A case study for sensitivity-based building energy optimization

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ABSTRACT: Building design optimization process is associated with uncertainties due to climate change, unpredictable occupant behavior, and physical degradation of building material over time. The inherent uncertainties in the design process reduce the reliability and robustness of the optimal design solution(s) and affect design decision-making results. This research studies the capabilities of parametric design tools in adopting probabilistic methods to handle uncertainties in building performance optimization. Variance-based methods, e.g., Monte Carlo sensitivity analyses are implemented to identify the most critical parameters in design optimization problems and improve the efficiency of design optimization. The optimal solutions achieved with variance-based methods are satisfying the design objectives more efficiently, also remain robust to changes and uncertainties.

KEYWORDS: Building design optimization; Variance-based methods; Parametric design; Sensitivity analysis; Monte Carlo;

INTRODUCTION

The building design process includes making important decisions about different issues such as building orientation, form, layout, Window-to-Wall Ratio (WWR), and material properties (Lim et al., 2015). Building design decision-making is essentially solving multi-criteria optimization problems (Rahmani Asl et al., 2015). Building performance simulation tools can be useful in the design optimization process to evaluate design options. Refs. (Attia, 2011; Attia et al., 2012) compare several building performance simulation tools and introduce the potentials and challenges of each one in solving design problems.

Parametric modeling and simulation platforms, e.g., Grasshopper facilitate the optimization process in architectural design (Touloupaki & Theodosiou, 2017). Multiple optimization methods using heuristic algorithms such as Genetic Algorithm (GA) and Simulated Annealing (SA), along with model-based optimization algorithms such as Gutmann and MSRSM (Wortmann, 2017), are developed in Grasshopper to solve architectural design problems. On the other hand, a typical building design optimization process using these tools is time-intensive, ignores the uncertainties, and lacks a systematic framework to incorporate expert knowledge. The absence of efficiency and the lack of a systematic approach for considering uncertainties and integrating expert knowledge necessitates the development of a new approach to building design optimization.

This paper aims to investigate the integration of probabilistic strategies with simulation-based optimization process to handle the uncertainties and improve the reliability and efficiency of architectural design decision-making. This paper examines the capabilities of visual programming interfaces, available in parametric tools, e.g., Grasshopper to handle uncertainties in building performance analysis and apply variance-based techniques to enhance the efficiency of building design optimization process. The Genetic Algorithm (GA) that is the most popular optimization algorithm in architectural optimization and variance-based methods such as Monte Carlo sensitivity analysis with random sampling are deployed to develop a probability-based optimization framework for parametric design decision-making. A test case of building thermal energy consumption analysis is presented to demonstrate the application of the proposed framework.

1.0 BACKGROUND

1.1. Uncertainties in building design optimization

The optimization process under uncertainty is one of the main challenges in performance-based building design (Evins, 2013; Kheiri, 2018; Nguyen et al., 2014; Shi et al., 2016). Solving this type of optimization problems with deterministic approaches leads to overestimation of design requirements and thus, inefficient design optimal solutions (Grille et al., 2017). Non-deterministic methods including variance-based methods are capable of improving the efficiency of building design decision-making (Hopfe et al., 2013).

Two main types of uncertainty sources in building performance optimization are known as epistemic and aleatoric uncertainties (Hopfe, 2009). The epistemic uncertainties, e.g., the thermal properties of building material exist due to measurement errors or model simplifications. Aleatoric uncertainties are unknown parameters that depend on other factors such as weather conditions and occupant behavior, and thus are irreducible (Grille et al., 2017).

Variance-based methods are the most commonly used approaches to handle uncertainties in building performance analysis (Tian et al., 2018). The variance-based methods such as Monte Carlo use random variables and input probability density functions to address the stochastic status of the problem. The applications of these methods in building performance analysis have been broadly studied (Bordbari et al., 2018; Ding et al., 2015; Hopfe, 2009; Hopfe et al., 2012; Lee et al., 2013; MacDonald, 2002; Rezaee et al., 2018; Shahsavari et al., 2018; Struck, 2012; Tian et al., 2018).

Various tools including MATLAB, Simlab, and jEPlus have been widely used in uncertainty and sensitivity analysis for building performance analysis (Tian et al., 2018). The integration of these probabilistic methods with parametric tools such as Grasshopper has not been fully covered, yet. This research intends to apply variance-based methods such as Monte Carlo sensitivity analysis in the design optimization process. The integration of variance-based methods with simulation-based optimization process enables designers to eliminate those input variables with a small effect from the optimization setting, and thus leads to a more efficient optimization process (Evins et al., 2012).

