Towards the Application of Uncertainty Analysis in Architectural Design Decision-Making

A Probabilistic Model and Applications

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To this day, proper handling of uncertainties -including unknown variables in primary stages of a design, an actual climate data, occupants` behavior, and degradation of material properties over the time- remains as a primary challenge in an architectural design decision-making process. For many years, conventional methods based on the architects' intuition have been used as a standard approach dealing with uncertainties and estimating the resulting errors. However, with buildings reaching great complexity in both their design and material selections, conventional approaches come short to account for ever-existing but unpredictable uncertainties and prove incapable of meeting the growing demand for precise and reliable predictions. This study aims to develop a probability-based framework and associated prototypes to employ uncertainty analysis and sensitivity analysis in architectural design decision-making. The current research explores an advanced physical model for thermal energy exchange characteristics of a hypothetical building and uses it as a test case to demonstrate the proposed probability-based analysis framework. The proposed framework provides a means to employ uncertainty and sensitivity analysis to improve reliability and effectiveness in a buildings design decision-making process.

Keywords: *Probability-based design decision, uncertainty analysis, sensitivity analysis, building energy consumption model*

INTRODUCTION

The preliminary stage of a building design process begins with a significant number of unknown variables. For instance, the exterior and interior conditions and the building design and construction are not known but estimated (Struck, 2012). Hence, building performance analysis will not be entirely reliable and robust at the early phase of a design. Research shows that the building design process is not immune to uncertainties even in later stages of design (Hopfe, 2009). Also, unexpected climate changes, users' behavior, and variations in material properties may deviate from the initial estimations and significantly impact the architectural, structural, or facility design. A slight change in the building properties may affect heating/cooling loads, thus altering the size of ductwork and building structure weight (MacDonald, 2002).

Building performance simulation (BPS) tools have been extensively used by the architects and engineers to simulate building performance. These tools rely on a wide range of input parameters that commonly come with outstanding uncertainties (Ding et al., 2015). In particular, energy simulation tools require inputs including the weather data, building construction thermodynamic properties, heating, cooling and air conditioning (HVAC) system specifications and space schedules to perform building performance analysis (Tian, 2013). The majority of these input parameters are subjected to significant alterations during the construction process or even later as a building is at use.

Uncertainty analysis (UA) is a critical aspect in all stages of building design, especially engineering design process. Probabilistic building performance analysis versus deterministic models will improve design decision-making process with quantifying uncertainties and determining the range of probability distribution. The sensitivity analysis (SA) methods, such as parameter screening and variance-based methods, will facilitate the UA process by ordering input parameters based on their significance and make simplifications possible (Hopfe, 2009). The SA/UA methods integrated into design decision making process act to support the architects with providing more reliable information.

The BPS tools, coupled with SA/UA techniques, deliver a design framework that leads to a more effective and reliable decision-making process. This paper introduces a framework to incorporate probabilistic models into the building design decision-making, demonstrated by a design case for improving energy efficiency. The ultimate goal of this research is to tackle data uncertainties in architectural design decision-making with a design framework, capable of being adopted for the other aspects of design decision-making including single and multi-objective design optimization problems.

BACKGROUND

Sensitivity Analysis and Uncertainty Analysis

A building design decision-making is a complicated process, as the design search space of possible solutions is vast. Several optimization methods are used to help the decision makers overcome the intricacies and select the optimum design option. The genetic algorithm is widely applied in building design tools to automate the design optimization process (Asl, et al., 2015; Lim et al., 2018). Such an optimization process requires setting the right sensitivity for each design variable, to reduce the computational process cost and time. The sensitivity analysis (SA) will contribute to finding the most significant input variables and limiting the design search space.

The SA methods applied in building performance analysis can be categorized into two groups of local and global (Delgarm, et al., 2018; Tian, 2013). Tian (2013) conducts a review of SA methods in building energy analysis and suggests a workflow for performing SA in building energy analyses. The first step in this process is a determination for the probability distribution of input variables. Next is to create a model for energy usage based on input variables. After collecting simulation results, an SA will be conducted, and the results will be presented.

Uncertainty analysis (UA) is widely used in other fields of study, such as structural reliability, risk analysis, forecasting, and calibration (Aghababaei & Mahsuli, 2018; Saltelli et al., 2004). Learning from these fields, the domain of architectural design decision-making will benefit from SA techniques along with UA methods for increasing reliability and robustness of the model, reducing complexity and improving building performance.

