Master's Thesis

# Uncertainty in Sensitivity of Building Design Variables by Building Usage Scenarios

# 건물 사용 시나리오에 따른 건물 설계변수 민감도의 불확실성

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# Uncertainty in Sensitivity of Building Design Variables by Building Usage Scenarios

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# Abstract

It is acknowledged that rational decision making at the design stage is important for energy efficient building design. In other words, the relationship between building energy use and design variables must be taken into account. For this purpose, the global sensitivity analysis (GSA) can be useful because GSA is a method to measure the unit change of a model's output against the unit change of the individual model input for the entire input space. With the use of GSA, important design variables can be identified.

However, sensitivity indices can be changed because of engineering assumptions for model's unknown parameters such as occupant density, equipment density, infiltration rate, etc. In general, these parameters are set as deterministic values based on analysts' subjective judgment, and it can be inferred that this subjectivity can cause uncertainty in GSA of the building energy model. With this in mind, the author proposes a sensitivity analysis process for building energy design variables considering the uncertainty of building use scenarios.

For this purpose, Sobol sensitivity analysis was performed on five design variables (wall U-value, fenestration SHGC, lighting power density, window U-value, window-wall ration) according to the assumptions of five building usage scenarios (occupant density, equipment density, infiltration, cooling and heating set-point temperatures). As a result, it was observed that uncertainty in the sensitivity of design variables were significant, also the sensitivity ranking between them could vary. This indicates that in order to reach rational decision making, the careful attention must be paid to selection of uncertain building usage scenarios, and sensitivity analysis must be based on stochastic approach.

**Keyword :** Building energy, Sensitivity analysis, Uncertainty analysis, Decision making

**Student Number :** 2019-23894

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# Chapter 1. Introduction

## 1.1. Background and objectives

Rational decision making at building design stage is of paramount importance for sustainable building energy saving throughout the building life cycle (Lechner, 2014). Meanwhile, as buildings and their systems within them are becoming more complex, required performance of occupants are also diversified (Hensen and Lamberts, 2012). That is, building design must be able to adequately reflect the complexity of the building systems and the uncertainties of the building usage scenarios.

Currently, prescriptive approach represented by building codes and regulations (e.g. Standard for Energy Saving Design of Building, G-SEED) are centric on decision making of building energy design (Park, 2006; Stein et al, 2006; Pati et al, 2006). This approach specifies the ‘means’ and ‘methods’ of design solution rather than the expected outcome of the solution. For example, there is an assessment process for each part of a building, which is defined the upper limit of the envelope insulation value by the belief that the lower the thermal transmittance of the envelope, the lower the building energy consumption (please see left part in Figure 1.1). However, it may not be effective in achieving required performance such as energy saving, because this approach cannot consider the interdependence between design variables and building performance (Park, 2006). For this reason, ‘performance-based approach’, which focuses on achieving objectives has drawn attention in building energy design (Park, 2006; NEN 1999; Foliente, 2000). In this approach, it is important to (1) derive influential factors corresponding to the building energy performance, and (2) quantify their importance for the building energy performance (Augenbroe, 2019). In other words, the introduction of scientific methods to quantify the factors’ importance is necessary, and sensitivity analysis can be a valuable tool.

In other words, it can be inferred that proper scientific methods to quantify the relationship between the design variables and the building energy performance will be introduced for making energy-saving design efficient. And for this purpose, the global sensitivity analysis (GSA) can be useful. GSA is a method to measure the unit change of a model’s output against the unit change of the individual model input for entire input space using simulation (Saltelli et al, 2008) and the important design variables can be identified for energy-efficient design of new buildings. In building energy domain, GSA has been widely used to explore the characteristics of building energy performance (Tian, 2013). The followings show the examples of where the GSA has been used in the building energy analysis.:

- Heiselberg et al. (2009) discussed that the sensitivity analysis plays an important role for derivating key design variable in sustainable building design.

- Hygh et al. (2012) argued that the influence of design variables on building energy consumption varies depending on the climate, and decision-making can vary.

- Yoo et al. (2020) used sensitivity analysis to improve energy performance indicators in South Korea, which resulted in improving the correlation between acquisition scores and energy consumption, and discussed that sensitivity analysis is helpful for objective building energy performance assessment.

