Journal of Building Engineering 68 (2023) 105977

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: www.elsevier.com/locate/jobe

Full Length Article

Universal design space exploration for building energy design

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ARTICLE INFO

MSC:
0000
1111

Keywords:
Building design
Energy
Machine learning

ABSTRACT

This paper proposes novel improvements to existing Design Space Exploration (DSE) workflows that enable detailed performance-analysis at the speed of design for all projects at little cost. The authors refer to this methodology as Universal Design Space Exploration (UDSE). Rather than apply DSE to a project-specific challenge, UDSE enables a single pre-simulated design space to be applicable across many projects. The novel scalability of these "universal" design spaces justify investment in ML-powered apps that make pre-simulated analysis instantly accessible, affordable, and impactful across multiple projects. This research showcases the feasibility and potential benefit of UDSE by applying it to the challenge of early conceptual energy modeling. First, a group of experts crafts the input parameters and output metrics of a massive Design Space so that it encompasses the common problem. Then an automated parametric simulation workflow is developed to model and simulate any combination of input parameters. Several hundred thousand iterations are then simulated and analyzed. The result of this analysis guides the design of a prototype app which is powered by an AI surrogate model that allows users to receive instantaneous analysis about any design contained within the design space. This research shows that it is feasible to simulate the massive design spaces required by UDSE using currently available computational resources. We show that the surrogate modeling process is capable of accurately extending relatively limited simulation data to fully map the design space. We also show that these surrogate models can be effectively integrated into custom apps that can automate advanced DSE analysis and deliver insights to design teams in real-time. This paper concludes that UDSE offers a novel and scalable approach to early conceptual performance analysis.

1. Introduction

1.1. Overview of universal design space exploration

Universal Design Space Exploration (UDSE) is a scalable approach to performance analysis that can provide detailed insights at the speed of design for all projects at little cost. UDSE improves the real-world applicability of Design Space Exploration (DSE) techniques by leveraging massive "universal" design spaces that encompass common design problems. These project-agnostic universal design spaces justify investment in ML-powered apps that make pre-simulated analysis accessible, affordable, and impactful across multiple projects.

UDSE addresses a fundamental reality that constrains our current tools: To analyze a design, we need a design to analyze. Critical early design decisions are too often guided by experience and rules of thumb while our analysis tools are relegated to checking the

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https://doi.org/10.1016/j.jobe.2023.105977
Received 13 June 2022; Received in revised form 18 January 2023; Accepted 26 January 2023
Available online 15 February 2023
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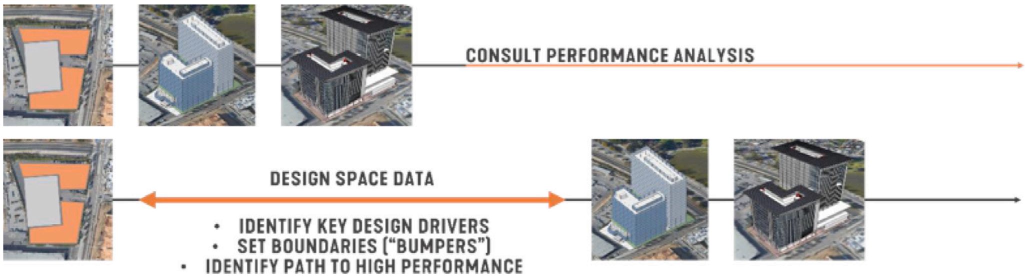

Fig. 1. Design challenge flowchart illustrating how Universal Design Space Exploration (UDSE) can improve the design process by providing energy performance feedback on design decisions during the design process whereas traditional design cannot.

end result of our design process. Rather than give feedback on several design options, UDSE delivers insight into the larger design challenge being explored and guides design teams through the various combinations of decisions that are most likely to improve performance. Rather than answer the question "How did we do?", UDSE answers the question "What should we do?"

UDSE accomplishes this by mining insights from databases of pre-simulated analysis that are thoughtfully crafted to represent all possible outcomes of common design challenges. These databases, or Design Spaces, become "Universal" when a single pre-simulated design space can be re-applied to future unknown projects. Unlike current simulation methods, which require a design to exist before it can be analyzed and often take hours to model, pre-simulated universal design spaces can be available to all projects on-demand and can deliver rapid and relevant insights as new designs are conceptualized. Universal design spaces act like maps of common design challenges that guide teams through the trade-offs and constraints associated with the myriad potential design paths that lead to higher performance.

Simulating universal design spaces and mining them for insights requires the application of statistical and machine learning algorithms that few in the AEC (Architecture, Engineering, and Constructions) industry have experience with. Making this analysis actionable to designers requires software development skills. By developing and publicly releasing a relevant universal design space we hope to encourage students and professionals to develop the skills they need to better leverage data in design. We hope these data, and the example of how to apply them, will reduce barriers to digital literacy in statistics, machine learning and artificial intelligence within the architecture, engineering and construction industry.

1.2. Early conceptual performance analysis issues

UDSE addresses limitations found in traditional performance analysis workflows, making it particularly applicable during early conceptual design when existing tools are least effective. In SmithGroup's experience, traditional performance analysis workflows that analyze detailed models of singular design options are well suited for later stages of the design process when the detailed inputs required for accurate results are determined and when analysis delivered days after it is requested is still relevant. Unfortunately, SmithGroup has found that these workflows fall short during the early conceptual design phase when major design changes occur by the hour, and when many decisions need to be made at the same time. We believe this is due in large part to an inherent flaw in the process: To analyze a design, one needs a design to analyze. This reality leads to a design approach where a limited number of design options are developed based on experience and then analyzed to confirm performance. As a result, many major design decisions like massing, orientation, program placement, and facade design are chosen before any analysis is considered. Furthermore, this option-based analysis only tells us how well each overall design performs, not why they perform as they do; the relative impact of individual design decisions are often lost within a single metric that represents a combination of design decisions. To summarize, the requirement that a design exist before it can be analyzed forces design teams to rely heavily on experience rather than analysis because traditional tools provide feedback, not guidance [1].

UDSE addresses this failure by modeling the entire design challenge rather than analyzing design options. Rather than deliver feedback on several options, it delivers insights about the forces and constraints that define the challenge, which can then guide design teams through the design process. By shifting the analysis paradigm from feedback to guidance, UDSE addresses fundamental flaws in current workflows and provides a new and valuable approach to early conceptual performance analysis [1]. The difference between typical design and utilization of design space are shown in Fig. 1.

1.3. Limitations of design space exploration

UDSE is an extension of Design Space Exploration (DSE) that resolves key deficiencies in DSE that currently limit its use. In doing so, it offers new opportunities to integrate engineering into the design process.

DSE leverages iterative simulation of parametric models to generate databases of simulation analysis that represent a comprehensive sampling of all possible design scenarios defined by the parametric model. Collectively, these data become what we call the Design Space, which can then be explored and mined for insight. An overview of the DSE process we intend to improve is shown in Fig. 2.

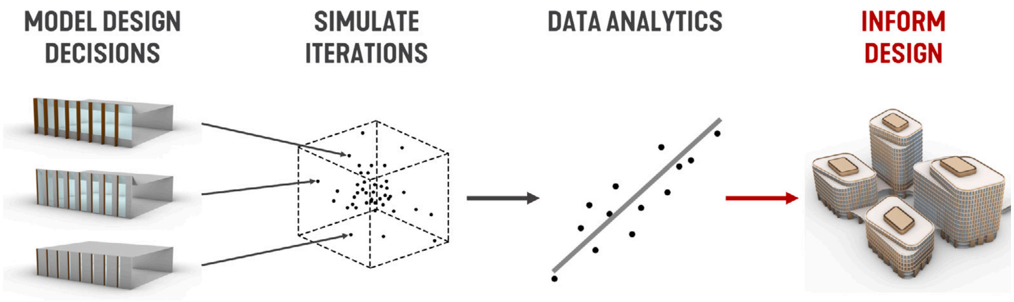

Fig. 2. The DSE process. (From left to right) Parametric modeling of design decisions, sample-based simulation of those parameters, analysis of results, and the application of metrics to inform better user decisions.

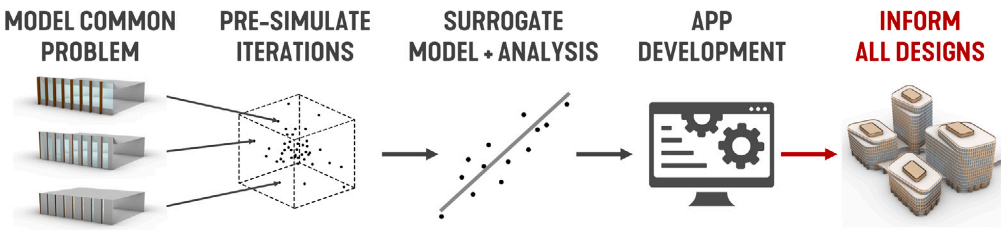

Fig. 3. The UDSE process. (From left to right) Parametric modeling of a common design problem, sample-based simulation of those parameters, centralized expert analysis and surrogate modeling of results, development of an app to deliver analysis to teams at scale, and the application of metrics to all projects to inform better user decisions.

DSE addresses some of the limitations of traditional performance analysis workflows: Rather than respond to several predetermined design options, DSE provides analysis of likely alternatives and variations of these predetermined options, allowing next steps to be directly guided by analysis rather than experience or rules of thumb. Analysis of alternatives is instantaneous because the analysis already exists [2]. SmithGroup has found that this approach supports real-time discussion of priorities and alternatives within integrated teams which enhances the impact of the analysis. However, SmithGroup's experience implementing traditional DSE on projects has shown it to be time-consuming and inflexible. Simulating the thousands of iterations required to make a useful design space can take days or weeks, undermining the speed advantage of instantaneous feedback. It is inflexible in that the analysis is only applicable to the design possibilities contained within the design space. By the time the design space is generated it is possible that the design space no longer represents the current design. Expanding the design space to account for more possibilities increases the simulation time required and further undermines the speed advantage of DSE. These limitations prevent SmithGroup from widely applying DSE in a conceptual design environment characterized by rapid change and short time frames. Instead, SmithGroup more often applies DSE towards specific, well-defined challenges in Design Development where multi-parameter exploration and optimization are required.