METHODOLOGY

Sensitivity and Uncertainty Analysis in Design Decision-Making

Several deterministic and non-deterministic decision- making approaches such as Simple Multi-attribute Rating Technique (SMART), Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) are discussed by Hopfe (2009). The AHP protocol is a classical method widely used in decision-making. The present research extends the AHP decision-making protocol by using variance-based SA and UA methods. The integration of AHP with SA/UA techniques will support the design decision makers with quantifying the effects of input changes on the output variation. As a result, design decision makers will be able to select the final design alternative, based on the more precise information. Figure 1 illustrates the framework proposed in this paper for supporting design decision making. This framework suggests integrating engineering SA and UA into an architectural design decision-making process.

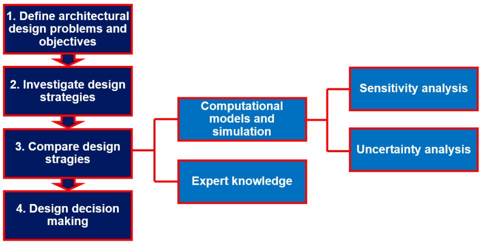


Figure 1
Proposed framework to employ uncertainty and sensitivity analysis in architectural design decision making.

Architectural design decision-making begins with identifying design problems and objectives. It sets boundaries for the designer's potential problem-solving methods. The next two steps in the design decision-making process, are investigating and comparing possible design strategies. The architects can select the ultimate design solution utilizing computational methods to get valuable insight into the building performance. Using the computer power allows the architects to explore a broader range of solutions more efficiently. SA and UA methods implemented in architectural models will highlight the most effective design parameters and support an informed design decision-making process.

Sensitivity and Uncertainty Analysis in Energy Efficient Building Design

Buildings use a significant amount of energy for cooling and heating, along with providing domestic hot water and artificial lighting (Asadi et al., 2012). The physical changes to a building such as improving the thermal performance of the building envelope and the use of advanced technologies can affect buildings' heat gain and heat loss (Ahn et al., 2015). Other changes including the air infiltration rate and modifications made to the building occupancy, lighting or equipment schedules that are defined as design and scenario modifications, can affect the building energy consumption (Hopfe, 2009).

The physical, design and scenario-related parameters can be categorized based on the level of building design development (LOD). The LOD 100 is about generic decisions, e.g., the orientation and layout of the building. The LOD 200 includes the decisions about sizes and quantities. More detailed design parameters such as the material properties are determined in LOD 300, and so on.

Design variables in every level of project development have a high impact on the building performance. According to Delgarm, et al. (2018) and Lim, et al. (2015), the building orientation (LOD 100) affects the amount of solar heat gain and building energy use intensity (EUI). Also, variations in thermodynamic properties of envelope materials (LOD 300) show a considerable influence on the thermal energy exchange of buildings (Lim et al., 2018). This paper focuses on LOD 300, to reduce a building envelope heat exchange as a case study. Figure 2 depicts the application of the proposed SA and UA framework for energy efficient building design, an example of implementing the proposed framework for design decision making. In this study reducing heat transfer through the envelope is the primary design strategy to achieve higher energy efficiency. The decision makers finally do design decision-making based on the information obtained through this process.

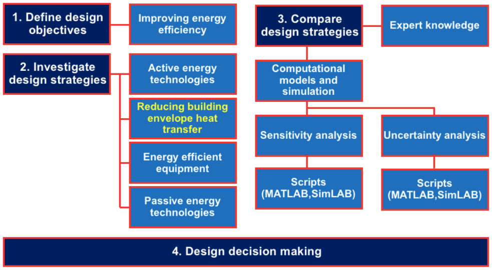


Figure 2
Application of proposed SA and UA framework for energy efficient building design.

ANALYSIS

As the prior model details, the proposed framework employs sensitivity and uncertainty analysis to assist architects in a building design decision making process. To demonstrate the application of the proposed framework, a case is performed to evaluate the importance of building material properties on the heating/cooling energy consumption over a period of one year. To this end, a building heat exchange model is developed and acts to predict heating/cooling energy load based on building design and material selections. The following is the description of a building heat exchange model as well as sensitivity and uncertainty analysis.