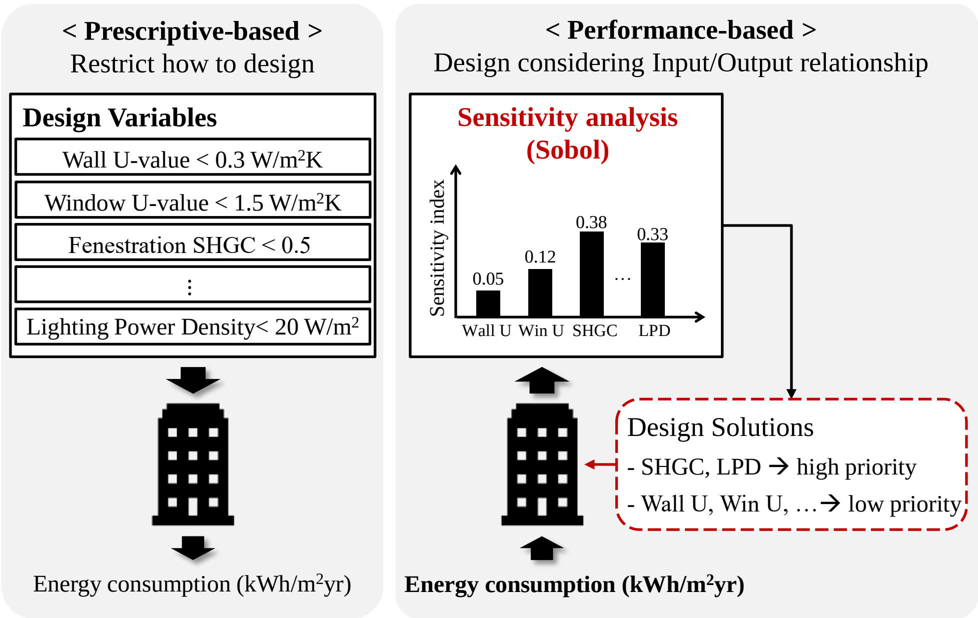


Figure 1.1 prescriptive approach vs. performance approach

However, despite making decisions using scientific methods in the building energy design stage, the results may vary depending on the subjective assumptions of the analyst. In particular, predicted results of energy consumption may vary depending on the building use scenarios during building life cycle applied (Hopfe, 2009). From this context, it can be inferred that results of the sensitivity analysis may also vary depending on how analyst assume model input variables (hereinafter referred to as building usage scenarios). Note that when performing the sensitivity analysis, the building usage scenarios are usually set as deterministic values based on the analyst's subjective assumption. Then, this may lead to an objectivity problem in which the analysis results change, despite targeting identical building and design variables. Therefore, uncertainty (or risk) in the sensitivity analysis must be considered for objective decision-making, which suggests that the sensitivity of the design variable must be represented as a stochastic form (i.e. probability distribution) rather than the deterministic values.

With this in mind, the author presents a sensitivity analysis process for building energy design variables considering the uncertainty in building usage scenarios assumptions. Also, the importance of the assumptions of the building usage scenarios in decision-making using sensitivity analysis is discussed. Through a case study, five design variables (wall U-value, fenestration SHGC, lighting power density, window U-value, window-wall ratio) are considered as the design variables to measure the sensitivity, and five building usage scenarios (occupant density, equipment density, infiltration rate, cooling/heating set-point temperature) are considered as the uncertain factors. In the sensitivity analysis, Sobol method is utilized, and uncertainty propagation of building usage scenarios is based on the Monte Carlo simulation implemented by Latin hypercube sampling. The results of the case study show that the sensitivity index and sensitivity ranking among design variables may vary depending on the assumption of building usage scenarios. The author suggests that the sensitivity analysis and the uncertainty quantification must be combined to make objective decisions in building energy design.

## 1.2. Research Process

In this paper, the author will show the uncertainty in sensitivity of design variables according to assumptions of building usage scenarios. For this purpose, an EnergyPlus reference building provided by the US DOE, was used as a target building. The case study is conducted as the following steps (please see Figure 1.2):

- Step 1: Select design variables and building usage scenarios. Design variables, the main passive design factor, are considered as (1) wall U-value, (2) fenestration SHGC, (3) lighting power density, (4) window U-value and (5) window-wall ratio. Building usage scenarios are considered as (1) occupant density, (2) equipment density, (3) infiltration rate, (4) heating set-point temperature, and (5) cooling set-point temperature.

- Step 2: Collect samples of variables using Latin hypercube sampling. The minimum and maximum ranges of the design variables and the building usage scenarios are determined by referring to domestic and international research papers. In this study, the distributions of these variables are assumed to be uniform.

- Step 3: Build building energy models using EnergyPlus based on the samples collected from step 2. Next, conduct EnergyPlus simulation.

- Step 4: Construct surrogate model for reducing computational time of sensitivity analysis. Artificial neural network can be considered as the surrogate model with design variables and usage scenarios as inputs and electricity and gas energy as outputs.

- Step 5: Create the various building use scenario using Latin hypercube sampling, which shows the assumptions of usage scenarios that are different for each analyst.

- Step 6: Conduct Sobol sensitivity analysis for the design variables under each cases creating in step 5.

- Step 7: Quantify uncertainty in sensitivity from the results of sensitivity analysis.

