: a full-circle application of computational approaches to performance-based architectural design. In: The 3rd International Conference on Computational Design and Robotic Fabrication.

Darke, J., 1979. The primary generator and the design process. Des. Stud. 1 (1), 36–44. https://doi.org/10.1016/0142-694x(79)90027-9. Elsevier BV.

Deb, K., 2005. Multi-objective optimization. In: Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques. Springer US, India, pp. 273–316, https://doi.org/10.1007/0-387-28356-0_10.

Eiben, A.E., Smith, J.E., 2015. Introduction to Evolutionary Computing. 2nd ed, Natural Computing Series, second ed. Springer-Verlag, Berlin Heidelberg, https://doi.org/10.1007/978-3-662-44874-8.

Evins, R., 2013. A review of computational optimisation methods applied to sustainable building design. Renew. Sustain. Energy Rev. 22, 230–245. https://doi.org/10.1016/j.rser.2013.02.004. United Kingdom.

Fogel, D.B., 1992. Evolving Artificial Intelligence. University of California, San Diego, CA. PhD thesis.

Fogel, D.B., 1995. Evolutionary Computation: Towards a New Philosophy of Machine Intelligence. IEEE Press, New York, NY.

Fogel, L.J., 1999. Intelligence Through Simulated Evolution: Forty Years of Evolutionary Programming. John Wiley & Sons, New York, NY.

Fogel, L.J., Owens, A.J., Walsh, M.J., 1966. Artificial Intelligence Through Simulated Evolution. John Wiley & Sons, New York, NY.

Frazer, J.H., 1995. An Evolutionary Architecture. Architectural Association Publications, London.

GenOpt, 2021. Available at: http://simulationresearch.lbl.gov/GO/. (Accessed 1 June 2021).

Givoni, B., 1994. Urban design for hot humid regions. Renew. Energy 5 (5–8), 1047–1053. https://doi.org/10.1016/0960-1481(94)90132-5. Elsevier BV.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Longman, Boston, MA.

Granadeiro, V., et al., 2013. Building envelope shape design in early stages of the design process: integrating architectural design systems and energy simulation. Autom. Constr. 32, 196–209. https://doi.org/10.1016/j.autcon.2012.12.003. Portugal: Elsevier B.V.

Harding, J.E., Shepherd, P., 2017. Meta-parametric design. Des. Stud. 52, 73–95. https://doi.org/10.1016/j.destud.2016.09.005. Elsevier BV.

Janssen, P.H.T., 2004. A Design Method and a Computational Architecture for Generating and Evolving Building Designs. Hong Kong Polytechnic University. PhD Thesis.

Janssen, P., 2013. Evo-devo in the sky. In: Proceedings of eCAADe 2013, pp. 205–214.

Janssen, P., 2015. Dexen: a scalable and extensible platform for experimenting with population-based design exploration algorithms. Artif. Intell. Eng. Des. Anal. Manuf. 29 (4), 443–455. https://doi.org/10.1017/S0890060415000438. Singapore: Cambridge University Press.

Janssen, P., Stouffs, R., 2015. Types of parametric modelling. In: Proceedings of the 20th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2015. Proceedings of CAADRIA 2015, 20-22 May 2015, pp. 157–166.

Janssen, P., Li, R., Mohanty, A., 2016. Möbius : a parametric modeller for the web. In: Proceedings of the 21st International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2021. Singapore: Proceedings of CAADRIA 2016, 22–26 August 2016, Melbourne, Australia, pp. 157–166.

Kaushik, V., Janssen, P., 2013. An evolutionary design process: adaptive-iterative explorations in computational embryogenesis. In: Proceedings of CAADRIA 2013, pp. 137–146.

Koenig, R., et al., 2020. Integrating urban analysis, generative design, and evolutionary optimization for solving urban design problems. Environ. Plan B Urban Anal. City Sci. 47 (6), 997–1013. https://doi.org/10.1177/2399808319894986. Germany: SAGE Publications Ltd.

Koza, J.R., 1992. Genetic Programming. MIT Press.

Lin, S.H.E., Gerber, D.J., 2014. Designing-in performance: a framework for evolutionary energy performance feedback in early stage design. Autom. Constr. 38, 59–73. https://doi.org/10.1016/j.autcon.2013.10.007. United States.

Martins, T.A.L., Adolphe, L., Bastos, L.E.G., 2014. From solar constraints to urban design opportunities: optimization of built form typologies in a Brazilian tropical city. Energ. Buildings 76, 43–56. https://doi.org/10.1016/j.enbuild.2014.02.056. Brazil: Elsevier BV.

Mobius, 2021. Available at: http://mobius.design-automation.net. (Accessed 1 June 2021).

Mobius Evolver, 2021. Available at: https://github.com/design-automation/mobius-evo. (Accessed 1 June 2021).

Mobius Modeller, 2021. Available at: https://mobius-08.design-automation.net/. (Accessed 1 June 2021).

Mode Fontier, 2021. Available at: https://www.enginsoft.com/solutions/mf.html. (Accessed 1 June 2021).

Nault, E., et al., 2018. Development and test application of the UrbanSOLve decision-support prototype for early-stage neighborhood design. Build. Environ. 137, 58–72. https://doi.org/10.1016/j.buildenv.2018.03.033. Elsevier BV.

Nguyen, A.T., Reiter, S., Rigo, P., 2014. A review on simulation-based optimization methods applied to building performance analysis. Appl. Energy 113, 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061. Belgium: Elsevier Ltd.

Phoenix Integration, 2021. Available at: https://www.phoenix-int.com/. (Accessed 1 June 2021).

Radford, A.D., Gero, J.S., 1980. On optimization in computer aided architectural design. Build. Environ. 15 (2), 73–80. https://doi.org/10.1016/0360-1323(80)90011-6. United Kingdom.

Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Pol. Sci. 4 (2), 155–169. https://doi.org/10.1007/BF01405730. United States: Kluwer Academic Publishers.

Rutten, D., 2013. Galapagos: on the logic and limitations of generic solvers. Archit. Des. 83 (2), 132–135. https://doi.org/10.1002/ad.1568. undefined.

Scott, S.D., Lesh, N., Klau, G.W., 2002. Investigating human-computer optimization. In: CHI '02: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 155–162, https://doi.org/10.1145/503376.503405.

Vierlinger, R., 2013. Multi Objective Design Interface. University of Applied Arts Vienna, https://doi.org/10.13140/RG.2.1.3401.0324.

Wang, L., Janssen, P., Ji, G., 2019. Progressive modelling for parametric design optimization. In: Proceedings of the 24th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2019. China: The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 1, pp. 383–392.

Wang, L., et al., 2020a. Enabling optimisation-based exploration for building massing design: a coding-free evolutionary building massing design toolkit in rhino-grasshopper. In: Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020. China: The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 1, pp. 255–264.

Wang, L., Janssen, P., Ji, G., 2020b. SSIEA: A hybrid evolutionary algorithm for supporting conceptual architectural design. Artif. Intell. Eng. Des. Anal. Manuf. 34 (4), 458–476. https://doi.org/10.1017/S0890060420000281. China: Cambridge University Press.

Woodbury, R., 2010. Elements of Parametric Design. Routledge.

Wortmann, T., Fischer, T., 2020. Does architectural design optimization require multiple objectives? A critical analysis. In: Proceedings of the 25th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA 2020. China: The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 1, pp. 365–374.

This page intentionally left blank

CHAPTER

16

Adaptive master plans: Flexible modular design strategies

Martin Bielik[a], *Reinhard Koenig*[b,c], *and Sven Schneider*[a]

[a]Bauhaus-University Weimar, Chair of Computer Science in Architecture and Spatial Planning, Weimar, Germany [b]AIT Austrian Institute of Technology, Digital and Resilient Cities, Vienna, Austria [c]Bauhaus-University Weimar, Professorship for Computational Architecture, Weimar, Germany

Introduction

The complexity of urban environments is one of the main challenges urban planners are facing when designing new urban quarters or even whole cities. They consist of thousands of elements and need to satisfy numerous requirements (ranging from technical and financial over ecological up to social). Therefore the relationship between these requirements and the design elements is highly nonlinear. In order to cope with this complexity, the employment of digital tools is indispensable in urban design. These tools on the one hand help to create urban design proposals much faster and at the same time allow for more control over many design parameters. On the other hand, they help to understand the parallel interactions of many different influencing variables in order to develop urban qualities. The use of modern data analysis techniques and simulations makes it possible to measure a wide range of ecological, economic, and social criteria in an urban context and make them available for informed decision-making processes. Furthermore, the flexibility of the computer programs allows to integrate a wide variety of stakeholders in a process-oriented manner, thereby responding to people's needs and contributing to a sustainable future.

In this chapter, we look at how these new digital tools can be utilized to form adaptive master plans (AMPs)—an urban design paradigm where the outcome of the design process is not a single urban plan but rather a computational model that is able to react to different boundary conditions and design performance requirements. We briefly summarize the origins of AMPs, show their basic components, and demonstrate their application in the context

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00011-1

of two international projects: small town development in Ethiopia and the design of a new urban district on Singapore's waterfront. Finally, we discuss the potentials and challenges that such AMPs have for urban design.

Background

The development of software for automating urban and architectural design began in the 1970s. The first publications on computer-aided architectural design (CAAD) already included sections on methods for optimizing designs (Mayer, 1971; Mitchell, 1977; Negroponte, 1975) and on automated design processes (Eastman, 1973; Flemming, 1978; Grason, 1971). Generative methods such as Shape Grammar (Stiny and Gips, 1971; Stiny and Mitchell, 1978) or methods for urban analysis (Hillier and Hanson, 1984; Negroponte and Groisser (1970) followed. However, generative approaches and automation were rarely used in architectural and urban designer practice and did not feature in CAAD software until the beginning of the 2000s. The development mainly focused on digital drawing and three-dimensional (3D) modeling (Rooney and Steadman, 1988) and led to the concept of a digital building information model (BIM) (Eastman et al., 2008) and city information model (CIM) on the urban scale (Gil et al., 2011; Stojanovski, 2013, 2018). While these methods provide a useful basis for representing architectural and urban environments, their capabilities for improving the design process remain restricted.

The availability of more powerful hardware in the early 2000s, along with new software that made the development of software tools easier, created the conditions for solutions that could be applied in practice (Parish and Muller, 2011; Braach, 2002; Coates and Derix, 2008; Hovestadt, 2009; Weber et al., 2009). The development of visual programming tools and their integration into CAD systems, such as Grasshopper for Rhino 3D, made automation in urban design accessible for regular designers. Based on the improved accessibility of advanced analysis and generative algorithms via Grasshopper, there are more and more urban design and planning projects that use computational tools in a comprehensive way. Some good examples are the projects presented by the City Intelligence Lab (Fink and Koenig, 2019; Duering et al., 2020a,b; Elshani et al., 2020, 2021) or (Duarte and Beirão, 2011). These projects can be summarized under the term adaptive masterplans (AMP) as we discuss them in the following.

AMPs are parametrically controlled 3D models that can automatically respond to different boundary conditions or design requirements and thus allow to generate a wide range of urban design variants. These variants can be used as basis for any kind of analysis (e.g., solar radiation, wind and microclimate simulations, accessibility, visibility, green space provision, costs) allowing to assess their qualities and in consequence optimize the design. Thus, AMPs are an ideal tool for negotiation processes between different urban stakeholders. By interactively creating urban plans and assessing their performance, the relationship between different design parameters and their effects can be explored and used as a profound basis for informed discussions.

Methods

Technically, AMPs are based on an interconnected set of generative and analytical algorithms. For achieving greatest flexibility, AMPs follow a modular approach, allowing to easily connect different algorithms with each other. Basically, one can differentiate between two types of modules: analytic and generative ones. The generative modules allow to generate variants for the configuration of urban design elements (e.g., streets, plots, buildings, land use). The analytic modules comprise algorithms, which extract features from an urban design proposal, that are relevant for the evaluation (e.g., what are the most accessible/frequented streets or which households are not properly supplied with drinking water). The analytic and generative modules can be used in combination in order to generate complex strategies for creating urban plans. These complex strategies finally allow to interactively control the urban plan by either changing the desired performance (e.g., a certain urban density or energy demand) or by directly manipulating geometrical elements (e.g., the curvature of a street or the boundary of an urban quarter).

The distinct feature of the modular approach is that thereby the designer operates on a high-level language. Thus, one does not need to know a programming language, but one works directly with typical urban elements (such as streets, buildings) and design parameters (such as width, length, density, movement flows). This makes it easier to comprehend the digital design strategy and integrate it into the design process.

The implementation of AMP presented in this chapter is based on Rhinoceros 3D (3D modeling software) as a geometric engine and Grasshopper3d as a software framework. Its advanced geometry-modeling capabilities provide rich functionalities to generate urban patterns and pipe networks. Through its visual programming language Grasshopper, parametric designs can easily be created. Further on, the community around this software has developed many plugins suitable for architecture and urban design, such as our self-developed DecodingSpaces Toolbox (https://toolbox.decodingspaces.net/) for street network analysis, visibility analysis, generative street networks, parcellation, etc. or URBANO (https://urbano.io/) for mobility analysis or Climate Studio for Energy Analysis (https://www.solemma.com/climatestudio).

Generative modules

The main generative modules of the AMP are categorized by the main elements of urban form, namely, streets, plots, and buildings (Kropf, 2017; Oliveira, 2016), and the uses that are assigned to these elements (such as residential, commercial, industrial). This concept was used by Weber et al. (2009) for the procedural modeling of cities, in which a typical generative sequence starts with the generation of a street network, from which street blocks are extracted. Next, these blocks are sliced into parcels, onto which buildings are placed on. Finally, there is a module for the distribution of land uses or urban functions on the parcels. In principle, these modules can—if designed appropriately—be used in various orders. In the following, the methods for the modules are described in more detail:

Street network generation module

For the generation of street networks and the placement of buildings, there are mainly two approaches—additive and dividing. In the additive approach, street segments are added step by step, where various rules concerning distances, angles, and intersections to or with other segments are checked for each segment. Additive approaches are used, for example, for the procedural creation of road networks based on L-systems (Parish and Muller, 2011) and tensor fields (Chen et al., 2008). In the subtractive approach, a defined area is subdivided into blocks, whereas the block borders define the street segments. The parameters for controlling both approaches can usually be defined by the designer or be informed by analysis modules (e.g., the slope of a terrain or the centrality of the network).

Urban block and parcel generation module

Street blocks are the areas that are enclosed by the segments of the street network. They are the basis for the generation of the parcels, for which several subdivision algorithms can be used. Thereby, however, it needs to be considered that each parcel should be connected to a street segment. The main control parameters are the parcel area and the width of a parcel at the street side (Miao et al., 2018).

Land use distribution module

Each land use type can be defined in terms of its spatial requirements such as area or accessibility to other land uses and environmental features (e.g., water, arable land). The land use distribution module lets the designer define a list of requirements for the overall land use program and iteratively search for the optimal placement. In addition to the automatic placement, the module also provides the option to allocate the land uses manually through a procedure similar to painting over the urban plan.

Building generation module

The buildings are placed as 3D volumes on the parcels (Fig. 16.1) by considering parameters that define primarily the allowed density, distances, and heights (Koenig et al., 2017). There may be other parameters included for the more detailed generation of building volumes that consider the inner logic and requirements of the buildings (Osintseva et al., 2020).

Analysis modules

With the help of analysis modules, qualities of a generated urban environment can be computed. This can be either used to assess the overall performance of the design proposal (e.g., energy consumption, construction costs) or to inform the design (e.g., traffic flow analysis informs the street width). In the past years, we created a number of different analysis modules that are particularly tailored for the urban context. The data structure thereby is aligned to the

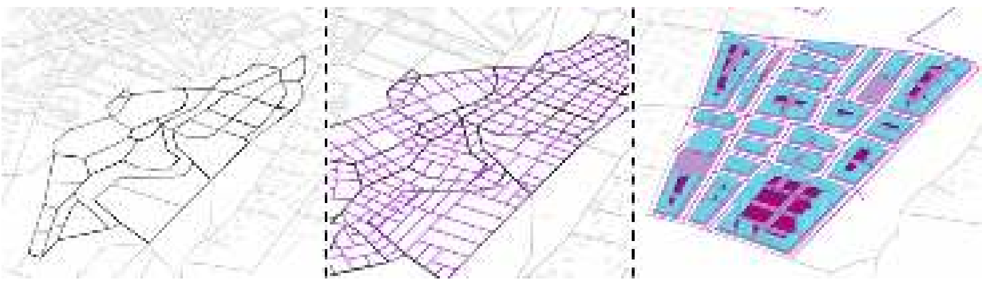


FIG. 16.1 Examples for different automatically generated urban elements: Street Network (left), Plots (center) and Buildings (right). *No permission required.*

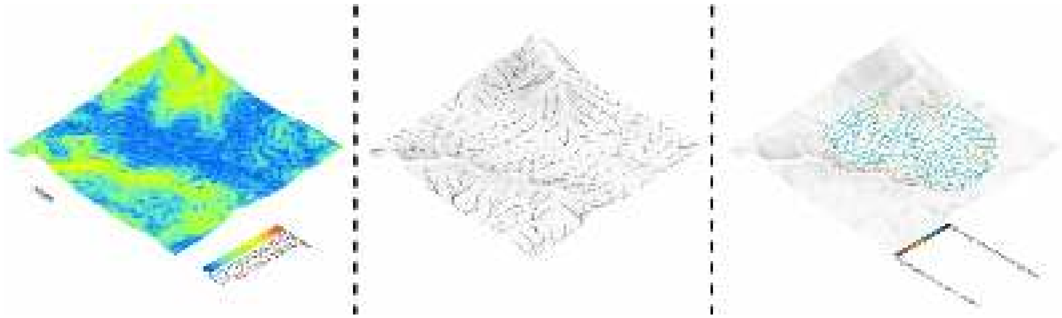


FIG. 16.2 Examples for different topography-based analysis modules: slope analysis (left), water rundown analysis (center) and storm water analysis (right). *No permission required.*

one of the generative modules, making it easy to analyze generated designs and in turn to inform the generative process. Some of these analysis modules are displayed in the following.

Topography and water

Topography is a fundamental boundary condition for urban design. Thus, an urban layout that is well aligned to its terrain can improve access and ease construction. The terrain analysis module identifies several features of the earth's surface, such as slope or roughness (see Fig. 16.2, left). This can inform the allocation of buildings (too steep to be built on?) or the layout of the street network (too steep to walk/cycle?). Furthermore, the topography influences the water flows. Considering these flows in urban design is crucial to protect streets and plots from flooding and to efficiently supply households with water, respectively, dispose wastewater.

For identifying the natural flow of rainwater, we developed a water runoff analysis. Based on a geometrical analysis of a grid-based terrain model, the main drainage lines and their intensity as well as local perpetual reservoirs (ponds) or temporarily sinks (swamps) are calculated (Fig. 16.2, center). These can be used for identifying flood risk streets (Fig. 16.2, right), inform the street network generation, or to find local high points for the water reservoir placement.

For water distribution analyses, we created a module based on the existing hydrologic analysis tool EPANET, an Open-Source library for the analysis of pressurized pipe networks (https://www.epa.gov/water-research/epanet). It allows the calculation of hydrologic network properties as well as water quality measures based on a given street network, water demand, and topography (Fig. 16.3). This allows testing, if households would be undersupplied with water, and in consequence change design parameters (such as the street network layout or the position of the water reservoir).