1.2. Sensitivity analysis in building design optimization

As (Saltelli et al., 2010) state, variance-based methods, e.g., Monte Carlo approaches, have shown more effectiveness and reliability when working with stochastic variables. Thus, this paper performs a sensitivity analysis based on the Monte Carlo approach. The following is a brief mathematical description of the Monte Carlo method for dealing with input uncertainties and sensitivity analysis.

Let a mathematical modeling $Y = f(X)$ define correlations between a vector of one-dimensional (1D) input variables $X = \{X_1, X_2, \ldots, X_k\}$ and an output (Y), where (f) is a deterministic integrable function which translates from a k-D space into a 1-D one, i.e., $R^K \to R$. The model produces a single scalar output Y when all input variables are deterministic scalars. However, if some inputs are uncertain or undecided, the output (Y) will also associate with some uncertainties. An input variable X_i is defined by a mean value μ_i, a variance σ_i, and a probability distribution, such as normal, uniform, etc. In the Monte Carlo methods, N sets of samples from possible values of each input variable are generated. These input values are fed into the simulation model to generate the probability distribution of the output (Y). Processing the output range (Y) delivers a mean value and a frequency distribution for the output. A sensitivity analysis further investigates into the contribution of each input variable on the total variations of the model output.

This paper details predictions for sensitivity index S_{Ti} , the total effect coefficient. The calculation of the sensitivity index S_{Ti} requires sampling sequences and estimators to act upon a single set of simulations and compute the sensitivity indices for all input variables (Saltelli et al., 2010). In this research, the Monte Carlo uncertainty analysis, random sampling technique, and the Jansen indices have proved applicable. Equation (1) indicates S_{Ti} calculation (Saltelli et al., 2010):

$$S_{Ti} = \frac{\frac{1}{2N}\sum_{j=1}^{N}\left(f(A)_j - f\left(A_B^{(i)}\right)_j\right)^2}{Var(Y)} \quad (1)$$

Note that A and B are two independent matrices of N samples (and thus N values) of k input variables, that are generated with normal distribution using the mean and standard deviation of each input variable. $f(A)_j$ denotes an output based on input values from the j[th] row of matrix A. $f\left(A_B^{(i)}\right)_j$ denotes an output based on input values from the j[th] row of the matrix $A_B^{(i)}$, which represents a matrix with all columns from matrix A except column i, which comes from matrix B. $Var(Y)$ is the output variance, having all input variables form matrix A.

2.0. A PROBABILISTIC FRAMEWORK FOR PARAMETRIC DESIGN OPTIMIZATION

2.1. Variance-based methods in parametric building design

Building design decision-making includes multi-objective optimization problems, dealing with financial, physical, functional, aesthetical, and performance-related concerns. This process requires a systematic workflow to meet the design requirements efficiently. This research focuses on performance-based building design including building energy consumption analysis. Figure 1 illustrates a general workflow of building design decision-making followed in this research.

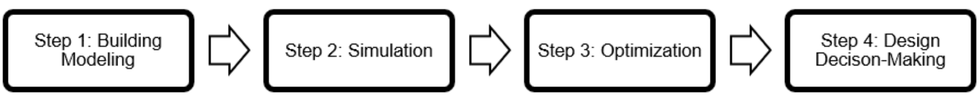

Figure 13. A general architectural design decision-making process

This research builds upon the optimization framework introduced in (Nguyen et al., 2014) to investigate the application of variance-based techniques in parametric building design decision-making. Nguyen et al., (2014) subdivide a generic simulation-based optimization process into three phases: 1- preprocessing, 2- optimization, and 3- post-processing. Modeling the building to be optimized, defining the optimization problem, selecting the input variables, objective functions and constraints, are the major tasks in the preprocessing phase. Integrating the variance-based methods with design optimization is an optional task in the preprocessing phase. In this research, the variance-based methods are deployed for sensitivity analysis to identify the key input parameters. The next phase is the optimization, and the important role of a designer in this phase is fixing the potential errors and keeping the optimization process running. The post-processing phase includes analyzing the optimization results and presenting the data by charts and graphs, e.g., scatter plots.