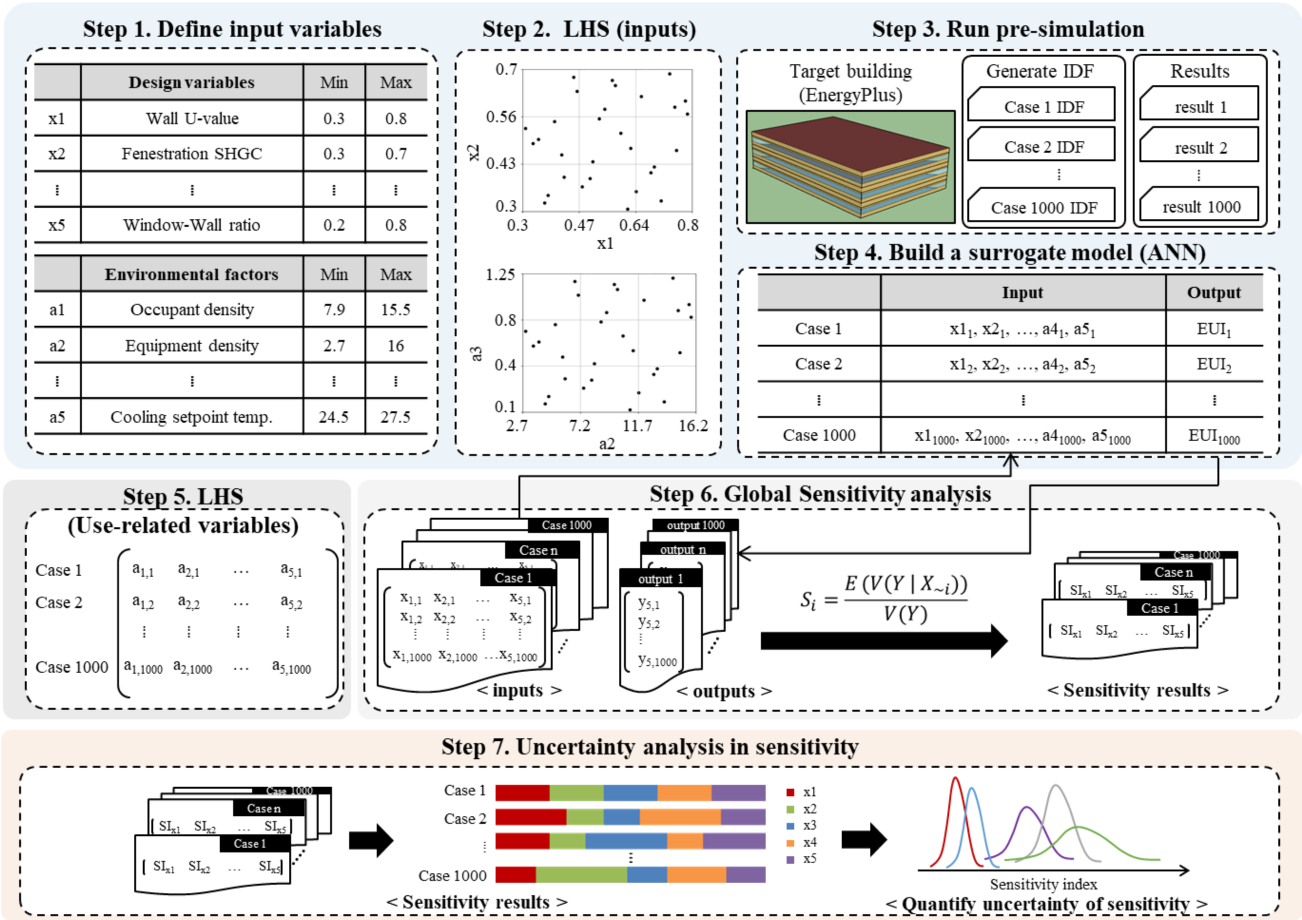


Figure 1.2 Whole Process

## 1.3. Thesis outline

Chapter 1 describes the need to use sensitivity analysis for design decision making based on performance-based approach, and introduces the research process. The contents dealing with in the next chapters are summarized as follows:

- Chapter 2 starts by giving an introduction in overview of sensitivity analysis. Types of the global sensitivity analysis are described and the detail of Sobol method that is utilized in this study is explained.

- Chapter 3 introduces the uncertainty analysis using in building energy simulation. Types of the uncertainty analysis are described and the detail of Monte Carlo simulation that is utilized in this study is explained.

- Chapter 4 introduces simulation model for case study. A target building and list of design variables are described. Also, the building usage scenarios are explained. Subsequently, surrogate model constructed to reduce computational time is illustrated.

- Chapter 5 presents results of the uncertainty analysis in sensitivity of design variables. Through this results, the author discusses the need for a stochastic approach to sensitivity analysis.

- Chapter 6 summarizes and concludes the paper with describing follow-up studies.

# Chapter 2. Sensitivity analysis

## 2.1. Overview

The sensitivity analysis (hereinafter referred to as SA) can be defined as a study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input (Saltelli et al., 2008). Basically, SA is based on derivatives and can be defined the derivative $\partial Y_j / \partial X_i$ of an output $Y_j$ versus an input $X_i$, which is called as derivative-based approach or local SA. The local SA is informative at the base point where it is computed, but unwarranted on uncertainty of the model inputs. From this point of view, global SA, exploring the space of the input variables rather than estimating derivatives at a single data point in the center of the space, is suggested (Saltelli et al., 2008). In other words, global SA is more reliable than local SA because all input variables can be changed simultaneously during the sensitivity quantification (Mara et al, 2008).

In the field of building energy simulation, the global SA is widely used for exploring the characteristics of building thermal performance in various types of applications such as building design, calibration of energy models, building retrofit, building stock, impact of climate change on buildings (Tian, 2013). Typical steps for implementing SA in building performance analysis are similar even though the different types of application in building energy analysis. The typical whole steps for SA are as follow: (1) Determine input variations, (2) create building energy models, (3) run energy models, (4) collect simulation results, (5) run SA, (6) presentation of SA results (Figure 2.1). The following Section 2.2 describes the types of global SA and the prior studies using it.

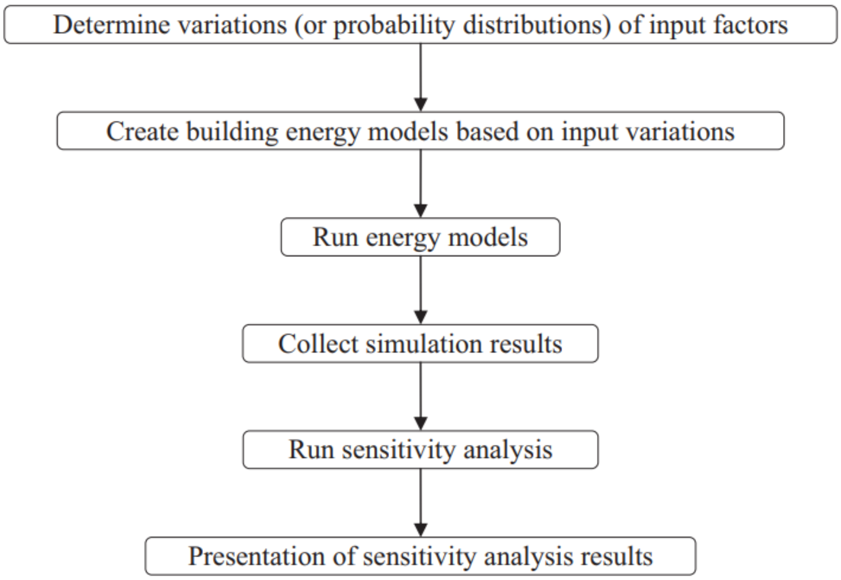


Figure 2.1 Typical whole steps for SA in building performance analysis (Tian, 2013)

## 2.2. Global sensitivity analysis methods

As a global SA method for building energy analysis, a regression analysis method, a main variable selection method, and a variance decomposition method are widely used (Tian, 2013).