1.4. Benefits of universal design space exploration

An overview of the UDSE concept put forth by this paper is summarized in Fig. 3.

The key to UDSE's effectiveness is in the term "Universal". Rather than analyze a single design, as traditional workflows do, or analyze a narrow collection of design possibilities, as DSE does, UDSE attempts to capture all possible outcomes of common design challenges within massive databases of pre-simulated analysis that are developed long before a project team needs it. These Design Spaces become "Universal" when a single pre-simulated design space can be re-applied to future unknown projects. The trick is to model common problems. Common problems are, by definition, well-defined and repeatable across multiple projects. If a well-understood problem is expected on a future project, a design space can be generated long before the project requires it and the time-pressure of modeling can be avoided entirely. If speed is no longer an issue, the design space can become gigantic to cover more possible scenarios, thus becoming more flexible and applicable to more projects. Analysis models can be made as complex as necessary to avoid the oversimplification that plagues most conceptual modeling tools. Instantaneous delivery of relevant analysis will encourage more project teams to ask for and use analysis that otherwise would arrive too late. Critically, a design space that is scalable across multiple projects justifies the investment required to produce it. In this way, a gigantic design space that encompasses a common problem becomes "universal", extending across all designs, schedules, and project fees.

Feasibly generating massive design spaces requires efficient sampling and simulation. This paper explores surrogate modeling methods that interpolate between samples and effectively increase the design space size that can be modeled from any limited quantity of simulation samples [3,4].

How one explores a Universal Design Space is the key to integrating insights into the design process. This can be accomplished with custom apps that are tailored to share the most relevant takeaways of that unique design space without requiring the user to have data science expertise. If the design space is truly universal, it is more likely to garner the investment required to build an app that maximizes impact. Key insights related to the challenge can be discovered by a team of experts before a project requires assistance. This centralized analysis can be used to guide the development of the app. Any app should balance automated analytics under the hood with an intuitive visual interface that serves to engage the design team and clearly explain complicated results.

The UDSE workflow of modeling common challenges, pre-simulating iterations, centralized expert analysis and surrogate modeling of the design space, and app development to deliver insights at scale could offer a new business model for integrating engineering into the architectural design process.

1.5. Public data to support digital literacy in architecture, engineering, and constructions

UDSE introduces new opportunities for statistical analysis, machine learning, and app development that the AEC industry is not well prepared to address. UDSE is intended to generate massive multi-dimensional design spaces that can easily exceed 15 dimensions and are difficult to comprehend through simple analysis. Exploring and analyzing such large design spaces either requires performance analysts to become proficient in data science, or requires AEC firms to hire data scientists.

This is both an opportunity and a challenge for the AEC industry. Data Science fields such as Machine Learning (ML) and Artificial Intelligence (AI) are transforming industries around the world, but to the AEC industry they are largely viewed as buzzwords with few useful applications within design. We might face a first-mover problem, where few invest in learning these skills in part because there are so few examples that showcase the value those skills might bring. This paper proposes one data-centric approach to leveraging ML within design, but we know there are many others to be discovered. Unfortunately, most existing machine learning examples and sample data sets are designed for other industries, making it difficult for AEC professionals and students to recognize the potential that new digital methods might offer. Generating AEC-specific data takes a significant investment of time and expertise, especially in the field of performance analysis where simulations can take hours per design iteration. Our goal is to make Universal Design Spaces that frame common design questions freely available to industry and academia; thereby lowering the barrier to entry for developing next-generation digital tools and applications [5].

We hope that other AEC firms, students and start-ups will be able to use these data to develop innovative design apps and AI algorithms that drive the market forward in unexpectedly useful ways. Expanding the reach of performance modeling to more firms and project types should result in reduced energy usage and improved indoor quality across the industry.

1.6. Automatic building energy modeling

The US Department of Energy's Oak Ridge National Laboratory has developed a collection of software and algorithms called Automatic Building Energy Modeling (AutoBEM), which enables users to model building energy for each structure at large geographic scales [6]. Within AutoBEM, building properties are detected, inferred, or predicted as inputs to generate building energy models using OpenStudio. The primary building properties necessary to generate building energy models using AutoBEM include physical characteristics, such as building footprint and height, and performance characteristics, such as building type and vintage (building code). These models are then simulated using EnergyPlus. OpenStudio is a collection of open-source software tools to support energy modeling in EnergyPlus, which is a physical building energy simulation engine [7,8]. The simulation results can be customized to provide any combination of thousands of simulation outputs, which typically include building energy end uses. These results can be aggregated, analyzed, and visualized in a variety of different ways to gain insights about a building or group of buildings. AutoBEM has been used to model a utility service area (180,000 buildings) in Chattanooga, Tennessee and to create a coarse model of every building in the United States (123 million buildings).

2. Literature review

Exploring design spaces has been a research topic for many years with many different methods for various use cases [9]. With buildings being a central part of anthropogenic development, a logical jump was to extend this DSE process to building design.

Many DSE applications in previous literature focus on a specific building type or use case. One such study created a simple model to predict energy consumption of artificially air-conditioned office buildings for 14 Brazilian cities [10]. The annual energy consumption of the model was compared to architectural and constructive variables to assess their impact on energy consumption and inform design decisions. Another study focused on DSE for embodied carbon in tall timber structural systems [11]. The authors of this study developed a parametric framework which enabled the evaluation of various geometries for buildings in early stage, large-scale timber construction. Greenhouses were at the center of a case study that utilized DSE techniques to improve early-stage greenhouse design and to measure the importance of current greenhouse design rules of thumb [12]. In an industrial building DSE study, a parametric design process for automated structural optimization and quantitative flexibility assignment was developed which aimed to satisfy both building and manufacturing requirements [13].

There are also some building DSE frameworks that have been developed to aid in building design. An app developed by Digital Structures is available to download allows for exploration of design spaces with interactive multi-objective optimization framework [14]. For this app, a parametric design space can be sampled from user specifications and the designs can be analyzed in several different ways including design variable importance, design clustering, and multi-objective optimization (to name a few).

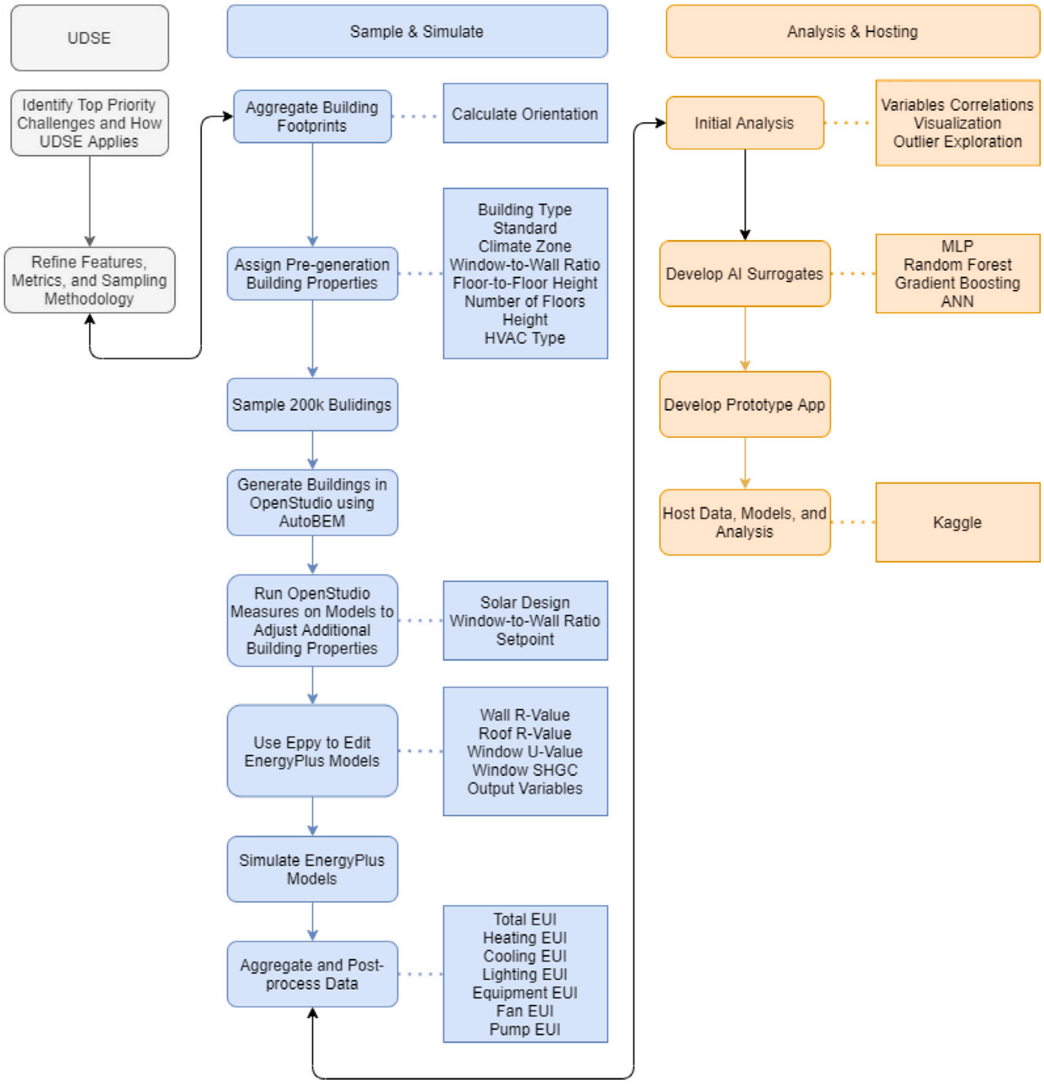

Fig. 4. Flow chart of the process to generate the UDSE data set. The generated UDSE data set involved (left) development of the design space, (middle) generation and simulation of the models, and (right) analysis-based development of derivative technology to improve design decisions.

