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Passive performance and building form: An optimization framework for early-stage design support

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Abstract

To achieve low and zero net energy performance objectives in buildings, designers must make optimal use of passive environmental design strategies. The objective of this research is to demonstrate the application of a novel Passive Performance Optimization Framework (PPOF) to improve the performance of daylighting, solar control, and natural ventilation strategies in the early design stages of architectural projects. The PPOF is executed through a novel, simulation-based parametric modeling workflow capable of optimizing building geometry, building orientation, fenestration configurations, and other building parameters in response to program requirements, site-specific building adjacencies, and climate-based daylighting and whole-building energy use performance metrics. The applicability of the workflow is quantified by comparing results from the workflow to an ASHRAE 90.1 compliant reference model for four different climate zones, incorporating real sites and urban overshadowing conditions. Results show that the PPOF can deliver between a 4% and 17% reduction in Energy Use Intensity (EUI) while simultaneously improving daylighting performance by between 27% and 65% depending on the local site and climatic conditions. The PPOF and simulation-based workflow help to make generative modeling, informed by powerful energy and lighting simulation engines, more accessible to designers working on regular projects and schedules to create high-performance buildings.

Keywords: Passive design; Daylighting; Multi-objective optimization; Natural ventilation

1. Introduction

Increasing awareness of the impact of buildings on energy consumption and indirect carbon emissions is driving a growing interest among design professionals to design projects that go beyond energy code compliance thresholds and achieve whole-building energy optimization. Rather than analyzing whether a predetermined building design surpasses or fails a compliance requirement in the late stages of design development, designers are increasingly interested in obtaining rapid and iterative performance feedback on decisions in the early stages of design, where the largest impacts on building performance and occupant comfort are set. To effectively meet low and Zero Net Energy (ZNE) performance objectives, the building geometry, orientation, fenestration configurations, and thermal management strategies must become supporting pieces of the whole-building energy concept. To achieve this, designers must go beyond incremental improvement in mechanical systems efficiency and make optimal use of environmental services provided by natural systems. Therefore, workflows are needed that enable designers to

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examine and optimize the application of passive environmental strategies in early stage design. However, due to the complexity and resources required to conduct reliable simulation-based thermal energy analysis, responsibility for energy performance is often shifted outside the discipline of architecture to Heating, Ventilation and Air Conditioning (HVAC) engineering consultants, where the focus is traditionally on incremental improvements in building assemblies and systems efficiency guided by energy standards (e.g. American Society of Heating and Refrigeration Engineers ANSI/ASHRAE/IES Standard 90.1-2013). Similarly, due to the complexity and resources required to conduct photometrically-accurate lighting simulations, lighting design is often performed by external consultants and late in the design process, where the emphasis is placed on specifying high-efficiency electrical lighting fixtures and photo-sensitive lighting controls for an existing design. This fragmented approach limits the potential to explore architectural strategies (e.g. building geometry, window–wall ratio, shading devices, etc.) to minimize heating and cooling loads and the application of environmental services such as natural ventilation, exposed thermal mass, and daylighting, as passive alternatives to HVAC and electrical lighting systems. The goal of this research is to increase the utilization of passive environmental strategies in the design process by developing a design framework and simulation-based workflow enabling designers to examine and optimize the application of passive environmental systems in early stage design using validated lighting and energy simulation tools.

In commercial buildings, which account for roughly half of the energy used by all U.S. buildings, decisions related to building geometry and fenestration affect the majority of energy end uses and are thus a central area of focus for performance improvements aimed at enabling low and ZNE buildings. In the United States, lighting represents the single largest commercial building electricity end use (35%) (U.S. DOE, 2011), and is consumed primarily during daylight hours. Of this energy, it is estimated that 60% is consumed in perimeter zones located 0–12.2 m (0–40 ft) from the building facade during typical daytime work hours (8:00–18:00) (Shehabi et al., 2013). Cooling loads represent another significant energy end use (14%), and one-third is due to electrical lighting and another one-third to solar heat gains through windows (Huang and Franconi, 1999). And, because ZNE projects often implement passive or low-energy cooling alternatives such as radiant systems or exposed thermal mass with night-flush ventilation, effective solar control is an additional requirement to avoid exceeding the peak cooling capacities of these systems, which are typically lower than mechanical HVAC, and consequently more sensitive to peak solar heat gains. Consequently, daylighting strategies that optimize distribution of useful daylight across the floor plate while controlling solar loads have the potential to significantly improve building energy performance.

Many designers strive toward achieving a holistic building design process where the numerous, sometimes conflicting, design objectives are resolved. Trade-offs are considered, and designs are reworked at each stage of the building's development from sketches to construction. As project phases move from pre-design to utilization, cumulative cost goes up and level of influence decreases (Paulson, 1976). The MacLeamey curve, fine-tuned from years of his experience in architecture and as a principal at HOK, illustrates that changes made during schematic design can be cheaper to implement than if done later and can have more impact on the project (Kensek, 2014). Analysis opportunities, for example for passive energy strategies, are thus best explored during schematic and early design development.

In a worse case scenario, design happens without consideration of local climate or context. Or energy reduction strategies are considered only later in the process for code-compliance based prescriptive processes, which often fail to capture the potential of local climates. Where passive strategies are applied, designers often face a range of challenges in reliably achieving the desired project outcomes. Although "rules of thumb" (AIA, 2012) and design "best practices" (e.g. the Architecture 2030 *Palette*) are available to guide design decision-making, how best to apply one or more strategies to achieve the optimal balance between daylighting and whole-building energy objectives is often unclear, particularly for sites where adjacent buildings can create complex overshadowing conditions and where building orientation and local climate can lead to non-intuitive solar control requirements.

As growth in the building sector is increasingly occurring in dense urban environments and executed by design teams working remotely who may have limited familiarity with the local climate, the application of conventional rules of thumb, case study precedent, the designer's own intuition or past project experience may be sub-optimal or even counter-productive to achieve performance goals. In addition, the optimization of daylighting with whole-building energy objectives requires consideration of broad set of architectural design parameters. These include building massing (i.e. the overall shape and size of the building), building orientation, and the configuration of fenestration, leading to the need to evaluate a multiplicity of prototype designs, each of which may have complex interactions between parameters. And all of this must be done at a rapid pace to impact design decision-making. In practice, the large number of parameter combinations paired with the complexity of the simulation tools and resources required for conventional modes of evaluation leads to designers facing the need to choose a limited set of options picked using intuition and judgment rather evidence-based feedback. Although one or more choices may lead to a low-energy project outcome, it is unlikely to make optimal use of available environmental services. Adding to the challenge, simulation-based design support is highly fragmented in practice, due to the specialized applications of lighting and thermal simulation engines and different skill sets required. Consequently, results from lighting and energy simulation tools are often de-coupled from the three-dimensional (3D) authoring environments used by designers and must be synthesized by various members of the design team into a single design outcome.

To address these issues, a Passive Performance Optimization Framework (PPOF) and corresponding generative modeling workflow were developed to inform early-stage design by optimizing building geometry, orientation, fenestration, and shading device geometry configurations in response to annual climate-based thermal comfort and daylighting performance outcomes. Passive Performance Optimization (PPO) is defined, in this context, as a process of taking a particular site condition, climate, and program requirement and maximizing all applicable Passive Performance Metrics (PPMs). The workflow is focused on the earliest stages of design, where limited, (if any) project detail has been developed, to quantify and visually present the environmental potential of the site prior to substantial development of the building. Novel elements of the workflow include accounting for urban overshadowing, implementation of daylighting, solar control, and natural ventilation. The applicability of the PPOF is demonstrated by comparing results from the workflow to an ASHRAE 90.1 compliant baseline model from the National Renewable Energy Laboratory (NREL) database of reference building models, which is used to signify best practices for energy efficient modern construction.

2. Background and literature review

The PPOF provides one solution toward assisting designers in the early stage of design. It is based on improving conventional design practices, integration of climate-based performance metrics, using energy simulation software for early design, incorporating visual programming languages, addressing limitations of existing approaches to optimization, and bridging research gaps.

Available for decades, software simulation has progressively improved in availability, ease of use, cost, and speed of calculations. Additionally, newer, climate based daylighting and adaptive thermal comfort metrics are recasting how designers approach daylight and thermal comfort performance criteria and make design decisions, especially about passive strategies. There is an increased emphasis on creating tools specifically for designers both from software developers and academic researchers.

2.1. Energy simulation based approaches for early-stage design support

Researchers have been exploring how to integrate software tools into the early stages of design process to achieve improvements in energy performance (Konis and Kensek, 2015). There are many examples of this, a few are listed to show a range of types: Excel tools, new software programs, building information modeling (BIM) software, and integration of visual programming languages (VPL) into the simulation process.

- Excel forms were created that can retrieve from information repositories, hold calculation results and be used for design comparisons during the early stage of design (Madrazo et al., 2010).
- “NewFacades assists the designer to pass from idea to architectural concept by using climate and visual comfort strategies that comply with an energy code” (Ochoa and Capeluto, 2009). “iDbuild tool helps designers to integrate the task of fulfilling energy and indoor environment performance requirements in all design decisions related to form, constructions and systems from the early design stages” (Petersen and Svendsen, 2010). And decision support tools for early stage designing of net-zero buildings (Attia et al., 2012).
- BIM was used to assist in energy modeling (Schlueter and Thesseling, 2009), and an additional tool was created to assist in moving BIM data to building energy performance software (Hijazi et al., 2015).
- Integrated dynamic models combine a design tool, a visual programming language (VPL), and a building performance simulation tool (Negendahl, 2015) and a VPL is used with BIM for whole-building energy simulation and dynamic solar shading studies (Kensek, 2015). Parametric analysis within these tools included examples of daylight and energy consumption (Hegazy et al., 2013) (Wu et al., 2012), use of DIVA/DAYSIM to generate operable blinds and electric lighting schedules for use in thermal analysis (Jakubiec and Reinhart, 2011), and multidisciplinary design optimization using genetic algorithms (Lin and Gerber, 2013).