Building thermal energy exchange model

The present section follows an approach used by Bengea et al. (2011) and Neill et al. (2010) to obtain a model for building heat exchange in a state-space form. This model is selected, as it is simple and better for implementing SA and UA techniques, compared to EnergyPlus and other existing energy simulation tools. A building, regardless of its number of rooms or floors, divides into three types of elements: interior spaces, exterior spaces, and thermal barriers. Exterior spaces consist of any area where its temperature is directly set with external sources. The temperature of all exterior spaces, "outside temperature" is assumed identical and equal to weather temperature. During the analysis, outside temperature is treated as a disturbance signal in the system. Thermal barriers include walls, windows, floor, and ceiling; now all referred to as envelope for convenience. Any space separated from exterior spaces with thermal barriers is interior space. The model assumes the air inside a room is perfectly mixed and uses a single-value time-dependent variable to represent room air temperature. Figure 3 depicts a schematic view of a thermal network in a single room with the definition of variables. Q_C and Q_D represents the HVAC heat load and disturbance heat load into a room, respectively.

The room temperature *TR* is determined by the rate of heat convection between the air and surrounding walls' surfaces, a controllable HVAC heat load to a room, and any disturbance heat load generated by people occupants and electrical devices. A model for heat convection resistance is shown below:

$$R_H = \frac{1}{A_w \cdot h_w} \quad (1)$$

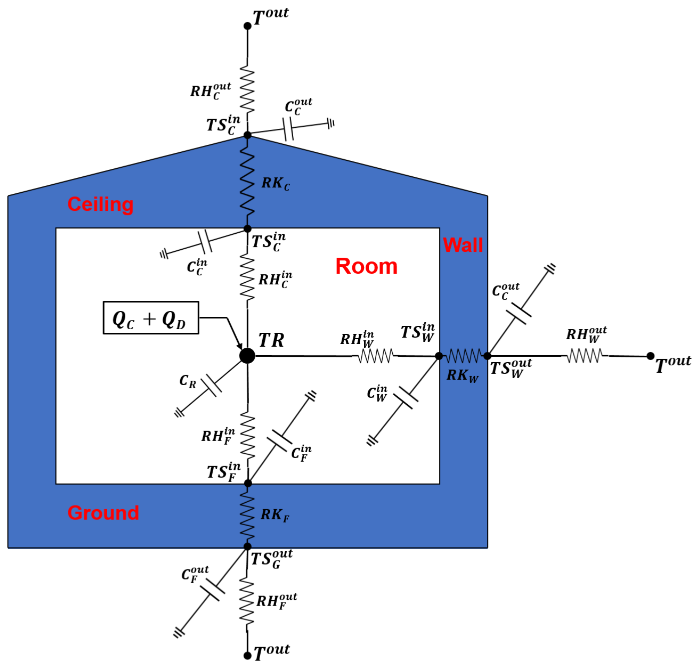
where A_w is wall area, and h_w is a heat convection coefficient. Hence, for a room surrounded by n walls (including floor and ceiling), the equation governing room temperature is,

$$C_R \frac{\partial TR}{\partial t} = Q_D + Q_C + \sum_{i=1}^{n} \frac{TS_i - TR}{R_H} \quad (2)$$

where, C_R is a heat capacity of the air inside a room, a function of air volume, density, and specific heat capacity.

A wall surface temperature TS is determined by the heat convection to the air and also the heat conduction across its thickness. A heat conduction resistance is,

Figure 3
Thermal energy exchange network model for one room in a building.



Variables

C_R	**Air heat capacity**	RH	**Surface heat convection resistance**
C_W	**Wall surface heat capacity**	RK	**Wall heat conduction resistance**
Q_C	**HVAC heat load**	TR	**Room air temperature**
Q_D	**Disturbance heat load**	TS	**Surface temperature**
		T^{out}	**Outside temperature**

$$R\kappa = \frac{t_w}{A_w \kappa_w} \tag{3}$$

where t_w is a wall thickness, and κ_w is a heat conduction coefficient.

In practice, equations for dynamical states $\{T\}$, including all rooms temperature and walls' surface temperature, are derived and manipulated into a matrix form. Hence, the state-space model for building thermal energy exchange network is,

$$\left\{\frac{\partial T}{\partial t}\right\} = [A]\{T\} + [B]\{U_D\} + [C]\{U_C\} \tag{4}$$

where matrices $[A]$, $[B]$, and $[C]$ are functions of building physical dimensions and material properties, assumed to be independent of temperature. $\{U_D\}$ includes disturbance heat generated in the building and outside temperature signals. $\{U_C\}$ is the controllable heat delivered to the building based on closed loop multiple-input and multiple-output proportional-integral-derivative (PID) controller . The inputs are the room temperature, and the controller decides on a load of energy supplied to each room.