Accessibility and centrality

As the aim of the street network is to connect and facilitate the flow of people and goods, we quantify the ability to do so by measuring its accessibility and centrality. We represent the street network as a spatial graph and calculate the relationships between different locations in terms of the shortest paths. Distances can be measured here in terms of the length of a path or

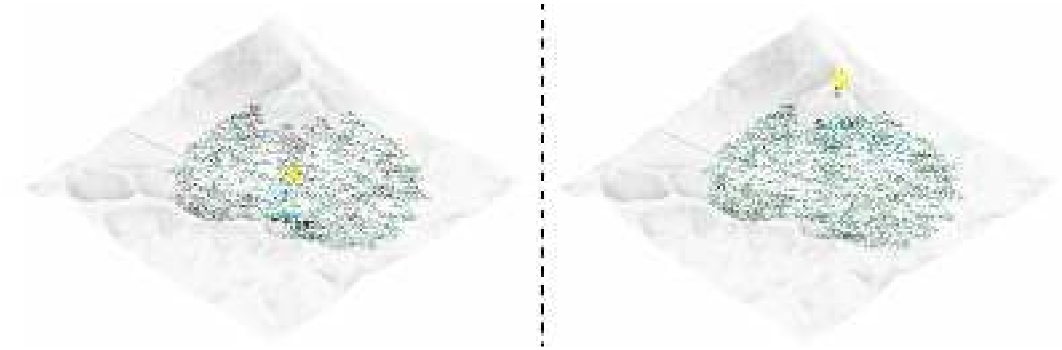


FIG. 16.3 Example for a water pressure analysis for two different water tank locations (green points indicate well supplied households and red points indicate undersupplied households). *No permission required.*

in terms of the ease of a path. The latter expresses the cognitive distance, i.e., how often one has to turn, or how easy it is to find a way between two places, independent of its length. By doing so, we are able to quantify how accessible and central each location is in respect to all other locations in the urban plan (Fig. 16.4). As demonstrated by Hillier and Hanson (1984), the street network centrality measures (e.g., closeness, betweenness) are closely connected to different aspects of human behavior (e.g., land use allocation, movement flow). Consequently, the results of the analysis can be used to inform the generative modules about the optimal distribution of land uses or adjust the road profile to accommodate the expected traffic.

Visibility

What we see in an environment affects our emotional and physical state (Bielik et al., 2019) as well as our ability to orient and navigate in space (Dalton, 2003). To quantify the visual perception at a given location, we use the concept of the isovist, first introduced by

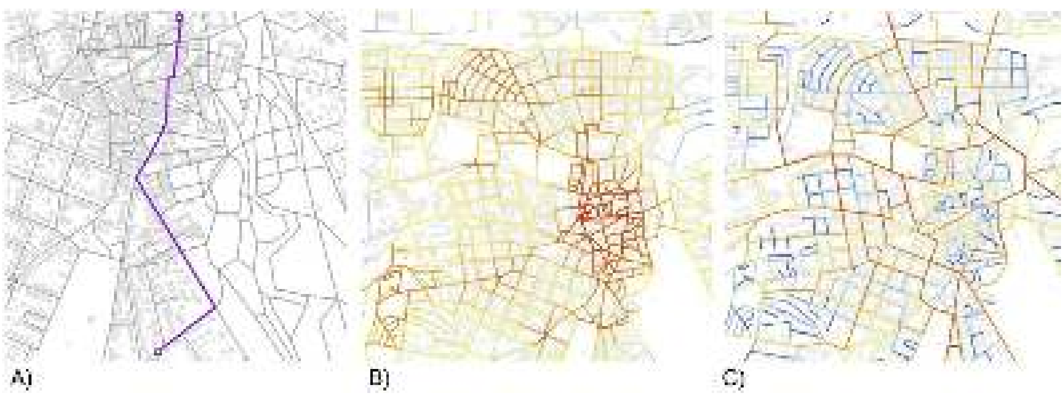


FIG. 16.4 Centrality analysis for an urban design variant. (A) Single shortest path between two locations. (B) The closeness centrality is shown, which indicates which streets are closest to all others (red = high values, blue = low values). (C) The betweenness centrality is shown, which indicates the most frequented streets (red = high values, blue = low values). *No permission required.*

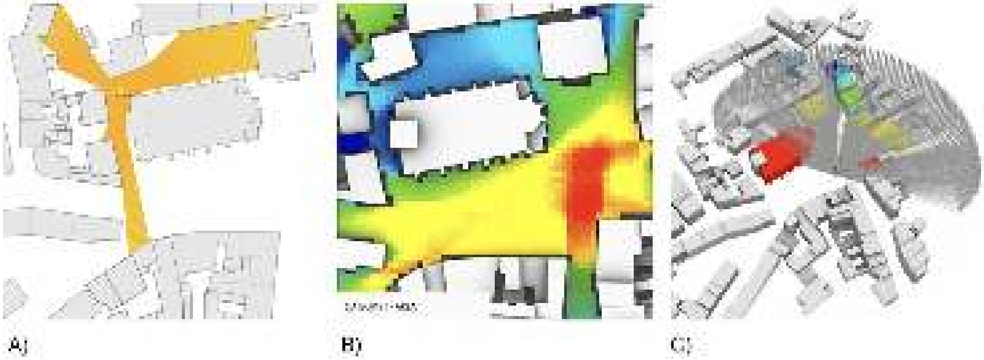


FIG. 16.5 Visibility analysis for design variant. (A) Single isovist. (B) Isovist field displaying the area property (red = high values, blue = low values). (C) 3d isovist highlighting buildings by their visibility. *No permission required.*

(Benedikt, 1979) and frequently used in environment-behavior studies (Franz and Wiener, 2005; Stamps, 2005). An isovist is defined as the area that can be seen from a single vantage point (Fig. 16.5). From the shape and rays of the isovist, different properties can be derived, such as the surface area of the isovist polygon, its perimeter, compactness (ratio of area to perimeter related to an ideal circle), or occlusivity (length of occluding edges). In turn from these calculations, it is possible to derive, among other things, perceptual qualities such as safety (Xiang et al., 2021) or assess which areas are particularly well seen and thus have a greater impact on the outdoor space. Originally, the concept of isovist was bound to reduction of space in two dimensions, however, the same principles can be extended to the third dimension as demonstrated by the authors in a previous publication (Bielik et al., 2019).

Connecting modules

All modules in the AMP toolbox can be seen as computational algorithms driven by a set of inputs and resulting in module-specific outputs. The central idea of AMP is that the individual modulus can be connected via their input-outputs into algorithmic pipelines as presented in the following section and illustrated in Fig. 16.6. It is important to note that the order of the modules in the pipeline is highly flexible and thus, the same assembly of modules can result

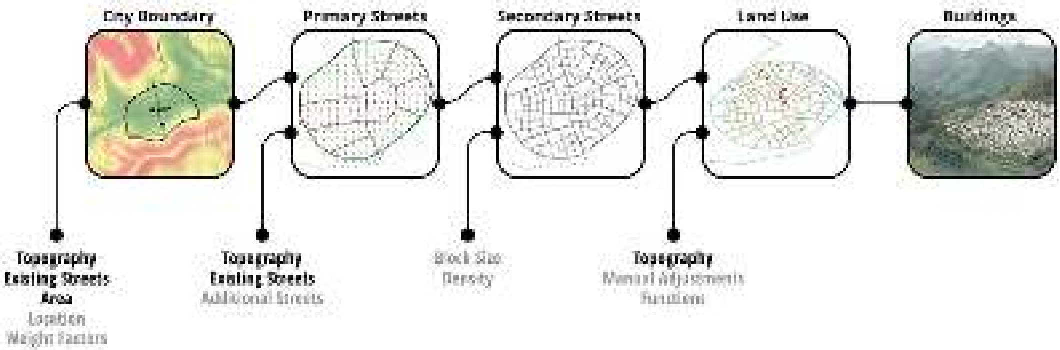


FIG. 16.6 Exemplary sequence of modules of an AMP for creating an urban plan. *No permission required.*

in a high variety of AMPs. For instance, the output of the street network generating module can serve as input for the land use distribution module with central streets serving as mix use, commercial center, and the less accessible locations being allocated to residential or agricultural land use. Nevertheless, it is also possible to define the land use distribution first and translate it into input parameters driving the generation of the street network. As a result, the planner is able to assemble a series of simple modules into a complex generative system in a flexible way, which is easy to control and adapt.

Applications

In the following two paragraphs, we display the application of the previously introduced AMP methods using two case studies. Therefore, for each case, we briefly describe the background of the urban design problem, then show how an AMP could be created for this problem, and finally discuss the results that were able to be produced using the AMP.

Spatial development scenarios for Ethiopia's fast-growing cities

The first case study deals with the development of small towns all over Ethiopia. Background of this case study is the rapid urbanization, with millions of people migrating from rural areas to cities each year, leading to shortages of resources, infrastructure, housing, and jobs. One strategy to cope with this process is the development of existing villages into small towns for around 10,000 inhabitants (see Growth and Transformation Plan II; https://europa.eu/capacity4dev/nexus_ethiopia/documents/growth-and-transformation-plan-ii-gtp-ii-201516-201920). This decentralized, regional planning policy is intended to prevent the rural population from increasingly migrating to informal settlements in the capital Addis Ababa. The citizens of the new rural–urban cities are to be supported in remaining in their region by offering them improved living conditions and new employment opportunities with the necessary infrastructure.

Given the ubiquitous diversity of the country, characterized by a multitude of languages, religions, cultures, landscapes, and climatic conditions, one of the challenges in this urbanization process is to design hundreds—or even thousands—of these new cities in a short time with a few trained urban planners and architects. To manage this in a conventional way seems almost impossible, especially when it is necessary to avoid a serial duplication of standardized urban design solutions, which do not reflect the specific conditions of the particular site (e.g., topography, existing buildings, and roads).

With this in mind, we have, together with students in design studios, developed several AMPs for Ethiopian cities with approximately 10,000 inhabitants, which can adapt to the respective local geographic conditions to a large extent automatically. Thereby many different approaches emerged (see the results on our Online Teaching Platform; https://otp.uni-weimar.de/design-studio-results/?filter=ethiopia&pid=3&pg=1), of which one strategy is described in the following. The AMP consists of four modules: (1) defining the urban area, (2) creating the main streets based on water flows, (3) creating secondary streets to ensure walkability and street blocks sized for various uses, and (4) the distribution of land uses,

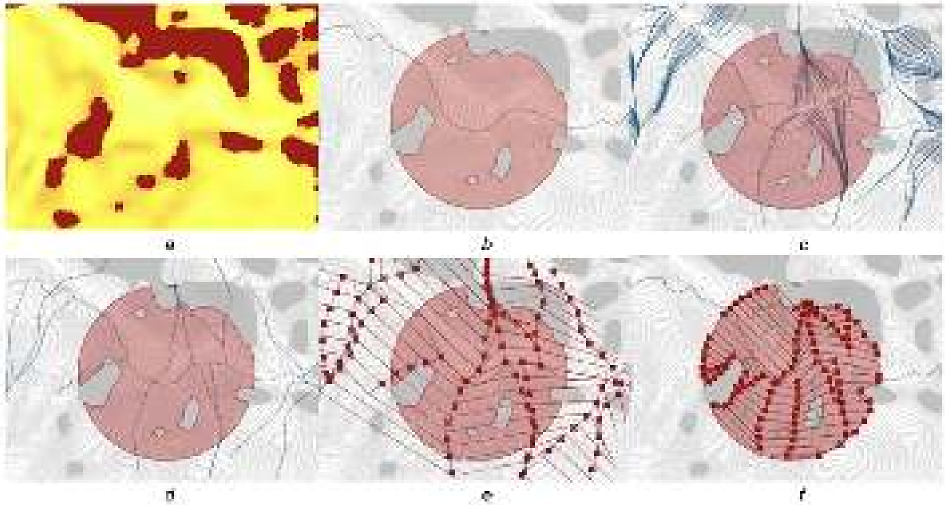


FIG. 16.7 Sequence to generate a street network based on city size, topographical boundaries, and watersheds. *No permission required.*

density, and building types. For each module, appropriate analysis methods are applied to control the generation process as follows.

To define the area on which the city shall be developed, a city boundary is calculated. Therefore, the necessary surface area is calculated on the basis of the expected population and the desired urban density. This surface area then defines the size of a circle (as a compact initial city shape), whose position can be freely chosen by the designer. Based on a topographical analysis (Fig. 16.7A), all regions steeper than a certain threshold are subtracted from this circle. To meet the necessary surface area, the size of the circle is increased iteratively (Fig. 16.7B). In addition to the steepness, other irreclaimable regions can be defined manually (e.g., areas with fertile soil, which are better used for farming).

After the boundary, inside which the city shall be developed, was defined, the street network is generated. Therefore, the watersheds are detected using a particle simulation on the topography (Fig. 16.7C). These watershed lines are then simplified (straightened) and used as street lines. This ensures the storm water to be efficiently drained out of the city, where it could be stored in tanks. Together with the existing road, these streets serve as the primary streets of the city (Fig. 16.7D).

Next the secondary roads are generated. Therefore, the watershed streets and the boundary are divided into similar segments. The end points of these segments are then connected forming parallel streets (Fig. 16.7E). Finally, the length of these generated street segments is analyzed. If they exceed a certain length, they are subdivided and additional segments between the parallel streets are inserted (Fig. 16.7F, displayed in green). This ensures short distances between inhabitants and thus increases walkability.

After the street network has been generated, a street network analysis is conducted in order to identify the most accessible locations and the most frequented street segments (Fig. 16.8, left). Based on the results of this analysis, the main city center with the big market square is

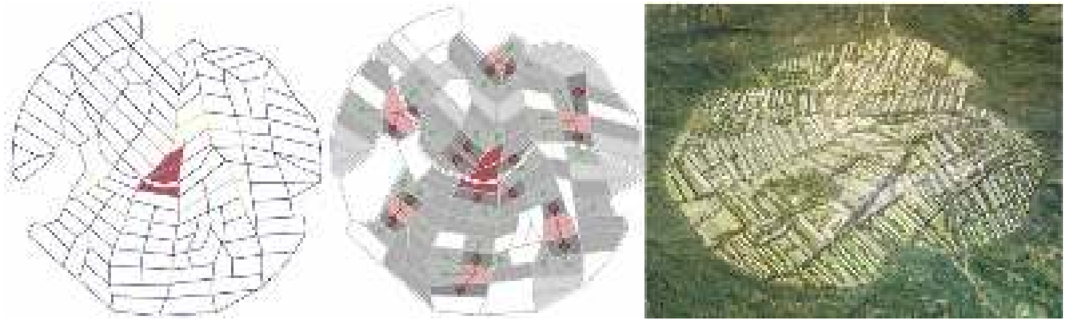


FIG. 16.8 The street network analyses (left) informs the distribution of centers and sub-centers as well as the density of the street blocks (center), which in turn influence the layout of plots and size of buildings (right). *No permission required.*

placed on the globally most accessible street block; the location of several small neighborhood centers are defined on locally well accessible street blocks. The location of these centers then informs the density of the remaining street blocks. The closer a street block to a center, the higher its density (Fig. 16.8, center). Thereby the density values are adjusted automatically in order to ensure the desired number of inhabitants. Finally, after this step, a parametric row house typology is applied. Thereby each street block is divided in two halves along its short edges. At the long edges, the block is divided into equally wide parcels. On each parcels, a building (simple volume) is placed (Fig. 16.8, right). The size of the parcels as well as of the building volume depends on the target density of the street blocks.

For each of the modules of an AMP, several input parameters exist. These range from fixed context information, such as the topography or the existing street network to flexible parameters for controlling the algorithms, such as the center point of the city, population size, or target density. Once these parameters change, the modules recalculate the solution. Thereby many different variants can be generated and tested. Fig. 16.9 shows exemplary the effect of changing topography. An AMP is applied to three different locations in Ethiopia. Thereby the main organization principle of the city remains, however, the layout of the streets is adapted to the terrain and in consequence also the location of centers and the distribution of densities adapts.

FIG. 16.9 Master plan variants for three regions in Ethiopia: Haro Welabu, Anko Golma, and Fefa Dildy Kebele. Visualization of a semiautomatically generated design variant. *Illustration by Ondrej Vesely and Iuliia Osintseva.*

Development of a new urban district on Singapore's waterfront

The second example was worked on in collaboration with the Future Cities Laboratory (FCL) in Singapore. It describes the development of an AMP for the future Tanjong Pagar Waterfront district in Singapore: A 400-ha container terminal is being relocated, freeing up a centrally located plot of land near the coast for new development. The specified criteria are limited to a defined boundary, existing surrounding development, desired population density, and height restrictions.

The AMP for this project has five modules: street network, shoreline, uses, transportation, and buildings (Fig. 16.10). Major streets, outlining large districts, are predefined as an extension of existing ones, while the secondary street grid is generated automatically. It needs the desired size of the street block and its proportions to be set as an input. Furthermore, the general contour of the shoreline was drawn manually according to the conceptual proposal, be it the same amount of land as existed, or reclaiming more areas to achieve lower density. Again, following a design concept to achieve more visual connection to water, we create urban elements, further referred to as fjords. They finalize the formation of the street network by carving small channels, radiating from the waterfront, and walking alleys alongside.

The next module of the AMP is devoted to functional distribution across the area. One of our flexible inputs is the relation between expected and current demographic structure, and dependent on its change in functional demand. This allows scenarios for a changed demand for urban functions to be examined. For example, a smaller proportion of the younger population would need fewer childcare facilities. Further, each particular function has its specific rule of distribution and location choice, such as biggest retail being placed next to the most integrated streets or secondary schools being distributed equally within walkable distance from all households. The distribution of functions may be extended by considering energy efficient combinations of uses within a block (Hsieh et al., 2017).

Based on the distribution of land uses, density, and the street network, we analyze the accessibility and centrality as the basis for the land use and building volume distribution. Finally, the rules for building typologies are applied. Generally, typologies were divided into three groups depending on the density and relation to the coast. In each group, there were predefined templates with functional combinations (developed earlier based on energy performance). For each of the three groups, we created a specific rule for building arrangement and heights.