The latter approach of integrated design models has tremendous potential for use in the early stage of design. It incorporates visual programming languages with 3D modeling tools for the improvement of passive design practices by showing alternatives and in some cases optimizing parameters.

2.2. Brief review of optimization techniques and visual programming languages

In architectural design, there are necessary trade-offs between many alternatives where optimization methods would be helpful. There are also several visual programming languages and scripting languages that provide a framework and methodology for combining modeling, simulation, and optimization tools to assist design decision making for green buildings.

2.2.1. Optimization techniques

Architects can use several types of techniques to discover an “optimal” solution including parametric analysis, genetic algorithms, multi-objective optimization, and even "passive" optimization (Sukreet and Kensek, 2014). "Passive" optimization is what many designers think they are doing by creating three or four options, mentally testing them against past experience, and then intuitively determining a "best" solution (Sukreet and Kensek, 2014). Although some architects can be very good at this, especially if they have a lot of experience with passive strategies, sometimes their intuition is wrong, especially for climate zones they might not have designed for before, and generally simulation is a safer method.

Parametric analysis can be used to find an optimized solution. In a simple case with only one variable, a user can manually change its value in a spreadsheet until a maximum or minimum result is obtained that indicates the best solution. Graphs can make this easier to visualize, especially if there is more than one variable. For example, a parametric analysis on daylighting performance by varying façade options considered the variables of location (three cities), four window–wall ratios (WWR), three types of glass, and four orientations; a set of tables and graphs were produced to make visualization of the results clear and concise (Shen and Tzempelikos, 2010). In another example, researchers created a new simulation platform, Fener, to evaluate office fenestration configurations. Designers can change blind types and shading control algorithms to assess energy and light performance, manually parametric (Bueno et al., 2015). Parametric analysis is not a new idea (Johnson et al., 1984), but automation and software availability has made it easier to pursue.

Applications in evolutionary multi-objective algorithms have more traditionally been in the engineering and scientific fields (Coello, 2005). Although the architecture field is not one that has traditionally been associated with these techniques, there are several automated methods of optimization including genetic algorithms and evolutionary algorithms that provide a search space for discovering architecture design solutions that met certain criteria. These can be used for complex design problems that architects face that require many iterations, produce a myriad of variations and alternatives and provide graphical methods of evaluation. "Using these tools, the parametric system becomes the genome, the field of alternatives becomes the population, and the architect's design goal becomes the fitness criteria" (Miller, 2011).

Often, multi-objective optimization is used for two variables (e.g. electrical energy for lighting versus cooling loads for different window sizes), but multi-objective optimization algorithms can handle an arbitrary number of objectives at the cost of computing speed. "Pareto ranking refers to a solution surface in a multidimensional solution space formed by multiple criteria representing the objectives" (Ciftcioglu and Bittermann, 2009). The Pareto front is often used to illustrate the results of the optimization; it is a curve that connects all optimal solutions for the defined objectives and constraints. For multi-variable solutions, a visual solution space is provided that ideally spans from one extreme trade-off to another. There have been many research projects that have embraced the use of evolutionary multi-objective algorithms, a sampling of those show that passive strategies for green buildings is a good area for this methodology: building envelope and fenestration design for optimizing thermal and daylighting performance (Gamas et al., 2014); building envelope including orientation, aspect ratio, WWR, and insulation (Wang et al., 2005); heating, cooling, and lighting (Echenagucia et al., 2015); floor shape optimization during conceptual design (Wang et al., 2006); angular dependence of direct solar heat gain of the façade (Ko et al., 2012); and optimization of dynamic light shelves for daylight harvesting (El Sheikh and Kensek, 2011).

2.2.2. Visual programming languages

Visual Programming Languages (VPL) have become one method of allowing designers access for changing design parameters and for inclusion of optimization components. Visual programming is a type of computer programming where users graphically interact with program elements instead of typing lines of text code. Examples include *GenOpt* (Wetter, 2001), *Simulink* (Mathworks, 2015), and *Grasshopper* (McNeel, 2015). In a visual programming environment, nodes are created: numbers, sliders, operators and functions, list manipulation tools, graphic creators, scripts, notes, customizable nodes, nodes from other developers (e.g. optimization components). They are then "wired" together virtually. The software tool *Grasshopper* (used with Rhino 3D) is a commonly used VPL in the building industry, but others like *Dynamo* (Autodesk, 2015), and *Marionette* (Vectorworks, 2015) are becoming more prevalent. Grasshopper has the capability to interact with numerous simulation-based environmental analysis tools ("plug-ins"), such as *Ladybug*, *Honeybee*, *Archsim*, *Geco*, *Gerilla*, and *DIVA* (McNeel, 2015). *Grasshopper* also contains components for single (*Galapagos*) and evolutionary multi-objective optimizations (*Octopus*).

2.3. Summary

Simulation-based optimization is a promising approach that could rapidly become a standard method for architects and engineers, but it is still in the early stages of development (Nguyen et al., 2014). In addition, it is often only used by expert users. The following methodology is applied to help to make generative modeling, informed by powerful energy and lighting simulation engines, more accessible to designers working on regular projects and schedules to create high-performance buildings.

3. Methodology

A simulation-based design workflow was developed in Grasshopper capable of evaluating the performance of multiple passive design alternatives in early stages of design. The workflow facilitates the exploration and optimization of the basic building information that designers would typically adjust and decide on during the early stages of design (e.g. building footprint, solar orientation, massing, number of stories, building fabric and fenestration). Each phase of the workflow consists of multiple steps that must be completed to setup and run the optimizations (Fig. 1). Once the geometry for an initial model is created and simulations are run, the building geometry and model parameters can be adjusted for the simulations and run again to compare differences in performance. Repeating the process many times may lead designers to improve their intuition for what building geometry variables have the greatest impact on annual performance. The workflow can be used in this manner to explore a series of quick design iterations based on predetermined geometry. However, because building geometry and the properties of the models are defined parametrically, this process can also be automated through an optimization component, which uses performance feedback to automatically find the building geometry and/or attributes of the model that will provide the lowest Energy Use Intensity (EUI), greatest spatial Useful Daylight Illuminance (sUDI), or a combination of both objectives. The workflow is divided into six sequential phases: site location, geometry creation, daylighting and thermal simulations, visualization, and optimization (Fig. 1). An overview of each step is provided in the following sections.

3.1. Site

The site is defined by importing the surrounding urban context and annual climate data in the form an Energy Plus Weather (EPW) file (U.S. DOE, 2015). The geometry of the surrounding urban context contributes to both thermal and lighting energy calculations. In order to facilitate the rapid visualization and modeling of the urban conditions of a specific site, the plugin *CADtoEarth* (AMC Bridge, 2015) is used to automatically import Google Earth images and building geometry from the open-source GIS site openstreetmap.org into the 3D authoring workspace (Fig. 2). Surface geometry from surrounding buildings is then modeled as shading objects in both the thermal energy analysis (EnergyPlus simulations) and the daylighting analysis (Radiance simulations) to account for the impact that the surrounding buildings have on project solar heat gains and daylight availability. An example quantifying the impacts of urban geometry on project thermal and daylighting outcomes is presented in Fig. 10. It is important to note that the urban geometry imported into the model does not include the possible presence of existing vegetation such as trees, which may provide additional shading. This is due to the fact that vegetation is not surveyed or recorded in the GIS database. Therefore, it is possible that simulation outcomes may overestimate solar heat gains and daylight availability for sites where significant vegetation such as large shade trees are present near the project.

3.2. Geometry

The second phase of the workflow consists of modeling the geometry of the building. This phase of the workflow is subdivided in three stages: building footprint and massing, windows, and exterior shading.