The regression method is used a lot because the calculation time is fast and it is easy to understand. However, there is a limitation in applying it to a complex nonlinear model (Hopfe and Hensen, 2011). SRC, PCC, SRRC, PRCC are the examples. Hygh et al (2012) used SRC sensitivity indicator to analyze the energy performance of office buildings in four USA cities. The results indicate that the influences of design parameters on building use different by the climate zones. Ballarini et al (2012) implemented SRC to identify the key parameters affecting the cooling energy of the residential building in Italy. The results show that solar shading, window area and window insulation are the most important parameters. de Wilde et al (2009) used SRRC to determine major variables for heating energy use of mixed-mode office building in UK. They found that infiltration rate, lighting gains and equipment gains are the most influential factors.

The screening-based method is used to determine the main input variable among many input variables, and the operation time is faster than other techniques. The Morris method is widely used as a representative method (Morris, 1991), and as a disadvantage, the influence of the input variable on the output variable cannot be quantified. Some examples using Morris method in building energy analysis are as follow. Heiselberg et al (2009). used Morris method to identify the key variables affecting energy use for an office building in Denmark. The results indicate that lighting control and ventilation during the winter are the major variables. Hyun et al (2008). implemented Morris for investigating the performance of natural ventilation in a high-rise residential building in Korea. The results show that the four most important factors are wind velocity, window opening area by occupants, local terrain constant and flow exponent. Corrado and Mechiri (2009). used Morris to determine the key factors for energy rating in a house in Italy. They found that five factors such as indoor temperature, air change rate, number of occupants, metabolic rate and equipment heat gains are important.

The variance-based method is based on variance decomposition, and suitable for complex nonlinear models and has the advantage of being able to quantify the influence of all input variables between 0-1. In addition, it is possible to explain the n-th interaction of each input variable. The Sobol method (Sobol, 1993) has a disadvantage that it takes a lot of computation time. Two commonly used examples are FAST and Sobol method. Mechri et al (2010). used FAST method to figure out the key design variables affecting building thermal performance in a typical office building in Italy. The results indicate show that the most important factor for heating and cooling energy is the envelope transparent surface ratio. Spitz et al (2012). implemented the Sobol method for identifying the most important parameters for an experimental house in France. The results show that heating capacity, infiltration, fiberglass thickness, heat exchanger efficiency, internal heat gains, and fiberglass conductivity are the influential factors affecting the air temperature. Yoo et al (2020). used the Sobol method to quantify the influence of design variables for developing the energy performance index in Korea. They found that the proposed energy performance index using the Sobol method is more rational, objective and performance-based than the existing approach.

In this study, the Sobol is used as the sensitivity measure. It is useful for the building energy analysis since this method is suitable for complex nonlinear and non-additive models (Tian, 2013). Section 2.3 explains the Sobol method in detail.

## 2.3. Sobol method

A total order index ($S_{T_i}$ in equation 2.1) that represents a sensitivity measure of the individual input factor corresponds of the sum of lower order indices. Note that the first-order index ($S_i$ in equation 2.1) indicates the sensitivity effect by the input factor $X_i$ itself, and the second-order index ($S_{ij}$ in equation 2.1) indicates the sensitivity effect generated by the interaction effect between $X_i$ and other input factor $X_j$. In Sobol method (Sobol, 1993), the variance decomposition has a main-role of the sensitivity decomposition in equation 2.1.

$$S_{T_i} = S_i + S_{ij} + \cdots + S_{ij\ldots k} \tag{2.1}$$

The Sobol method can compute interaction effects between the input factors. The total order index of each input factors corresponds to the sum of single effects and higher-order interaction effects (Saltelli et al, 2008). When the sensitivity indices that are duplicated by the interaction effects are ignored, the sum of all sensitivity indices with regard to all variables is equal to 1 (equation 2.2). From this, it can be inferred that the Sobol method can quantify the importance of all input factors through entire input space, and each sensitivity has a value between 0 and 1.

$$\sum_i S_i + \sum_i \sum_{j>i} S_{ij} + \sum_i \sum_{j>i} \sum_{k>j} S_{ijk} + \cdots + S_{123\ldots k} = 1 \tag{2.2}$$

Given a mathematical model $Y = f(X_1, X_2, \dots, X_k)$, with $Y$ a scalar, the Sobol first-order effect of $X_i$ on $Y$ can be written as equation 2.3. This effect can be defined as a variance term ($V_{X_i}$ in equation 2.3) of model's output variable that estimated by sampling all input factors except target input factor ($X_{\sim i}$ in equation 2.3).

$$V_{X_i}(E_{X_{\sim i}}(Y|X_i)) \tag{2.3}$$

Where,

$X_i$: $i$-th input factor

$X_{\sim i}$: the matrix of all input factors but $X_i$

$E_{X_{\sim i}}$: the mean of $Y$ taken over all possible values of $X_{\sim i}$ while keeping $X_i$ fixed.

$V_{X_i}$: the variance is taken over all possible values of $X_i$

Equation 2.4 shows a low of total variance with regard to output variable $Y$. In this law, the variance $V(Y)$ can be decomposed to (1) a variance of expectation and (2) an expectation of variance for a given input samples. If $E_{X_i}(V_{X_{\sim i}}(Y|X_i)$ is small or $V_{X_i}(E_{X_{\sim i}}(Y|X_i))$ is large, it indicates that $X_i$ is an important factor.

$$V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right) + E_{X_i}\left(V_{X_{\sim i}}(Y|X_i)\right) = V(Y) \tag{2.4}$$

Equation 2.5 shows the definition of the first-order sensitivity index $S_i$ for input variable $X_i$. $S_i$ can be defined as the first-order effect (equation 2.3) divided by the variance of model's output. $S_i$ is expressed as a number between 0 and 1. If $S_i$ is closer to 1, it can be considered as the more important variable.

$$S_i = \frac{V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right)}{V(Y)} \tag{2.5}$$

Equation 2.6 presents a total sensitivity index $S_{Ti}$ for input variable $X_i$. It is defined as the expected value of variance for a given input samples divided by the variance of the output variable. Also, it can express as subtracting the first-order index from 1. It is observed that equation 2.6 is the identical form with equation 2.4 after transposing the first-order index and multiplying the variance of $Y$.

$$S_{Ti} = \frac{E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i}))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}\left(E_{X_i}(Y|X_{\sim i})\right)}{V(Y)} \tag{2.6}$$

The Sobol method is based on Monte Carlo simulation and mainly uses (1) Sobol quasi-random sequences (Sobol, 1998), and (2) Saltelli's sampling scheme (Saltelli et al, 2008). In this study, Saltelli's sampling scheme was used in the sensitivity calculation and the total-order index was applied as the design variable's importance measure.