Despite the completely different context as in the previous example in Ethiopia, we use a similar generative approach: starting with the generation of the road network and land use distribution, we go further into details up to building typologies, building heights, and street

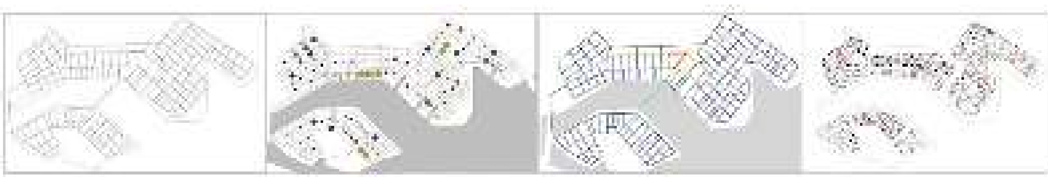


FIG. 16.10 Five modules of the AMP for the Singapore case study. From left to right: (1&2) street network and fjords, (3) land use, (4) roads and transportation, and (5) buildings. *Konieva, K., Knecht, K., Osintseva, I., Vesely, O., Koenig, R., 2018. Parametric assistance for complex urban planning processes: three examples from Africa and South-East Asia. In: Architecture, Civil Engineering and Urbanization (ACEU) Conference. Singapore.*

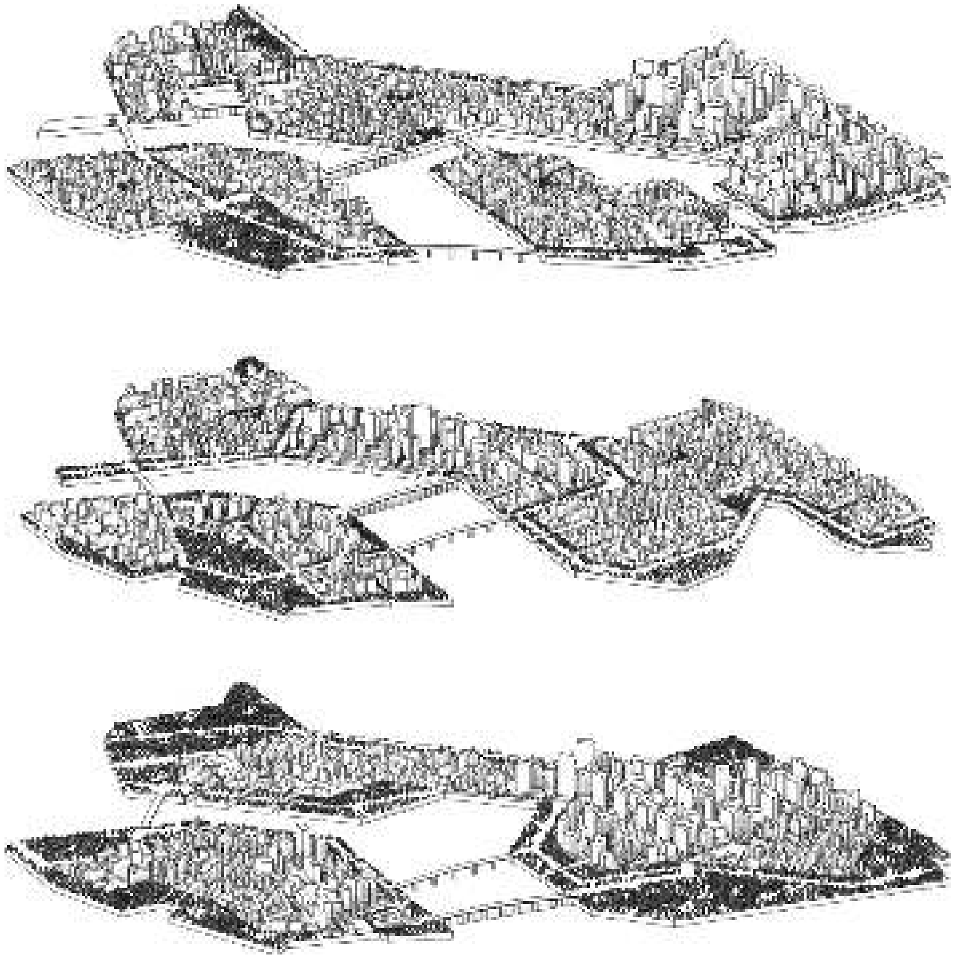


FIG. 16.11 Three design variants were generated using the adaptive master plan for the Tanjong Pagar waterfront area. *Konieva, K., Knecht, K., Osintseva, I., Vesely, O., Koenig, R., 2018. Parametric assistance for complex urban planning processes: three examples from Africa and South-East Asia. In: Architecture, Civil Engineering and Urbanization (ACEU) Conference. Singapore.*

design. The potential of the AMP is demonstrated here by generating several design alternatives based on different urban design concepts for the same site. These concepts explore different variants of coast-line shape, amount of greenery, and number of bridges (see Fig. 16.11).

To ensure the smoothest possible human-machine interaction, the work process for applying the AMP was approximated to a traditional urban design process, in which initial conceptual decisions play a critical role and are reconsidered and modified throughout the process. The most important conceptual decisions are made during the initial design phase, and subsequent conceptual changes are treated as separate variations. Urban analysis methods play an important role in comparing the performance of different variants: in the land use distribution module evaluation the energy performance was evaluated; and the road width was analyzed to provide an optimal amount of space for traffic. Moreover, the fully digital model is used for various kinds of physical simulations (e.g., solar radiation, wind simulations), urban analyses (e.g., accessibility to facilities, green vs built-up ratio), and cost calculations. The evaluation results are used for negotiations, especially in the case of confronting interests of stakeholders.

Conclusions

The presented techniques and application examples for AMPs demonstrate the potentials that lie in the digital methods for urban design. This new form of urban design allows to perform efficiently the successive stages of analysis, generation, and optimization while keeping the process transparent and negotiable for all possible stakeholders (from engineers to citizens). The enormous flexibility to integrate comprehensive data sets and analyses and to generate multiple design variants very quickly will permanently change the working practice of urban planners.

AMPs shall take into account highly divergent local conditions. This was demonstrated in the example projects presented in one of the poorest as well as one of the wealthiest countries in the world. The modular design of adaptive master plans allows for efficient sharing of expertise, involvement of experts, high variability of design, and transparency of decision-making. The presented digital design methods are largely based on information that can be formalized. In the simplest case, these are, for example, key figures for distances or building densities. Consequently, human-machine interaction is very important to bring in the nonformalizable knowledge of urban planners.

The degree of automation of adaptive master plans will advance inexorably with the development of AI. As in other professions, urban designers and architects could be displaced from their previous jobs by computer programs and will probably have to redefine their role: In contrast to the classic self-image of designers and architects, plans are no longer drawn today, but are increasingly generated automatically. Undoubtedly, it remains essential that the design of our world be in the hands of humans and controlled and managed by them. However, many aspects of urban design and design processes can be implemented more efficiently and effectively by computers as a synthesis of digitally available knowledge. In the future, the designers of our cities will have a completely new and equally complex role, namely as mediators between the different requirements of interest groups and the possibilities of consulting computer programs in the generation of future urban living environments.

Notes

There is a collection of individual modules of the AMP as components for Rhino3D/Grasshopper in the DeCodingSpaces-Toolbox: https://toolbox.decodingspaces.net/.

Demonstration videos of the sample projects can be found at: Ethiopia: https://vimeo.com/210051656. Singapore: https://vimeo.com/240964157.

References

Benedikt, M.L., 1979. To take hold of space: isovists and isovist fields. In: Environment and Planning B: Planning and Design. SAGE Publications, pp. 47–65, https://doi.org/10.1068/b060047.

Bielik, M., Koenig, R., Fuchkina, E., 2019. Evolving Configurational Properties: simulating multiplier effects between land use and movement patterns. In: Proceedings of the 12th Sp Syntax Symposium, pp. 1–20.

Braach, M., 2002. Programmieren statt Zeichnen: Kaisersrot. archithese.

Chen, G., Esch, G., Wonka, P., 2008. Interactive procedural street modeling. ACM Trans. Graph. 27 (10). https://doi.org/10.1145/1360612.1360702.

Coates, P., Derix, C., 2008. Smart solutions for spatial planning: a design support system for urban generative design. In: 26th eCAADe: Architecture "in computro,", pp. 231–238.

Dalton, R.C., 2003. The secret is to follow your nose: route path selection and angularity. Environ. Behav. 35 (1), 107–131. https://doi.org/10.1177/0013916502238867. United Kingdom.

Duarte, J.P., Beirão, J., 2011. Towards a methodology for flexible urban design: designing with urban patterns and shape grammars. Environ. Plann. B. Plann. Des. 38 (5), 879–902. https://doi.org/10.1068/b37026. Portugal: Pion Limited.

Duering, S., Chronis, A., Koenig, R., 2020a. Optimizing urban systems: integrated optimization of spatial configurations. In: SimAUD: Symposium on Simulation for Architecture and Urban Design, pp. 509–515.

Duering, S., Sluka, Koenig, R., 2020b. Planning with uncertain growth projections—a computational framework for finding resilient, spatiotemporal development strategies for new town developments. In: 25th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). Association for Computer-Aided Architectural Design Research in Asia (CAADRIA).

Eastman, C.M., 1973. Automated space planning. Artif. Intell. 4 (1), 41–64. https://doi.org/10.1016/0004-3702(73)90008-8. United States.

Eastman, C., et al., 2008. BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors. John Wiley & Sons Inc.

Elshani, D., Vititneva, Gilmanov, 2020. Rural urban transformation: parametric approach on metabolism-based planning strategies in Ethiopia. In: SimAUD: Symposium on Simulation for Architecture & Urban Design. Society for Modeling & Simulation International (SCS).

Elshani, D., Koenig, R., Duering, S., 2021. Measuring sustainability and urban data operationalization. In: International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA). Association for Computer-Aided Architectural Design Research in Asia, pp. 407–416.

Fink, T., Koenig, R., 2019. Digital integrative urban planning. In: Naboni, E., Havinga, L. (Eds.), Regenerative Design in Digital Practice: A Handbook for the Built Environment. Eurac Research, Bolzano, pp. 207–214.

Flemming, U., 1978. Representation and generation of rectangular dissections. In: Proceedings—Design Automation Conference. Institute of Electrical and Electronics Engineers Inc, United States, https://doi.org/10.1109/DAC.1978.1585160.

Franz, G., Wiener, J., 2005. Exploring isovist-based correlates of spatial behavior and experience. In: Proceeding of the 5th Space Syntax Symposium.

Gil, J., Almeida, J., Duarte, J., 2011. The backbone of a City Information Model (CIM). In: 29th eCAADe conference, pp. 143–151.

Grason, J., 1971. An approach to computerized space planning using graph theory. In: Proceedings—Design Automation Conference. Institute of Electrical and Electronics Engineers Inc, United States, https://doi.org/10.1145/800158.805070.

Hillier, B., Hanson, J., 1984. The Social Logic of Space. Cambridge University Press.

Hovestadt, L., 2009. Beyond the Grid—Architecture and Information Technology: Innovative Solutions for Complex Systems. Birkhauser, Berlin.

Hsieh, S., et al., 2017. Defining density and land uses under energy performance targets at the early stage of urban planning processes. Energy Procedia. https://doi.org/10.1016/j.egypro.2017.07.326. Singapore: Elsevier Ltd.

Koenig, R., Miao, Y., Knecht, K., 2017. Interactive urban synthesis. In: Cagdas, G., et al. (Eds.), Computer-Aided Architectural Design. Future Trajectories. Springer, Singapore, pp. 23–41.

Kropf, K., 2017. The Handbook of Urban Morphology. John Wiley & Sons Inc.

Mayer, T., 1971. Computer as an Aid to Architectural Design: Present and Future. Construction Science and Technology.

Miao, Y., et al., 2018. Computational urban design prototyping: Interactive planning synthesis methods—a case study in Cape Town. Int. J. Archit. Comput. 16 (3), 212–226. https://doi.org/10.1177/1478077118798395. Singapore: SAGE Publications Inc.

Mitchell, J., 1977. Computer-Aided Architectural Design. Van Nostrand Reinhold Company, Inc.

Negroponte, N., 1975. The architecture machine. Comput. Aided Des. 7 (3), 190–195. https://doi.org/10.1016/0010-4485(75)90009-3. United States.

Negroponte, N., Groisser, L., 1970. URBAN 5: A machine that discusses URBAN design. In: Moore, G.T. (Ed.), Emerging Methods in Environmental Design and Planning. MIT Press, Cambridge, pp. 105–114.

Oliveira, V., 2016. Urban Morphology—An Introduction to the Study of the Physical Form of Cities. Springer, Berlin.

Osintseva, I., Koenig, R., Berst, A., 2020. Automated parametric building volume generation : a case study for urban blocks. In: SimAUD: Symposium on Simulation for Architecture & Urban Design. Society for Modeling & Simulation International (SCS), pp. 211–218.

Parish, Y., Muller, P., 2011. Procedural modeling of cities. In: SIGGRAPH. ACM, pp. 301–308.

Rooney, J., Steadman, P., 1988. Principles of Computer-Aided Design. Prentice Hall.

Stamps, A.E., 2005. Isovists, enclosure, and permeability theory. Environ. Plann. B. Plann. Des. 32 (5), 735–762. https://doi.org/10.1068/b31138. United States: Pion Limited.

Stiny, G., Gips, J., 1971. Shape Grammars and the Generative Specification of Painting and Sculpture. Congress.

Stiny, G., Mitchell, W.J., 1978. The Palladian grammar. Environ. Plann. B. Plann. Des., 5–18. https://doi.org/10.1068/b050005. SAGE Publications.

Stojanovski, T., 2013. City information modeling (CIM) and urbanism: blocks, connections, territories, people and situations. In: SimAUD '13: Symposium on Simulation for Architecture and Urban Design. Society for Computer Simulation International, pp. 86–93.

Stojanovski, T., 2018. City information modelling (CIM) and urban design morphological structure, design elements and programming classes in CIM. In: eCAADe Conference. Lodz University of Technology, Lodz, Poland, pp. 507–529.

Weber, B., et al., 2009. Interactive geometric simulation of 4D cities. In: Eurographics, pp. 481–492.

Xiang, L., Papastefanou, G., Ng, E., 2021. Isovist indicators as a means to relieve pedestrian psycho-physiological stress in Hong Kong. Environ. Plan B Urban Anal. City Sci. 48 (4), 964–978.

This page intentionally left blank

CHAPTER

17

SASAKI: Filling the design gap—Urban impressions with AI

Thiyagarajan Adi Raman[a], *Justin Kollar*[b], *and Scott Penman*[a]

[a]Sasaki, Boston, MA, United States [b]Department of Urban Studies and Planning, Massachusetts Institute of Technology, MA, United States

Introduction

Planning and design disciplines face increasing pressure to address complexity in urban environments. This includes the recognition that conventional land-use planning and development projects should place more emphasis on resilience and climate adaptation, with more focus on inclusivity and social justice (Crawford et al., 2013; Meerow et al., 2019). However, at the same time project scopes are expanding, the length of projects and the amount of firm resources required to undertake them have not changed much. This intensifies pressure on project teams, driving a need for more efficient, creative workflows within tighter and tighter constraints. As design and planning functions increasingly overlap and data-driven analyses inform a wider range of decisions, it is the hope that technologies such as machine learning (ML) and other digital tools will evolve and proliferate to address these challenges—reflecting the growing importance of "data space" in the realms of practice. On the flip side, this has raised both interest and concern over how urban planners and designers should engage with big data (French et al., 2017), and places constraints on aspects of practice for design and planning firms. First, it means that many projects increasingly rely on open data and data developed by other organizations that may or may not be suitable to a given planning project. This dependency makes the task of optimizing and translating certain forms of data into formats, such as maps, drawings, and diagrams, more important than ever. Second, in project settings where data is sparse, the translation of satellite imagery and other kinds of proxy data into usable base-level data for design and planning is increasingly important. For example,

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00002-0

tracing satellite imagery and assessing land-use options can take significant amounts of time and labor that may otherwise be spent on exploring options and scenarios with more client feedback. Third, there is a need for more accessible means of interacting with "data space" for practitioners and the public in general; yet, the technical requirements of data management can introduce rigidity into the design and planning process due to lag times where data-based analyses are needed before beginning a more creative design phase.

Machine learning has the potential to address these constraints in novel ways. The goal of this research project was to identify a machine learning approach and develop a prototype application that is suitable for current areas of design and planning practice, which could be pursued within the constraints of a business environment, and, most importantly, that allows for creative feedback and input.

Given the still nascent development of machine learning approaches within planning and design practice, the first phase of work involved evaluating existing tools with the potential capacity to translate between analytical and creative components of project work to better communicate the implications of land-use planning and other design decisions. The second phase involved exploration of the use of generative adversarial networks (GANs) to develop novel impressionistic aerial imagery—or *urban impressions*—based on a variety of inputs common to practice such as variations of land use and/or land cover. Urban impressions were evaluated based on a range of qualitative criteria, including their ability to foster increased dialogue between parties.

Sasaki's approach to project work also aims to center more direct and effective client communication. Thus, while exploring the edges of applicable machine learning research for practice, the third phase included the development of a prototype tool that can create urban impressions based on selected inputs early on in the predesign phase. This prototype "sketch tool" will allow practitioners to test out initial "sketched" approaches and communicate them to the client for early feedback using GANs. This tool was heavily informed by the research into urban impressions: Only by identifying what visual characteristics effectively and efficiently generate impressions approximating those yielded by urban design sketches could we propose a tool that would be appropriate for the early design process.

A sketch is a critical tool in the designer's workflow. A sketch helps the designer externalize ideas from their mind, which can be used to communicate aesthetic and functional strategies. Sketching also allows the designer to produce quick visual iterations without the need to spend significant time to "work out the details." However, working with geospatial data presents both challenges and opportunities for sketching. Machine learning tools like GANs can play a key role in the urban design process by translating land-use inputs—which can be difficult for nondesigners to read—into novel aerial imagery.

The prototype presented in this chapter was developed within a quick timeframe to make efficient use of resources and demonstrate the approach within the firm. This prototype illustrates how machine learning can be applied to aid existing workflows by minimizing the time inputs for developing material or generating new impressions quickly. The research process and prototype described in this chapter are still in the early stages of development. Thus, we have dedicated more space to elaborate on the research process so that academic researchers may learn about the challenges of applying machine learning to practice-based settings and develop practical tools accordingly. Early applications of machine learning hold incredible promise for creative practice, but more testing is certainly needed.

Background

Current machine learning usage in planning practice

While machine learning research in planning and design is still in its early stages, there is abundant related research on remote sensing capabilities in generating geospatial data on land use and land cover that planners and designers use. (One need only look at the plethora of work in this field in journals like Remote Sensing, the Journal of Applied Remote Sensing, and others.) In recent years, improvements in techniques and applications have made ML more accessible to a wider range of GIS-based practitioners. This is very useful in developing usable "base layer" data with land cover and urban land uses in places with poor data accessibility. For example, the UN Food and Agriculture Organization's land-cover classification toolbox has aided a range of international planning work. (See Food and Agriculture Organization of the United Nations.) The Global Facility for Disaster Prevention and Recovery has also utilized machine learning in its work across various contexts to map physical and social vulnerability, monitor urban growth and informality, and enhance territorially based understandings of risk and resilience (GFDRR, 2018). Additionally, recent research has explored a wide variety of ML applications such as Robosat, which can extract features from aerial and satellite imagery. (Available at: https://github.com/mapbox/robosat.) Image Analyst is a toolkit developed by ESRI to perform feature extraction, geo-spatial analysis, and pixel manipulation on raster images. (Available at: https://www.esri.com/en-us/arcgis/products/arcgis-image-analyst/overview.) More exploratory applications like RunwayML allow users to browse a range of prebaked models and create models of their own. (Available at: https://runwayml.com.) Similarly, Pix2Pix provides an easy-to-use platform for image translation using GANs, where a lightweight model is able to generate novel imagery through a repetitive process of learning by doing. (Available at: https://github.com/phillipi/pix2pix.)

Generative adversarial networks (GANs)

There has been little utilization of GANs in planning and design to date, but they hold promise for creative application. GANs involve a machine learning feedback loop that creates novel output by automatically detecting—and learning to generate—patterns within a base set of images. There are two parts to a GAN: The generator acts like an art forger attempting to create a counterfeit work of art by mimicking a particular style. The discriminator acts like an art critic assessing whether or not the image created by the generator is genuine. The two models are placed in an adversarial relationship: The generator creates images, and the discriminator evaluates whether those images are good enough to be considered part of the training set, at which point the generator reassesses. This process is repeated until the discriminator is more and more "convinced" by the generator's output, thus reinforcing certain "pathways" within a generative network to create more consistent outputs. Larger models and more extensive datasets typically enable more complex criteria to be crafted, leading to more realistic imagery being generated.