3.2.1. Building footprint and massing

A custom form-finding component (Fig. 3) was developed in order to facilitate the modeling and adjustment

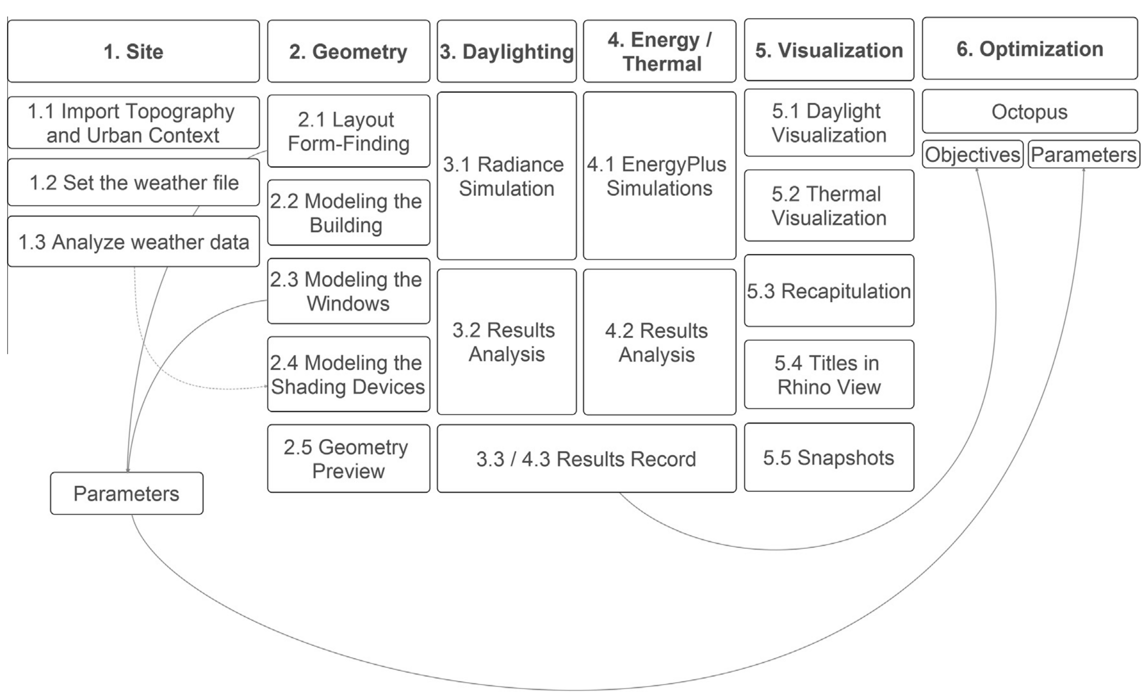

Fig. 1. Workflow diagram showing sequential steps to initialize passive performance optimization.

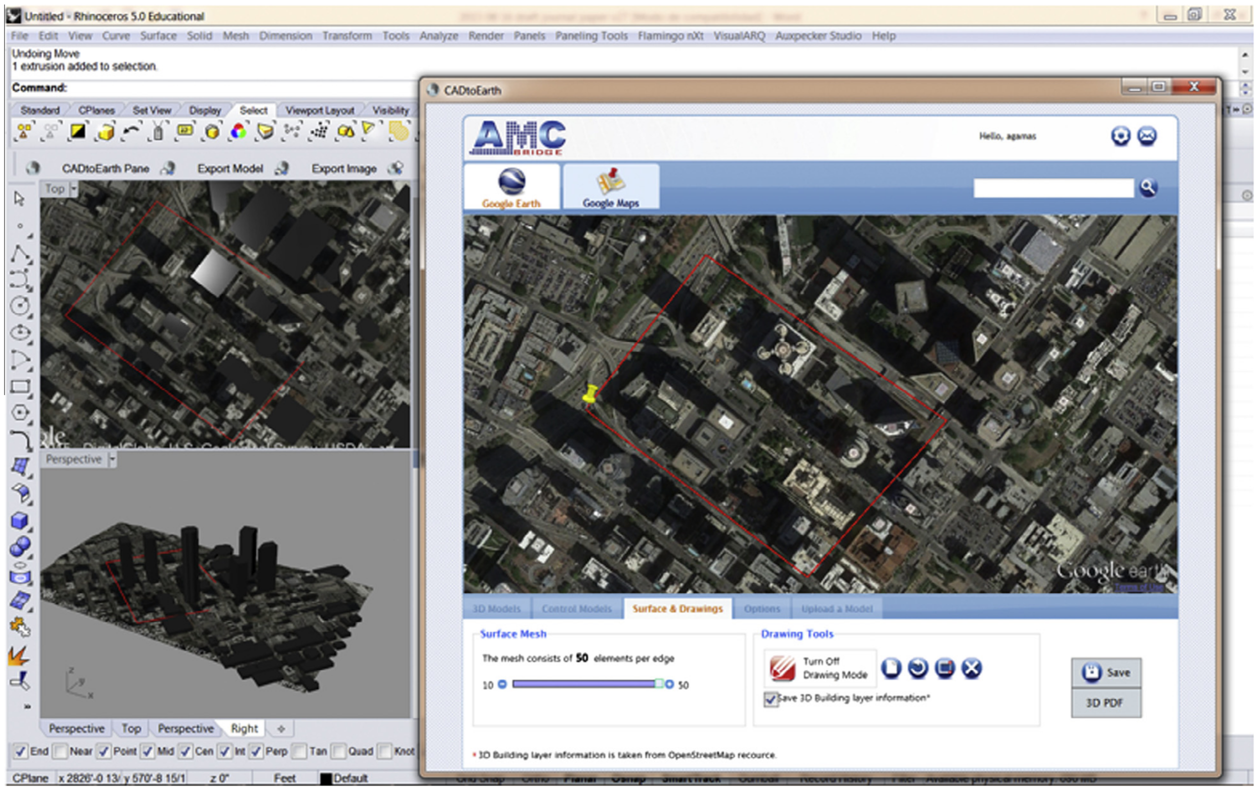

Fig. 2. Example use of *CADtoEarth* to identify surrounding urban context of project site and import 3D building geometry into the simulation environment.

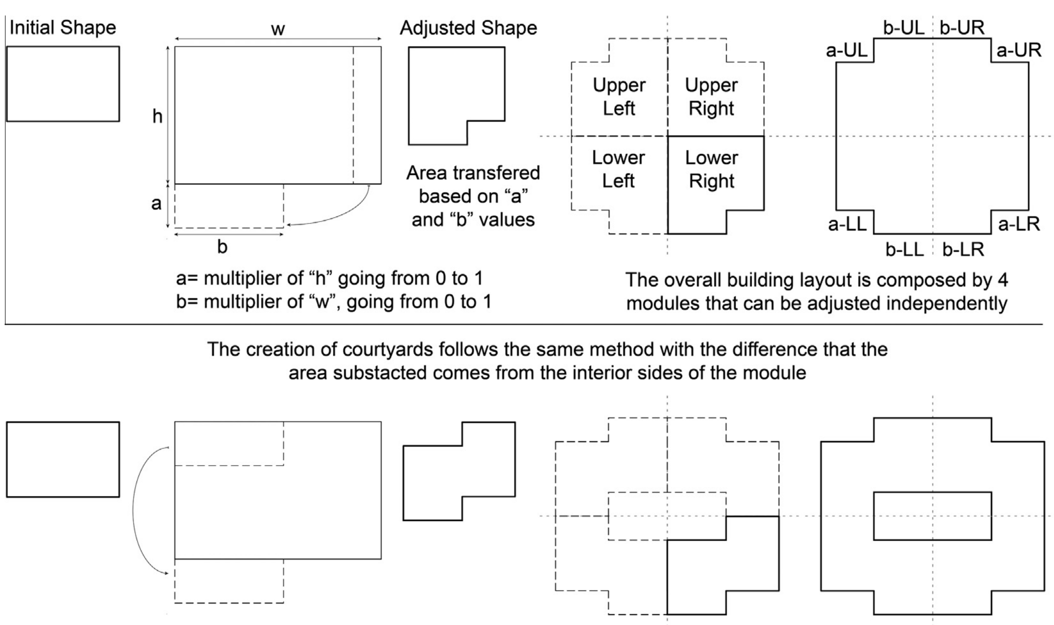

Fig. 3. Adjustment of building floor plate using the form-finding component.

of building masses parametrically. The footprint of the building is defined by setting a simple aspect ratio (height (h):width(w)) and specifying a total project floor area (e.g. 30,000 sq.ft), and number of floors (e.g. 3). The component takes two multipliers (a and b) and uses them to automatically generate more complex shape boundaries

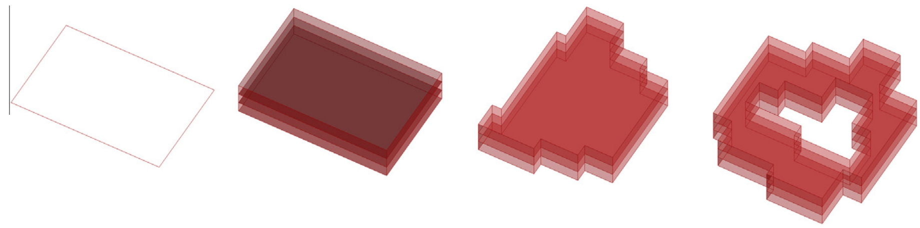

Fig. 4. Parametric development of building massing from simple rectilinear footprint (left) to more complex forms with additional corners and the addition of an interior courtyard void (right).

including courtyards and building layouts with an increasing number of exterior corners while maintaining the original project floor area specified by the user. Since this occurs parametrically, these parameters can be automatically adjusted during the optimization stage to generate forms that maximize daylighting and energy performance objectives within the geometric constraints of the form-finding component. A range of complexity can be achieved in the form-finding component (Fig. 4).

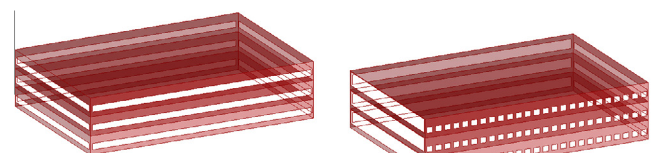

Fig. 5. DOE baseline model (left) where all facades have the same WWR (33%) and the same model massing (right) with variable WWRs applied at the facade level.

3.2.2. Windows

Windows are generated automatically based on a Window-to-Wall Ratio (WWR) value specified for each facade to enable the optimal WWR for each facade to be determined in response to local climate and site conditions. Fig. 5 shows the DOE commercial building baseline model (left) where all facades have the same WWR (33%) and the same building massing (right) with variable WWRs applied at the facade level.