Validation of the Building Thermal Energy Exchange Model

Predictions for heating and cooling energy consumption are compared against those delivered from a popular building performance simulation (BPS) software tool, i.e., OpenStudio, to verify the accuracy of the current building thermal energy exchange model. Heating/cooling load predictions are obtained for a five-room one-floor building with 40 m. in length, 20 m. in width, 3 m. in height, and with 4.57 m. in the perimeter zone depth. Each room is defined as one thermal zone. See Figure 4 for a schematic view of the building. The building is assumed to be located in College Station city, Texas, USA and 2015 is selected for the year of simulations. The typical weather files obtained from the EnergyPlus website is used in this simulation.

This model assumes that the building is on the ground and thermal energy exchange happens between the building and the ground as well as the outside air. The interior heat gain sources such as people, lighting, and equipment are eliminated from the simulation, and thermal energy exchange through the envelope is the only focus of simulation. A single-duct VAV system with reheat is assumed as the HVAC system used for this building.

Figure 5 shows predictions for the monthly heating (a) and cooling (b) energy consumption from the current model against OpenStudio simulations for the year 2015. Both heating and cooling energy loads show a good agreement with OpenStudio simulations. OpenStudio predicts some cooling load, even for the coldest months of the year (December-February). This cooling load is used for the air condition purposes. However, the energy used for air conditioning is not the focus of this study and is not included in the model. This note explains the minor discrepancies between the current model predictions and OpenStudio simulations in the cooling load. The total heating and cooling energy consumption delivered by the current model for the entire 2015 year differs less than 5% from OpenStudio simulations.

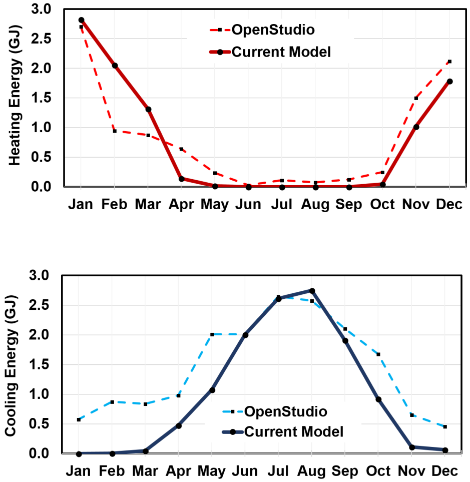


Figure 5
Comparison of the predicted monthly heating and cooling energy consumption against OpenStudio simulations for a five-room building. (2015 year)

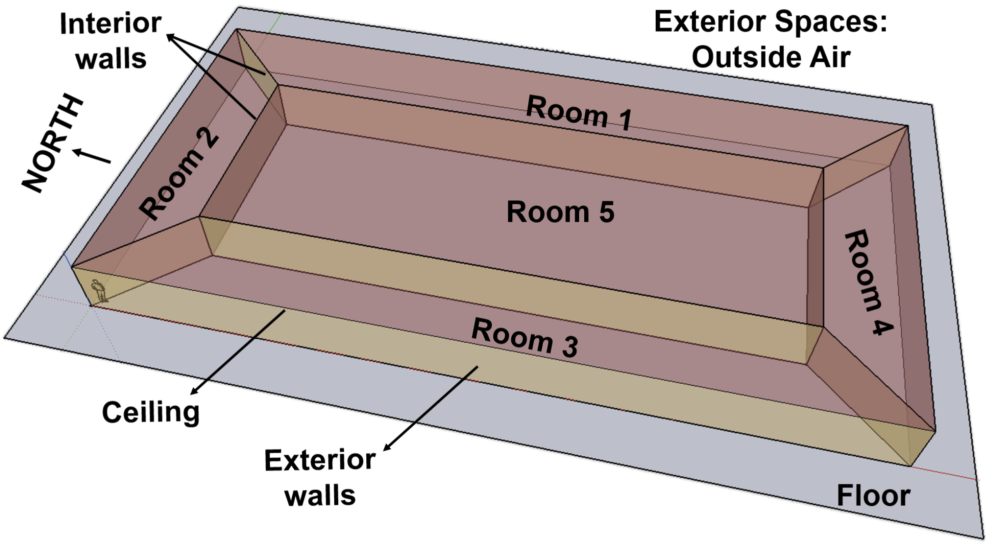
Sensitivity and Uncertainty Analysis Techniques