Sasaki's approach to ML research

Even with many recent advancements in machine learning techniques and applications, utilizing machine learning in practice is still nearly impossible for many planning and design firms without contracting out or hiring in specialized skill sets. Given the still-nascent state of research on machine learning in general, including the few existing tools available to build on, decisions to fund research in a practice-based setting are made carefully. There is also the potential for a mismatch between the needs of preliminary research and ongoing projects. Therefore, this research project was developed within the Strategies group, which serves as an important technology incubator and research arm within Sasaki. Strategies includes a mixture of planning and design professionals with advanced computational skills and acts as a support arm for work on engagement tools, data management, and analysis for a variety of planning and design projects. The Strategies group also conducts independent research outside of the firm's primary project loop, which allows it to operate within different timeframes, consider outcomes independent of client needs, and autonomously pursue technical proficiency. However, it was also necessary to identify clear pathways for integrating research findings and new applications within existing, somewhat entrenched workflows. This clarifies the practical uses ML may have in practice, such as conserving resources (maximizing cost efficiency, ease of access, speed, etc.) needed to perform necessary but repetitive tasks, aid in monotonous workflows, and even leverage existing tools to novel use cases that could evolve into new applications.

Identifying a "good enough" tool

The first phase of the research involved identifying existing tools on which to build. Given the lack of an obviously novel tool within the design and planning fields that could be directly applied to existing workflows, we opted for a "good enough" approach to selecting a tool. This approach included interviews with specialists in the design and planning field and a survey of existing tools. Five were chosen for more in-depth exploration and evaluated based on questions derived from the stated research goals. After careful evaluation, we opted for the use of GANs as exemplified by Pix2Pix.

Tools we explored

The first task was to identify existing tools to evaluate which approach was best suited to a creative process in design and planning. We selected five tools to evaluate key features applicable to design and planning.

- *RunwayML's* image manipulation is easy to use for people with no coding experience. For example, a "prebaked" model named "Dynamic Style Transfer" picks up on colors, textures, shadows, and other visual characteristics in order to generate new styles for any given input image. This tool is well suited for those with limited resources to build machine learning models. Its model customization options are limited.
- *ESRI Image Analyst* has a wide array of features including feature extraction, analysis, image processing, editing, and postprocessing. Its machine learning capabilities focus on image classification, and it is available as commercially licensed software.
- *SPADE* has capabilities to do advanced image synthesis. This tool can generate high-quality outputs with its sophisticated approach. It needs complex machine setup to run, which requires additional cost. (Available at: https://github.com/NVlabs/SPADE.)

- *Robosat* extracts features from aerial or satellite imagery such as buildings, parking lots, and roads. Better outcomes are possible with high-quality training datasets.
- *Pix2Pix* is a platform for image generation and translation using GANs. This tool is useful in generating novel visuals based on simple color- and shape-based inputs. The tool also allows for wide variations for generating imagery driven by variation in training datasets.

Decision matrix

We then evaluated each tool along five categorical questions based on our stated research goals. The resulting decision matrix (Fig. 17.1) acts as a formula for selecting a viable approach. These questions include:

	Enough data available	Novel and interesting	Solves a business problem	Cost effective	Open source
Robosat	✓	✗	✓	✗	✓
Runway ML	✗	✓	✗	✓	✗
Pix2Pix	✓	✓	✓	✓	✓
SPADE / GauGAN	✓	✓	✓	✗	✓
ESRI Image Analyst	✓	✗	✓	✗	✗

FIG. 17.1 Decision Matrix, with each row representing a tool that was tested and the columns indicating whether it satisfied the relevant criteria. *No permission required.*

- *Is there enough data available to test?* In the world of machine learning, good quality and sufficient data is critical. As more data is used in the training model, the probability of prediction increases.
- *Can this process create novel and interesting outputs?* As this tool is targeting early design phases, it is important that it be able to generate novel imagery that is of interest to humans, thus informing the creative process.
- *Does this solve a business problem?* The tool should also help address key business-related challenges in the design industry such as addressing repetitive tasks or adding value to key phases of a project.
- *Is it cost effective?* The steep price of machine learning (including the time to conduct research) makes it less accessible for individuals, small teams, and startups that want to tackle new problems or automate their processes and decision making.[5] A primary goal is to identify a tool that is more accessible to a wider range of users.
- *Is it open source?* Software that is open source is typically accompanied by a generative and resourceful development community. Having a broader community developing the tool enables anyone to develop new features or resolve bugs as needed without waiting for the next version release, which is common with proprietary software. This communal approach opens up many additional possibilities for future development and helps to produce secure and stable software.

Choice of Pix2Pix

Based on our decision matrix, we decided to move forward with Pix2Pix's GAN-based platform for its ability to go beyond mere recognition and classification techniques in order to produce novel content. Pix2Pix is an open-source, free-to-use platform that enables users to easily deploy GANs for their own creative purposes and using their own datasets. It is also supported by browser-based platforms such as Google Colaboratory (Colab), which avoids setting up dedicated machines to the application.

In devising a practical research direction we asked ourselves: How can we utilize the power of GANs within the creative process? GANs hold potential for more creative applications of ML by generating content whose value lies not in its realism, but in its impression: relatively straightforward tools can be used to generate content that is *good enough* for both representation and "creative feedback." As an open source and easily manipulable platform, Pix2Pix enabled us to test various ideas rapidly and discover areas of research that are not only novel and interesting, but that hold potential for practice-based application as well.

Fundamentally, Pix2Pix creates a mapping from one dataset of images to another. For example, the tool is trained to recognize the outlines of a sketch of a bag by creating a "mental mapping" of original images of bags to baseline sketched inputs. After the model has learned to "map" the image to the sketch—learning what kinds of sketch marks typically indicate folds, handles, textures, etc.—it is then able to generate new images of bags from input sketches, using the GAN methodology described in the background section. The original images themselves represent the "ground truth" that defines the space of all possible imagery. The sketch and the output are labeled the "input image" and the "predicted image," respectively.

Using GANs to generate urban impressions

Introducing urban impressions

Using Pix2Pix, we generated novel urban impressions by manipulating the readily available datasets used for both training and testing. Here, *urban impressions* refer to a set of procedurally generated, aerial-style images of an urban area. Urban impressions are not intended to recreate perfectly realistic aerial imagery of an area; rather, they are focused on creating a *perception* of certain urban characteristics. An urban impression succeeds when it provides imagery that convinces the viewer to consider an area anew—to believe, read into, think about, or imagine urban scenarios or conditions. The sketch tool prototype helps put these things together in an engaging way. Developing the urban impressions took place through a series of several different types of studies involving urban blocks, building footprints, land-use studies, and urban patterns.

In each of the studies described in this section, different characteristics of the aerial imagery were tested, from the number of colors available in the image to the level of detail provided by the image. Typifying the analyses in this way allowed us to identify which characteristics yielded the most viable urban impressions as the basis for developing the sketch tool prototype.

Segmented slippy maps

These impressions are formed by tiling together square images into a composite whole. By using datasets that consistently adhere to the tiled web map (or "slippy map") format popular in web browser-based mapping services, individually generated images can easily be tiled together to create much larger images. Each individual generated image is 256×256 pixels, in accordance with Pix2Pix's requirements, and aligning with slippy map standards.

Similar to their use in the training of computer vision models, segmented maps simplify an aerial image down to a small set of categories, with corresponding colors. A simple map may highlight the outlines of all buildings in one color, hardscape in a second color, and softscape in a third, while more complicated maps subdivide the maps into categories such as zoning, building program use, or even types of vegetation (Fig. 17.2).

Using Pix2Pix with aerial imagery and segmented maps

Developing urban impressions requires choosing the urban areas and datasets for both the training and testing steps of the GAN. The use of readily available map-based datasets, such as the MassGIS Parcel database (Available at: https://docs.digital.mass.gov/dataset/massgis-data-standardized-assessors-parcels.) or Land Cover and Land Use (LCLU) database, (Available at: https://massgis.maps.arcgis.com/home/webmap/viewer.html?useExisting=1&layers=ca1f06d458f0477c9c90cb00a314a49c.) enables us to test various styles of segmented maps in our Pix2Pix model. In addition, this imagery is relatively easy to group by semantic categories, such as country, city, or level of development. Perhaps most notable for our research, however, is the ability to vary the input "sketch" to which the aerial imagery gets mapped. In our case, segmented maps (again based on the slippy map format) were used for training the model alongside the aerial imagery. These "training images" are created in the form of individual images of 256×512 pixels. The square at left half of this rectangle is the

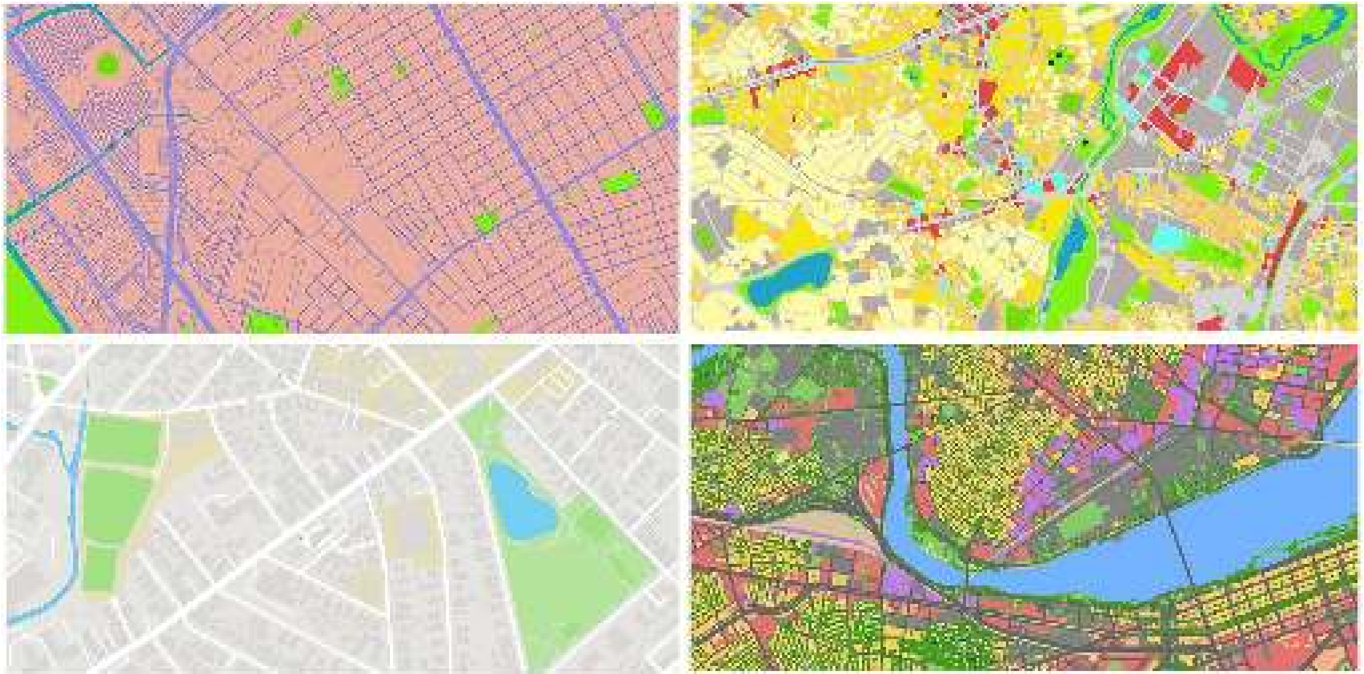


FIG. 17.2 Images of segmented maps compiled from slippy map tiles. *No permission required.*

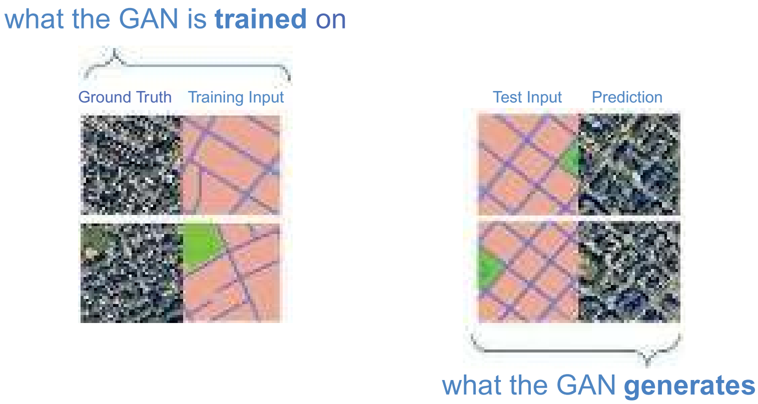


FIG. 17.3 Pix2Pix is trained on paired sets of ground truth aerial imagery and corresponding segmented map tiles. Once trained, the model is tested on new segmented map tiles, which it uses to predict, or generate, new aerial imagery. *No permission required.*

"ground truth" aerial image tile. The square at right half is the segmented map tile that corresponds to that location. For testing predictions, only a new segmented map tile is supplied—the test input image. The model then assesses the test input and generates a predicted image based on its trained understanding of the segments and associated colors (Fig. 17.3).

The choice of a segmented image map influences how the patterns, textures, and composition of the urban impressions are interpreted by the model and subsequently deployed in new images. Choosing a "broader" segmentation strategy—for instance, grouping all buildings together into one color, regardless of distinguishing characteristics such as program or size—forces the model to either generalize its understanding of built form across various physical typologies or find other ways to correlate building diversity with map imagery (e.g., parcel shape/size). The same segmentation style was always used for both training and testing, with respective studies.

Urban impression inputs

By varying several inputs associated with the model, we were able to generate qualitatively different urban impressions. These include:

1. **Varying the segmentation map.** Maps varied in the number and accuracy of their segmentation: Some contained broad categories and abstractly drawn shapes, while others contained numerous categories and shapes that closely approximated the forms in aerial imagery.
2. **Varying the pairing of training and testing datasets.** While the same segmentation map dataset was used in both the training and testing phases, the location of these maps around the world varied. Thus, a model that was trained on the urban fabric of one region or city could be used to generate imagery in an entirely different region or city.
3. **Varying the training time associated with the model.** As is typical with neural networks, the performance of the GAN generally improves as its training time increases based on a loss function associated with the generator. Pix2Pix enables users to stop this training at any point.

Urban impression evaluation criteria

The output imagery of the various studies was evaluated qualitatively, according to several different visual considerations. Our evaluations revolved around discussions of:

1. **Believability of the imagery.** Does the generated imagery pass the visual "Turing Test"—do these tiles look like actual aerial imagery? Various visual artifacts affected this, ranging from overly repetitive textures to a lack of clarity and contrast between neighboring shapes. Conversely, some details significantly improved the visual believability of the imagery, such as consistent shadows, crisp edges around buildings, and subtle variations between similar buildings. While some artifacts were less noticeable as images were tiled together, others were still evident, or even amplified, as images were compiled (Fig. 17.4).
2. **Apparent unscripted behavior.** Is the model picking up on features that weren't explicitly outlined by the segmentation maps? The model goes beyond shapes to recognize textures and patterns within shapes to capture content that can significantly affect the urban impressions in unplanned ways, such as by generating tree textures or shadows (Fig. 17.5).

FIG. 17.4 Less- and more-believable generated imagery. *No permission required.*

FIG. 17.5 The segmentation map used to train the model (left) is sparse; the generated imagery (right) contains a significant amount of content that has been captured within segmentation boundaries, indicating a high level of unscripted behavior. *No permission required.*

The model does this with very limited context since it processes tiles one at a time. This "reading into" the images presents an interesting, if unscripted, behavior.

3. **Tradeoffs between specificity of input and quality of output.** How does the visual quality of the urban impression change with the amount of time, effort, and information input? The idea of a "sketch" or "impression" suggests that the final result merely needs to spark the viewer's imagination with minimal effort. With this in mind, we evaluated our studies to determine which ones required the least amount of effort to create in comparison to the total impact they yielded.
4. **Novelty and impact.** Perhaps the most important question in our decision matrix asks: *"Is it novel and interesting?"* While the generated imagery may pass as realistic, the overall impression may end there, without inspiring further conversation. Regardless of quality, other impressions had a much different impression, inspiring thought and sparking discussion about the kinds of urban conditions that might result. We recognize that, in terms of value to the creative process, an urban impression's success may lie beyond the visual realism of the image.

Types of urban impression studies

These qualitative observations were then applied across four different sets of urban impression studies to evaluate their viability for use in prototyping a sketch tool for planners and designers:

1. **Urban block studies.** These modes were trained on one city dataset and tested on a city with an urban fabric composed of noticeably different block shapes and sizes. The segmented map was created using Mapbox (Available at: https://www.mapbox.com.) and depicts the urban area using only a handful of colors, including light purple for roads, pink for city blocks, green for landscape elements, and blue for water (Fig. 17.6). With these

FIG. 17.6 Urban block study imagery showing the actual aerial imagery (ground truth—left), the corresponding segmentation map supplied to the GAN (input image—center), and the generated output of the model (predicted image—right). This model was trained on imagery from Barcelona and predicted on segmentation maps of Cambridge and Boston. *No permission required.*

FIG. 17.7 Mapbox imagery showing Worcester, Massachusetts. Building footprints help convey an idea of built density in the urban area. *No permission required.*

studies, the goal was to determine if this minimal amount of information—such as the size and shape of urban blocks—would be enough for the model to capture an overall impression of an urban area, and if so, how that impression might compare to the actual impression of the aerial imagery.

2. **Building footprint studies.** These models are trained on building footprints in one city and tested on a city with a similar composition of building typologies. The segmented map was created using Mapbox and contained a fairly minimal number of colors for roads, parks, and building footprint shapes that give an idea of an area's built density (Fig. 17.7). With these studies, the source cities for the training data and testing data were close to each other geographically, with the understanding that impressions of these neighboring areas would be similar. The goal of these studies was to determine if adding object-level detail (such as building footprints) had a significant impact on the generated images. In other words, we wanted to see if more closely approximating the physical, visually apparent built form of the ground truth aerial imagery would enable the model to extract additional information or lead to more convincing, or more interesting, urban impressions.
3. **Land-use studies.** The next set of studies used a segmentation map that subdivided areas based on parcels, which were color-coded according to types of land cover and land use. While the resulting shapes are usually not indicative of building outlines, they offer more categories for various building types. We tested several different maps, each varying in their quantity and types of categories as well as the accuracy of their segmentation boundaries. With these, we aimed to study how this classification-level information (as compared to the physically apparent information of the building footprint studies) would affect the output of the model. Additionally, we conducted three studies aimed to determine how the urban impressions would vary as the level of detail in the segmentation maps changed, and if more segmentations led to urban impressions that were closer to the ground truth aerial imagery.