A similar app was developed by Autodesk [15]. This framework allows the user to set the design variables and their ranges to investigate hundreds of building design variations. The case study using the framework illustrated how it can be used to minimize energy use while maximizing daylighting of an individual residential building. Both of these frameworks require training or experience to use and do not have pre-simulated systems would be considered to be DSE, rather than UDSE.

3. Methodology

The UDSE methodology can be split into three main pieces and is separated by column (and color) in Fig. 4. The first main step of the process is to generate a set of building parameters that are useful to building designers at SmithGroup. The second step is to generate and simulate physics based building energy models for each of the building design parameter combinations. The final step is to develop an AI surrogate model which is trained on the design parameters to predict the building energy use. This surrogate model is then integrated into an app for use by SmithGroup designers. Each of these main steps has several sub-steps, which are described in more detail in the following subsections.

3.1. Refine features, metrics, and sampling methodology

Energy modeling is highly sensitive to a variety of simulation inputs, so traditional conceptual energy models that leverage default settings deliver misleadingly precise results that describe only the specific design option with those default settings, not the myriad

Table 1
Parametric sampling of design space variables, resulting in a total of about 3.35 million individual buildings.

Sampling Parameters	Inputs	Notes
Program Type	Secondary School	
	Lab	
	Office	
	Hospital	
	Outpatient	
	Residential	
Climate Zone	1A	
	2A	
	2B	
	3A	
	3B	
	3C	
	4A	
	4B	
	4C	
	5A	
	5B	
	6A	
	6B	
	7A	
	7B	
Total Area	low	See Massing Matrix for values
	typical	
	high	
Target Floor Area	low	See Massing Matrix for values
	typical	
	high	

Sampling Parameters	Inputs	Notes
Plate Depth	low	See Massing Matrix for values
	typical	
	high	
Floor-to-Floor Height	low	See Massing Matrix for values
	typical	
	high	
Solar Design	Bad	N-S Orientation. All glazing on E/W
	Typical	E-W Orientation. Glazing evenly distributed
	Good	E-W Orientation. All glazing on N/W
Average Window-to-Wall-Ratio	0.25	
	0.4	
	0.7	
Envelope Quality	Baseline	See Envelope Matrix for values
	High Performance	
	Ultra Performance	
Lighting Power Density (LPD)	Baseline	Baseline LPD from DOE Reference Building
	Better	30% reduction from baseline
	Best	60% reduction from baseline
HVAC System	Baseline	See HVAC Matrix for system type
	Good	20% increase in COP from baseline
	Great	35% increase in COP from baseline
	Ultra	50% increase in COP from baseline
Set Points	Baseline	Default settings for program and system
	Expanded	Cooling +1.67 °C, Heating -1.67 °C

potential designs that are more likely to result from a normal conceptual design process. UDSE returns a range of outputs that reflect all potential designs, which better reflects the probable potential performance of a design that has undetermined features. Traditional energy modeling workflows (including model preparation, simulation, analysis and design integration) are slow processes that can easily take between 15 min for a simple analysis using automated software and a week or months for a much more detailed model. UDSE can provide real-time feedback by leveraging pre-simulation. Most importantly, traditional early conceptual energy modeling provides limited guidance because it requires a design to exist before it can be analyzed. This results in option-based feedback that tells the team how they did, not what they should do. UDSE offers a fundamentally different approach that can guide design teams through the complex drivers of building energy performance which can have a greater impact on the design process.

The features, metrics, and sampling methodology of the energy model design space were developed by surveying designers and engineers as well as current standards. These experts defined which areas of the design space were most important and should be selected for simulation based on past project experience while the Department of Energy prototype building energy model standards [16] were used to establish baseline values for properties such as envelope quality, lighting power density, setpoint, etc. Though it has been shown that the expertise of design teams when it comes to the sensitivity of building characteristics impact on building energy use may not be perfect [17], the developed parametric matrix included all design parameters that could be easily modified and represented general design decisions. By using all general design decisions and simulating a vast range of possibilities, we may use the simulation results to better inform designers as to which design decisions are most impactful on building energy use and update their prior knowledge. Ideally, over time, this will help foster building designers that have a good understanding of how their design decisions affect the energy performance of their future buildings. A summary of the chosen parameters and values is shown in Table 1. Detailed parameter settings that enforce realistic parameter values across all sub-regions of the design space are shown in Table 3, 4, 5, 6, and 8.

6 Program types were selected to best represent a large range of project types with varying intensities of internal load and ventilation requirements as shown in Table 2. It is hoped that in the future additional building types might be estimated within the design space by interpolating between the internal load and ventilation requirements of simulated building types. These building types were selected by SmithGroup experts to match typical SmithGroup projects as well as to cover common building types seen across the industry.

Office building type iterations with a total area less than 9300 m^2 used the Medium Office DOE reference model, while Office building type iterations with a total area greater than 9300 m^2 used the Large Office DOE reference model. Apartment building type iterations with less than or equal to 10 floors used the Midrise Apartment DOE reference model, while Apartment building type iterations with greater than 10 floors used the Highrise Apartment DOE reference model.

Climate zones were chosen based on the Continental US climate zones where SmithGroup most commonly works. Chosen climate zones are shown in Table 1.

All massing parameters were derived from the Total Area, Target Floor Area, Plate Depth and Floor-to-Floor Height parameters shown in Table 3. The number of floors was determined by dividing the Total Area by the Target Floor Area and rounding to the nearest integer. The Actual Floor Area was calculated by dividing the Total Floor area by the Number of Floors. The Plate Length

Table 2
Table showing ventilation and internal load descriptions of various program types.

Building loads		
Program type	Ventilation requirement	Internal load
Lab	High	High
Hospital	High	Medium
Secondary School	Medium	Medium
Outpatient	Medium	Low
Office	Low	Medium
Residential	Low	Low

Table 3
Massing matrix used to identify realistic "Low", "Typical", and "High" parameter ranges for Total Area, Target Floor Area, Plate Depth, and Floor-to-Floor Height across all Building Type options. Values were determined by surveying SmithGroup experts and a review of past project data.

Massing matrix							
Parameter	Setting	Secondary school	Lab	Office	Hospital	Outpatient	Residential
Total Area (m^2)	low	9,294	9,294	3,717	9,294	3,717	4,647
	typical	11,617	13,941	9,294	18,587	10,223	13,941
	high	13,941	18,587	18,587	92,937	25,093	27,881
Target Floor Area (m^2)	low	1,394	1,394	1,394	1,394	1,394	1,394
	typical	2,323	2,323	2,323	2,323	2,323	2,323
	high	3,717	3,717	3,717	3,717	3,717	3,717
Plate Depth (m)	low	19.8	35.0	22.8	27.4	22.8	16.7
	typical	22.8	38.0	30.4	33.4	30.4	19.8
	high	36.5	41.0	41.0	45.6	41.0	24.3
Floor to Floor Height (m)	low	4.0	3.6	4.0	4.3	4.0	3.0
	typical	4.6	4.6	4.6	4.6	4.6	3.6
	high	5.2	5.5	5.2	4.9	5.2	4.3

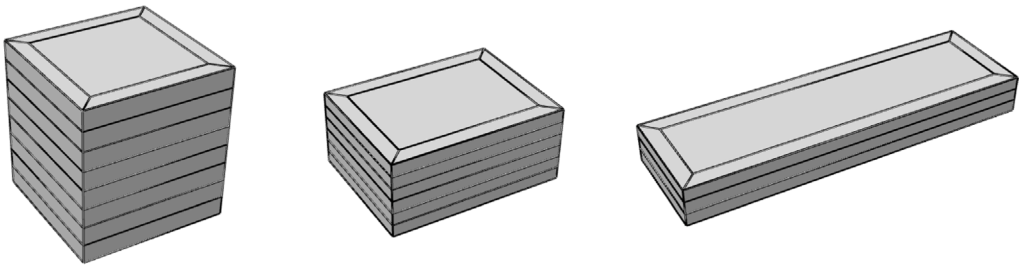

Fig. 5. Examples of energy model massing forms generated from Total Area, Target Floor Area, Plate Depth and Floor-to-Floor Height parameters.

was calculated by dividing the Actual Floor Area by the Plate Depth. All massing forms are rectilinear with a single core zone and perimeter zones as shown in Fig. 5.

Orientation and facade design was simplified to be as generalized as possible. The intent was to help design teams focus on the major design drivers without introducing dependent design parameters whose differential impact would be difficult to separate. To accomplish this the team combined all orientation and facade design decisions into three major general design decisions; Window-to-wall ratio (WWR), Envelope Quality, and Solar Design. WWR simply scales the overall amount of glass on a project. Envelope Quality focuses on conductive heat transfer through the envelope by ramping up or down the insulative properties of the envelope. Solar Design focuses on those design decisions that impact solar heat gain without affecting conductive heat transfer, notably orientation and window placement (but not total window area, which is determined by WWR). In this way, the Universal Design Space can be applicable to any facade design without it having to look like the facade design. Design teams can focus on the major drivers of envelope performance in a generic way and then design a unique solution to target that level of performance.

Solar Design uses three basic orientation and window placement options to represent a "Good", "Typical" and "Bad" solar design, who is corresponding monthly solar gain profiles are diagrammed in Fig. 6.

The facade design and orientation combinations used to achieve these solar profiles are shown in Fig. 7. In general, a bad solar design has high solar gain during the hot summer months, especially during peak hours, and has lower solar gain during the winter months when it is potentially beneficial. Although solar gain during winter months is not necessarily beneficial in all climate zones for all building types, a solar design that has more solar gain during the summer than the winter is typically worse. This solar profile is generated by choosing a massing orientated N–S with all glazing evenly distributed along the east and west facades.