# Chapter 3. Uncertainty analysis

## 3.1. Overview

Uncertainty analysis (UA) is a technique to quantify the uncertainty in the model outputs propagated from the uncertain input variables (Macdonald, 2002). UA has received a lot of attention in the field of building energy analysis because there are a number of uncertain variables influencing building energy performance (Tian et al, 2018). These variables can be divided into three categories: design parameters, inherent uncertain parameters, and scenario parameters (Hopfe and Hensen, 2011; Tian et al, 2018). Uncertainty in design parameters exists in the design stage of determining design variables. For example, building insulation material and window types are unknown at the early design stage, but are known at the detailed design stage. Inherent uncertain parameters represent uncontrollable variables such as occupant behavior, the deviations between rated and actual plant system efficiencies. Scenario parameters refer to potentially changing factors such as economic or climate conditions. There are two types of UA for these uncertain parameters, and described in Section 3.2.

## 3.2. Forward and backward uncertainty analyses

UA in building energy assessment can be divided into forward and backward UA (Tian et al, 2018). The details of each type are as follows:

- Forward UA: Uncertainty in the model system output, propagated from uncertain input variables, is quantified through mathematical models. In building energy analysis, it is usually used to predict energy use of building energy models with uncertain input parameters. This type consists of two approaches such as probabilistic and non-probabilistic methods. Probabilistic uncertainty approaches are based on rigorous probability theory under the sufficient data, while non-probabilistic approaches are conducted to deal with a lack of data. Probabilistic approaches are sub-categorized into sampling-based methods and non-sampling methods. Sampling-based method regards original deterministic model as a black-box model by running this deterministic model with various samples many times. Non-sampling methods include perturbation methods, moment equations, spectral representations methods, and classical stochastic differential equations (Tian et al,2018; Xiu, 2009; Lee and Chen, 2009; Dwight et al, 2013). Sampling-based method is considered more reliable than non-sampling method since it is applicable to most simulation environments and cover various probability functions of input variables for correlated variables (Tian et al,2018; Lee and Chen, 2009).

- Backward UA: This type determines unknown variables through mathematical models from measurement data. In the building energy analysis, unknown input variances are quantified through the building energy model after collecting building energy data. Statistical method for backward UA can be largely classified as frequentist and Baysian approaches. The frequentist approach is classical parameter estimation method to infer the unknown parameters relying on measured data (Fumo and Biswas, 2015; Masuda and Claridge,2014). This approach includes the assumption that unknown parameters have atrue value, and produce a single estimate and associated deviation (Tian et al, 2018). Baysian methods include expert knowledge with measurements into the model calibration process. The unknown parameters in this method are assigned with prior distributions quantifying prior beliefs about true parameter values based on expert knowledge (Tian et al, 2018).

In this study, the sampling-based method which is one of the forward UA is used as the uncertainty analysis approach. Monte Carlo simulation was chosen to sample an uncertain variables' environments. Section 3.3 describes the Monte Carlo simulation.

## 3.3. Monte Carlo Simulation

Monte Carlo simulation is one of the forward UA method and used extensively in the field of building energy assessment (Kim et al, 2014). This method solves a problem based on random number extraction. The advantage of this method is intuitive and easy to implement compared to other forward UA approaches (Tian et al, 2018). However, when conducting it, the computational cost is very high. To overcome this, efficient sampling methods have introduced such as Latin hypercube sampling (Mckay et al, 2000) or Sobol sequence. Also, surrogate models can be used instead of original models (Tian et al, 2018).

In particular, LHS is widely used in the area of building energy analysis because it can sufficiently explain input variable space with a small number of samples (de Wit and Augenbroe, 2002; Kim and Park, 2016). LHS is a pseudo random generator in order to improve the sample bias problem of the existing simple random sampling and stratified sampling methods. The sampling process is as follows: (1) Equally split the cumulative probability distribution into N intervals, (2) Random sampling by interval, (3) Calculate the inverse-cumulative distribution function for each sample.

# Chapter 4. Simulation model

This chapter summarized the details of a simulation model used for the case study to quantify the uncertainty of the sensitivity of architectural design variables. Section 4.1 summarized the basic information of the simulation model used in this study and the architectural design variables for sensitivity analysis. Section 4.2 summarized uncertain variables which can be changed during the stage of use of building. Section 4.3 describes the surrogate model used for sensitivity and uncertainty analysis. The results of the case study are presented in Chapter 5.

## 4.1. Target building

The reference building for a medium-size office, located in Atlanta developed by the US DOE (Deru et al, 2011), was selected as a target building (Figure 4.1). EnergyPlus 8.9 was selected as an energy simulation tool. Table 4.1 summarized main characteristics of this model. The model has a gross floor area of 4982m$^2$ and three stories above ground. Each floor consists of four perimeter zones and one interior zone. The values of parameters are derived from ASHRAE Standard for non-residential buildings. Considering that it is in the early design stage, the HVAC system of the model was selected as 'Ideal load air system' with no ventilation for the internal zone. The weather data of Incheon, South Korea, is used.