In the first study, we used segmentation maps from the MassGIS Parcel database (https://docs.digital.mass.gov/dataset/massgis-data-standardized-assessors-parcels)

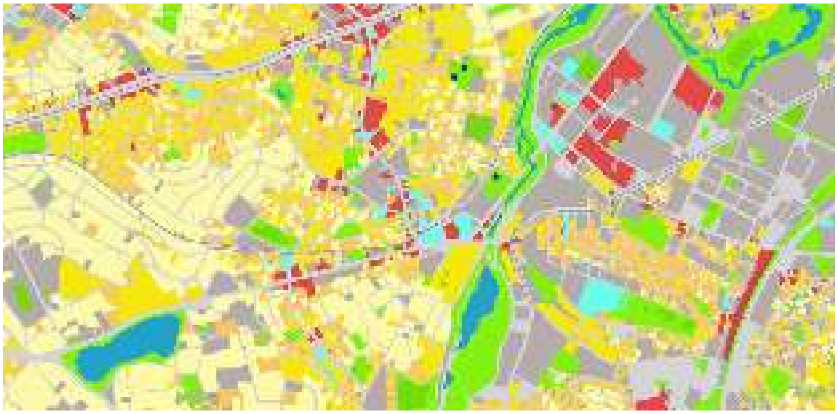


FIG. 17.8 MassGIS Parcel imagery. *No permission required.*

(Fig. 17.8). Notably, the maps provide no accounting for density; in many cases, they provide a fairly generic grouping for some land uses. For instance, the "commercial" land use included everything from low-density strip malls to skyscrapers in the urban core.

The second study used maps from the LCLU dataset (Fig. 17.9). These maps divided the built area by program use, with the added feature of including the outline of various types of vegetation. The result is a map that incorporates both classification-level information (land use) with physically apparent information (land cover). However, these maps still provided no distinctions of density.

The third study used a dataset that was specifically created to account for both land cover and density. The maps begin as MassGIS Parcel imagery, with land cover overlaid. In order to further segment the maps based on density, areas were split based on floor area ratio (FAR) (Fig. 17.10). This makes a distinction between low-density commercial strips and high-density urban towers.

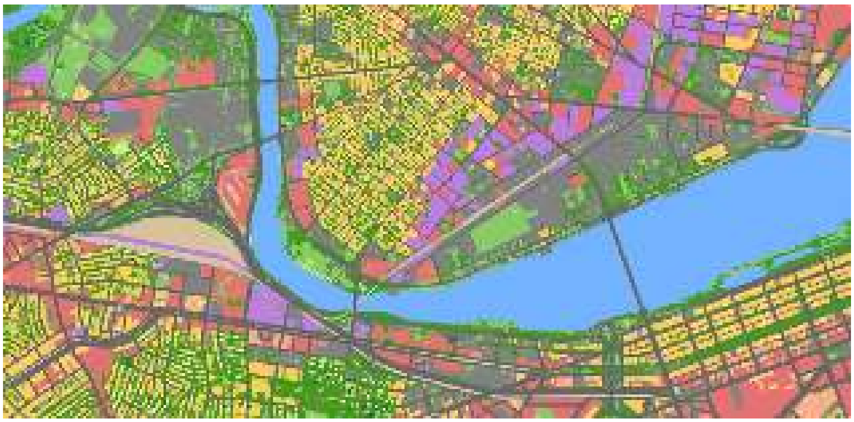


FIG. 17.9 LCLU imagery from MassGIS. *No permission required.*

FIG. 17.10 LCLU data reworked to include FAR-based density and include land cover. *No permission required.*

4. **Urban pattern studies.** In the final set of studies, we turned back to the original goal of generating urban impressions based on basic physical, visually apparent properties of the urban fabric, as opposed to categorized and labeled information. Rather than study block sizes, however, we attempted to see if overly "patterned" urban conditions—such as highly planned communities with repetitive constructions and little visual variation—would be enough to capture an impression. While organically grown cities include a significant amount of variability in their urban fabric, more planned developments are incredibly repetitive, and these patterns would be easily picked up either by the repetition of shapes in the segmentation map or by the model's unscripted behavior. For this study, we focused on the communities of Northern and Southern Boynton Beach, Florida, and tried two different segmentation maps from OpenStreetMap (Available at: https://www.openstreetmap.org.) (Fig. 17.11). The first included exact building footprints with no density distinction. The second included building footprints with a slight perimeter offset and was color-coded according to low-, medium-, and high-density buildings.

FIG. 17.11 Segmented maps of Boynton Beach, Florida. The map on the left shows precise building footprints with no density distinction, while the map on the right categories buildings by density and adds a perimeter offset around the buildings. *No permission required.*

Key takeaways

Evaluation of the tool

Pix2Pix served as an appropriate medium for conducting this initial research due to its ease of use and its ability to rapidly produce new models. It was thus chosen as the basis of the sketch tool prototype. Pix2Pix also supplies a training loss metric, allowing users to see how the model is improving with increased training time (Fig. 17.12). The model was tested with varying numbers of epochs, or passes through the training dataset. As the model trains, line chart plots are created visualizing the results of the loss functions for both the discriminator and generator parts of the GAN. The goal of training the GAN is to find a point of equilibrium between both discriminator and generator as they "compete" against each other. After several iterations during which we tested different training durations, we found that training for 150 epochs gave us satisfactory results. While further training would invariably lead to different results, this number helped keep training time relatively low while still producing compelling urban impressions.

Other tools, such as the ones introduced earlier, may provide alternative advantages, such as faster training times, or the ability to produce larger or higher fidelity images. While these may assist other researchers in their work, we found that these features were not necessary in order to produce urban impressions.

Study-specific takeaways

Urban block studies produced compelling urban impressions, but do not allow for customization

The urban block studies produced some of the most interesting urban impressions, clearly meeting our criteria for overall novelty and visual impact.

In one study, the model was trained on Barcelona and tested on Boston and Cambridge. Despite the remarkably different sizes and shapes of urban blocks, the resulting imagery bore an unmistakable resemblance to Barcelona's urban fabric. Barcelona's regular, symmetrical

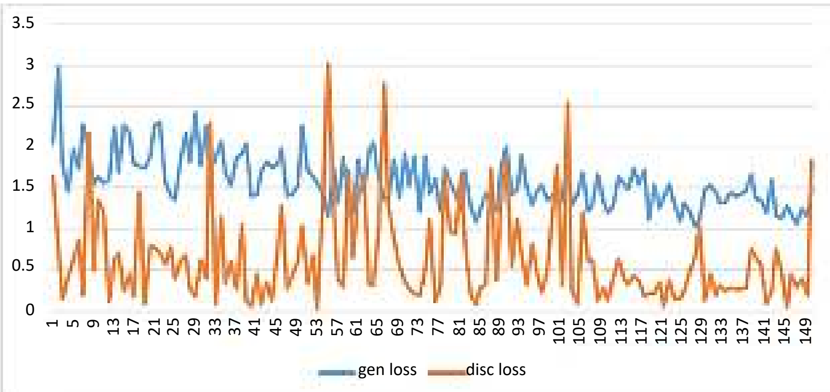


FIG. 17.12 Image of GAN training loss over time, for both generator and discriminator. After initial variations, the model begins to stabilize. *No permission required.*

blocks were adapted to fit the proportions of Cambridge's grid. The red roofs that dominate the view of Barcelona from above appeared as a dominant feature, bordering the deep shadows that dominate both the interior courtyards of Barcelona's blocks as well as the streetscapes along its more narrow roads. Wider streets even took on a greenish texture, indicating tree-lined avenues. The images prompt thoughts of Barcelona's street life in the context of Cambridge, and encourage users to critically consider the differences between the two cities. Notably, these characteristics arose despite the relatively low visual believability at the individual tile level (Fig. 17.13).

In a reverse study—with a model trained on Boston and tested on Barcelona—Barcelona's superblocks were subdivided into Boston's more typical separated lots with individual buildings. Recreational areas such as grouped tennis courts were interpreted as parks. In a notable twist, the narrow, dense, highly regular grid that defines La Barceloneta in the Southeast of Barcelona was completely transformed from a built-up area into what resembles a parking lot (Fig. 17.14). What was most remarkable about these studies was the unscripted behaviors. Only a handful of segmentation categories were needed in order to capture rich urban fabrics. Detailed imagery of blocks arose where only outlines were drawn, as the model "filled in the gaps" with its trained understanding of specific urban patterns.

These studies point to the potential for this tool to be used at the macro-level as an iterative and rapid method for imagining alternative urban densities across whole neighborhoods. This imaginative process is not a replacement for design, or even the efforts that generate final representations; rather, it is a way to initiate conversation. With the ability to generate specific urban impressions on a large scale, this process can help to create "working drawings" over which designers and nondesigners alike can have conversations about the many complex variables that go into urban planning at this scale. The impressions generated here—beyond simple sketches, yet, shy of full-blown renderings—appeal to our ability to spark thought through visual comprehension. This GAN-based workflow adds to those used by urban

FIG. 17.13 Individual image tile (left) along with tiled urban impression (right) of "Bostelona"—a neighborhood near Boston that was generated using a model trained on Barcelona. The resulting fabric is far denser than the ground truth and captures notable characteristics of Barcelona's urban fabric, all while adhering to the underlying block layout. *No permission required.*

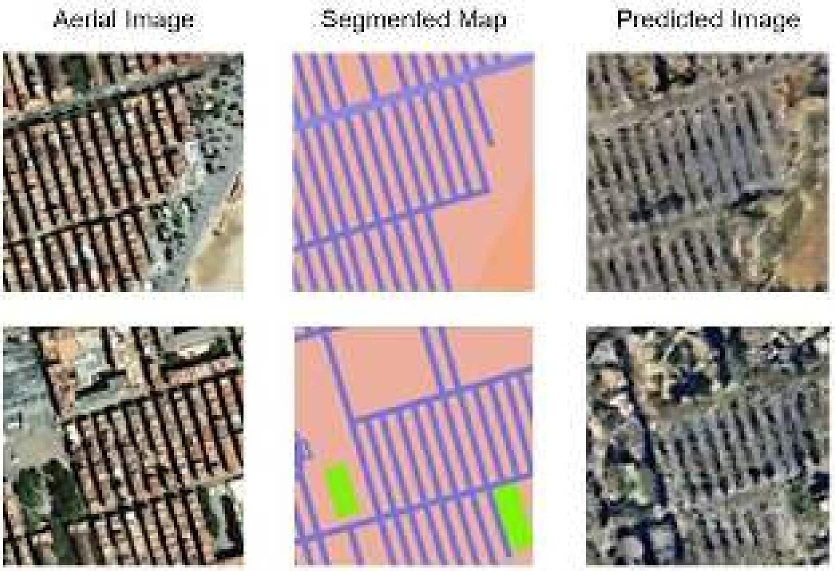


FIG. 17.14 The generated imagery at the far right is the result of a model that has been trained on Boston, but predicted on Barcelona's grid. The result looks more like an expansive parking lot than the dense-urban-block ground truth. *No permission required.*

planners and designers, and has the potential to generate new visual and mental connections between 'data space' and the design of the urban fabric. Furthermore, the urban impressions elicit a visceral reaction from those whose familiarity with a place puts them at odds with the generated imagery. The images challenge long-held impressions and encourage viewers to reconsider what a place's potential might be.

Building footprint studies are more accurate, but add unnecessary complexity. While building footprints did add visual accuracy to the resulting urban impressions, they did not necessarily make impressions that were more useful than what could be achieved with simpler methods. For instance, the variety of LCLU datasets available exceeded those containing accurate building footprints, and required less effort to source and generate, while yielding believable urban impressions. Even a few years of difference between the creation date of the aerial imagery and the segmentation maps is likely to cause a mismatch between building footprints and corresponding imagery (Fig. 17.15). The specificity tradeoff here indicates that building footprints add accuracy, but are not required in order to generate compelling urban impressions.

Urban pattern studies were less believable, but reveal the importance of nuance. To our surprise, the results of the urban pattern studies nearly always failed our visual believability check. The urban impressions fared well with entirely blank areas, such as constructed ponds, and occasionally produced convincing impressions of green areas, but consistently failed to produce impressions of buildings that appeared believable, or interesting (Fig. 17.16). Visual artifacts that might otherwise have gone unnoticed in an impression of a less regular urban area here became clear signs of artifice.

FIG. 17.15 Imagery showing an empty construction site (left) where a building footprint is indicated (right). *No permission required.*

FIG. 17.16 The predicted images, at right, consistently failed our visual believability check, despite the presence of repetitive patterns in the ground truth aerial imagery. *No permission required.*

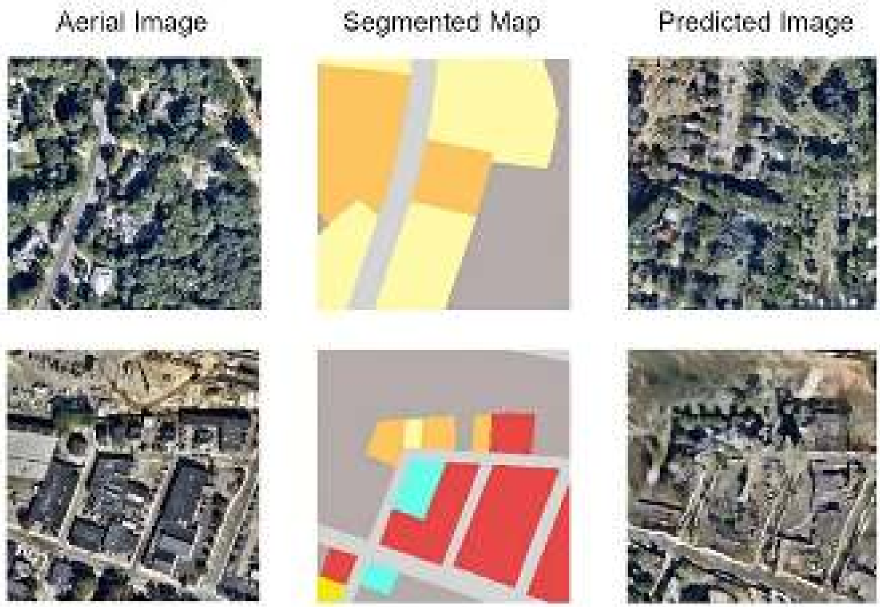


FIG. 17.17 In the above image, the detailed divisions increasing the number of segmented categories in the map do not appear to translate into improved quality of the output. *No permission required.*

The urban pattern studies highlight an important nuance in this work: While open-ended, impressionistic imagery can be useful for sparking creative imagination, it can also easily become too impressionistic for viewers to read or engage with. The results of these studies, while interesting, did not pass the visual quality check, and the resulting discussions around the urban impressions focused on the technical issues underlying the model, as well as the lack of quality data, rather than the possibilities around urban planning or design possibilities.

Land-use studies highlight the pitfalls of overly segmented images, but hold the greatest potential for the sketch tool. Studies using land use indicate quite clearly that more segmentation and accuracy do not always lead to better urban impressions. Using more segmentation categories (than the urban block studies, for example) resulted in dividing of the training dataset into smaller and smaller subsets (Fig. 17.17). Consequently, more training data was needed in order to properly represent the segmented categories. Evaluating the specificity tradeoff here led to the insight that there must be a careful balance between level of segmentation detail and size of the dataset, and that more effort put into segmenting a relatively small dataset does not pay off in terms of visual quality.

The uneven distribution of imagery within particular segmentation categories led to inconsistent results. While certain categories represent fairly consistent building types, others provide a catch-all for numerous types of structures. For instance, the category of commercial buildings can include a number of different building types, from low-density strip mall buildings to tall urban towers (Fig. 17.18). As the size, shape, and overhead view of these different types varies, the model's ability to capture (and generate) a consistent aesthetic diminished,

FIG. 17.18 The category of commercial buildings in black, above, captures everything from tall towers to low-rise buildings, below. *No permission required.*

resulting in less than convincing imagery. More information was needed in order to distinguish the wide variety of certain categories, leading to the inclusion of FAR-based density divisions in subsequent studies.

These studies also highlighted the relative importance of particular features, not only in training the model, but in conveying particular impressions. In numerous urban impressions, visual textures such as shadows, trees, roof colors, and pavement or landscape colors played a significant role in conveying the overall urban impression (Fig. 17.19). Moreover, when these textures were missing or rendered strangely, the visual quality of the impression was negatively impacted. These features also illustrate unscripted behaviors. A few key trees or red roof tiles was often enough to carry an entire segment of the map, thus allowing the other details to lag in visual believability without sacrificing novelty and visual impact.

Land-use studies hold great potential for use in the urban design process at the neighborhood scale. By segmenting the map into more defined categories, the model enables the user to change between specific land uses. Varying land-use categories as inputs, a user may quickly generate alternative micro-conditions within the urban fabric, such as parks or commercial blocks within specific neighborhoods. These rapidly generated impressions can serve both as creative feedback and immediate representations, useful either for internal design efforts or external communications. Land-use shapes are thus the most viable inputs for developing a sketch tool prototype.

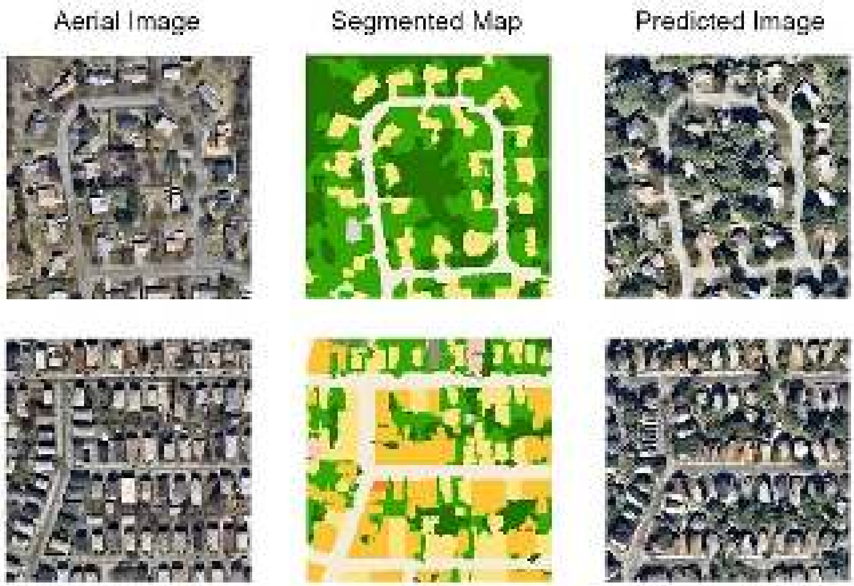


FIG. 17.19 Despite obvious visual artifacts, these urban impressions are carried by the convincing presence of tree canopy textures and shadows. *No permission required.*

Toward a sketch tool prototype

By mimicking building typologies, green spaces, and other features of aerial images, GAN-based urban "sketch-tool" can allow designers to quickly visualize large-scale urban impressions through rapid iteration, acting an "assistant" that can augment the ways in which designers creatively interact with geospatial data.

In various studies conducted, we found that the quality and quantity of training is critical when generating urban impressions. This process can be slow, depending on the amount of input data and number of iterations the training needs. During this phase, the model creates index files that are gathered based on the training and used during the generation phase. Once we have this trained data, applying it on another dataset is a much quicker process.

The sketch tool accesses the trained index. When a designer starts to sketch, the data is fed to the model which in turn predicts and generates new imagery. In the screen captures of the tool in (Fig. 17.20), the model was trained to map Land Use Land Cover imagery to its corresponding aerial imagery. We chose part of the greater Boston area to train the model. As the designer starts to sketch on a new area (another part of the greater Boston area which was not included in the training phase), the model predicts and generates corresponding aerial imagery. As we can see when the user starts to draw a green rectangle on the LCLU map, the model generates an open space. White lines are transformed into pathways (Fig. 17.21).