The Genetic Algorithm (GA) is applied for optimization in this research. The GA process imitates the natural genetic evolution and requires preparation, consisting of input chromosome generations, setting the objective function, and defining the constraints (Lim et al., 2018). The optimization begins with the first generation of design inputs, and the performance of different combinations of design inputs is compared. The fittest combinations remain in the next generation, and the weakest combinations are removed. The remaining chromosomes create new combinations through the cross over and mutation. The GA selects the fittest combinations, and this process goes on until there is no better solution found (Nguyen et al., 2014).

Sensitivity analysis with the variance-based techniques guides the search for the optimal solution and improves the efficiency of the optimization process in two ways. First, designers can use the sensitivity analysis results to find input parameters with the highest impact on the output and adjust the optimization input parameters, accordingly. Second, the probability distribution of the values of input parameters, that are generated based on the expert knowledge or previous research, can be used as a source of input selection in the mutation and cross-over processes of the GA optimization. These two applications of sensitivity analysis in design optimization will lead to more reliable optimization results since the optimization is based on expert knowledge and probabilities.

This research deploys Rhino and Grasshopper to illustrate the benefits of sensitivity analysis in building design optimization. Ladybug and Honeybee, the two plugins available in Grasshopper are used to upload the weather data, prepare building model, and run the energy analysis with EnergyPlus (Toutou et al. , 2018). The model preparation with these energy modeling plugins in Grasshopper includes creating thermal zones from masses and surfaces, followed by solving space adjacencies, setting the WWR for each façade, material selection, and adjusting occupants, lighting, and equipment schedules (Figure 2).

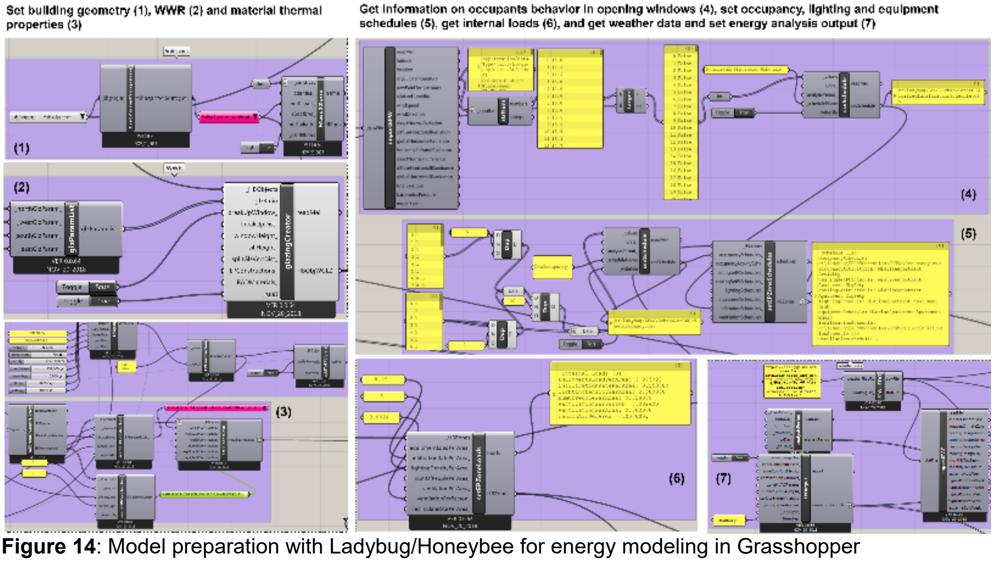

Figure 14: Model preparation with Ladybug/Honeybee for energy modeling in Grasshopper

After preparing the building model, energy analysis simulation is executed using the Honeybee energy analysis component in Grasshopper. The user defines the timeframe for energy analysis, and the weather data is imported from the EnergyPlus website.

CPython component in Grasshopper is used to import statistical tools such as Numpy and Scipy into Grasshopper. The CPython also enables the designers to present statistical results in Grasshopper by charts and graphs (Abdel Rahman, 2018). To conduct optimization, Galapagos is applied for a single-objective design problem such as thermal energy consumption analysis. Figure 3 illustrates the proposed optimization framework with probabilistic techniques, that includes the addition of sensitivity analysis to guide designers in input selection for optimization.