During the analysis, the building material thermodynamic properties are considered as the input variables x_i and heating/cooling energy consumptions as the cost function Y, hereby written as,

$$Y = f(x_1, x_2, \ldots, x_m) \tag{5}$$

where m shows the total number of input parameters. The input probability distribution of building materials is set as normal or Gaussian since the variations take place due to unpredictable changes during construction, climate change, age, and maintenance. Input parameters, if not assumed fixed, are defined with a mean value and a range of deviation from the mean value. The SA investigates the contribution of each input variable to the uncertainty in model output. To this end, the SA perturbs input parameters concerning the mean values and monitors the variations in the cost function. Perturbations of an effective input variable are followed by a significant change in the cost function while parameters with insignificant role result in marginal changes. For nonlinear functions with a large number of in-

Figure 4
Schematic view of five-room one-floor building with 40 m in length and 20 m width.



put variables, SA is a relatively complicated procedure and involves extensive computational volume. In case of stochastic input variables, variance-based methods have been more effective and reliable compared to other various sensitivity analysis methods. The present study refers to a variance-based method detailed by Jansen et al. (1994) and Jansen (1999).

Later, an uncertainty analysis predicts a mean value and a range of deviation for the cost functions using the mean values (μ) and deviations (σ) defined for the input variables. The UA also determines a probability distribution over the predicted range for the cost function.

RESULTS

The variables studied in this research are heat convection coefficient (h), heat conduction (λ), specific heat capacity (cp) and density (ρ), of 22 building elements. These elements, including interior walls, and envelope are all made of the concrete material, with varying thickness for different elements. The properties of concrete in the interior walls are different from the building envelope.

The mean values (μ) and deviations (σ) for the input variables, shown in Table 1 are extracted from previous research done by Hopfe (2009) and MacDonald (2002). The Jensen method was applied to 1000 different simulations and obtained the results shown in Figure 6. The total number of uncertain parameters studied here is 88, and they are all thermodynamic properties of the building envelope and interior walls. The uncertainties of the heat convection coefficient and the heat conduction of the floors contribute the most to the variation of building EUI. The changes of the heat convection coefficient and the heat conduction of the ceilings are the next, followed by the exterior walls. The contribution of other input variables is insignificant. For instance, the density and the specific heat capacity of the interior walls have almost no effect on the building EUI. These two parameters may be critical in occupants' thermal comfort analysis since they affect the time response of the structure. However, they do not have a notable effect on the building EUI.

Table 1
Building material properties: heat convection coefficient (h), heat conduction (λ), specific heat capacity (cp). and density (ρ).

Material (Concrete) Properties	Convection U (W/m²K)		Conduction λ (W/mK)		Density ρ (kg/m³)		Heat Capacity Cp (J/kg K)	
	μ	σ	μ	σ	μ	σ	μ	σ
Interior Walls	15	1.5	0.53	0.048	1280	19.2	840	89.04
Exterior Walls	15	1.5	1.729	0.156	2243	33.64	837	88.72
Ceiling	15	1.5	1.729	0.156	2243	33.64	837	88.72
Ground	15	1.5	1.729	0.156	2243	33.64	837	88.72

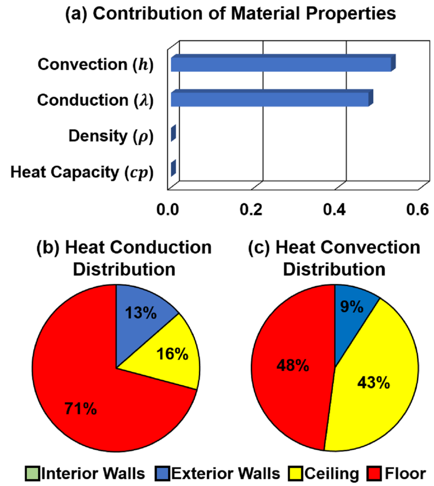


Figure 6
The result of the sensitivity analysis for building EUI.