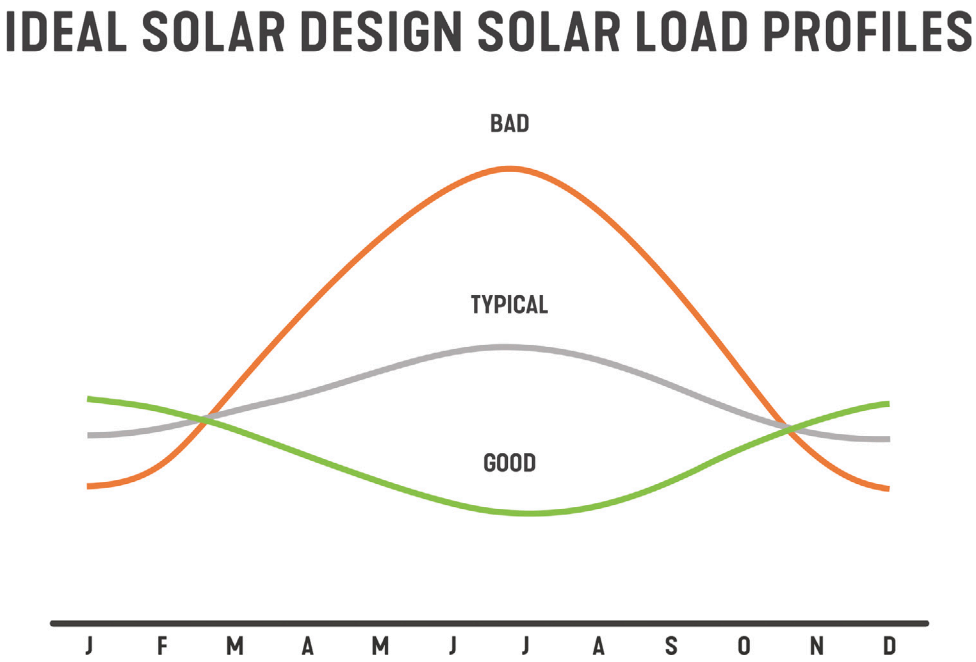

Fig. 6. Schematic diagram showing the amount of solar gain per month that prototypical “Bad”, “Typical”, and “Good” facade design would have. Diagram is not to scale.

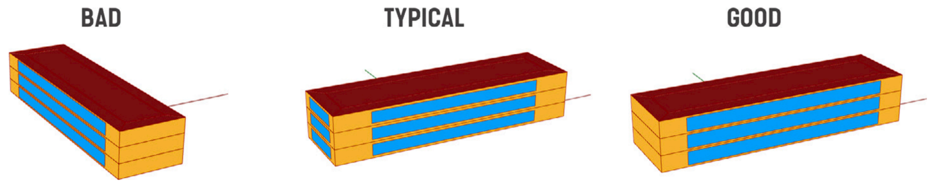

Fig. 7. Images showing the physical massing and facade forms used the generate “Bad”, “Typical”, and “Good” solar load profiles. Bad is oriented N–S with all glazing on the East and West facades. Typical is oriented E–W with glazing evenly distributed on all facades. Good is oriented E–W with all glazing on the North and South facades.

A typical solar design has a solar profile that is naturally occurring if neither good nor bad design decisions are made. This is generated by choosing a massing orientated E–W with all glazing evenly distributed along all facades.

In general, a good solar design would minimize solar gain during the hot summer months, especially during peak hours, and would accept more solar gain during the winter months. Although solar gain during winter months is not necessarily beneficial in all climate zones for all building types, a solar design that has less solar gain during the summer than the winter is typically preferable. This solar profile is generated by choosing a massing orientated E–W with all glazing evenly distributed along the north and south facades.

Envelope baseline settings used ASHRAE 90.1–2013 code minimum values per climate zone. High Performance represents a typical “better than code” envelop selection commonly used in high performance sustainable building design. Ultra Performance represents the realistic maximum performance our experts would ever strive for. High performance envelope improved upon the baseline R-value by an average of 30% while ultra performance improved upon the baseline R-value by an average of 110%. Values were determined by surveying SmithGroup experts and are shown in Table 4.

Baseline Lighting Power Density (LPD) values were set by the DOE prototype reference buildings. Better and Best settings were defined as 30% less than baseline and 60% less than baseline based on surveying SmithGroup experts.

The appropriate realistic heating, ventilation, and air conditioning (HVAC) System for each Building Type varies by Building Type, Total Area, and Climate Zone. Appropriate values were determined by surveying SmithGroup experts and are shown in Tables 5, 6, and 7. The authors initially hoped to run more complicated “Refined” and “Enhanced” HVAC system types to represent design with improved HVAC systems, but this required more time than was available. Instead, the authors used a simplified “Improved COP” approach to represent a theoretical improved system. COP improvement percentages were determined by surveying ORNL experts and are shown in Table 8. This simplification has the benefit of representing any general system that could possibly achieve that performance, and allows design teams to consider the potential impact of novel HVAC systems.

Table 4
Envelope matrix used to identify realistic “Baseline”, “High Performance”, and “Ultra Performance” parameter ranges for envelope parameters across all climate zone options.

Envelope matrix									
Climate zone	Quality	Wall R-value (m2-K/W)	Roof R-value (m2-K/W)	Slab R-value (m2-K/W)	Glass U-value (W/m2-K)	Glass and Frame U-value (W/m2-K)	VLT	SHGC	LSG
1A	Baseline	1.47	3.76	0.33	3.57	3.75	0.31	0.25	1.25
1A	High Performance	2.35	4.64	1.01	1.70	2.10	0.38	0.25	1.50
1A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
2A	Baseline	2.17	4.64	0.33	3.57	3.75	0.31	0.25	1.25
2A	High Performance	2.88	5.52	1.01	1.70	2.10	0.38	0.25	1.50
2A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
2B	Baseline	2.17	4.64	0.33	3.57	3.75	0.31	0.25	1.25
2B	High Performance	2.88	5.52	1.01	1.70	2.10	0.38	0.25	1.50
2B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
3A	Baseline	2.35	4.64	0.33	3.24	3.46	0.31	0.25	1.25
3A	High Performance	2.88	5.52	1.01	1.70	2.10	0.38	0.25	1.50
3A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
3B	Baseline	2.35	4.64	0.33	3.24	3.46	0.31	0.25	1.25
3B	High Performance	2.88	5.52	1.01	1.70	2.10	0.38	0.25	1.50
3B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
3C	Baseline	2.35	4.64	0.33	3.24	3.46	0.31	0.25	1.25
3C	High Performance	2.88	5.52	1.01	1.70	2.10	0.38	0.25	1.50
3C	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.50	0.25	2.00
4A	Baseline	2.88	5.52	1.01	2.69	2.95	0.50	0.4	1.25
4A	High Performance	3.58	5.52	1.01	1.70	2.10	0.60	0.4	1.50
4A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
4B	Baseline	2.88	5.52	1.01	2.69	2.95	0.50	0.4	1.25
4B	High Performance	3.58	5.52	1.01	1.70	2.10	0.60	0.4	1.50
4B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
4C	Baseline	2.88	5.52	1.01	2.69	2.95	0.50	0.4	1.25
4C	High Performance	3.58	5.52	1.01	1.70	2.10	0.60	0.4	1.50
4C	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
5A	Baseline	3.23	5.52	1.01	2.69	2.95	0.50	0.4	1.25
5A	High Performance	4.40	7.93	1.01	1.70	2.10	0.60	0.4	1.50
5A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
5B	Baseline	3.23	5.52	1.01	2.69	2.95	0.50	0.4	1.25
5B	High Performance	4.40	7.93	1.01	1.70	2.10	0.60	0.4	1.50
5B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
6A	Baseline	3.58	5.52	1.01	2.69	2.95	0.50	0.4	1.25
6A	High Performance	5.28	7.93	1.01	1.70	2.10	0.60	0.4	1.50
6A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
6B	Baseline	3.58	5.52	1.01	2.69	2.95	0.50	0.4	1.25
6B	High Performance	5.28	7.93	1.01	1.70	2.10	0.60	0.4	1.50
6B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.4	1.80
7A	Baseline	3.58	6.40	1.01	2.29	2.61	0.56	0.45	1.25
7A	High Performance	5.28	8.81	1.01	1.70	2.10	0.68	0.45	1.50
7A	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.45	1.60
7B	Baseline	3.58	6.40	1.01	2.29	2.61	0.562	0.45	1.25
7B	High Performance	5.28	8.81	1.01	1.70	2.10	0.675	0.45	1.5
7B	Ultra Performance	5.28	10.57	1.89	0.57	1.14	0.72	0.45	1.6

Baseline HVAC set point values were set by the DOE prototype reference buildings. Expanded set points were determined to be +1.67 degrees Celsius for cooling systems and −1.67 degrees Celsius based on surveying SmithGroup experts. The use of relative parameter settings like Low, Typical and High rather than explicit settings based on the absolute parameter value has many advantages when exploring the massive design spaces required by UDSE.

First, it simplifies interpretation of a massive design space by embedding detailed decisions made by experts within the high level decisions made by designers. Rather than get bogged down by the minutiae of what a decision entails, designers often prefer to leverage an expert’s best practice and quickly get a sense of the magnitude of a potential design decision. Designers usually do not care about the exact HVAC system at this stage, only that the assumptions for baseline, good or great HVAC systems are reasonable.

Second, it helps limit the simulated design space to only realistic options. For example, the expert knows that a reasonable baseline, good or great envelope will change depending on the climate zone. Simulating the same envelope parameters across all iterations would result in many unrealistic designs that defy common sense, interfere with accurate analysis of the design space, and require wasteful simulation of useless iterations.