The proposed optimization process with parametric tools, e.g., Rhino and Grasshopper begins with creating the building model. The initial input variables are selected based on the needs and requirements of the design project. The input parameters along with design constraints and design objective functions define the optimization setting. A normal distribution of all input variables is generated with *N* number of values (defined by the user), using the mean and standard deviation (MacDonald, 2002). The lists of input variables are connected to the simulation engine, e.g., Energy Plus and the outputs of each simulation run are recorded for later comparisons.

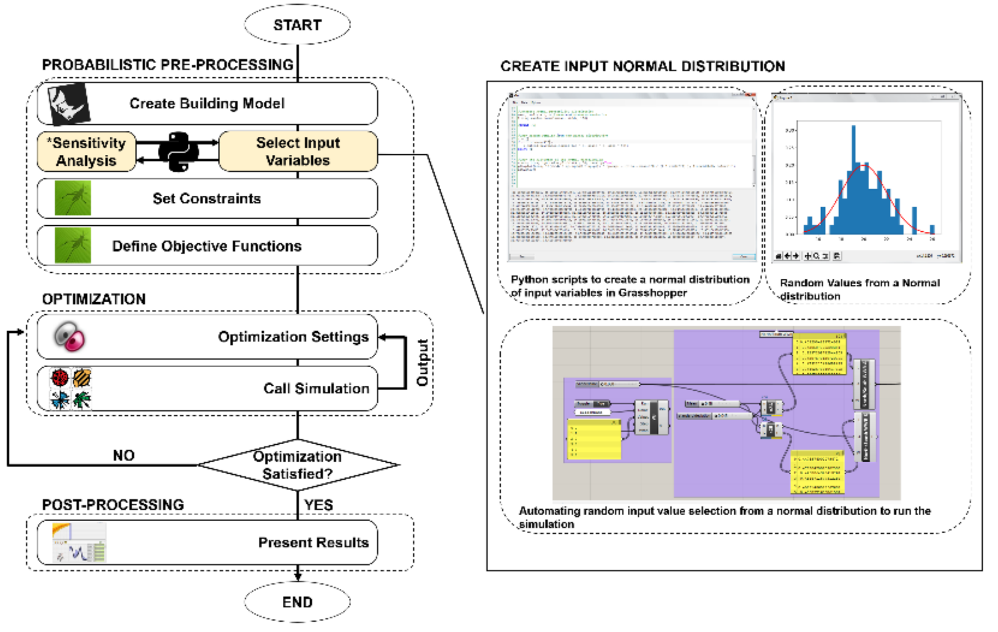

Figure 15: Sensitivity-based building design optimization

The simulation model is executed repeatedly using the samples of input parameters. To automate the random value selection for each input and run EnergyPlus for *N* times, a number slider, that is remotely controlled ("Grasshopper3D", 2017), is connected to the list of input variables and selects a random index of each list automatically and feeds the associated input value to the simulation. The simulation runs through all the input values, and the results are used in further calculations to identify the sensitivity index of each input parameter. In this proposed method, the sensitivity indices associated with each input parameter is calculated through sensitivity analysis techniques, and the input variables with higher impact on the output will remain in the optimization process. Figure 4 shows the implementation of variance-based methods for sensitivity analysis in Grasshopper, using list management and CPython programming.

2.2. Test case results

A hypothetical five-zone building is modeled in Rhino/Grasshopper to demonstrate the application of the proposed probabilistic optimization framework. The Typical Meteorological year for College Station, Texas is imported from the EnergyPlus website ("EnergyPlus", 2018). The weather data and HVAC specifications are kept constant, while building material thermal properties including wall thermal conductivity, density, and specific heat capacity, along with WWR, and occupant behavior in the opening and closing windows, are varying. Figure 5 shows the 3-D model of this test case in Rhino/Grasshopper.