3.2.3. Exterior shading devices

The workflow includes the capability of generating horizontal or vertical exterior louvers to minimize incident solar radiation during unwanted times of the year. Shading elements are automatically generated in response to solar vectors. In order to define the solar vectors, a peak date (e.g. summer solstice, warmest day of the year), and a range of hours where the sun will be blocked are specified (e.g. 11:00–17:00). This deterministic approach differs from the form-finding approach used to explore and optimize other building parameters such as form and solar orientation and is implemented to avoid unnecessary computing time. Solar vectors are used to generate horizontal exterior louver systems for the south and east facades of an example building where shading devices are generated to block direct sun from 9:00 to 17:00 on the 21st of September (Fig. 6).

3.3. Daylighting

After creating the building zones, windows, and shading devices, an annual climate-based daylighting simulation is executed utilizing the plug-in Honeybee, which interfaces with the lighting simulation engine *Radiance* (Larson and Shakespeare, 1998) to perform photometrically accurate lighting calculations. To quantify and evaluate annual daylighting performance, a modified version of the metric Spatial Daylight Autonomy (sDA) was used. Spatial Daylight Autonomy describes annual sufficiency of ambient daylight levels in interior environments (IES, 2012). It is a spatial application of the climate-based daylighting metric Daylight Autonomy (DA) developed by Reinhart and Walkenhorst (2001). Spatial Daylight Autonomy is defined as the percent of an analysis area (typically a theoretical work plane elevated above occupied floor area) that meets a minimum horizontal daylight illuminance level for a specified fraction of operating hours (e.g. 9:00–17:00 local clock time) per year.

Our approach was to modify the metric to exclude periods of the year where interior daylight illuminances within the analysis region were lower than 100 lux or above 2000 lux. These limits were chosen based on field evidence of occupant preferences in daylit offices with user-operated shading devices (Konis, 2013) and serve as the threshold criteria for the Useful Daylight Illuminance (UDI) metric developed by Nabil and Mardaljevic (2006). Useful Daylight Illuminance is a variation on the sDA approach. It lowers the "sufficiency" threshold to 100 lux and incorporates an upper, 2000 lux discomfort threshold as a proxy indicator for glare. Consequently, in our workflow, the resulting daylighting performance indicator is entitled Spatial Useful Daylight Illuminance ($sUDI_{100–2000}$). A grid of analysis points located 0.7 m above the floor and spaced at 3 m apart is used to assess $sUDI_{100\text{-}2000}$. An example spatial outcome is presented in Fig. 7. The false-color mapping indicates the level of useful daylight (sUDI) ranging from 0% to 100% on an annual basis, where blue[1] indicates poor

[1] For interpretation of color in Fig. 7, the reader is referred to the web version of this article.

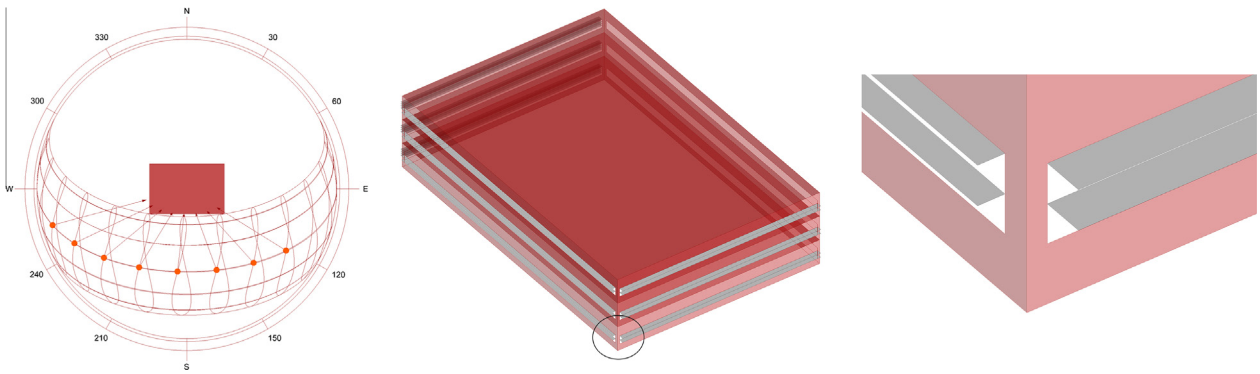

Fig. 6. Generation of exterior shading devices based on blocking of solar vectors during peak solar control conditions.

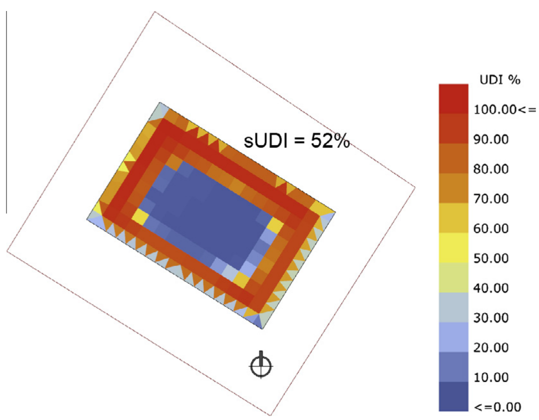

Fig. 7. Building floor plan illustrating $sUDI_{100–2000}$ outcome.

performance, and red indicates good performance. Due to the application of the 2000 lux threshold as an upper limit for useful daylight, it can be seen that performance outcomes diminish near the southeast and southwest facades due to increased frequency of daylight levels exceeding 2000 lux, which are penalized in the evaluation approach as in real buildings these illuminance levels are associated with occupant assessments of glare (Konis, 2014) as well as the potential for solar overheating of occupants working in perimeter zones.

3.4. Energy performance

3.4.1. Energy Use Intensity (EUI)

The metric Energy Use Intensity (EUI) expresses a building's energy consumption as a function of its conditioned floor area. It is defined as the energy consumed during the year per unit area. This facilitates the comparison of energy consumption between different buildings despite their overall variations in size. Energy consumption is measured in kBtu (or GJ) divided by the total floor area of the building (kBtu/sf/yr). The lower the EUI values, the more energy efficient the building is.

3.4.2. Energy Use Intensity incorporating mixed mode natural ventilation (EUI.NV)

In addition to the calculation of space conditioning energy solely through the application of mechanical HVAC, an additional simulation was conducted that incorporates the benefits of natural ventilation through windows for both ventilation and space cooling (EUI.NV). The approach implemented is "mixed-mode" ventilation, which consists of using design geometry and climate data to estimate the periods during the year where natural ventilation could meet the cooling demands of the indoor space, thereby reducing the equipment size and annual operating hours of mechanical HVAC. The settings are based on the fraction of facade glazing which is operable, minimum and maximum indoor and outdoor temperatures, and the stack discharge coefficient (Table 1).

3.5. Visualization

The next stage of the workflow is the visualization of simulation outcomes for each set of parameters explored by the user. Visualizations combine an axonometric view of the building geometry with annual window heat transfer (kW h/m^2) and daylighting (sUDI) outcomes applied using a false-color tone-mapping (Fig. 8).

3.6. Optimization

The last phase of the workflow is the optional implementation of a multi-objective optimization. Multi-objective optimization is an approach used to systematically explore various combinations of parameters and examine outcomes relative to one or more performance goals. The best trade-offs between the designated objectives are searched, producing a set of possible optimum solutions that ideally reach form one extreme trade-off to the other. This stage is implemented using the Grasshopper plugin *Octopus*. An example visualization of the first 25 simulation iterations of an optimization is presented in Fig. 9.

Table 1
Natural ventilation settings.

Settings	Description	Value
Fraction of glazing to be operable	Fraction of the window that can be opened	0.5
Min. indoor temp. for nat.vent	Min. indoor temp. to naturally ventilate	22 °C
Max. indoor temp. for nat.vent	Max. indoor temp. to naturally ventilate	28 °C
Min. outdoor temp. for nat.vent	Min. outdoor temp. to naturally ventilate	17 °C
Max. outdoor temp. for nat.vent	Max. outdoor temp. to naturally ventilate	28 °C
Stack discharge coefficient	Multiplier for friction from louvers, etc.	0.75

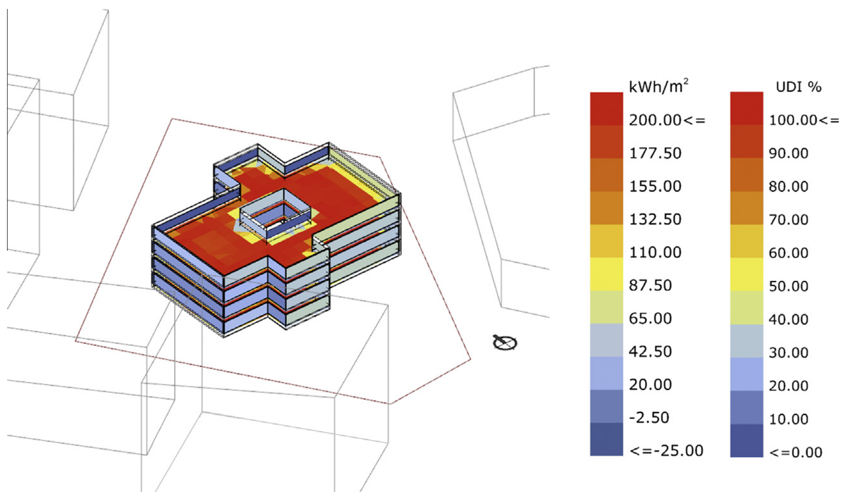

Fig. 8. Axonometric visualization of annualized outcome using false-color scales to illustrate sUDI and annual thermal flux through façade glazing. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Validation experiment

To validate the applicability of the PPOF for improving performance over existing practices, a series of early-stage design scenarios were created to compare outcomes from the PPOF with an ASHRAE 90.1 compliant benchmark building from the U.S. Department of Energy (DOE) set of commercial building reference models. The experimental design makes paired comparisons between performance outcomes from the PPOF and the reference building in four urban sites (Los Angeles, Helsinki, Mexico City, and New York City), each with a distinctly different climate, incorporating real urban context from each site.