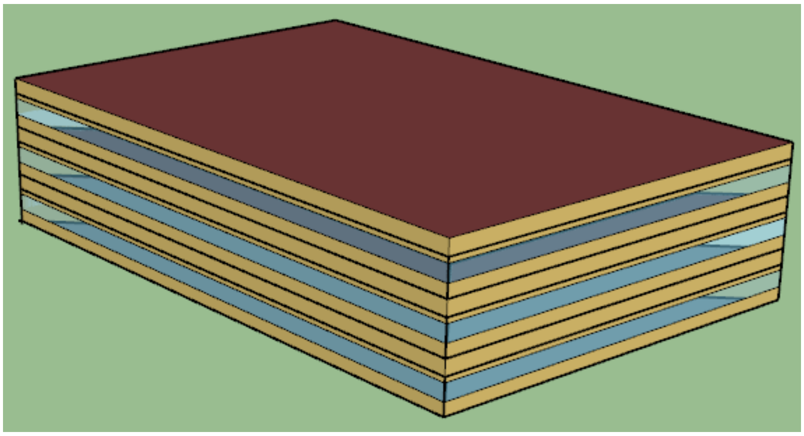

Figure 4.1 Target building

Table 4.1 Main characteristics of the target building

| Component | Item | Parameters |
|---|---|---|
| Envelope | Floor area ($m^2$) | 4,982 |
| | Floor levels | 3 |
| | Zone number | 15 |
| | Roof U-value ($W/m^2K$) | 0.44 |
| | Floor U-value ($W/m^2K$) | 3.40 |
| HVAC | - | Ideal loads air system, no ventilation |

The “passive” design variables are chosen that are usually determined by the designer of the design process. Wall U-value, fenestration SHGC, lighting power density, window U-value and window-all ratio are selected as the design variables (Table 4.2). The ranges of these variables were derived from ASHRAE, 2017; Tian et al. 2016; Yoo et al, 2020, which were set in consideration of the international buildings. The model outputs are selected annual energy use (electricity + gas, unit: kWh/m$^2$yr).

Table 4.2 List of the design variables

| Design variable | Abbreviation | Range | Reference |
|---|---|---|---|
| Wall U-value (W/m$^2$K) | Wall U | 0.3–0.8 | ASHRAE, 2017 |
| Fenestration SHGC (-) | SHGC | 0.3–0.7 | Tian et al, 2016 |
| Lighting power density (W/m$^2$) | LPD | 8–20 | ASHRAE, 2017 |
| Window U-value (W/m$^2$K) | Win U | 1.5–3.5 | Tian et al, 2016 |
| Window-wall ratio (-) | WWR | 0.2–0.8 | Yoo et al, 2020 |

Note that the case study does not use on-site measured data because the on-site data are usually influenced by unknown noises. This study intends to show the uncertainty in sensitivity of building design variables, so a simple 'toy experiment’ EnergyPlus model was used.

## 4.2. Building usage scenarios

In the design stage of a building, it is not likely to accurately know the values of factors, which is relevant to occupant behavior, indoor environment, and these factors are determined in usage stage of the building. In this study, the author considers the uncertain factors as occupant density, equipment density, infiltration rate and heating/cooling set-point temperature, coined as 'building usage scenarios' in this thesis. Table 4.3 shows the building usage scenarios and their ranges.

Samples of the building usage scenarios are generated through LHS, and are considered various indoor environments. The Sobol sensitivity analysis is performed on each sample of the environments, reflecting the uncertainty of the building usage scenarios.

Table 4.3 List of the building usage scenarios.

| Usage scenarios | Range | Reference |
|---|---|---|
| Occupant density ($m^2$/person) | 7.9–15.5 | ASHRAE, 2017 |
| Equipment density ($W/m^2$) | 2.7–16 | ASHRAE, 2017 |
| Infiltration rate (ACH) | 0.1–1.25 | Heo et al, 2015 |
| Heating set-point temperature (℃) | 18.5–21.5 | ASHRAE, 2017;<br>Lee et al, 2015 |
| Cooling set-point temperature (℃) | 24.5–27.5 | ASHRAE, 2017;<br>Lee et al, 2015 |

## 4.3. Surrogate Model (ANN)

Because the Sobol method targets all input variable spaces, it requires a significant number of simulations, and has high computational cost. Therefore, approximation models, known as surrogate models, can be used. Surrogate models mimic the behavior of original model as closely as possible while being computationally cheap to evaluate. Surrogate models are usually constructed using a data-driven approach. In particular, artificial neural network has been widely used due to its high prediction accuracy. In this context, the author constructed ANN based on EnergyPlus models.

For generating the surrogate model, it is necessary to collect the input/output samples of model. In this study, LHS was performed to collect input/output samples and 1000 EnergyPlus simulation models were made. The process for developing the surrogate model is as follows:

(1) Perform Latin hypercube sampling based on Table 4.2, Table 4.3 (variables' distribution: uniform) and generate 1000 EnergyPlus models.

(2) Run EnergyPlus simulation based on the generated EnergyPlus models in step (1).

(3) Collect simulation results such as electricity and gas energy.

(4) Construct ANN models using inputs (design variables + building usage scenarios) and outputs (electricity and gas energy) of EnergyPlus models.

The number of datasets for training and test is 700 and 200 EnergyPlus simulation runs, respectively.

As the structure of artificial neural network models, multi-layer perceptron regressor was selected. The optimization solver of the model was set 'Adam' and the activation function was considered as 'Relu'. Also, the number of hidden layer and neuron was 1 and 5, respectively. All the process wes performed by Python with the modules: pyDOE for LHS, geomeppy for generating EnergyPlus models, and scikit-learn for training the ANN model. The prediction accuracy of the generated ANN models was measured using the coefficient of variation of the root mean square errors (CVRMSEs). Through the verification results, it was found that the predictive performance of the ANN surrogate model for the EnergyPlus model was satisfactory with CVRMSE 3% (Figure 4.2).