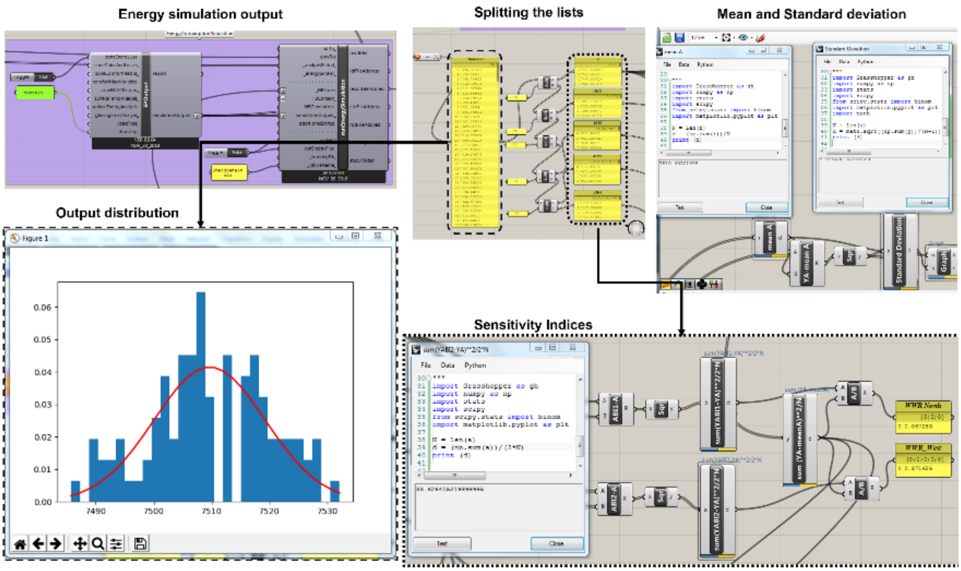

Figure 16: Get the probability distribution of the output and sensitivity indices of input variables

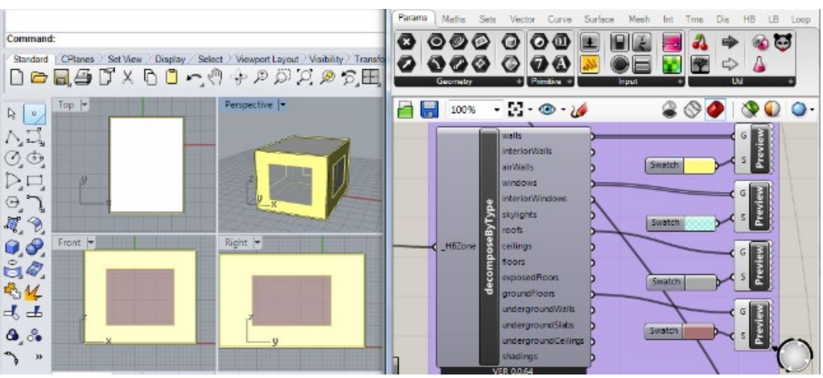

Figure 17: A hypothetical five-zone building model in Rhino/Grasshopper

Two random lists of values (list A with 100 samples and list B with 100 samples) for each input variable are generated. The mean and standard deviation values for the thermal properties of exterior walls are listed in Table 1.

The mean values of WWR for north, south, east, and west facades are 0.45, 0.45, 0.3, and 0.3, respectively. The WWR values are varied by 10% of their mean values. The occupant behavior in the opening and closing windows is defined based on the Outdoor Air Temperature (OAT) and is connected to the infiltration schedule. This variable is studied through the possibility of opening windows when the outdoor air temperature (OAT) reaches a certain point. For example, if OAT is larger than 20°C (with 0.2°C variation), the user will probably open the windows. This probability status is recorded through the year as zeros and ones (for opening and closing windows). This list of zeros and ones is saved as an Excel file, and the Excel file is linked to the infiltration schedule, which is used in the EnergyPlus analysis.
All the input variables are fed into the simulation to get the output, which is building annual heating/ cooling energy consumption. Sensitivity indices for input variables are calculated and presented to guide the user in selecting the most important input parameters to participate in design optimization. Figure 6 compares the sensitivity indices of the input variables in this study.

Table 3: The mean and standard deviation values for the thermal properties of exterior walls (MacDonald, 2002)

	Density ρ (kg/m^3)		Heat Capacity c_p (J/kgK)		Thermal Conductivity λ (W/mK)	
	μ	σ	μ	σ	μ	σ
Exterior Walls Thermal Properties	1900	28.5	1000	106	1.41	0.1269