Third, it simplifies filtering of a massive design space. Realistic parameter ranges will often change depending on the sub-region of the design space being explored. If parameter range filters are labeled with generic terms like Low, Typical and High, a single control can be used to apply a complex filter that enables users to explore the design question behind that parameter. For example, if exploring a subset of designs with baseline HVAC system designs across multiple climate zones, a user can simply filter down to

Table 5
HVAC system selection matrix used to identify realistic HVAC system selection across all Building Types, Total Area, and Climate Zone options. Values were determined by surveying SmithGroup experts. Two building types are shown.

HVAC matrix		
<4.6 k m^2	Secondary school	Lab
1A	PSZ-AC with no heat	DOAS 50PCT Enthalpy, PSZ-AC with no heat
2A	PSZ-HP	DOAS 50PCT Enthalpy, PSZ-HP
2B	PSZ-HP	DOAS 50PCT Enthalpy, PSZ-HP
3A	PSZ-HP	DOAS 50PCT Enthalpy, PSZ-HP
3B	PSZ-HP	DOAS 50PCT Enthalpy, PSZ-HP
3C	PSZ-HP	PSZ-HP
4A	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
4B	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
4C	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
5A	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
5B	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
6A	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
6B	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
7A	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
7B	PSZ-AC with electric coil	DOAS 50PCT Enthalpy, PSZ-AC with electric coil
4.6k–14 k m^2	Secondary school	Lab
1A	PVAV with PFP boxes	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
2A	PVAV with PFP boxes	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
2B	PVAV with PFP boxes	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
3A	PVAV with PFP boxes	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
3B	PVAV with PFP boxes	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
3C	PVAV with PFP boxes	VAV air-cooled chiller with gas boiler reheat
4A	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
4B	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
4C	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
5A	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
5B	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
6A	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
6B	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
7A	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
7B	PVAV with gas heat with electric reheat	DOAS 50PCT Enthalpy, VAV air-cooled chiller with gas boiler
>14 k m^2	Secondary school	Lab
1A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
2A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
2B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
3A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
3B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
3C	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
4B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
4C	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
5A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
5B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
6A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
6B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
7A	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler
7B	VAV chiller with gas boiler reheat	DOAS 50PCT Enthalpy, VAV chiller with gas boiler

"Baseline" HVAC systems without having to know the potentially complicated collection of specific HVAC systems that exist in this sub-region.

Defining relative terms like Baseline, Good and Great requires a process of careful evaluation by experts. By engaging in this exercise, defining the features and sampling settings of the design space becomes the process by which we embed best practice and expertise into the design space.

3.2. Parametric sampling and building model generation

To generate the parametric sampling for building-energy models, the AutoBEM 1.0 workflow was modified to generate custom buildings rather than existing buildings. A previously developed data set of 122.9 million US buildings [18] was used to select building geometries that fit a parametric sampling of simulation inputs commonly considered during building design. Buildings were simplified to the relevant footprint area and used only four vertices for a rectangular footprint. Because footprint geometry can be extruded to any user-defined height, only the footprint area, plate length, and plate width were considered for geometry selection. If a building geometry was selected, then the orientation of the building was stored so it could be rotated properly after

Table 6
HVAC system selection matrix used to identify realistic HVAC system selection across all Building Types, Total Area, and Climate Zone options. Values were determined by surveying SmithGroup experts. Two building types are shown.

HVAC matrix		
<4.6 k m^2	Hospital	Outpatient
1A	PVAV with PFP boxes	PSZ-AC with no heat
2A	PVAV with PFP boxes	PSZ-HP
2B	PVAV with PFP boxes	PSZ-HP
3A	PVAV with PFP boxes	PSZ-HP
3B	PVAV with PFP boxes	PSZ-HP
3C	PVAV with PFP boxes	PSZ-HP
4A	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
4B	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
4C	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
5A	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
5B	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
6A	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
6B	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
7A	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
7B	PVAV with gas heat with electric reheat	PSZ-AC with electric coil
4.6 k–14 k m^2	Hospital	Outpatient
1A	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
2A	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
2B	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
3A	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
3B	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
3C	VAV air-cooled chiller with gas boiler reheat	PVAV with PFP boxes
4A	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
4B	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
4C	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
5A	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
5B	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
6A	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
6B	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
7A	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
7B	VAV air-cooled chiller with gas boiler reheat	PVAV with gas boiler reheat
>14 k m^2	Hospital	Outpatient
1A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
2A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
2B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3C	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4C	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
5A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
5B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
6A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
6B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
7A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
7B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat

generation. Each building's data was saved as a row of a table; additional design parameters could be appended to the table as columns to complete the design space. This building data table is one of several inputs required for AutoBEM's building-energy model generation. Several physical and functional building properties could be added to the table, with a new row for each variation of the design parameters. The following parameters (i.e., columns of the building data table) are required parameters in this project:

- Building type
- Building energy code (standard 90.1–2013 for this study)
- Climate zone
- Window-to-wall ratio (typical)
- Floor-to-floor height
- Number of floors (total area ÷ floor area)
- Height (number of floors × floor-to-floor height)
- HVAC type

Table 7
HVAC system selection matrix used to identify realistic HVAC system selection across all Building Types, Total Area, and Climate Zone options. Values were determined by surveying SmithGroup experts. Two building types are shown.

HVAC matrix		
<4.6 k m^2	Office	Residential
1A	PSZ-AC with no heat	Residential AC with no heat
2A	PSZ-HP	Residential heat pump
2B	PSZ-HP	Residential heat pump
3A	PSZ-HP	Residential heat pump
3B	PSZ-HP	Residential heat pump
3C	PSZ-HP	Residential heat pump
4A	PSZ-AC with electric coil	Residential AC with baseboard electric
4B	PSZ-AC with electric coil	Residential AC with baseboard electric
4C	PSZ-AC with electric coil	Residential AC with baseboard electric
5A	PSZ-AC with electric coil	Residential AC with baseboard electric
5B	PSZ-AC with electric coil	Residential AC with baseboard electric
6A	PSZ-AC with electric coil	Residential AC with baseboard electric
6B	PSZ-AC with electric coil	Residential AC with baseboard electric
7A	PSZ-AC with electric coil	Residential AC with baseboard electric
7B	PSZ-AC with electric coil	Residential AC with baseboard electric
4.6 k–14 k m^2	Office	Residential
1A	PVAV with PFP boxes	PVAV with PFP boxes
2A	PVAV with PFP boxes	PVAV with PFP boxes
2B	PVAV with PFP boxes	PVAV with PFP boxes
3A	PVAV with PFP boxes	PVAV with PFP boxes
3B	PVAV with PFP boxes	PVAV with PFP boxes
3C	PVAV with PFP boxes	PVAV with PFP boxes
4A	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
4B	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
4C	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
5A	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
5B	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
6A	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
6B	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
7A	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
7B	PVAV with gas heat with electric reheat	PVAV with gas boiler reheat
>14 k m^2	Office	Residential
1A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
2A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
2B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
3C	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
4C	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
5A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
5B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
6A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
6B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
7A	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat
7B	VAV chiller with gas boiler reheat	VAV chiller with gas boiler reheat

The following optional design parameters are part of the design space and can be added to a building's row in the data table for model generation:

- Wall R-value
- Roof R-value
- Window U-value
- Window solar heat gain coefficients
- Lighting adjustment
- Setpoint adjustment
- Solar design adjustment
- Unique ID based on all distinct parameters

The typical AutoBEM workflow implements a default HVAC type for each building type, vintage, and climate zone combination. This default was adjusted to include 16 new HVAC types, each with multiple settings, for AutoBEMs generation process. These

Table 8
HVAC COP improvement matrix used to identify realistic COP improvements associated with "Baseline", "Refined", and "Enhanced" HVAC system selections. Values were determined by surveying ORNL experts.

HVAC COP improvement matrix			
HVAC_level	Total area (m^2)	Heating COP improvement	Cooling COP improvement
Baseline	< 4,645	0.0%	0.0%
	4,645–13,935	0.0%	0.0%
	>13,935	0.0%	0.0%
Refined	< 4,645	2.5%	5.0%
	4,645–13,935	5.0%	10.0%
	>13,935	15.0%	20.0%
Enhanced	< 4,645	5.0%	10.0%
	4,645–13,935	15.0%	20.0%
	>13,935	20.0%	30.0%

baseline HVAC types were chosen as they were the most common HVAC types for each building type and area combination for the design firm. The good, great, and ultra HVAC systems represent coefficient of performance improvements to those baseline HVAC systems. The building input table initially consisted of 3.3 million rows of buildings. This number was randomly sampled down to 256,000 for computational feasibility and initial analysis. This initial analysis indicated that a high-quality AI, with a very small difference between actual simulation results and those from the AI-generated surrogate model, could be trained on a much smaller sample of the data. The models were then generated using AutoBEM and executed as a fully parallelized workload on a 72-core server.

Two model post-generation steps were completed using OpenStudio measures and an application programming interface to make changes to the model of a building. OpenStudio measures are typically used for more complex building changes (e.g., HVAC replacements), whereas smaller changes can be made via EnergyPlus measures or direct text-based replacement in the EnergyPlus model. The first OpenStudio measure invoked was building rotation for solar design. Building models were rotated a variable amount based on their original orientation to 0 or 90 north. Only 0 and 90 degrees were required as building form and facade are symmetrical around 1 axis. 0 and 90 degrees essentially covers a full rotation of the building where 0 degrees represents a building that is oriented north and south while 90 degrees represents a building that is oriented east and west. Adding further degrees such as 180 or 270 would be repetitive. Another measure was then used to adjust the window-to-wall ratio to either a good or bad solar design by adding all of the windows to two faces and removing windows from the other two (the typical prototype model solar design kept even window spacing across all four faces). The post-generation adjustments were implemented in the models using EPPY, a python library used for editing EnergyPlus models [19]. These changes included adjustments to wall and roof insulation (R-value), window insulation (U-value), solar heat gain coefficient, lighting power density, and heating and cooling coefficients of performance. A final python script defined the simulation output files, variables, and frequency to be generated. A tabular hypertext markup file (with HVAC sizing data), comma-separated values file (time series end-use energy data), and log files were output for each simulation in this analysis. The settings for the output included 14 reporting variables at a monthly resolution. These reporting variables included building electricity and natural end-uses such as heating, cooling, equipment, lighting, etc.