When the user draws enough green pixels on the map, the model recognizes them as open space, and begins to generate an impression of trees and shrubs. Drawing white pixels along

FIG. 17.20 Sketch tool interface. *No permission required.*

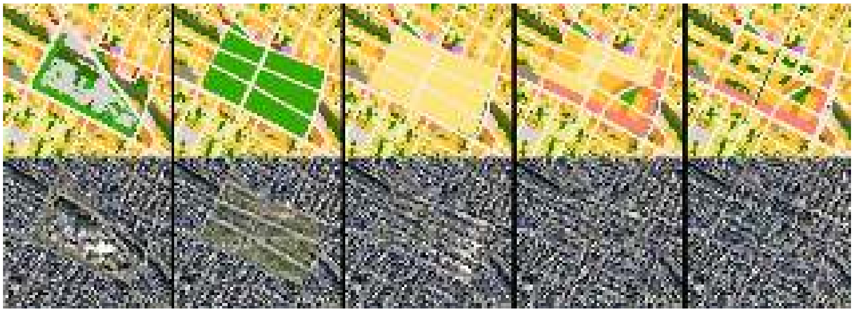


FIG. 17.21 Various stages of the sketching process. As the sketch on top is changed, the model generates new urban impressions, below. *No permission required.*

the green space causes the model to generate pathways. Yellow pixels are interpreted as low density housing, leading to houses in the corresponding urban impression. When pale red pixels are sketched, the model recognizes them as commercial buildings. Notably, the urban impression contains nuanced details that were not drawn by the user, such as shadows next to the trees and buildings.

Due to the open, flexible nature of Pix2Pix, the tool has the capability to have any input/output image generation based on the training dataset. Using this tool to engage the designer's thought process in the moment promotes rapid and iterative feedback, which opens up endless creative possibilities during the design process.

This tool can be used by the designers and planners at the initial stages of design when there is an opportunity for creating rapid design iterations. This also allows for effective communication with the clients during a design process. This rate at which the creative ideas are getting generated and communicated allows numerous possibilities.

Conclusions

Rapid GAN-based iteration in the creative process

Creativity thrives on constant, iterative engagement within the thought process of one or more designers. What happens when machine learning is introduced into this mix? What if a model trained on a particular style of urban design or multiple styles can suggest or generate a new urban impression? These considerations drove the research and development of a sketch tool that can encapsulate a trained model and generate novel imagery on the fly.

Balancing intellectual novelty with business viability is quite a challenge in machine learning applications. Some tools address a specific need but may not be universally applicable. Furthermore, in conversational environments and practices such as design it is critical to keep all involved parties engaged. The sketch tool is flexible and open-ended enough to allow designers to express their creativity when sketching, enabling them to engage with the tool and generate novel impressions. These types of engagements would be difficult to standardize across the whole design workflow as there are multiple phases of design creation. Identifying parts of the workflow that allow automated processes to coexist with designers without sacrificing creative potential is critical in order to apply machine learning effectively. In contending with evolving design challenges, we feel this tool can be a starting point for many creative applications to evolve in the realm of machine learning.

Overall takeaways

The fact that there are numerous, readily available datasets that can be used to quickly and intuitively train various models for generating different impressions points to the valuable role of GANs in the creative process. Rather than create high-quality images that can pass as photorealistic aerial imagery, GANs such as the model available with Pix2Pix have the potential to produce imagery that is good enough to create an impression—and, in doing so, spark conversation, or even drive design. Urban impressions succeed by virtue of their ability to reveal patterns, textures, and formal tendencies that evoke specific urban fabrics. In this sense, urban impressions are one step removed from the ground truth of an area, and instead focused on the *perception* of that area.

There is a significant amount of novelty and interest generated by the urban impression even with relatively poor visual quality of the imagery. In fact, there is an argument to be made for holding back from producing perfectly realistic imagery. By leaving the results ambiguous and open-ended, more impressionistic images leave room for interpretation and creativity. With this, the generated images can contribute to the creative process by sparking imagination in a creative feedback loop.

Further directions

Further research and development of the sketch tool is needed through direct application in a project context. Sasaki Strategies is uniquely positioned to test the viability of this kind of research. Continued development of the sketch tool will require the willingness of project teams to conduct more testing and introduce new methods into existing workflows. One particular area of research could focus on teams' willingness to adopt this technology. Several new questions have emerged from the research presented in this chapter: What barriers are there to adoption, from the technical to the social and cultural? Does the relatively unpolished nature of the tool seem to impact designers' willingness to incorporate it into their creative process? What is the range of perceptions of this tool, and how do those affect designers' approach to the technology in general? In what ways is the tool providing content that is useful for the creative process, be it for the designer's internal practice or external communication?

This work is best conducted simultaneously as the tool is being improved. The actual application and implementation of machine learning for creative processes depends on the successful adoption of this technology. Proper input from practitioners, gathered through focused research in applied settings, is key to both the development and adoption of GANs for creative design. Furthermore, while incremental improvements around performance metrics are important, it is critical to note that the development of machine learning for creative practice deals with far less objective—and subsequently harder to quantify or optimize—evaluation criteria. The actual value of these models is not captured only by loss functions, but rather is incorporated into the design process itself. In other words, there is a need for more nuanced metrics pertaining to the value of machine learning in creative practices, and these criteria are best identified in conjunction with work that is embedded in design practice.

By shifting the conversation away from one-dimensional issues of "good" and "bad" scores, GANs can begin to feed into the design process directly. Visually engaging with the imagery generated by GANs creates a bridge between biological and artificial neural networks. Using urban impressions, GANs are relinquished of the need to be perfect, and can instead be viewed as creative partners in an imperfect process. They can spark ideas, rapidly capture representations, and help communicate complexity. By situating GANs in the middle of the design process rather than at the end, their at-times messy output can be reframed as creative potential rather than computational failure, and concepts of image discrimination, iterative development, and content generation can be advanced as issues shared by both machine learning and design.

References

Crawford, K., Faleiros, G., Luers, A., Meier, P., Perlich, C., Thorp, J., 2013. Big Data, Communities and Ethical Resilience: A Framework for Action. The Rockefeller Foundation.

French, S.P., Barchers, C., Zhang, W., 2017. How should urban planners be trained to handle big data? In: Springer Geography. Springer, United States, pp. 209–217, https://doi.org/10.1007/978-3-319-40902-3_12.

GFDRR, 2018. Machine Learning for Disaster Risk Management. World Bank.

Meerow, S., Pajouhesh, P., Miller, T.R., 2019. Social equity in urban resilience planning. Local Environ. 24 (9), 793–808. https://doi.org/10.1080/13549839.2019.1645103. Informa UK Limited.

CHAPTER

18

KPF: A retrospective view on urban planning AI for 2020

Snoweria Zhang, Kate Ringo, Richard Chou, Brandon Pachuca, Eric Pietraszkiewicz, and Luc Wilson

Kohn Pedersen Fox (KPF), New York, NY, United States

Preamble

Greetings. This chapter is an excerpt from the Proceedings of the Annual Conference of the City Science Society, published on June 1, 2120. The Conference this year provides a focused retrospective on historical trends in city building. As city makers and urban historians in the 22nd century, we have been commissioned to conduct a survey of the evolution and use of artificial intelligence and data-driven approaches in urban planning and design in 2020, a time marked in history by multifaceted crises. A mere hundred years later, the planning practice is markedly different and decidedly more collaborative, and the resultant cities support higher Gini coefficients (The World Bank Group (2022) defined Gini coefficient as measuring "the extent to which the distribution of income or, in some cases, consumption expenditure, among individuals or households within an economy deviates from a perfectly equal distribution.") and Thunberg Indices (Introduced by climate activist Greta Thunberg in the Year 2030, the Thunberg index measures the ratio of greenhouse gasses generated to the abatement mitigation or offsetting efforts in a given region). The genealogy of such improvements in city living can be traced back to the early design developments involving AI. As such, a systematic study of the metamorphic stages of both tools and case studies is warranted.

Crises frequently concur with sudden spurts of growth and paradigmatic shifts, and much of what is considered standard practice in city building today can be traced back to climacteric resolutions germinated amidst the confluence of disasters in 2020. As such, it is worth studying the challenges presented to the city makers of 2020 and the tools that emerged and thrived in addressing such issues. This chapter not only functions as a retrospective to mark the centennial anniversary of the course-changing year, but also traces the trajectory from then to

Artificial Intelligence in Urban Planning and Design
https://doi.org/10.1016/B978-0-12-823941-4.00004-4

modes of practice now. It is our hope that a study of the path that traverses the last hundred years can illustrate a useful path forward.

In addition, as is customary with the conference proceedings, this publication will be transmitted to journals in 2020 for review under the Dual Temporal Publication Agreement. Therefore, even though the format of research publications has changed in the last century since the year in question, this chapter is written deliberately in the style of a typical research publication in 2020. The goal is twofold: (1) to provide a retrospective that examines the historical practices in the pivotal year that arguably provided a mold for the current trend of urban praxis and (2) to create a retro-submission to journals on June 1, 2020, under the Dual Temporal Publication Agreement. The potential retro-publication would allow the designers and builders of the early 21st century to have a closer and critical look at their own city making processes. Future historic reports like this one do not attempt to function as a crystal ball for past architects and planners, though such readings may be inevitable. Rather, this writing serves as a macroscopic study of a historical moment whose recency to readers in 2020 might obscure a clear and holistic assessment. In fact, 2020 was indeed such an anomalous year that many jokes were made around how future historians would study the year. Yet this attempt is neither facetious nor divinatory. The power that we, your future historians of 2020, possess does not center around the prediction of futurecraft but rather a holistic assessment of trends and opportunities. In many ways, we are still very much in the moment about which we write.

Crises and inventions

Architectural historians have been fascinated by the Year 1000, as the expectation of an impending apocalypse drove the sharp contrast between a dearth of construction before and a booming market after (Smith, 2000). Much of the architectural scholarship of this period focuses not only on theories around the projected apocalypse but also on the change in design and construction technologies. The enthusiasm of having avoided an apocalyptic event (at least one portrayed as such in the popular imagination) prompted a burgeoning building economy.

There are many similar historical accounts of crises driving change. Frequently, dramatic transformations can slip by under the veil of the crisis itself. The catastrophe that dominated the collective fear in Medieval Europe, driven by liturgical prophecies, is one that did not manifest. One thousand years later, residents of 2020 found themselves at the crossroads again with cascades of crises, this time supported by overwhelming scientific evidence. Climate change was looming as a global threat, and the health and economic shock waves of COVID-19 cast a heavy miasma over the future of cities. In response to the global exigencies, conceptions of city life morphed, and so did the tools of city building.

Such parallel occurrences between shock and permanent shifts in policy had already been well documented for the readers in 2020. For instance, *The Shock Doctrine*, written by Canadian journalist Naomi Klein and published in 2007, details many tales where crises were exploited for the implementation of questionable policies. Klein's litany of examples spans an impressive breadth, from Chilean coups to the aftermath of Hurricane Katrina. However, the catalyst for change in a crisis can induce positive advancements as well. In 2020, much of the paradigmatic shifts that occurred in the building industry and city making were not strictly the invention of new ideas. Instead, the confluence of climate-related disasters and a pandemic created an impetus for implementing concepts that had existed on a smaller scale for a few decades. For instance, the concept of healthier interiors and shared streetscapes had long been championed by designers and activists alike. However, the onset of COVID-19, the global pandemic caused by the SARS-COV2 virus, brought about an urgency for realizing such ideas.

It is estimated that the City of New York had 67 miles (NYC Open Data, 2021) of streets closed to automobile traffic and an additional 15 miles (Hu and Rosa, 2020) of outdoor dining space at the height of the pandemic. An estimated 70% of the mileage dedicated to open streets would outlive the pandemic and become permanent fixtures of the city as we know it in 2120. The "Sidewalk Stress" section will expand upon how computational tools and city-wide data provided the foundation for the continuation of these exercises.

Before introducing a more detailed account of the city making capacities and trends of 2020, it is prudent to review the social and technological conditions in which 2020 situated itself. The year is marked by tumult, but much of the breakages were results of long-standing social issues that then gave way to the adoption of technological solutions. One could argue that the leap year from 1000 to 2020 is equivalent in scale to the change from 2020 to now. As such, as city makers today, it is worth studying the technological moment as encapsulated in 2020.

Evolution of tools

The year 2020 marked an interesting and important time for the design and planning industry. The prevalence of cloud computing and machine learning was finally finding homes in the architectural process. The next sections illustrate some prototypical examples in and around 2020 that benefited from and leveraged the tools of the time. However, before highlighting the case studies, it is imperative to examine the tools that contributed to and enabled the development of such projects.

Considering the development over the last hundred years, 2020 saw a burgeoning of design tools. The advent and ease of cloud computing had brought about paradigmatic shifts across industries, and the architecture and planning sectors were in some ways the last ones to innovate on this front. However, with the accessibility of open data in many cities, web tools, and digital twin technologies, the attitude toward what a *tool* was shifted as well. Rather than to help designers converge upon an optimal option, the tools' role had evolved to inform and invite collaboration. Instead of having the designer dictate executable commands to the tool, the interaction between the two became more communicative and exploratory in this period.

This relationship is most visible through the open data platforms that many cities in 2020 championed. New York City was certainly such an example. In 2020, NYC Open Data (NYC Open Data, 2021), a web portal that provided citizens access to data about the city, brought together sources generated by the municipality itself as well as those from citizen data collectors. The aggregation, combined with the ease of access, opened the possibility for manifolds of data to be mapped and cross-referenced efficiently. Through critically examining and contributing to NYC Open Data, citizens could participate in the act of city making in informed ways. A cursory count brings up more than 100 cities in this time period that had open data policies (Stone, 2018) to allow citizen participation. Much of the historical literature focusing on the Open Data Age—roughly delineated as the years between 2010 and 2030—describe 2020 as a defining time for building a symbiotic relationship between a city's data palimpsest and its users. As the Sidewalk Stress example below demonstrates, the open data portal provided an opportunity to close the loop in exploration, experimentation, and contribution.

In parallel to accessible data practices, the use of computational design (most commonly developed in McNeel's Rhinoceros and its subsidiary visual programming platform, Grasshopper) in the early urban planning process had started to become common in 2020. While there existed many divergent definitions and practices around computational design, one of the most fruitful explorations came from Scout (In order to preserve these early important examples of Scout, the authors have retrieved the code of several projects and re-rendered them. The content is available at http://scout.build. Our careful restoration follows the instructional videos uncovered from Youtube, a video hosting site popular in the early decades of the 21st century. The re-rendering relies on web technologies commonly used in the Year 2020, many of which have long faded from the Internet's collective memory. Specifically, most of the computational design process was carried out in a combination of Rhinoceros, a 3D modeling software, and Grasshopper, a subsidiary platform that allows for parametric control. In addition, it was common practice in the Year 2020 for designers and architects to develop custom plug-ins using Rhino.compute and C#, development tools made specifically for individualized augmentation of the Rhinoceros environment. It is evident in our archaeological research that KPF Urban Interface had well leveraged many of these tools available to them. In fact, evidence suggests that they might have been the first global architecture office to do so. Beyond the computational capabilities, Scout is a 3D web renderer. It relied on Vue.js, an open-source Model–View–ViewModel front end JavaScript framework, and Three.js, a JavaScript library for displaying three-dimensional geometries. The 2010s saw the flourishing of web-based frameworks, which indubitably enabled the development of urban collaboration platforms like Scout.) (Fig. 18.1). Developed by the Urban Interface team at Kohn Pedersen Fox, Scout is a shared web platform that helped the global architecture firm gain quick data-driven insights, present to clients, and engage with the community. Through Scout, designers and collaborators easily explored and compared thousands of options, made more informed decisions, and enjoyed the creative freedom of visualizing results in real time.

Prior to Scout and similar computational design platforms, the design and planning process typically manually explored three or four options before quickly settling on one. By automating certain components of design, Scout freed focus for deeper development, innovation, and craft. The case studies below expand on the genesis and usage of Scout within the Kohn Pedersen Fox ecosystem in 2020.

While computation in architecture was not a novel subject at the time, Scout became a course-defining tool as it successfully shifted the narrative around computation away from the search for an optimal. Scout represented a recognition that the city making process embodied many conflicting and competing interests. As such, a design pipeline can only be successful if it allows for informed and participatory decision-making. This was precisely what the 2020 version of Scout enabled citizens and designers alike to do. Certainly, digital

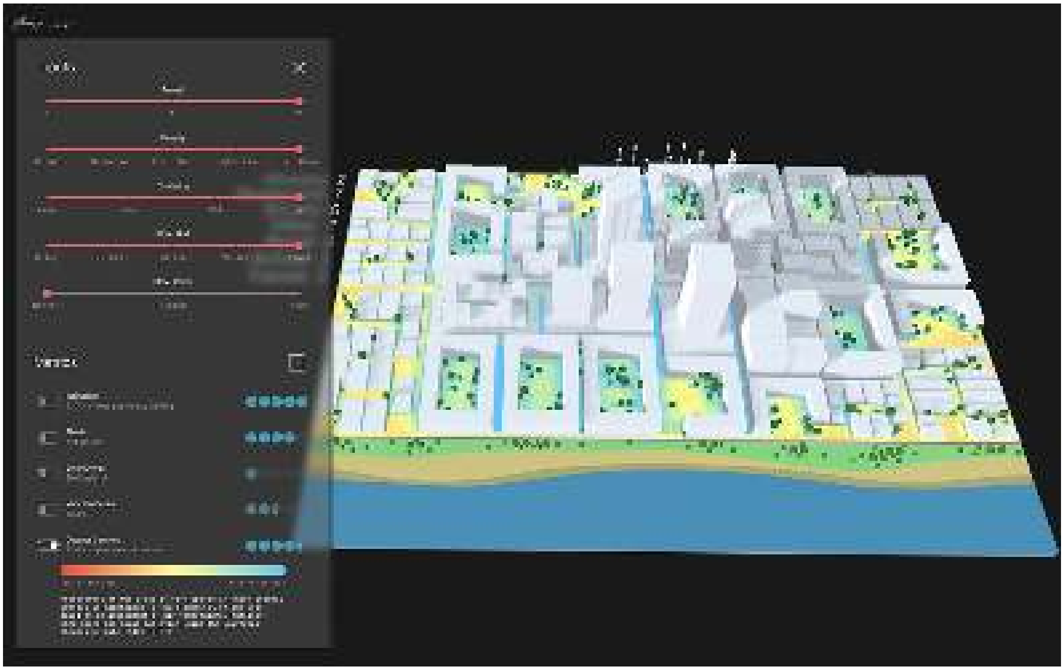


FIG. 18.1 Developed by the Urban Interface team at Kohn Pedersen Fox, Scout is a shared web platform that helped the global firm gain quick data-driven insights, present to clients, and engage with the community. *Scout* From KPF Urban Interface (2021). *Available at: http://scout.build.*

archeologists can trace a clear lineage to more developed versions of Scout and the modern use of digital representations. However, even in its nascent stages, Scout's main aim was to present complex information about design that at the time would stay hidden otherwise. By highlighting trade-offs between metrics that might conflict with each other (such as daylighting and views), Scout enabled more critical and transparent examinations of the city making process.

Such intentions are clear in one of the first projects we excavated in Scout featuring the design of a master plan in the Hangzhou region in China for a 37-million-sqft mixed-use development. Early design documentations showed a challenge to develop an optimal block type that met daylight regulations, offered good views, and created comfortable outdoor spaces. However, in practice, many massing options could achieve these goals and there was not one "optimal" block type. Instead, Scout articulated a diversity of urban experiences and morphology, from narrow and intimate streets to wide boulevards with continuous street walls. The design questions centered around how the podium height, street width, building density, block size, and tower locations would impact certain goals. The design space tested variations of a sample block type, where the inputs captured courtyard and tower placements, block type densities, building heights and orientations, and block dimensions and proportions. The resulting set of models with accompanying data was used to filter for specific design criteria for a variety of goals. Fig. 18.2 shows a subset of the design options that were

FIG. 18.2 A subset of the design options that were tested and their accompanying daylight analyses. *No permission required.*

tested and their accompanying daylight analyses. The computational design model became an aide that allowed the designer to define their own set of optimal outcomes for varying conditions across the plan.