4.1. Building type

The DOE benchmark models were developed to serve as a consistent baseline of comparison (Deru et al., 2011). A three-floor medium office building of 4982 m^2 (53,819 sq.ft) was selected to represent a standard energy efficient building for comparison against PPOF outcomes. The medium office building type was selected for several reasons. First, office buildings within the size (10,000–100,000 sq.ft) represent the largest portion of U.S. office building stock (46%) (EIA, 2012). Therefore, design tools that can demonstrate effective reductions for this segment of the building stock have the potential to have a large impact on energy use in the built environment as new buildings are constructed and retrofits implemented in the segment. Second, office buildings of all sizes are ideal candidates for the application of daylighting as a passive alternative to daytime use of electrical lighting. As noted in the introduction, lighting represents the single largest electricity end use in office buildings in the U.S. (35%) (U.S. DOE, 2011), and is consumed primarily during daylight hours. Third, medium-sized commercial buildings are at an appropriate size and scale for the effective application of mixed-mode ventilation. It should be noted, however, that mixed-mode ventilation is also applicable for small size commercial buildings, and could be applied to perimeter zones of large commercial buildings. The DOE medium commercial building reference does not have operable windows. Consequently, two versions were used to compare energy outcomes from the PPOF: (1) the original “sealed” version, and (2) a mixed-mode version. The latter was included to differentiate the level of

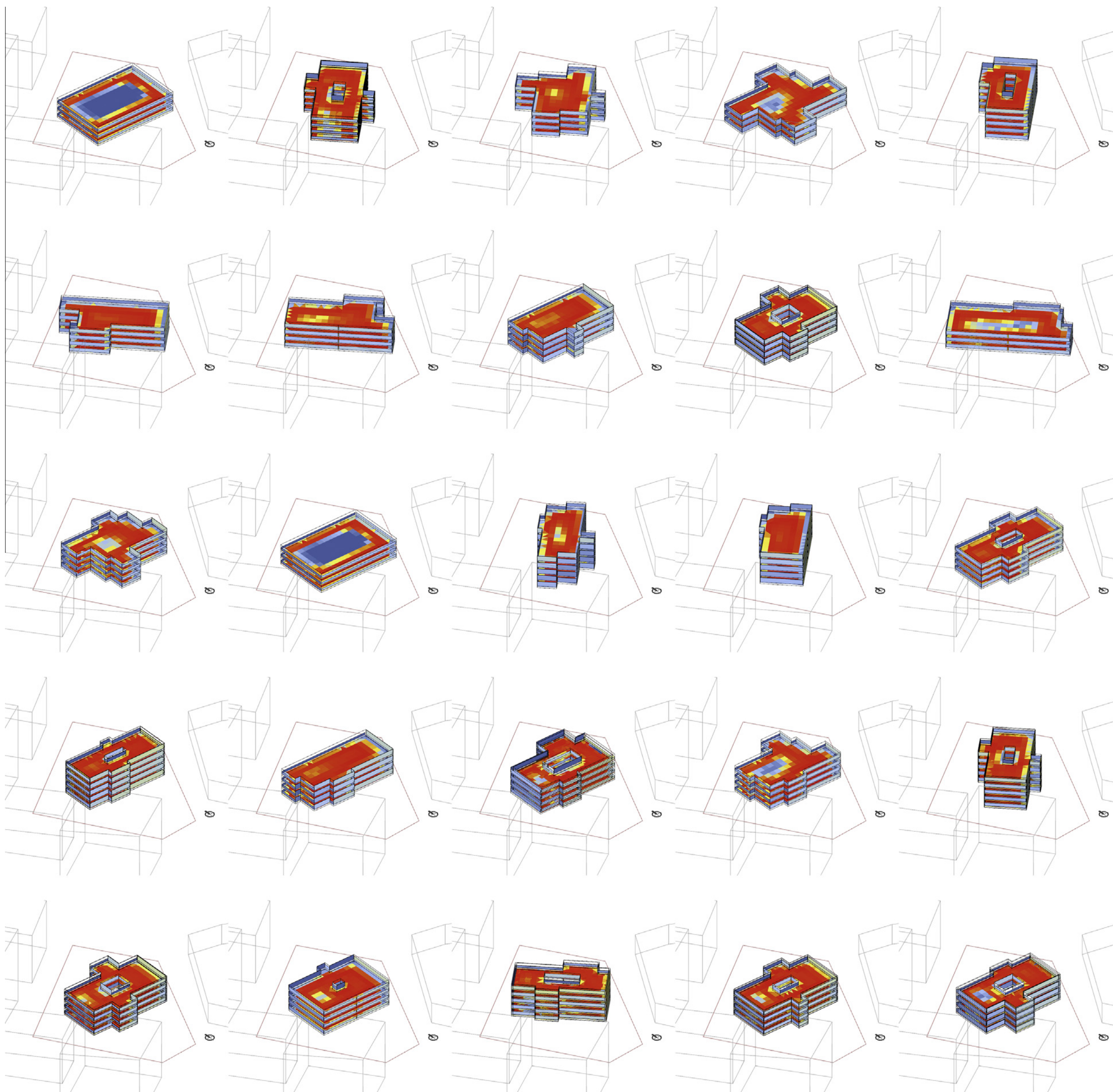

Fig. 9. The first 25 simulation iterations of an optimization.

Table 2
Climate summary.

	Latitude	CDD (Annual)	HDD (Annual)	Dir. Norm. Rad. (Avg. hourly W h/m^2)	Global Horiz. Rad. (Avg. hourly W h/m^2)
Helsinki	60°10′N	293	11,496	137	175
New York	40°42′N	1186	7158	304	312
Los Angeles	34°02′N	1208	3856	468	410
Mexico City	19°26′N	1012	4160	261	412

improvement achieved by the PPOF due to manipulation of building geometry and orientation from the level of improvement achieved by the PPOF simply from introducing operable windows.

In order to ensure that the results obtained from the PPOF could be directly compared to the reference office building results, a number of parameters were kept identical between test and reference models including floor area,

Table 3
Building parameters fixed across all climates.

Attributes (Fixed)	Values
Project type	Medium office
Floor area	4982 m^2
Floor	Exterior floor
Floor *U*-value	0.10 Btu/h ft^2 °F
Zones program	Open office
Operating hours for sUDI analysis	9 AM–5 PM
Solar vectors for shading devices	September 21 from 9 AM to 5 PM
Windows sill height	1 m
Equipment load per area	7.6424 W/m^2
Infiltration rate per area	0.0002 m^3/s m^2
Lighting density per area	11.8404 W/m^2
Num. of people per area	0.05382 ppl/m^2
Ventilation per area	0.0005 m^3/s m^2
Ventilation per person	0.01 m^3/s
Fraction of glazing to be operable	0.5
Min. indoor temp. for nat.vent	22° (71.6°)
Max. indoor temp. for nat.vent	28° (82.4°)
Min. outdoor temp. for nat.vent	17° (62.6°)
Max. outdoor temp. for nat.vent	28° (82.4°)
Stack discharge coefficient[a]	0.75

[a] Multiplier for friction of airflow due to obstacles (e.g. louvers, insect screens, etc.).

Table 4
Building parameters fixed within each climate.

Attributes	Helsinki	New York	Los Angeles	Mexico City
Walls	CBECS 1980–2004 Exterior wall, steel frame, climate zone 6A	CBECS 1980–2004 Exterior wall, steel frame, climate zone 4A	CBECS 1980–2004 Exterior wall, steel frame, climate zone 3A	CBECS 1980–2004 Exterior wall, steel frame, climate zone 3B
Walls *U*-value	0.07 Btu/h ft^2 °F	0.10 Btu/h ft^2 °F	0.15°Btu/h ft^2 °F	0.27 Btu/h ft^2 °F
Glazing	ASHRAE 189.1-2009 Exterior window, climate zone 6A	CBECS 1980–2004 Exterior window, climate zone 4A	ASHRAE 90.1-2004 Exterior window, climate zone 3A-3B	ASHRAE 90.1-2004 Exterior window, climate zone 3A-3B
Glazing *U*-value	0.78 Btu/h ft^2 °F	0.59 Btu/h ft^2 °F	0.57 Btu/h ft^2 °F	0.57 Btu/h ft^2 °F
Roof	CBECS 1980–2004 Exterior roof IEAD climate zone 6A	CBECS 1980–2004 Exterior roof IEAD climate zone 4A	CBECS 1980–2004 Exterior roof IEAD climate zone 3A	CBECS 1980–2004 Exterior roof IEAD climate zone 3B
Roof *U*-value	0.05 Btu/h ft^2 °F	0.06 Btu/h ft^2 °F	0.08 Btu/h ft^2 °F	0.11 Btu/h ft^2 °F

occupancy schedule, lighting power density, ventilation rates equipment loads, etc. A full list of fixed parameters is discussed in Section 4.4 and Tables 3 and 4. It is important to note that if the PPOF were to be applied in a scenario involving a different building type, such as a school, then appropriate programmatic assumptions for school buildings would need to be applied to both the test and reference cases for results to be comparable.