3.3. Building model simulation

The building models are simulated using Python and EnergyPlus to run in parallel on the 72-core server. Another parallelized python script is then used to aggregate building simulation results, including annual simulation energy data. This output data can be joined with the input data to obtain a single table, including all relevant inputs and outputs for the design space. A representative sample of 4506 building models took 1023 s to simulate on a 72-core server. The average simulation time of each of these buildings was 16 s.

3.4. Simulation utilization (AI and prototype app)

While there is value in the simulation results alone, training an AI algorithm allows for faster and more general use of the data. An AI, in this use case is basically a function that uses the design parameters (building type, climate zone, window to wall ratio, HVAC type, etc.) to predict building energy usage. It essentially serves as a surrogate model for AutoBEM and EnergyPlus within this particular design space and makes building energy use estimation much faster than a simulation engine. In addition to speed, the other reason an AI is valuable for this use case is it allows for interpolation between data points that were simulated. For example, if buildings with a WWR of 10% and 50% were simulated, using this AI allows for estimation of how a building with 25% WWR would perform. In addition to interpolating directly between simulations, the AI will learn patterns between similar feature combinations to accurately predict areas that were not simulated from the design space. For example, predicting the performance of a specific building at 25% WWR does not require direct interpolation of that building's unique feature combination at 10% and 50% WWR (which would require millions of simulations to cover all feature combinations). Rather, the AI can learn trends from a relatively

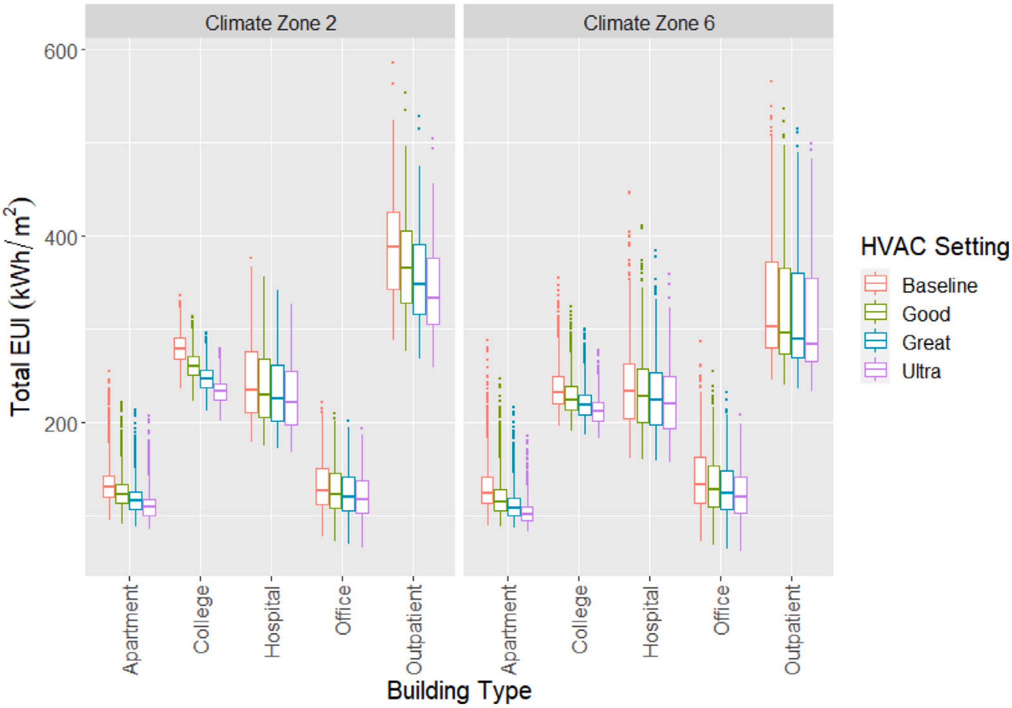

Fig. 8. The total building EUI is shown for each building type and two climate zones. The EUI decreases with the improvement in the HVAC quality.

small subset of similar simulations and accurately predict the performance of a specific building. This drastically reduces the amount of simulations necessary if the AI is constructed properly and enables gigantic design spaces to be feasibly modeled.

This AI was employed in a prototype app that was developed to maximize ease of use of the data. The purpose of the prototype app is to allow designers to understand how their design decisions may impact building energy. It is not meant to replace the development of a representative building energy model, rather to generally understand how each design decision will generally impact building energy usage.

4. Results

4.1. Data visualization

Initial data visualization, including box plots and violin charts, illustrate statistical trends and distributions of relationships among input and output variables within the design space. Energy use intensity (EUI), is a well-recognized metric used by architects to normalize energy use by the floor area of the building. It is useful for designers as (unlike total energy use) it is an area agnostic metric, allowing for comparison of building types of all sizes. A box-plot comparing EUI per building type for each of the HVAC settings and sample two climate zones (one hot, one cold) is shown in Fig. 8. This type of visualization was useful in analyzing general trends in the simulation results and ensuring the simulation results were as expected.

4.2. Correlations

Relationships between building properties and building energy use is a critical component of UDSE. Correlations are useful for designers as they illustrate how design parameters affect building performance. Correlation values were calculated on this data set by filtering by building type and climate zone. Pearson, Spearman, and Kendall correlations between each input variable and building EUI were calculated on the filtered data set. The Spearman and Kendall correlation statistics were employed explicitly because they can process ordinal variables, of which there were several in the feature set. These correlation values are shown in Table 9 for a sample of building types and climate zones.

4.3. AI surrogate model development

An AI surrogate model was developed for prediction across the design space. Total building EUI was selected as the target modeling performance metric and involved all input features from the input table consisting of 256,000 rows. Numerical (non-categorical) values were used if multiple variables described the same building property. For example, the actual floor area was

Table 9
Pearson input variable correlation coefficients to building EUI for building types and climate zones.

	Outpatient 1A	Outpatient 2A	Outpatient 3A	Outpatient 4A	Outpatient 5A	Outpatient 6A	Outpatient 7A
Height	-0.50	-0.57	-0.55	-0.42	-0.50	-0.44	-0.44
NumberFloors	-0.50	-0.56	-0.57	-0.45	-0.51	-0.45	-0.46
TotalArea	-0.77	-0.79	-0.78	-0.67	-0.68	-0.65	-0.62
WindowWallRatio	-0.02	-0.06	0.11	0.00	0.07	0.05	0.19
FloorHeight	0.06	0.00	-0.04	0.19	0.02	-0.01	0.15
PlateDepth	0.05	0.14	-0.13	0.08	-0.12	-0.02	-0.24
PlateLength	-0.13	-0.22	-0.09	-0.16	-0.15	-0.09	-0.14
SkinArea	-0.47	-0.52	-0.51	-0.39	-0.44	-0.40	-0.45
SkinFloorRatio	0.28	0.25	0.17	0.26	0.11	0.22	0.02
GlassArea	-0.43	-0.50	-0.46	-0.36	-0.39	-0.34	-0.38
EnvelopeFloorAreaRatio	0.30	0.27	0.19	0.28	0.14	0.25	0.04
EnvelopeQuality	0.04	-0.04	0.01	0.13	-0.01	-0.04	0.06
LightingPowerDensity	-0.18	-0.47	-0.37	-0.17	-0.27	-0.24	-0.09
SetpointSetting	-0.14	-0.14	-0.12	-0.18	-0.17	-0.17	-0.14
HVACSetting	0.36	0.27	0.19	0.15	0.13	0.13	0.10
SolarDesign	-0.02	-0.03	-0.02	-0.02	-0.03	-0.03	-0.04

Table 10
Cross-validation metrics for fivefold, three-repeat cross validation. MAE and R^2 metrics are shown.

Model	MAE in EUI (kWh/m^2)	R^2
Random Forest	7.5	0.9997
Gradient Boosting	153.2	0.9349
Multilayer Perceptron	24.8	0.9987
Multiple Linear Regression	172.1	0.9346

Table 11
Random forest hyperparameter values were determined from a grid search over the same fivefold, three-repeat cross validation.

Hyperparameter	Value
Max features	Auto
Minimum samples per leaf	1
Minimum samples per split	2
Number of estimators	300

used instead of the floor area description (low, medium, high). Any variables that were categorical were converted to a type suitable for ML using one-hot encoding. One-hot encoding is the process of extracting each level of a multilevel categorical variable into a separate binary variable to prevent the model from assuming an ordinal relationship between the levels of the variable.

The data were split into 80% training data and 20% testing data. Four different ML models were evaluated in predicting building EUI: multiple linear regression, random forest [20], gradient boosting [21], and multilayer perceptron [22]. Multiple linear regression is the simplest of these models: it assumes linear relationships between the independent variables and the dependent variables. It is also easy to develop, which makes it a good model to use as a baseline to evaluate the other three, more complex models. Fivefold cross validation with a grid search was used to tune each model's hyperparameters and evaluate each model's performance. It is typical to use five or ten folds for cross validation [23]. Table 10 lists the metrics for each model. The models are evaluated using mean absolute error (MAE) and R^2. Mean absolute error measures the average error in a set of predictions while R^2 represents the proportion of the variance in the output variable which is explained by the model. Together, the metrics provide a good representation of model performance. Because the random forest model had the best metrics, it was chosen as the AI implementation for this analysis. Additional, more complex models were not explored as the metrics for the random forest were satisfactory for initial design decisions. Then, the best hyperparameter values were selected, and a final model was trained to use for UDSE. These hyperparameters are listed in Table 11.