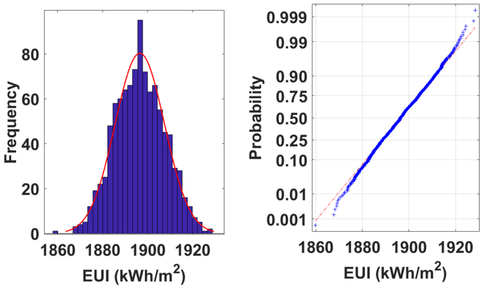


Figure 7
Frequency distribution and normality plot of the building EUI (considering the heat convection and the heat conduction)

Figure 6 (a) illustrates the contribution of four main variables to the output variations. A higher value in this chart shows a more significant parameter. The convection coefficient with about 0.52 has the most contribution to the amount of building EUI. The heat conduction is the next with a value of about 0.47. The specific heat capacity and density with a value of about 0.01, have the least contribution to the amount of building EUI.

The analysis in Figure 6 (b,c) shows that among all building elements in this paper, the floors are the most significant regarding thermal energy exchange. About 71% of the building EUI variation is caused by the uncertainties in heat conduction of the floors, and 48% of the EUI uncertainties happens due to changes in the convection coefficient of the floors.

The uncertainties of the heat convection coefficient and the heat conduction coefficient of the ceilings are the second most important variables with 16% and 43% of contribution to the building EUI. The percentage of effectiveness of the heat convection coefficient and the heat conduction coefficient of exterior walls are 13% and 9%, respectively. The interior walls have less than 1% contribution in both the heat conduction and the heat convection.

The uncertainty analysis in this research shows the effects of variations of material properties on the building EUI uncertainties with 1000 iterations done. Figure 7 illustrates the UA result in this study. The analysis describes the probabilistic distribution of the building EUI, using the mean values and deviations defined for the input variables.

The analysis in Figure 7 shows that the probability of 1900 kWh/m^2 of EUI for this model is the highest-probable result. As the normality plot in Figure 7 shows, the distribution of the output is Normal and falls in the range of 1860 kWh/m^2 and 1930 kWh/m^2. It should be noted that the only parameters considered in the UA, are the heat convection coefficient and the heat conduction coefficient, due to the findings from the SA process. Finding the most effective design parameters by SA and discarding the other parameters from the simulation makes the UA process more accessible and less time intensive.

DISCUSSION AND CONCLUSION

The lessons learned from general engineering SA and UA, such as the simple case study described above, can be applied in architectural design decision-making. The proposed framework is implemented in our Excel interface with a user-friendly environment. Meanwhile, the SA and UA are programmed in Fortran, to be integrated into Excel background. The architects will find it easy to move along the tabs in the Excel interface to submit the building properties required for the analysis. By running the analysis, this framework provides the sensitivity analysis and probability distribution of results associated with different design scenarios. The program produces all these scenarios randomly and based on the user's initial input.

The proposed framework is demonstrated in a case of building EUI analysis. The result of this case is discussed in previous sections. Extending this framework to various aspects of architectural design will lead to a lower level of complexity in design decision-making and higher efficiency and reliability. The SA and UA methods integrated with architectural design will simplify complex design problems and allow the architects to make more robust and practical design decisions. This SA/UA framework will enable the architects to understand the significance of each input parameter and the range of the output variations. This framework is capable of supporting the architects in making informed decisions for single and multi-objective design optimization problems.

Further research will be conducted in solving multi-objective design optimization problems. As an example, this SA/UA framework can be implemented in multi-objective design optimization problems such as aviation facility planning. It will support the architects to design more efficient ticketing halls based on the probability distribution of different passenger flow situations. The uncertainty of the number of passengers in the ticketing halls in different times will be analyzed to allow the architects to test different design scenarios. Multiple objectives such as minimizing travel distance, maximizing usable area, minimizing construction and operational cost among others can be taken into consideration. For multi-objective design problems, like this case, a weighting system could be applied to determine the level of importance for each objective. The architect should be able to assign the level of significance for each objective based on the project's requirements.

This framework can also be applied in adaptive façade design process. The uncertainties of external environment such as weather data or internal environment such as occupants' behavior, make the adaptive façade design challenging. Further research in adopting this framework to identify the most significant input variables in adaptive façade design is valuable.

Development of Building Information Modelling (BIM) tools allows modeling complicated building models, transferring data from design tools to analysis tools and searching a considerable design space to find the best possible design options. The SA and UA related data may also be modeled inside the Building Information Models (BIMs) as parameters with appropriate probability distributions to facilitate more reliable simulation and optimization to accommodate the future changes during the design-construction-operation processes.

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