Of course, the dashboard approach to city science was not new. By 2020, the notion of a digital twin had been well established. Extant digital twins relied on networks of sensors and real-time displays of every aspect of a city's operation, from plumbing to electricity. This approach to city making was inspired by popular games in the early 2000s, such as Sim City (Mead, 2014), but even the most complete digital simulations aimed at taking a snapshot of a moment rather than providing a path forward. Such approaches, as city makers have since realized, are inherently limited in application. Intelligence must extend beyond knowledge to include decision-making, and tools from 2020 began to shift in this direction. This renders 2020 an interesting moment for the development of the digital twin concept. Rather than focusing strictly on a momentary snapshot that was periodically updated, 2020 marked an emergence of designers using the digital twin to test out designs in a flexible and de-risked mode. As the Open Data Age thrived in its maturity at this time, the AI Age (The exact delineation of the Artificial Intelligence Age is a much-debated subject among historians. While the term can be used broadly and varies based on industry, we will refer to the Artificial Intelligence Age as the Year 2020 to the Year 2050, during which a growing interest in a shared sense of agency between human and machine intelligence drove the development of tools at the urban scale. This period also witnessed a growing worry around biases and automation exhibited by AI practices. Such collective anxieties served as driving factors in the 2042 creation of the International Council of Human and Machine Intelligence, an entity that is central to today's ethical AI practice.) in planning and design was just seeing nascent applications. The below case study depicting the fictional city of Leeside illustrates these early forays.

The fictional city of Leeside

As the devastating effects of climate change became increasingly pervasive in 2020, the urban planning issue of how to equitably and efficiently house an influx of climate migrants needed special attention. Imagining the future was an integral part of 2020 as the year presented growing uncertainties. As the impact of climate change evolved into progressively direr manifestations, city dwellers were confronted with evermore disastrous depictions of the future. A plethora of such imagery rendered it difficult to envision a hopeful path where climate disasters could be avoidable or mitigated. Amidst the widespread denial and catastrophic thinking, designers at KPF's Urban Interface team partnered with journalists at Quartz to tackle the specific issue of climate migration (Shendruk, 2020). The result was a computational model used by the hypothesized city government to test scenarios and make choices.

The collaboration created the fictional city of Leeside (Fig. 18.3). Pawlowski (2020) hypothesized that American Rust Belt cities, given their abundance of available land and existing infrastructure, could serve as a welcoming ground for migrants affected by extreme climate events. Many of these cities (e.g., Buffalo, Detroit, Rochester) are located further inland and relatively unaffected by imminent climate disasters, and their shared postindustrial malaise meant high vacancy rates and underused infrastructure. This unique combination of features rendered Rust Belt cities particularly suitable candidates to accommodate an influx of migration.

The otherwise thorny and complex issue of situating the project in a real Rust Belt city was addressed by the creation of a fictional city in the image. Since the beginning of the decline in American manufacturing in the 1950s (Kahn, 1999), there had been many proposals of urban renewal in the famously abandoned Rust Belt cities. In fact, Detroit had become synonymous with ruinous urban landscapes. As such, the Leeside thought experiment focused not on tackling the manifolds of social issues and baggage associated with the existing landscape in the Rust Belt but instead on building a fictional twin based on distilled characteristics from similar areas of interest.

In the case of Leeside, the computational process was applied in the initial construction of the city as much as it was in the subsequent decision-making. Fig. 18.4 shows some of the characteristics that were considered in the process of constructing Leeside. It is also worth

FIG. 18.3 The fictional city of Leeside allowed the user to decide building priorities for the task of housing incoming climate migrants. *No permission required.*

FIG. 18.4 Example characteristics that were considered in the process of constructing Leeside. *No permission required.*

noting that Leeside is a microcosm of a city encapsulated in one square mile that includes a "downtown" area, industrial zones, as well as varied housing densities. In comparison, most Rust Belt cities in 2020 inhabited the skeletons of sprawling metropolises, and the neighborhoods included in Leeside were rather far apart from one another. As a result, a realistic one square mile would not capture much diversity in the landscape.

The scale of climate migration is difficult for any city to mitigate on a moment's notice. In fact, Hurricane Maria alone displaced 129,000 residents from Puerto Rico from July 2017 to July 2018 (Acosta et al., 2020). With the rapid development of climate-related disasters on the horizon for 2020, it was not hard to imagine most coastal cities and their millions of residents at risk. Therefore, the task of welcoming climate migrants was one to be treated delicately and extended far beyond housing. KPF Urban Interface approached the problem as a process rather than a finished state. Instead of asking "what will 2050 look like?," Leeside provided a breakthrough in how the art of futurecraft was conceived. The designers asked, "what is the process that takes Leeside from now to 2050 in order to equitably house and provide for the incoming migrants?".

The audience is assigned the role of a city councilor of Leeside in charge of the square mile, and the computational model (Large computational models such as the one produced for Leeside presented both a narrative and a resource challenge for the designers of the Year 2020. The decisions and background stories of Leeside are complex. Yet the Year 2020 relied on media that was mostly consumed through smart phones whose screens measured no more than six inches. This constraint necessitated a shift from Scout's usual interface to a storytelling mode that was much more sequential. Such tools relied heavily on available computing capabilities as well. The commercialization of cloud computing by 21st century companies like Amazon, Google, and Microsoft changed the landscape of large-scale computing projects. Excavated expense reports from this period show that models at the scale of Leeside likely used around one hundred Elastic Compute Cloud instances on Amazon Web Services at a time. This mode of distributed computing was relatively new at the time for the urban design field, even though it had already been successfully adopted by other industries with large data sets, such as genetics (Hail Team, 2021). guides users through detailed thought exercises to accommodate climate migrants. The model presents the user with an existing population of 6000 and 10,000 incoming migrants. This is roughly based on the 2020 density of Rochester (5884/sqm) (United States Census Bureau, 2019a), with the goal of eventually reaching the 2020 density of San Francisco (17,179/sqm) (United States Census Bureau, 2019b). Through the interaction, the city councilor made decisions about where and what to build. Should demolition happen? Should vacant land be used for energy generation rather than housing? What about business opportunities and amenities? Citizens of 2020 inhabited a landscape where COVID-19 put the notion of access to outdoor space at the forefront of one's mind. Should empty land be used as parks instead of housing? All of these questions existed somewhat in conflict with each other. This was and continues to be the reality of addressing urban issues: there are frequently a multitude of "good things" that could happen, but given the limited resources, Leeside served a model that helps decision-makers see transparently what the trade-offs were and what surprises lay ahead.

A central goal of Leeside was to paint a positive yet realistic image of the future and, more importantly, set an example of how to get there. It was well established by 2020 that climate-related disasters, though global in scale, did not affect all equally. Therefore, the establishment of a framework for equitable collaboration as well as experimentation was imperative for the healthy development of the cityscape we have witnessed since. Urban planning was and continues to be a complex and multidimensional Rubik's Cube, where moving pieces have long-term effects and dependencies. Therefore, to establish such a collaborative framework, city makers of 2020 interrogated the conflicting needs of its citizens.

The evolution of tools in 2020 meant a newfound ability to quickly iterate through design options, evaluate their viability, and study potential trade-offs quantitatively. Decisions that were previously made through estimations could instead be laid out transparently through tools like Scout. As a result, designers, planners, and city makers alike were equipped to make informed decisions.

For many, the impacts around climate change were hard to imagine on a personal level and even harder to think of in a positive light. However, as we now know, dire climate events galvanized the 2020 population into action, and a combination of design and social movements created a sense of hope for the future. Using computational models in such speculative urban design exercises not only expanded design possibilities, but it de-risked and elucidated the process. This is a crucial contribution from a historical perspective. Leeside laid out a blueprint for informed future making that was focused on processes (and hopeful ones too), which is now central to the urban planning practice in 2120. (The speculative digital twin approach developed for Leeside became a prototype that cities today heavily rely on. This early development was critical in the planning for many major changes, including the development of New York City's public network of autonomous vehicles in 2030. In addition, Detroit and Buffalo successfully housed two million climate migrants after Hurricane Mary in 2046 using a progeny of the model developed for Leeside. Shenzhen's rapid adoption of housing typologies that integrate personal data centers both for energy and data storage can be partially attributed to experimentation made available through Leeside as well.)

Sidewalk stress

It is undeniable that COVID-19 shaped 2020 for many city dwellers. The issue of indoor air quality transformed from a niche topic of interest in the building industry to a salient issue in the popular psyche.

Airborne diseases have a history of permanently altering the building practice. The 1918 Spanish Flu brought clanging, overheated radiators to New York City apartments to allow windows to stay open, even in the dead of winter. Similarly, at the height of COVID-19, the issue of outdoor "social distancing" (the ability to stay 6 ft apart) changed the rules of occupying public space. Thermally controlled parklets, digitally augmented open-air markets, the prevalence of semioutdoor spaces are all design vestiges from the COVID-19 era. This posed a problem in many cities in 2020, as much of the sidewalk spaces were not wide enough to accommodate the health recommendation. As a result, the function of the street became a popular subject of study.

It would become clear a few months into the COVID-19 pandemic declaration that the virus is airborne (the United States Center for Disease Control declared as such on October 5, 2020). In other words, the likelihood of the disease being passed along from individual to individual during a brief sidewalk encounter was relatively low, given the large volume and movement of air in outdoor spaces and the brevity of the interaction. At the same time, however, the usage of street space and sidewalk areas became more varied as strict restrictions on indoor gathering were enacted. The period from late March to June in 2020 marked a dramatic transition in New York City's streetscape, where a bustling metropolis that was first overcome with eerie calm then transfigured its brief caliginous landscape into a multiuse fun house.

The definition of a street was no longer a rigid conduit. As indoor space became restricted, many of the indoor functions forcibly migrated to their curb counterparts. Supermarkets limited their capacity, which meant that the ground outside was marked as space for socially distanced queuing. Restaurants appropriated parking space for outdoor dining facilities. Workers who had returned to in-office employment faced a longer and more spaced-out queue for just entering the building. Sidewalks had become hosts to a variety of new activities: seating for restaurants and cafes, space for queuing to enter buildings, and retail pickups/drop-offs, among others. In addition to continuing to provide circulation for pedestrian access and other pre-COVID-19 uses, municipal governments had to make room for these curbside newcomers and do so in accordance with social distancing and other public safety protocols.

To mitigate the growing set of demands and uses for street and sidewalk space, New York City, like many of its contemporary metro areas, restricted car traffic on certain streets. At the peak of pedestrianization, New York City had 67 miles (NYC.GOV, 2020) of such shared streets where car traffic was either banned or extremely limited.

COVID-19 was not the only driving factor for this reconsideration of the streetscape. The early 21st century was marked by a rise in social justice movements. In the summer of 2020, protests galvanized by the killing of George Floyd propelled many first-time protestors into the streets. In this regard, the street also became a place of mobile assembly and of civic engagement. Paradoxically, city-imposed curfews transformed the street, the beacon of public space, into areas that were inaccessible and restricted.

The complex and frequently conflicting uses of the street made a systematic organizational strategy around the streetscape difficult. However, as we discussed in the "Evolution of Tools" section, urban mapping and associated data had become a widely accessible endeavor in 2020. Leveraging this newfound asset and ability, the Urban Interface team at KPF created a set of web tools that evaluated sidewalk population density in order to aid NYC decision-makers in the immense challenge of reopening the city in an effective, safe, and equitable way. These tools leveraged detailed data sets and simulated new COVID-era sidewalk uses. They empowered the city and community groups to make decisions to reduce the risk of sidewalk crowding in New York City rapidly and with a higher degree of confidence.

The suite consisted of two primary tools—a Citywide tool that highlighted areas where high levels of sidewalk crowding were likely, and a Neighborhood tool that used routing analyses to locate specific street segments that were within high instances of pedestrian movement, queuing, and business activities relative to sidewalk width.

The City-Wide Tool (An archival version of the tool can be found at https://sidewalk.kpfui.dev/. The Supplemental Materials presents samples of the technical artifacts of the tool's development.) (Fig. 18.5) determined which areas of New York City were most likely to have high levels of sidewalk crowding. The tool aggregated a variety of data sets—ranging

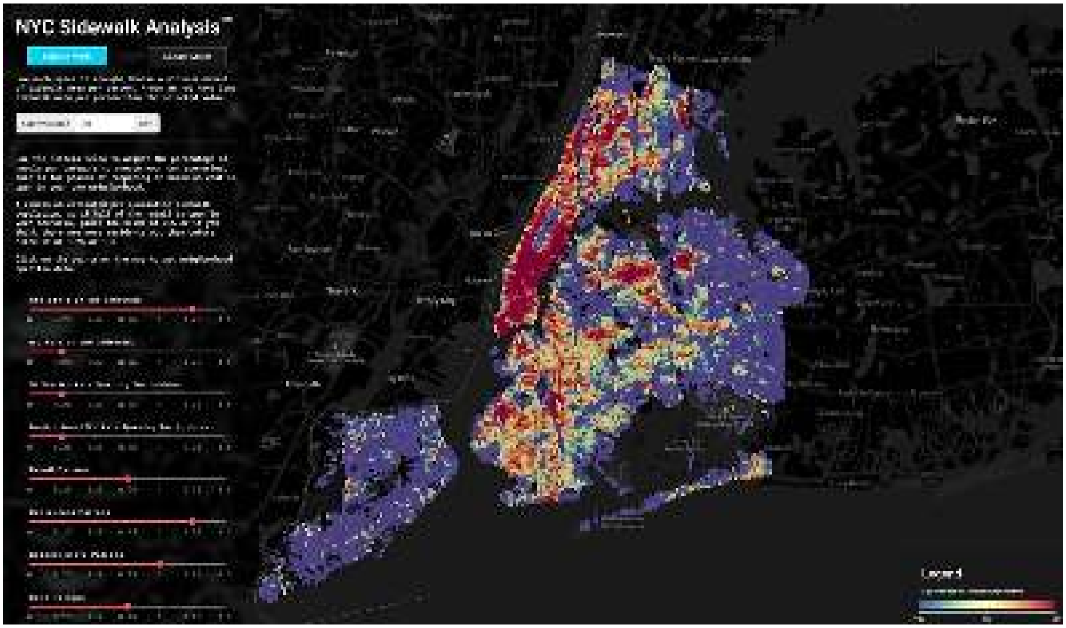


FIG. 18.5 The Citywide tool determined which areas of New York City were most likely to have high levels of sidewalk crowding. *No permission required.*

from resident and job population figures to business locations and building information—into a composite score of square feet of sidewalk per pedestrian.

Given the fluid and complex nature of cities, the varying priorities of different NYC agencies and community groups, as well as the unpredictable nature of COVID-19, creating a model that could be adjusted and calibrated in real time was essential. The utility of the dynamic web maps was clear when simulating different scenarios—weekday and weekend peak hours, for instance. Clustering (A machine learning model called 'K Means' was used to cluster the hex bins, optimizing for the number of clusters required to achieve the highest information gain with the smallest sum-of-squared error (SSE). This was the precursor to the 'Z Means' machine learning model used commonly today.) the most stressed grid cells allowed a better understanding of the factors that were most important in sidewalk crowding in the analysis. The clustering algorithm grouped areas of the city together based on similar reasons for crowding: Midtown New York and the neighborhood known in 2020 as the Financial District scored high in offices and working populations, whereas the Upper East Side and Flatbush experienced crowding because of large residential populations, etc.

The Citywide tool identified neighborhoods with potentially high sidewalk crowding, which could then be analyzed in the Neighborhood (An archival version of the tool can be found at https://neighborhoods.kpfui.dev/. The Supplemental Materials presents samples of the technical artifacts of the tool's development.) (Fig. 18.6) map for a detailed simulation of pedestrian density along sidewalks at different times of day, relative to the effective width of each sidewalk. It did so by simulating pedestrian traffic to and from local

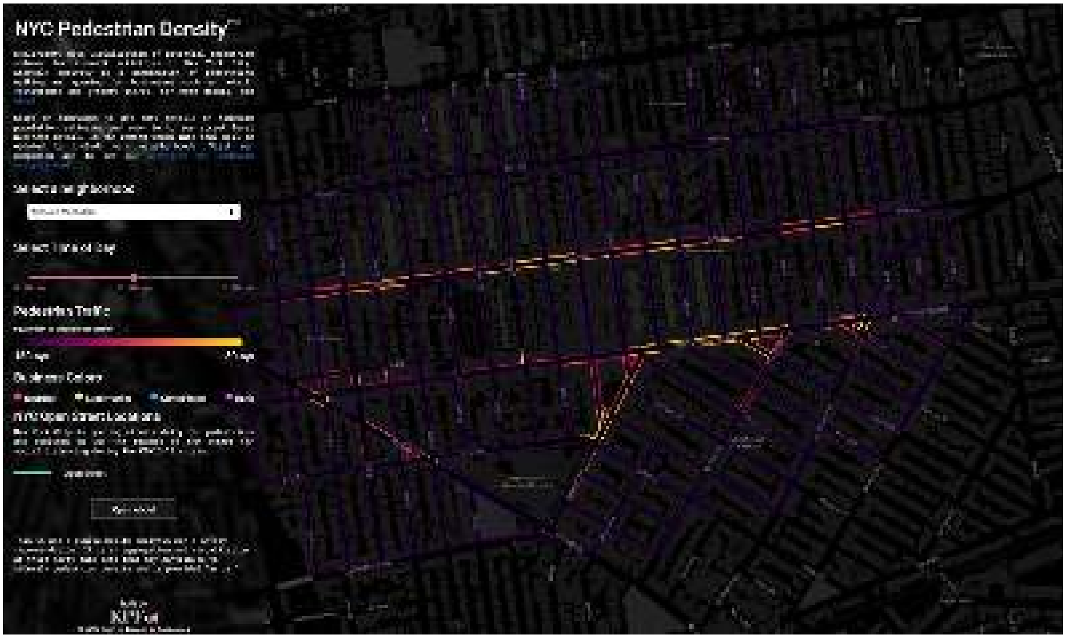


FIG. 18.6 Neighborhood map for a detailed simulation of pedestrian density along sidewalks at different times of day, relative to the effective width of each sidewalk. *No permission required.*

destinations—transit stops, businesses, etc.—and included both moving and standing pedestrians. Some wide sidewalks counterintuitively did not have enough space given business and pedestrian flow, whereas some narrow sidewalks were so lightly trafficked that they did not experience much stress. The Neighborhood map provided a resource for identifying hotspots within the neighborhood where large numbers of pedestrians congregated and the demand for more sidewalk space was high.

Given that many regulations aimed at mitigating the spread of COVID-19 were explicitly tied to spatial thresholds and indicators, knowing the amount of sidewalk space per pedestrian throughout the city was a powerful resource for decision-makers. Given the variation in sidewalk space throughout New York City, plotting the constituent and composite data relative to sidewalk area produced unexpected and informative findings for users of the tool in 2020.