4.2. Urban climates

Four climates were chosen to examine the applicability of the PPOF to various climatic conditions. The climate data come from four urban locations: Helsinki, New York City, Mexico City, and Los Angeles (Table 2).

4.3. Urban site conditions

Within each city, a real (vacant) urban site was chosen as the basis for an early stage design proposal. Adjacent building massing was imported into the workflow to represent site-specific solar overshadowing conditions. Fig. 10 presents a comparison of basecase model performance outcomes for the Los Angeles climate and site, with (right) and without, (left) taking into account the surrounding urban building geometry. Comparison of the impacts of urban building geometry for the other three sites is presented in Appendix Fig. A1. Comparison between the left and right cells of Fig. 10 visually and quantitatively demonstrates the significant impact of the urban context on annual performance outcomes.

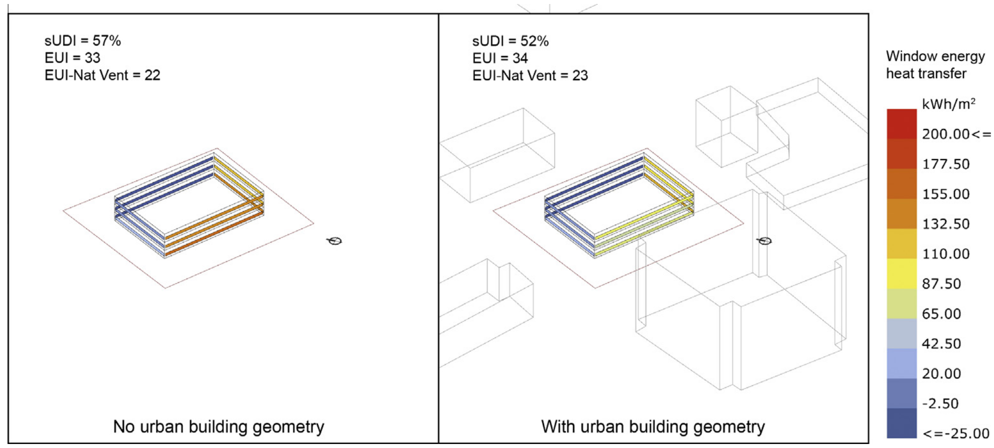

Fig. 10. Comparison of base case model performance outcomes in Los Angeles without taking into account the surrounding urban context (left) and with taking into account the surrounding urban context (right).

4.4. Building parameters fixed

Table 3 presents the building parameters that are constant between baseline and optimized models based on the rationale that they represent non-variable project requirements (e.g. project type and total floor area) or appropriate controls (e.g. envelope constructions, schedules, window opening and closing criteria). Table 4 presents building attributes that are fixed for each climate chosen, based on regional differences in envelope constructions.

4.5. Building parameters optimized

Multiple building parameters were explored during optimization in an effort to improve performance. The number of parameters were selected based on site-specific criteria in order to represent real project constraints. The building parameters that were explored for the Los Angeles test case are presented in Table 5. In total, 14 unique parameters were explored for the Los Angeles test case. The total possible solutions can be quantified by multiplying the number of values explored for each parameter. For the Los Angeles test case, this leads to 6,718,464 possible solutions. The choice for which parameters to explore and what attributes to assign was varied slightly for each climate. For example, the range of window-to-wall area explored for Helsinki (a cold climate) was reduced relative to Los Angeles and Mexico City. Additionally, the site chosen for Los Angeles did not realistically allow for rotations of the building off the street grid. Consequently, the building orientation was fixed. The rationale for this decision is that a signifi-

Table 5
Building parameters adjusted during optimization for Los Angeles.

Parameters	Attributes	No. of values
Side a-lower right	0 (basecase), 0.25, 0.5, 0.75	4
Side b-lower right	0.25, 0.5, 075 (N/A when a = 0)	3
Side a-lower left	0 (basecase), 0.25, 0.5, 0.75	4
Side b-lower left	0.25, 0.5, 075 (N/A when a = 0)	3
Side a-upper left	(basecase), 0.25, 0.5, 0.75	4
Side b-upper left	0.25, 0.5, 075 (N/A when a = 0)	3
Side a-upper right	0 (basecase), 0.25, 0.5, 0.75	4
Side b-upper right	0.25, 0.5, 075 (N/A when a = 0)	3
Courtyard	True (1); False (0)	2
Orientation	−32°	0
No. floors	3	0
Aspect ratio	1.5	0
Win-wall ratio_north	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_west	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_south	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_east	0.33 (basecase), 0.5, 0.7	3
Shading devices	True (1); False (0)	2
Window type	Compliant	0
Wall type	Compliant	0

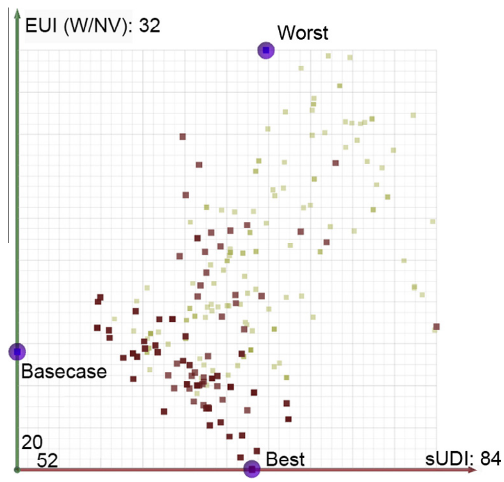

Fig. 11. Solution space for optimizations run in Los Angeles urban site and climate indicating "base case," "best," and "worst" outcomes.

cant number of unrealistic outcomes can be avoided in the optimization process through making appropriate assumptions when initializing the optimization parameters. The parameters and attributes explored for the other three test cases (Helsinki, Mexico City, and New York) are detailed in Appendix Tables A1–A3.

4.6. Objective function

To identify and rank design outcomes, an objective function assigning equal weight to EUI.NV and sUDI was used. The objective function (Eq. (1)) seeks to identify the design outcome which maximizes sUDI and minimizes EUI.NV. In order to determine this quantitatively, the results for each performance indicator (sUDI and EUI.NV) first need to be scaled to the same numerical range. Scaling avoids overweighting one indicator over the other in the final sum. For example, a 32 maximum EUI.NV would not equate properly when weighted against an 84 maximum sUDI value, because both would be the upper thresholds in the set. Instead, each should be normalized to the same numerical range (e.g. 0–100). After scaling, the values can be summed to provide the final result. However, because the goal is to minimize EUI.NV, it is multiplied by −1.

Objective function

$$y = (\mathrm{sUDI}_i - \mathrm{sUDI}_{\min})C_1 + -1(\mathrm{EUI.NV}_i - \mathrm{EUI.NV}_{\min})C_2$$

maximize (y)

where: (1)

i = result of iteration.
min = minimum value in optimization set.
max = maximum value in optimization set.

$$C_1 = \frac{100}{\mathrm{sUDI}_{\max} - \mathrm{sUDI}_{\min}}$$

$$C_2 = \frac{100}{\mathrm{EUI.NV}_{\max} - \mathrm{EUI.NV}_{\min}}$$

Fig. 11 presents the solution space for the Los Angeles climate scenario as an example, where the "base case" (DOE ASHRAE 90.1-compliant reference model), "best," and "worst" outcomes are highlighted with purple circles. The "best" solution is defined as the solution from the optimization set achieving the highest objective function score (Eq. (1)). The "worst" solution is that which results in the lowest score. The solution space for the other three climate scenarios are presented in Appendix Figs. A2–A4. The solution space is defined by the numerical ranges of the performance outcomes. The y-axis indicates whole-building energy intensity incorporating natural ventilation (EUI.NV), where values lesser than the base case indicate an improvement, and the x-axis indicates daylighting performance (sUDI), where values greater than the base case indicate an improvement.

5. Results

The objective of this research is to demonstrate the potential of the PPOF for optimizing the collective potential of daylighting, solar control, and natural ventilation strategies in early stage design. Table 6 quantifies the change in performance achievable in terms of sUDI, EUI, and EUI.NV for the best outcome found for each of the four climates (positive changes in sUDI indicate improvements in performance, negative changes in EUI and EUI.NV indicate improvements). Results show that daylighting performance can be improved across a diverse range of climates while simultaneously reducing EUI and EUI.NV to varying degrees depending on climate. The

Table 6
Results summary.