4.4. Prototype app

A prototype app was developed to streamline the exploration of the universal design space and improve the integration of insights into the design process. It leverages a surrogate model to generate all required data and provides the user with three useful data visualizations: a traditional single-option visualization, a colored scatterplot for the exploration of up to three parameters, and a real-time sensitivity analysis. It was built in Grasshopper for Rhino using the Human UI, Design Space Explorer, and Owl plugins, as well as a variety of custom C# components that used the Accord.NET machine learning library. The app leverages a simple single layer Artificial Neural Net surrogate model that was trained using python, pandas, and keras in a Jupyter notebook. The prototype app did not use the final accurate surrogate model developed for this study in order to simplify app development.

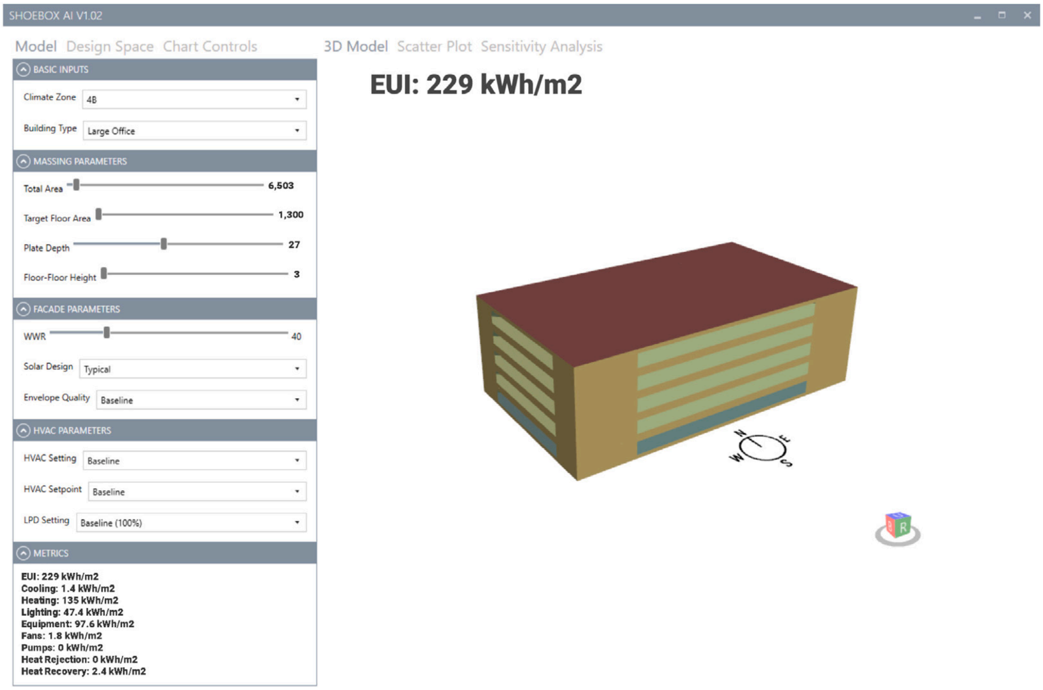

Fig. 9. The 3D model visualization within the prototype app.

A view of the app's 3D model visualization is shown in Fig. 9. It visualizes the result of a single collection of parameter settings and provides the user with sliders or pull-downs to control each input parameter. The resulting design option geometry is shown alongside the resulting overall Energy Use Intensity (EUI) and component EUI metrics. This analysis matches what traditional tools offer and helps users better understand the data by providing a geometric representation of a single design. Unlike traditional static tools, users are able to play with parameters in real time to manually discover trends and patterns. Meeting the user where they are most comfortable builds trust in the data and provides the analysis users expect and know how to use.

The scatterplot visualization provides a view of any sub-region of the design space and encourages users to explore relationships between design decisions rather than pursue an option-based approach. A visualization is shown in Fig. 10. Rather than requiring a single setting for each input parameter, this visualization requires the user to select a range for each parameter. This range filters the design space to only those options deemed relevant by the designer. It can filter out unrealistic options, such as buildings of the wrong type or climate zone, or it can represent undetermined design decisions. Adjusting the range allows the user to expand or narrow design constraints while exploring the results in real time. Results are plotted in a 2-D scatterplot with a third dimension of color added to the dots. The user can choose any input parameter for the X, Y and color dimensions. The dynamic nature of a scatterplot that adjusts in real-time to user queries enables a playful exploration of design decisions, but the scatterplot format is foreign to the design process. Most designers do not want to interpret complicated charts. Multi-dimensional exploration techniques are inherently complicated, and additional work is required to make this analysis impactful. The ability to hover over any single dot and see a visual representation of that design would be helpful.

In addition to scatterplot visualization, the app provides real-time subset sensitivity analysis. The subset sensitivity analysis visualization attempts to resolve the issues of the scatterplot by requiring as little interpretation by the user as possible. It attempts to answer the question "Which design decision is most impactful, and by how much?". To do this, it runs a Multiple Linear Regression analysis on a small sample of the selected sub-region (as defined by the parameter range) and displays the regression coefficients in a bar chart as shown in Fig. 11. The larger the bar, the larger the impact that parameter has on average. Critically, this graphic shows the sensitivity of all chosen design decisions side by side, allowing users to compare multiple key decisions at once. This analysis helps the user clearly determine the sensitivity of EUI to the design features within the user-defined design space.

The prototype app is a rough example of what is possible once a universal design space has been simulated. It proves that a surrogate model can provide a lightweight data generation engine that replaces the need to reference a large database. It exposes the difficulties of visualizing complicated multi-dimensional data and supports the need for targeted visualizations that do not require user interpretation. Further development can leverage visualizations like parallel coordinate plots to assist input range selection, use clustering algorithms to replace a thousand dots on a scatterplot with a visualization of several representative design alternatives, or automate the answering of common design questions in order to make the app more impactful.

Overall, the prototype app enables users to conduct detailed, flexible analysis to make critical design decisions without requiring simulation of their project. This capability encourages the design team to consider building performance early in the design process

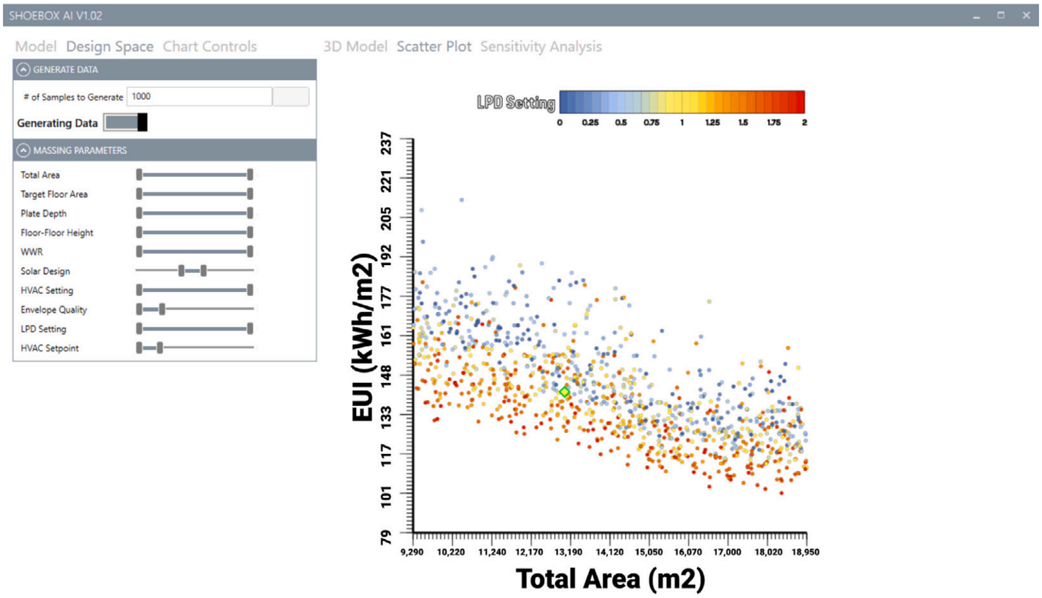

Fig. 10. The scatterplot visualization within the prototype app.

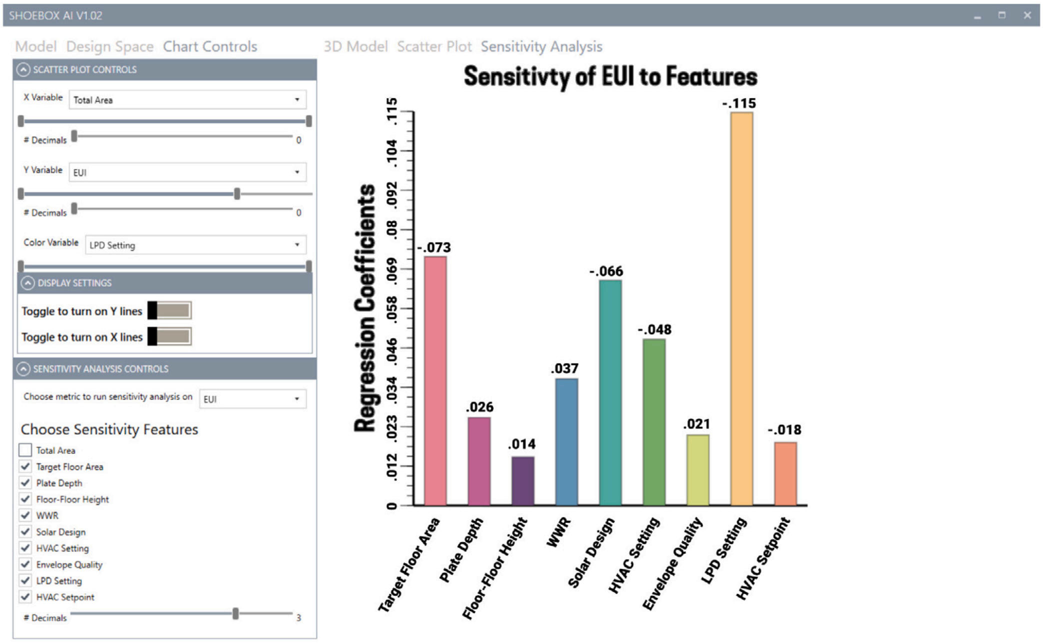

Fig. 11. The real-time sensitivity analysis within the prototype app.

when lack of expertise, time, or money would typically prevent such considerations. This app is not meant to replace the high-resolution modeling step of the building design process, rather to inform the designer as to how key design decisions will impact the energy use of the building.