The neighborhood analysis simulated the travel demands of the three busiest times of day—morning rush hour, lunchtime, and evening rush hour. Taking the aggregated pedestrian travel demand from Google Places data, the analysis model simulated pedestrian commutes or visits to businesses per sidewalk. The tool further broke down the category of pedestrians on each street to understand what activities contribute to the most sidewalk stress. For instance, Jackson Heights during lunchtime witnessed a high pedestrian traffic to restaurants along commercial streets, contributing to its sidewalk stress. This information helped guide decisions about phased reopenings for small businesses and strategies for locating outdoor dining space. (Similar to the restoration of Scout mentioned earlier, we have successfully re-rendered two web maps discussed in the Sidewalk Stress section. They can be found at the following links: Neighborhood pedestrian density: https://neighborhoods.kpfui.dev/, City-wide study: https://sidewalk.kpfui.dev/. In addition to the reconstruction of the above web maps, the about section of both web tools included extensive data sources and methodology sections.)

As businesses adapted to new COVID-19 operation strategies, they transformed the sidewalk as extensions of their stores through measures such as designating queuing lines along store perimeters or setting up outdoor seating. The widespread availability of open data as well as the mapping tool together provided insights to better inform urban interventions led by the community or by city agencies, such as expanding pedestrian zones on commercial streets and creating better synergy with the Open Streets initiative. The availability and accessibility of these tools marked the inchoate stage of such collaboration and transparency.

Developments in the 20th century seemingly ossified the streets into automobile-only zones. Even though this remained to be true for many rural parts of the world, cities of the 21st century embraced the use of open data and visual interfaces for participatory decision-making. The street was no longer a mere conduit for movement. Rather, it became grounds for open and flexible exploration based on the citizens' needs. Features that our readers in 2120 enjoy, such as fluid conversions between indoor and outdoor spaces and flex-use modules, can be considered direct spawns of the experiments in 2020.

Human-AI collaboration

The year 2020 was one of anomalous collective anxiety. However, faintly visible in the background was the continuation of a general miasma of worry, specifically around automation. Among the litany of societal concerns, the issue of agency was particularly prominent in the intersecting spheres of artificial intelligence (AI) and urban design. The social discourse in 2020 was one of conflicting drives: one marked by the excitement of technological advancements and one of caution, especially of the implicit biases that were often so deeply embedded and obscured in algorithms. However, 2020 also marked the beginning of a shifting attitude toward AI: one of mutual augmentation and collaboration. It is worth noting that this was both a change in attitude *and* a change in the approach to the technology that was developed around this period. Such developments were evident in the effort to recognize that the practice of city making was complex and needed to allow for asynchronous growth.

Urban planning operates today on an assumption of agreement, especially at the edge where differences meet. This was not always the case in 2020. What happened when the edge condition could not assume agreement and the production of space became a contentious act? In unequal power gradients, spatial negotiation was key. However, the burden of negotiation frequently fell on the less powerful. As such, the KPF Urban Interface team developed a design paradigm that relied on multivalent collaboration, where AI acted in the role of the spatial negotiator.

The production of an urban artifact, as it was intimately affects one's access to housing and public space, highlighted the importance of recognizing such power disparities. In a playful thought experiment, Urban Interface sought to reserve space for AI to assume the role of the negotiator that bridged the fraught interstitial space. Using a tool similar to Scout, human participants generated urban designs with the desired characteristics in an asynchronous fashion (Figs. 18.7–18.9). As the process developed, an AI agent continuously learned from the extant materials and generated new spatial boundaries. This model could not only allow for a less contentious human-human collaboration, but it also introduced the notion of human-AI collaboration and a paradigm that accommodated divergent needs and voices.

What rendered this mode of collaboration possible was not just the technological possibilities but also the development of shared agency. The year 2020 had already seen an established development of machine learning and other AI methods doing impressive predictions and creation. Open AI's DALL-E, for instance, allowed one to turn potentially nonsensical textual inputs (e.g., "an armchair in the shape of an avocado") into coherent image representations (Ramesh et al., 2021). However, against the social backdrop of Black Lives Matter and a reckoning with power and privilege, 2020 ignited a collective pursuit of a much needed restructuring of power that allowed for the eventual shift in designers' abilities to envision a collaborative and equal future with AI.

Prior to 2020, much of the popular depiction of AI was centered around a fight for power. The concept of the "singularity"—a niche but powerful notion about AI that dominated much of the imagination of the late 20th and early 21st centuries—planted deep seeds of fear. Though this idea had largely dissipated in AI practices in the last 50 years, it certainly dominated the thought exercises around AI in 2020. In the late 20th century, it was customary to either imagine that humans would use machines to facilitate better lives or that insubordinate

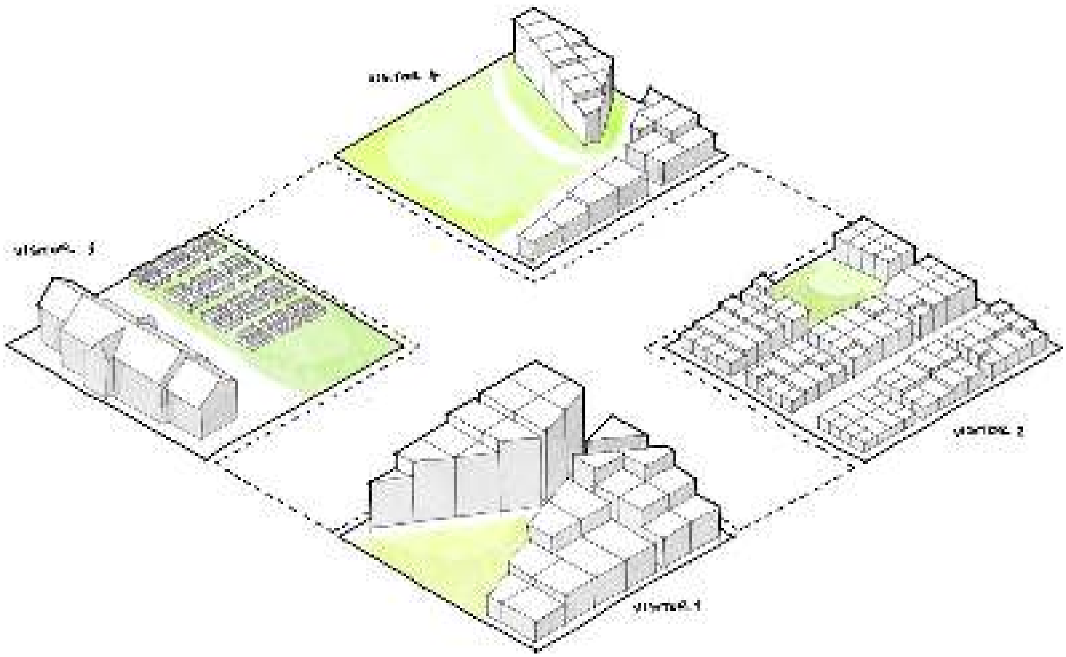


FIG. 18.7 Using a tool similar to Scout, human participants generated urban designs with the desired characteristics in an asynchronous fashion. *No permission required.*

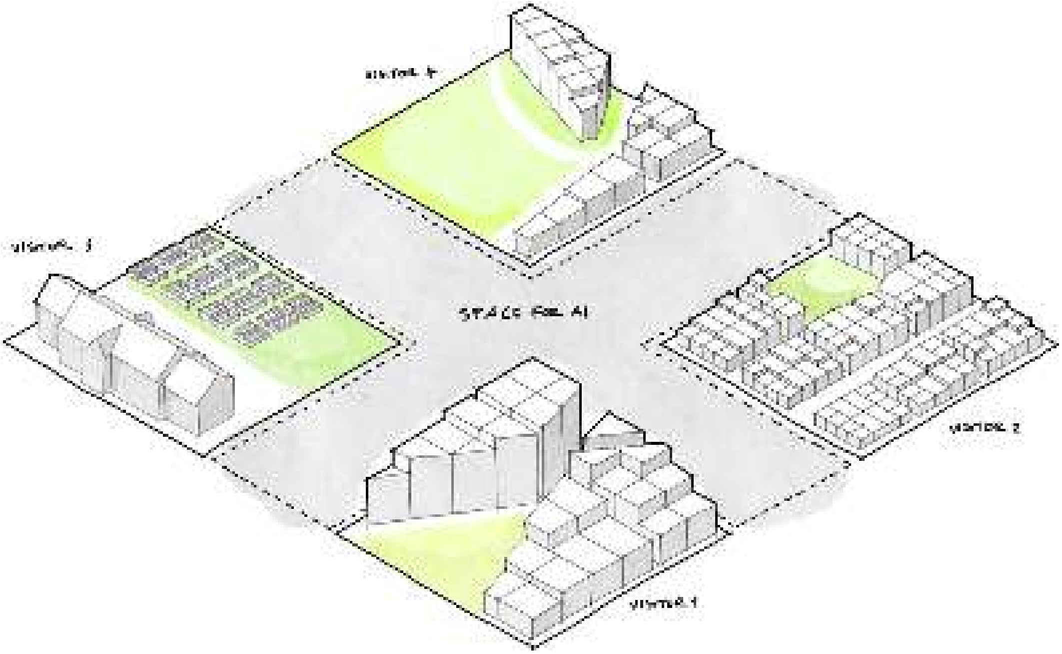


FIG. 18.8 The interstitial space was reserved for AI. *No permission required.*

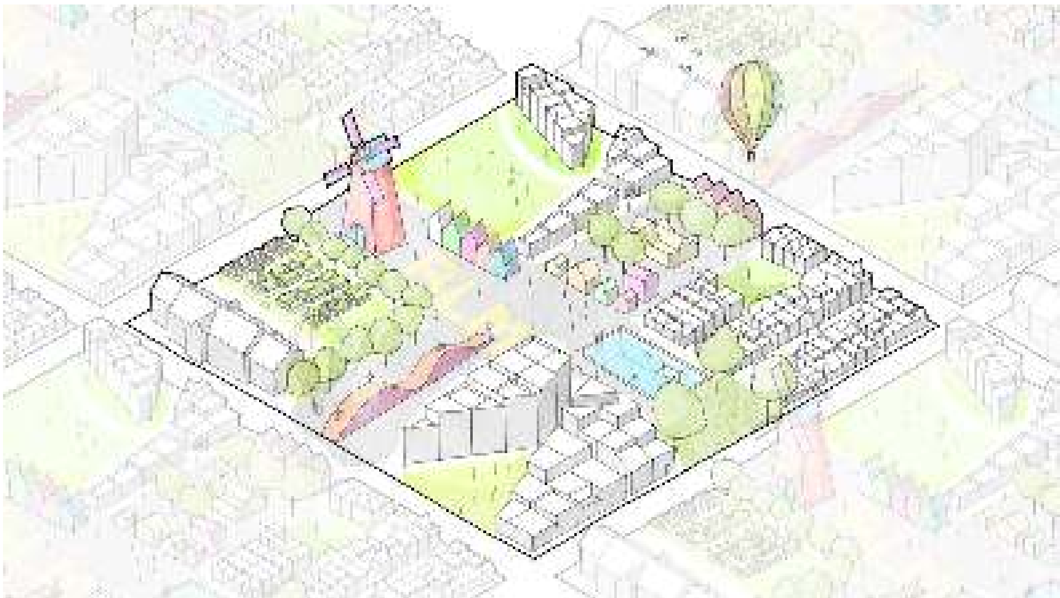


FIG. 18.9 As the process developed, an AI agent continuously learned from the extant materials and generated new spatial boundaries.

AI agents would seek dominion. Very few records showed thinking that deviated from this mode, and a truly equal collaboration seemed improbable.

The approach that the KPF Urban Interface team took was paradigmatically challenging, because it not only physically allocated space to AI agents but also allowed for its intelligence to participate in the design and planning process. In this framework, AI was treated as not only a cocreator but also a negotiator. More importantly, the results were ever evolving. That is to say, the space and designs were always iterated upon as participants' input grew.

The city making practices of 2120 are heavily indebted to this notion of collaboration, even though the execution had naturally experienced many cycles of iteration. Even though the technology involved represented AI in its infancy, the proposal featuring AI as a collaborator and negotiator has shaped technological narratives for the last century of development.

The legacy of Modernism had a stronghold on the architectural imagination and could still be seen in most buildings that were designed in 2020. Even intentionally inventive architecture could not break the mold. However, 2020 saw AI develop into an explorative and speculative tool, especially around the notion of collaboration. Used first by the Museum of the City of New York as an experimental civic engagement tool, this mode of working with AI at an urban scale was adopted more broadly by city planning departments worldwide. It has since become a standard of civic engagement by 2120. The mystic public, here manifested as machinery, acted to bridge the interstitial space that is often so fraught. It generated the playful, sought the just, and manifested the imaginative.

Conclusions

It is commonly accepted among urban historians that 2020 was a transformative time. It was not only marred by a global pandemic but also witnessed social uprisings and collective cultural reckonings. Simultaneously, computational and data-driven tools had reached a level of maturity that allowed them to have profound impacts directly on the design industry. The confluence of a crisis and the maturation of tools meant that many imaginative approaches to city making flourished and were successfully adopted. Such inventive changes, necessitated by a moment of crisis, became permanent fixtures. We present three examples where citizens of 2020 leveraged such tools to address the issue of climate migration, healthy streets, and collaborative human-AI relationships. Leeside reimagined the digital twin for speculative planning rather than infrastructural management through computational design and an interactive user interface. Similarly, at the height of the COVID-19 pandemic and the cusp of urban change, the Sidewalk Study allowed information and tools usually only accessible to experts to be available to the general public through data exploration, machine learning, and interactive mapping. Both projects then naturally led to the thought experiment on transforming the Human-AI relationship from one of prediction and generation to one of collaboration.

The projects presented in this study, even in their inchoate stage, provided an excellent bedrock for future development. The initial community engagement process in urban planning today in 2120 is able to welcome and meaningfully absorb public feedback as a direct result of the early experimentation that emerged in 2020. Analogously, architects and planners today can incorporate multidimensional data with ease. In addition, 2020 witnessed a rise in the use of cloud computing services in architecture and planning. Not yet a public infrastructure then, cloud computing was both financially and technically prohibitive to the average citizen. The design industry's incorporation and eventual reliance on it played an instrumental role in the public investment of the infrastructural development of cloud computing today. Costly cloud computing services are no longer an underpinning of computational design, as decentralized cloud computing has become the mainstream in the last century. Equitable access to AI, facilitated through widespread cloud computing capabilities, has made immeasurable contributions to transparency and accountability in urban design.

This marks the end of this timed transmission from June 1, 2120.

References

Acosta, R.J., et al., 2020. Quantifying the dynamics of migration after a disaster: impact of hurricane Maria in Puerto Rico. medRxiv. United States: medRxiv, https://doi.org/10.1101/2020.01.28.20019315.

Hail Team, 2021. Hail 0.2. https://github.com/hail-is/hail.

Hu, Rosa, A., 2020. Outdoor Dining in N.Y.C. Will Become Permanent, Even in Winter. The New York Times.

Kahn, M.E., 1999. The silver lining of Rust Belt manufacturing decline. J. Urban Econ. 46 (3), 360–376. https://doi.org/10.1006/juec.1998.2127. United States: Academic Press Inc.

Mead, D., 2014. This 107 Million Person "SimCity" Region Is a Portrait of Our Megacity Future. Available at: https://www.vice.com/en/article/mgb3mb/this-107-million-person-simcity-region-is-a-portrait-of-our-megacity-future. (Accessed 29 September 2021).

NYC Open Data, 2021. Available at: https://opendata.cityofnewyork.us. (Accessed 29 September 2021).

NYC.GOV, 2020. New York City Expands Nation-Leading Open Streets Program. Available at: https://www1.nyc.gov/office-of-the-mayor/news/467-20/new-york-city-expands-nation-leading-open-streets-program-23-more-miles-areas-hit-hard-by. (Accessed 29 September 2021).

Pawlowski, T., 2020. Rust Belt Climate Refugee Resettlement Program. Available at: https://newcities.org/the-big-picture-rust-belt-climate-refugee-resettlement-program/. (Accessed 29 September 2021).

Ramesh, A., et al., 2021. Zero-shot text-to-image generation. arXiv. United States: arXiv. Available at: https://arxiv.org.

Shendruk, A.O., 2020. Welcome to Leeside, the US's first climate haven. Available at: https://qz.com/1891446/welcome-to-leeside-the-uss-first-climate-haven. (Accessed 29 September 2021).

Smith, 2000. Before and after the End of Time: Architecture and the Year 1000. Harvard Design School.

Stone, A., 2018. Are Open Data Efforts Working? Available at: https://www.govtech.com/data/Are-Open-Data-Efforts-Working.html. (Accessed 29 September 2021).

The World Bank Group. Available at: https://databank.worldbank.org/metadataglossary/gender-statistics/series/SI.POV.GINI, 2022, 13 March 2022.

United States Census Bureau, 2019a. QuickFacts Rochester City, New York. Available at: https://www.census.gov/quickfacts/rochestercitynewyork. (Accessed 29 September 2021).

United States Census Bureau, 2019b. QuickFacts San Francisco City, California. Available at: https://www.census.gov/quickfacts/fact/table/sanfranciscocitycalifornia/BPS030219. (Accessed 29 September 2021).

Index

Note: Page numbers followed by *f* indicate figures, and *t* indicate tables.

This page intentionally left blank

Artificial Intelligence in Urban Planning and Design

Technologies, Implementation, and Impacts

Edited by Imdat As, Prithwish Basu and Pratap Talwar

Launching a new level of debate about what Artificial Intelligence (AI) will and will not achieve as applied in real cities, *Artificial Intelligence in Urban Planning and Design* is the most comprehensive resource available on the state of Artificial Intelligence (AI) as it relates to smart city planning and urban design. It explains nascent applications of AI technologies in urban design and city planning, providing a thorough overview of AI-based solutions.

The book offers a framework for discussion of theoretical foundations of AI, AI applications in urban design, AI-based research and information systems, and AI-based generative design systems. AI generates unprecedented city planning solutions without defined rules in advance, a development raising important questions for urban design and city planning. The book articulates current theoretical and practical methods, offering critical views on tools and techniques, and suggests future directions for meaningful uses of AI technology.

Artificial Intelligence in Urban Planning and Design is a valuable resource to Smart Cities graduate students, researchers, and scholars, as well as civil engineers, city planners, and urban designers.

Key features:
- Offers a cutting edge catalogue of AI tools applied to smart city design and planning
- Provides case studies from around the globe at various scales
- Includes diagrams and graphics for course instruction

Edited by:
Imdat As is the recipient of the prestigious International Fellowship for Outstanding Researchers from the Scientific and Technological Research Council of Turkey (TUBITAK) at Istanbul Technical University. He has a doctoral degree from Harvard University (2006), a M.Sc. in Architecture from MIT, and B. Arch. from the Middle East Technical University (METU), Ankara (2000).

Prithwish Basu is a principal scientist at Raytheon BBN Technologies (BBN). He has a PhD in computer engineering from Boston University (2003) and a BTech in computer science and engineering from the Indian Institute of Technology (IIT), Delhi (1996).

Pratap Talwar is an urbanist who over three decades has led pioneering integrations of sustainable planning and design in over 30 cities and regions in United States, Europe and Asia, as Managing Principal at TDG/Thompson Design Group. He received graduate degrees in City Planning and Urban and Environmental Design from MIT (1988), and a B. Arch. from the School of Planning and Architecture, Delhi (1989).

ISBN 978-0-12-823941-4
9 780128 239414

ELSEVIER elsevier.com/books-and-journals