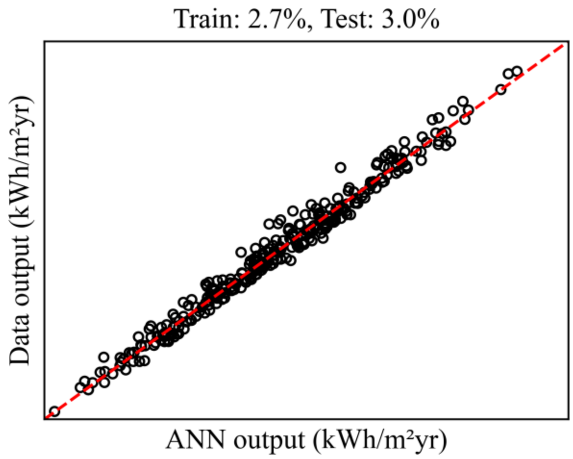


Figure 4.2 Comparison between EnergyPlus and ANN models (300 test data used)

# Chapter 5. Result analysis

This chapter shows the results of the case study (Sobol sensitivity analysis and uncertainty analysis) conducted based on Chapter 4. The Sobol method was performed based on the module, SALib in a Python 3.7 environment. Section 5.1 summarizes the results of Sobol sensitivity analysis for the design variables (wall U-value, fenestration SHGC, lighting power density, window U-value, window-wall ratio). Section 5.2 describes the results of uncertainty in sensitivity and the sensitivity ranking of design variables.

## 5.1. Results of the Sobol sensitivity analysis

Figure 5.1 suggests the results of the Sobol sensitivity analysis for total energy. The x-axis represents 1000 cases of building usage scenarios, and the y-axis represents the Sobol sensitivity index (equation 2.5). When the sensitivity criterion is determined as 0.05 (Zhang et al., 2015), it can be seen that fenestration SHGC (orange color), lighting power density (green color), window-wall ratio (purple color) are the most influential variables on the total energy for all cases. On the other hand, is can be seen that the influence of the insulation-related variables (wall U-value, window U-value) is not large. Through these results, the following can be inferred.

- When making decision based on sensitivity analysis at the design stage, design of appropriate window-wall ratio, installation of high-efficiency windows (i.e. windows with low SHGC) and high-efficiency lighting should be considered. The sum of their sensitivity indices account for 99% of the sum of the total influences of the five design variables, which indicates their significant impact on total energy reduction.
- The building envelope insulation should be determined to be sufficient to satisfy only the minimum standards (e.g. building codes or regulations, the max value [W/m$^2$K] in Table 4.1).

Figure 5.2 shows the probabilistic density function of the sensitivity distribution of aforementioned three variables (wall U-value, fenestration SHGC, window-wall ratio). The uncertainties of the sensitivity of these three variables exists significantly. The minimum and maximum values of sensitivity indices are as follows: Fenestration SHGC has 0.25-0.54, lighting power density has 0.33-0.40, window-wall ratio has 0.15-0.40. The details of uncertainty analysis are described in Section 5.2.

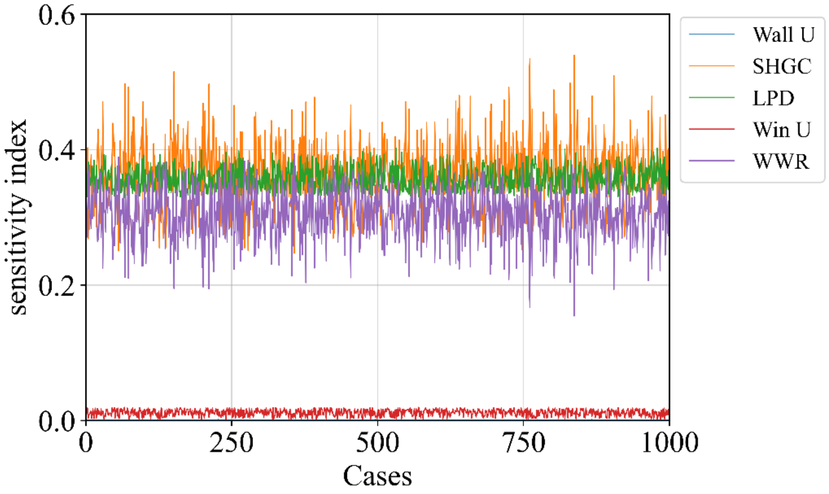


Figure 5.1 Sensitivity analysis result based on 1000 building usage scenarios

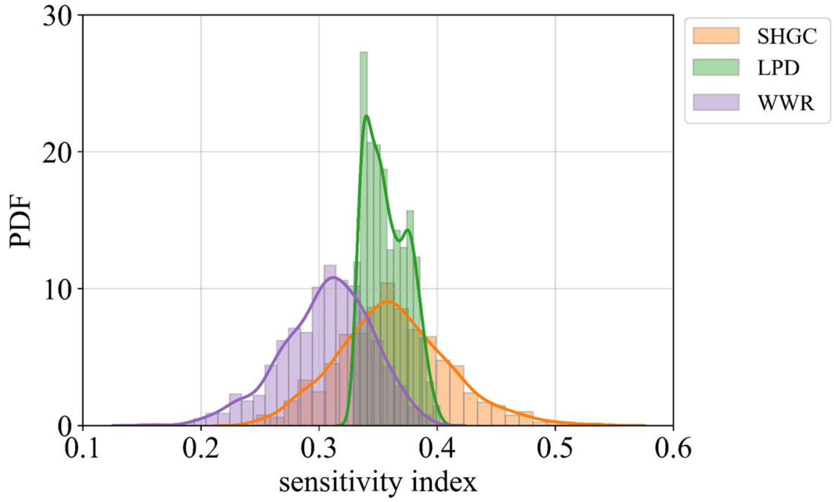


Figure 5.2 Distributions of sensitivity index (the most influential variables)

## 5.2. Uncertainty analysis in sensitivity

Figure 5.3 suggests the boxplot showing the uncertainty of the sensitivity indices for all design variables. Note that leftmost ($whisker_{lower}$) and rightmost ($whisker_{upper}$) vertical lines of each box indicate the boundary of boxplot (equation 5.1-5.3) for the sensitivity index, and the distance between vertical lines were considered as a uncertainty of sensitivity for each variable. Table 5.1 summarizes the information of the boxplots.