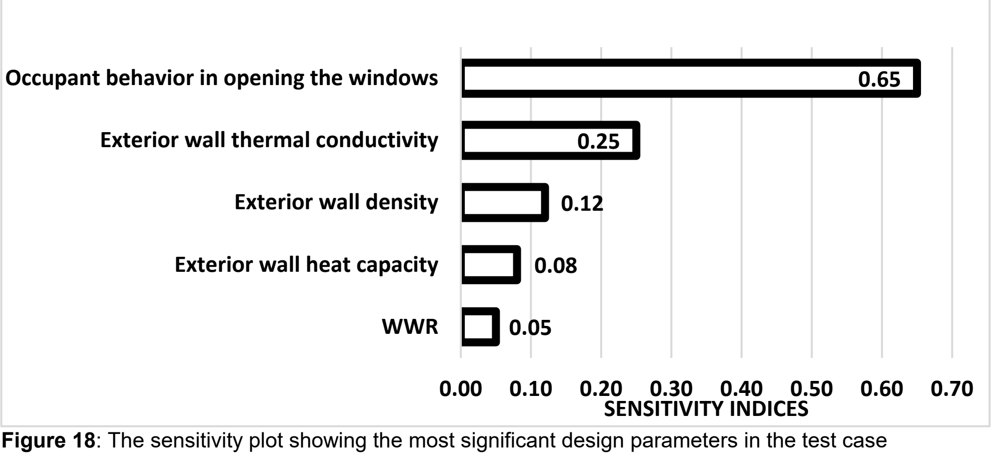

Figure 18: The sensitivity plot showing the most significant design parameters in the test case

The input variables with higher sensitivity indexes have a higher impact on the output. In this test case, the output is building annual heating/cooling energy consumption. The sensitivity analysis result shows that occupant behavior in the opening and closing windows is the most important parameter, compared to exterior wall thermal properties and WWR. Exterior wall thermal conductivity, density, and heat capacity are the next most impactful variables in this model. The WWR (sum of the sensitivity indices of WWR for four facades in this model) shows a small contribution to the output. The reason for this small sensitivity index of WWR is that the sensitivity index of a specific variable in a certain model is highly dependent on the sensitivity indices of other variables. It means that if a variable shows a significantly high index compared to the other variables, it will affect the values of sensitivity indices of the other variables (Saltelli et al., 2010). In this example, the occupant behavior shows much more significance than WWR, and it affects the sensitivity indices of WWR.

Considering the sensitivity analysis results, the list of input parameters for the optimization process is limited to the thermal properties of exterior walls. The effects of WWR on building energy consumption in this case study is negligible (Figure 6) and can be ignored in the optimization process. Also, the occupant behavior is excluded from this list, since it is an aleatoric uncertain variable which is dependent on many other factors. Figure 7 illustrates the input setting for this design optimization, also the optimization output.

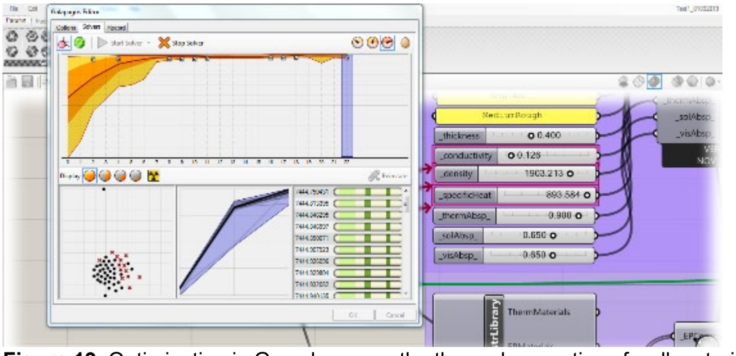

Figure 19: Optimization in Grasshopper – the thermal properties of wall material (highlighted in pink color) are varying to minimize building thermal energy consumption

DISCUSSION AND CONCLUSION

This research investigates the integration of sensitivity analysis into design optimization to improve the efficiency of parametric building design optimization. Since the sensitivity study helps to reduce the number of input variables, the optimization search space is reduced, which leads to less computing time than a conventional optimization process.

The occupant behavior is one of the most important uncertain design variables and understanding different patterns of occupant behavior and reflecting the effects of this parameter in building performance simulation requires further research. Also, further development of the proposed optimization framework may focus on using probability distributions of important input variables to search for the optimal solution. Choosing the input values for an optimization process out of a normal distribution allows searching for the optimal solutions considering their probability of occurrence. This method may improve the reliability of optimization results since the probability of occurrence of each design option is considered.

The conditional probability and Bayesian network are also promising fields of research related to probabilistic optimization. The Bayesian inference updates the prior belief, which is a starting point for the optimization, to a posterior outcome based on additional data and information. This method allows the integration of expert knowledge with design optimization and may improve the simulation-based optimization in architectural design decision-making.

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