4.5. Public data hosting

An important part of this project was to make the full parametric design and related simulation data publicly available so they could be used and analyzed by the broader buildings' community. The data were shared to Kaggle, an online community developed by data scientists to find, publish, analyze, and model data [5].

5. Discussion

This paper focuses on how making design spaces "universal" improves the feasibility and applicability of DSE techniques in design. Several key innovations make this approach possible:

Targeting a design space to a common problem as opposed to a unique project-specific problem enables a pre-simulated design space to be applicable across multiple projects. This has the effect of making pre-simulated analysis instantaneous, which addresses the time constraints of early conceptual analysis. Analysis that is applicable across multiple projects can share the cost burden of development, which makes the analysis less expensive and thus more feasible. The natural scalability of project-agnostic analysis enables the development of ML-powered apps, which would otherwise be cost-prohibitive. These apps make the analysis more impactful, which increases the value of DSE techniques and further improves the cost–benefit ratio of DSE techniques. However, targeting common problems is a limitation in and of itself. UDSE is not applicable to unique or detailed design challenges. As a result, UDSE is better suited to conceptual design, when high-level guidance is needed most, as opposed to detailed design development, when fine-tuning of unique design solutions is required. For example, in the case of energy modeling, UDSE will not replace existing compliance modeling workflows, but it may replace early conceptual energy modeling workflows.

This paper showcases how AI Surrogate modeling techniques, powerful computation, and efficient AutoBEM software enable a relatively sparse sampling to accurately describe massive design spaces. This is critical because design spaces that are too small fail to generalize across multiple projects and design spaces that require too many simulation samples are not feasibly generated. In short, less efficient sampling methodologies would fail to support the UDSE concept. This paper showcases how the massive design spaces required for UDSE can be feasibly generated. However, the reliance of UDSE on AI "expansion" of sparse simulations means that results from a UDSE workflow are limited to being predicted outputs generated by a surrogate model, rather than being direct outputs from a trusted simulation engine. The accuracy of the AI surrogate thus becomes paramount. Our analysis shows that accuracy is quite high for the specific energy model design space explored in this paper, but a different design space may not yield such promising results. Further research is required to understand what design challenges are well suited to UDSE.

A prototype app was developed to explore how a dedicated interface could automate the DSE analysis process and make complicated analytics relevant to designers who may not have a background in data science. Although promising, the prototype is far from perfect. The challenge of simplifying complex analysis into legible data visualizations and actionable next steps is a difficult one. It is possible that the ideal sweet spot between simplicity and impact is unattainable. If designers are required to understand complex analytics and data visualizations to get value out of UDSE workflows it might limit the applicability of UDSE.

6. Conclusion

6.1. Summary

The authors have presented a novel Universal Design Space Exploration methodology that improves the real-world applicability of DSE techniques by leveraging massive "universal" design spaces that encompass common design problems. These project-agnostic universal design spaces justify investment in ML-powered apps that make pre-simulated analysis accessible, affordable, and impactful across multiple projects. The authors have showcased the applicability of this methodology using the example of early-stage energy modeling analysis. Design space parameters were selected by a team of building designers and engineers based on the company's previous projects. The building energy models were developed using AutoBEM, an urban-scale building energy modeling software which uses OpenStudio and EnergyPlus for model augmentation and simulation. The model simulation results consisting of end-use building energy were used as the target of an AI, with the building properties being used as predictor variables. The AI is valuable for this use case because it allows for a coarse sampling of the design space as the AI can effectively interpolate between sampled values. This increases the maximum size of any design space that can be feasibly built, which enables the creation a design spaces that are broad enough to be applicable to many projects. A random forest was the AI used and had R^2 values close to 1. The AI was integrated into a prototype app to provide real-time estimations of how building design decisions affect building energy use. A 3D visualization, scatterplot, and sensitivity analysis were developed for the first stage of the app but could be modified with designer input. The purpose of this app is not to replace high resolution building energy model development, but rather to provide insights to designers as to how their design decisions will impact building energy use early in the design process, when designs are most flexible.

6.2. Future work

Since UDSE is a generic methodology, future work could focus on applying the UDSE methodology to additional common design problems. For example, a conceptual structural analysis universal design space could help designers explore how bay size and construction type affect embodied carbon and cost, or a single-zone façade model could explore how façade design in various climate zones affects peak load, thermal comfort, daylight, and HVAC system selection. Also, the building properties selected for the universal design space in this analysis were based on SmithGroup's common designs. This work could be extended to include more building types, sizes, and properties to make it useful for buildings of all types.

Additional work could be done to refine input parameters so that the design space can be most efficiently modeled using as few simulations as possible. For example, many massing combinations were generated using the explicit parameters of Total Area, Target Floor Area, Plate Depth and Floor-to-Floor Height. The goal of these parameters is to understand how massing impacts energy

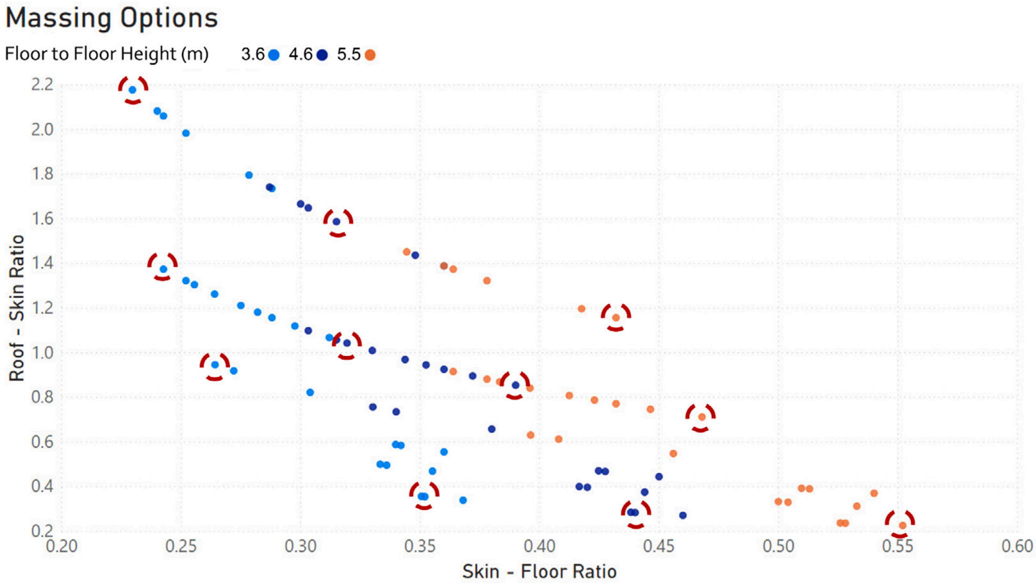

Fig. 12. A plot of massing options generated using Total Area, Target Floor Area, Plate Depth and Floor-to-Floor Height parameters. Highlighted options show a potential subset of massing options that would well-describe the range of meaningful massing options.

performance. If we instead chose samples based on more generic massing metrics tied to this higher goal, such as Roof-to-Skin ratio and Skin-to-Floor ratio, we might not need as many simulations. As shown in Fig. 12, a smaller number of massing options might be able to cover the range of meaningful massing options, assuming that Roof-to-Skin ratio and Skin-to-Floor ratio better describe the underlying physics that affects performance. Similar analysis could be done on all parameters to improve sampling methodology efficiency.

Additional investigation of UDSE app design could consider a refined user interface that better engages designers and more effectively communicates complex analysis. The MLR sensitivity analysis deployed in the prototype could be replaced by dynamic subset-sensitivity analysis as described by Hinkle et al. [24]. The scatterplot could be replaced with a more intuitive visual collection of representative design options that are identified using clustering or iso-performance sampling of the filtered design space. Monte Carlo simulation techniques with corresponding probabilistic data visualizations could be added by enabling the user to set a probability function along with the parameter ranges. These results could be particularly useful in early conceptual design when any single number is assumed to represent a probability, not a certainty. A histogram could with built in analysis could identify a statistically probable EUI range associated with a collection of design decisions.

Additional open-source data sets could encourage the development of digital literacy within the AEC industry as students and professionals would have access to data that is more relevant to their particular niches. Problems common to the AEC industry could be captured and explored via UDSE apps that serve as learning platforms for students and professionals alike. This might be of particular interest to organizations like Architecture2030 who currently host the 2030 Palette [25]. All of these areas of future study could expand the use of computation and data analytics within the AEC industry as we strive to design more intelligently.

CRediT authorship contribution statement

Brett Bass: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Software development. **Leland Curtis:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Software development. **Joshua New:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Stet Sanborn:** Supervision. **Peter McNally:** Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was funded by field work proposal CEBT105 under the Department of Energy Building Technology Activity Number BT0305000. We would like to thank Amir Roth and Madeline Salzman for their support and review of this project. This research used resources of the Oak Ridge Leadership Computing Facility at the Oak Ridge National Laboratory, which is supported by the Office of Science of the US Department of Energy under Contract No. DE-AC05-00OR22725.

Oak Ridge National Laboratory is managed by UT-Battelle, LLC, for the US Department of Energy under contract DE-AC05-00OR22725. This manuscript has been authored by UT-Battelle, LLC, under Contract Number DEAC05-00OR22725 with the US Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jobe.2023.105977.

This excel workbook contains all building parameter tables used for generation of building energy models.

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