	Reference			Optimized			Change in performance		
	sUDI (%)	EUI	EUI.NV	sUDI (%)	EUI	EUI.NV	sUDI (%)	EUI (%)	EUI.NV (%)
Helsinki	37	55	55	47	54	53	27	−2	−4
New York	38	51	41	49	48	38	29	−6	−7
Los Angeles	52	35	24	70	28	20	35	−20	−17
Mexico City	43	23	14	71	16	12	65	−30	−14

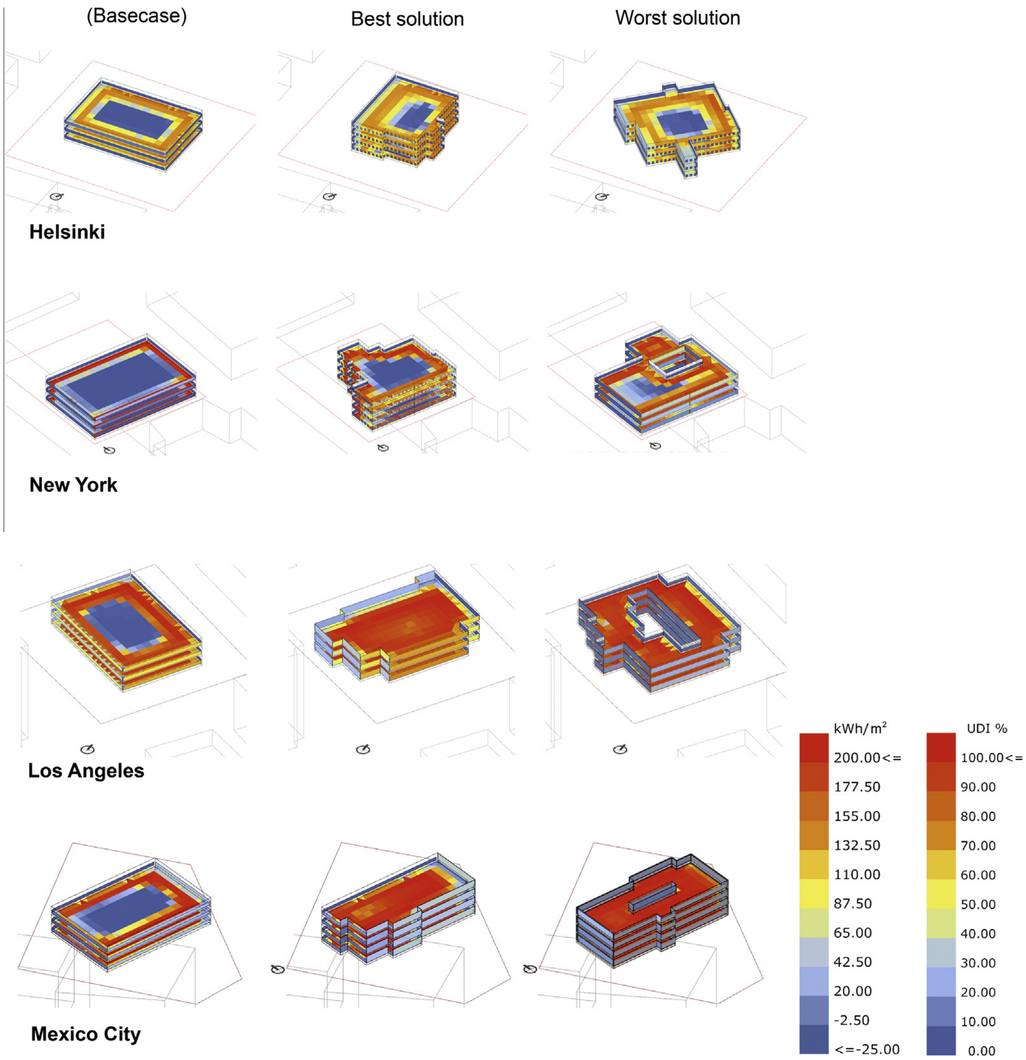

Fig. 12. Parametric building models generated by the PPOF leading to the best (center column) and worst (right column) performance outcomes for each of the four climate-based scenarios. The basecase model for each scenario is included in the left column.

greatest overall improvements in combined performance (sUDI and EUI.NV) were found for the warmer climates (Mexico City and Los Angeles); however, improvements were also achieved for Helsinki and New York, where the improvement was largely driven by increased sUDI due to the limited applicability of natural ventilation in these heating dominated climates. Fig. 12 presents the best and worst outcomes for each of the four climates compared to the respective ASHRAE 90.1-compliant basecase model.

6. Discussion and future work

6.1. Validation experiment

The validation experiment demonstrates that the PPOF is capable of generating design solutions that outperform an ASHRAE 90.1-compliant reference building of equal floor area. The quantitative and visual outcomes generated by the PPOF are not intended to serve as final design solutions, but rather serve as more aggressive site and climate specific reference targets for design development, where more refined designs could be expected to achieve even greater performance outcomes. Of particular note is the level of improvement in daylight availability achievable by adjustments to building geometry, solar orientation, and fenestration configurations, while providing adequate solar control to achieve reductions in energy metrics of EUI and EUI.NV. The improvements in daylighting (sUDI) performance, (between 27% and 65%), while also reducing whole-building EUI and EUI.NV (Table 6) demonstrate the capability of the PPOF to achieve significant performance improvements over standard benchmarks for energy-efficient buildings. The building parameters shown to achieve superior performance outcomes can then serve as design guidance to develop a more detailed design solution and potentially achieve further improvements.

6.2. Use of the PPOF

The capability to develop design scenarios that respond to unique project constraints provides preliminary evidence of the applicability of the PPOF in a diverse range of climates and urban settings to an aggressive, climatically-responsive performance benchmark and to guide the development of key building parameters in early design. It is important to emphasize that the validation experiment was designed to deliver results in under 48 h using a conventional desktop computer resources. Consequently, the performance improvements demonstrated where achieved with relatively few values (between 2 and 4) set for a limited number of building parameters (e.g. 14 for the Los Angeles climate scenario). Even with this "minimal" level of parametric variation, over 6.7 million design solutions exist, and it would be impossible for the user to explore the range of possible solutions without a systematic tool. More refined outcomes are achievable by exploring a greater number of parameters and an expanded range of values at the expense of additional simulation time or computing resources. It should be noted, however, that successful project outcomes are only generated if the user chooses appropriate design variables and constraints prior to running the optimizations. This is important because despite the vast number of iterations that an optimization can explore, performance outcomes will always be constrained within the boundaries set by the user, and unless those boundaries are appropriately defined, the optimization might be looking for a solution in the wrong place. For example, a cold climate like the one of Helsinki might not require a building with shading devices for most of the year, yet having highly-tuned window–wall ratios is likely to be critical. In this case, an effective outcome could be achieved by removing the parameters to enable shading devices and by increasing the range of window–wall ratios to be explored. In addition, although the PPOF enables detailed exploration of key parameters such as solar orientation, building massing, WWR, and the application of exterior shading devices, in most real projects, one or more of these parameters may be highly constrained by the project site, program, or preferences of the client. Consequently, the effectiveness of the PPOF as a design guide is improved by the user's knowledge of key project constraints in early stage design and incorporation of those constraints into the workflow to generate appropriate design reference models.

6.3. Limitations

The current workflow does not incorporate the behavior of operable shading elements such as automated interior shades or adjustable exterior louver systems. In addition, the static shading systems automatically generated by the workflow are sized to provide full solar control during peak outdoor temperatures, which may lead to excessive shading during other periods of the year depending on the climate. In addition, the workflow presently does not incorporate the choice to apply complex fenestration systems such as light redirecting louver systems that have been demonstrated to significantly improve transmission of useful daylight to larger areas of the floor plate (Konis and Lee, 2015), in turn affecting the optimal building geometry and fenestration configurations. Finally, the urban geometry import feature does not account for the potential shading effects of vegetation, or other objects that may exist but are not recorded in surveys of urban building geometry. Therefore, it is possible that simulation outcomes may overestimate solar heat gains and daylight availability for sites where significant vegetation such as large shade trees are present near the project.

6.4. Future work

Applicability of the PPOF is currently demonstrated for a 4982 m^2 (53,819 sq.ft) medium office building test case for four different urban setting and climates. However, the current findings present only a first step in understanding the potential of the PPOF. Because the PPOF design solutions are informed by the unique urban geometry of each site, it should not be assumed that results will be similar if the PPOF is applied to a different urban site, even if the climate and project type are kept the same. Future work will examine the generalizability of current findings by applying the PPOF to a broader range of building sizes, building types, urban density conditions, and climates. Future development tasks for the simulation-based workflow includes addressing the limitations noted in the previous paragraphs, namely the integration of dynamic interior and exterior shading systems and complex fenestration systems. Usability studies with designers testing real world projects will also be helpful to inform future development of the PPOF.

7. Conclusion

A Passive Performance Optimization Framework (PPOF) was developed to incorporate and improve the performance of daylighting, solar control, and natural ventilation strategies in early stage design. Applicability of the PPOF was demonstrated through a validation experiment where outcomes from the PPOF were compared to results from an ASHRAE 90.1 compliant reference building across four different climates and urban sites (Los Angeles, Helsinki, Mexico City, and New York City), incorporating real urban context from each site. The validation experiment demonstrated that the PPOF is capable of generating design solutions that outperform the reference building. Optimization results were obtained in under 48 h using a conventional desktop computer. Results show that daylighting performance can be enhanced (improvements of sUDI ranging from 27% to 65%) across a diverse range of climates while simultaneously reducing whole-building energy use to varying degrees (between 4% and 17%) depending on climate. The PPOF enables the rapid identification of a realistic reference model that is unique to the local site conditions and climate and which presents a more appropriate and aggressive performance target compared with existing, generic energy efficient building benchmarks.

The PPOF and simulation-based workflow helps to make generative modeling informed by powerful energy and lighting simulation engines more accessible to ordinary designers working on regular projects and schedules.

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Appendix A

(See Figs. A1–A4 and Tables A1–A3).

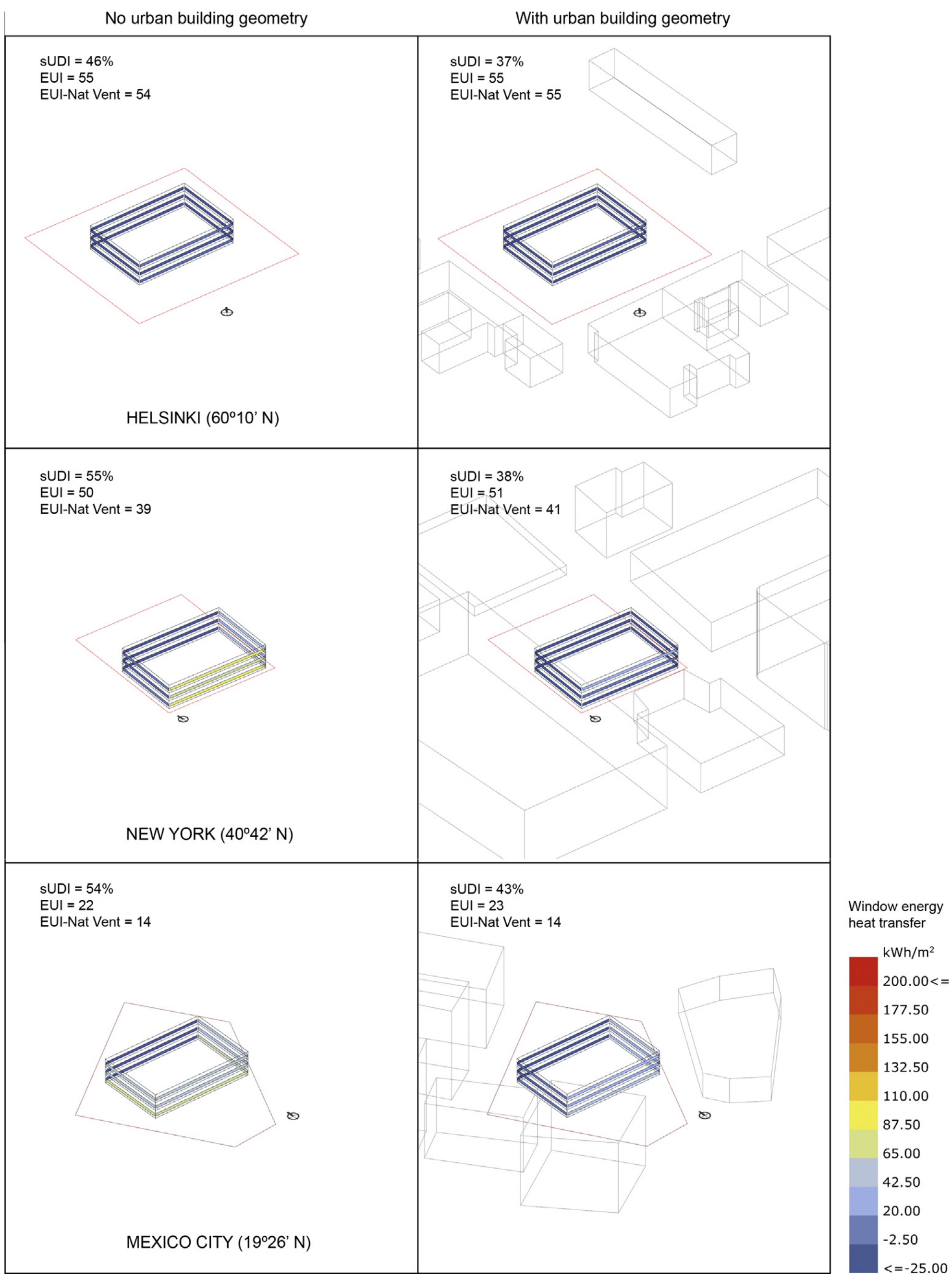

Fig. A1. Comparison of basecase model performance outcomes for Helsinki, New York, and Mexico City scenarios, without taking into account the surrounding urban context (left) and with taking into account the surrounding urban context (right).

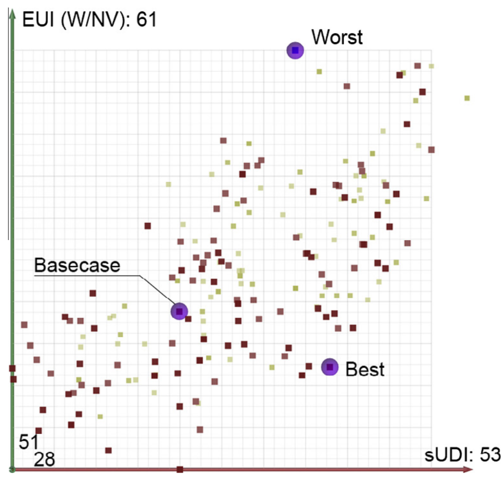

Fig. A2. Helsinki.

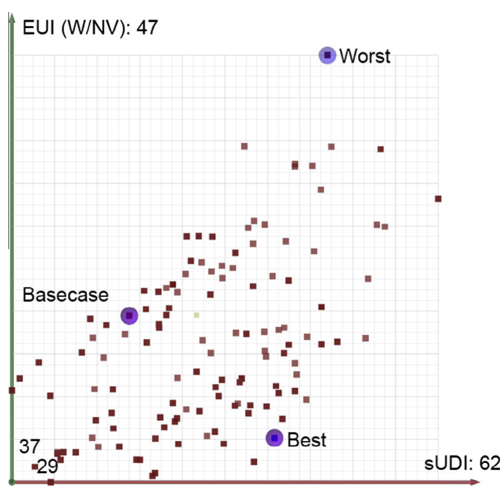

Fig. A3. New York.

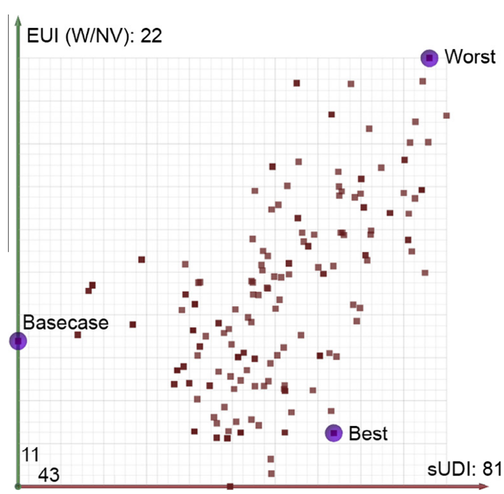

Fig. A4. Mexico City.

Table A1
Building parameters adjusted during optimization for Helsinki.

Parameters	Attributes	No. of values
Side a-lower right	0	0
Side b-lower right	0	0
Side a-lower left	0 (basecase), 0.25, 0.5, 0.75	4
Side b-lower left	0.25, 0.5, 075. (N/A when a = 0)	3
Side a-upper left	0	0
Side b-upper left	0	0
Side a-upper right	0 (basecase), 0.25, 0.5, 0.75	4
Side b-upper right	0.25, 0.5, 075. (N/A when a = 0)	3
Courtyard	False	0
Orientation	35 (basecase), 80, 125, 170	4
No. floors	2, 3 (basecase), 4	3
Aspect ratio	1.1, 1.3, 1.5 (basecase)	3
Win-wall ratio_north	0.15, 0.33 (basecase), 0.5	3
Win-wall ratio_west	0.15, 0.33 (basecase), 0.5	3
Win-wall ratio_south	0.15, 0.33 (basecase), 0.5	3
Win-wall ratio_east	0.15, 0.33 (basecase), 0.5	3
Shading devices	False	0
Window type	Compliant (basecase), improved	2
Wall type	Compliant (basecase), improved	2

Table A2
Building parameters adjusted during optimization for New York.

Parameters	Attributes	No. of values
Side a-lower right	0	0
Side b-lower right	N/A when a = 0	0
Side a-lower left	0	0
Side b-lower left	N/A when a = 0	0
Side a-upper left	0 (basecase), 0.25, 0.5, 0.75	4
Side b-upper left	0.25, 0.5, 075. (N/A when a = 0)	3
Side a-upper right	0 (basecase), 0.25, 0.5, 0.75	4
Side b-upper right	0.25, 0.5, 075. (N/A when a = 0)	3
Courtyard	True (1); False (0)	2
Orientation	−9°	0
No. floors	2, 3 (basecase), 4	3
Layout scale factor	1.5	0
Win-wall ratio_north	0.2, 0.33 (basecase), 0.5	3
Win-wall ratio_west	0.2, 0.33 (basecase), 0.5	3
Win-wall ratio_south	0.2, 0.33 (basecase), 0.5	3
Win-wall ratio_east	0.2, 0.33 (basecase), 0.5	3
Shading devices	False	0
Window type	Compliant (basecase), improved	2
Wall type	Compliant (basecase), improved	2

Table A3
Building parameters adjusted during optimization for Mexico City.

Parameters	Attributes	No. of values
Side a-lower right	0	0
Side b-lower right	N/A when a = 0	0
Side a-lower left	0 (basecase), 0.25, 0.5, 0.75	4
Side b-lower left	0.25, 0.5, 075. (N/A when a = 0)	3
Side a-upper left	0	0
Side b-upper left	N/A when a = 0	0
Side a-upper right	0 (basecase), 0.25, 0.5, 0.75	4
Side b-upper right	0.25, 0.5, 075. (N/A when a = 0)	3
Courtyard	True (1); False (0)	2
Orientation	−45, 0 (basecase), 45	3

(*continued on next page*)

Table A3 (*continued*)

No. floors	3 (basecase), 4, 5	3
Layout scale factor	1.5 (basecase), 2, 2.5	3
Win-wall ratio_north	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_west	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_south	0.33 (basecase), 0.5, 0.7	3
Win-wall ratio_east	0.33 (basecase), 0.5, 0.7	3
Shading devices	True (1); False (0)	2
Window type	Compliant	0
Wall type	Compliant	0

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