$$Interquartile\ \ range\ \ (IQR) = Q3 - Q1 \tag{5.1}$$

$$whisker_{lower} = Q1 - 1.5 \times IQR \tag{5.2}$$

$$whisker_{upper} = Q3 + 1.5 \times IQR \tag{5.3}$$

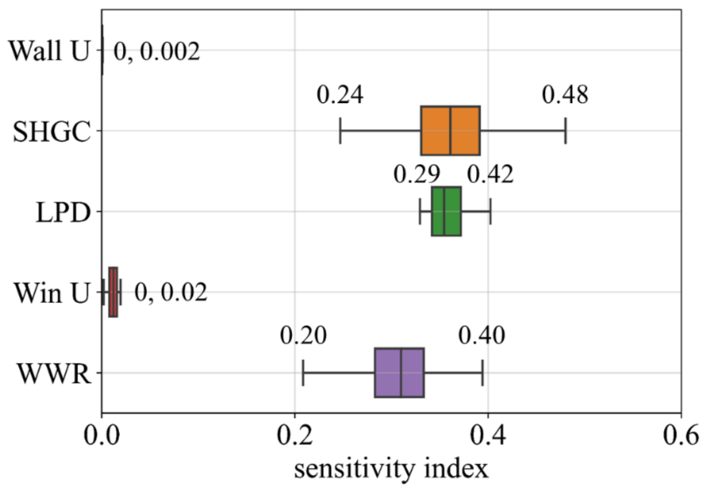


Figure 5.3 Uncertainty in sensitivity

Table 5.1 Result of uncertainty analysis

| Design Variables | $Q1$ (25%) | $Q2$ (25%) | $Q3$ (75%) | $whisker_{lower}$ (a) | $whisker_{upper}$ (b) | Uncertainty (b-a) |
|---|---|---|---|---|---|---|
| Wall U | 0 | 0.0005 | 0.001 | 0 | 0.002 | 0.002 |
| SHGC | 0.33 | 0.36 | 0.39 | 0.24 | 0.48 | 0.24 |
| LPD | 0.34 | 0.355 | 0.37 | 0.29 | 0.42 | 0.13 |
| Win U | 0 | 0.005 | 0.01 | 0 | 0.02 | 0.02 |
| WWR | 0.28 | 0.305 | 0.33 | 0.20 | 0.40 | 0.20 |

Uncertainty for each design variable is as follows: Wall U-value has 0.002, fenestration SHGC has 0.24, lighting power density has 0.13, window U-value has 0.02 and window-wall ratio has 0.20. The important ranking of variables is 1) fenestration SHGC, 2) lighting power density, 3) window-wall ratio, 4) window U-value, 5) wall U-value, based on the median of sensitivity. However, the risk in ranking of the median sensitivity is 1) fenestration SHGC, 2) window-wall ratio, 3) lighting power density, 4) window U-value, 5) wall U-value, based on the uncertainty. Three highly sensitive variables mentioned in Section 5.1 (fenestration SHGC, lighting power density, window-wall ratio) also have high uncertainties (0.24, 0.13, 0.20). That is, these variables have a significant influence on the assumptions of building usage scenarios. In addition, sensitivity rankings of these variables can be changed. Figure 5.4 represents the sensitivity rankings and their rates of the design variables based on the 1000 Sobol sensitivity results. Four sensitivity groups are shown. Based on the primary variables, fenestration SHGC (Group 1) tends to dominate (55.2%), but lighting power density (Group 2+Group3) also tends to be non-negligible (38.7%). In addition, window-wall ratio showed a level of 6%, which has the smallest rates. Considering this, inefficient decision making such as failure to achieve expected performance in building operated stage can occur if fenestration SHGC is simply considered as the most important factor in the design stage. (e.g. group 3 and group 4 in Figure 5.4 shows that fenestration SHGC corresponds to the 3$^{rd}$ rank at a rate of 25.2%). On the other hand, although window-wall ratio is ranked 3$^{rd}$ in group 1 and 2, it is also highly likely that it is 1$^{st}$ (6%) and 2$^{nd}$ (19.2%) from group 3 and 4. These results show that it cannot simply be judged that it is less important than the other two design variables (fenestration SHGC, lighting power density).

In the end, the following can be suggested: Sensitivity of design variables may change depending on assumptions of building usage scenarios, so the results may be biased when interpreted as a deterministic approach. Therefore, it is necessary to analyze the sensitivity of the stochastic approach with considering the uncertain usage scenarios.

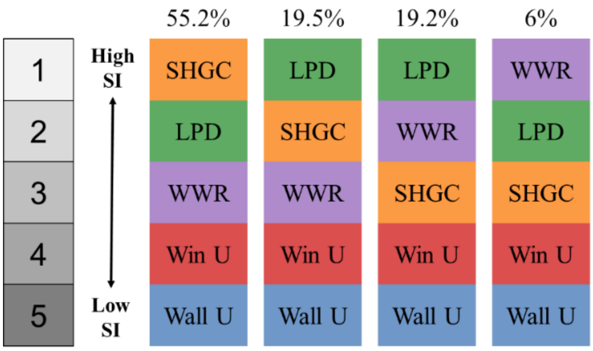


Figure 5.4 Clustering results of 1000 cases of sensitivity analysis

# Chapter 6. Conclusion

Global sensitivity analysis (GSA) can play aa important role in decision-making at building design stage, since it can quantify the influence of design variables on building energy consumption. However, it is obvious that GSA is useful, but it is not well known that sensitivity indices can be changed because of assumptions for model's unknown parameters such as occupant density, equipment density, infiltration rate, etc. In general, these parameters are set as deterministic values based on analysts' subjective judgment, and it can be inferred that this subjectivity can cause uncertainty in GSA of the building energy model though both the building and the design variables are same. From this perspective, the author proposed a sensitivity analysis process for building energy design variables considering the uncertainty of building use scenarios.

In the case study, The Sobol sensitivity analysis was conducted according to the assumption of five building usage scenarios (occupant density, equipment density, infiltration rate, cooling/heating set-point temperature) based on the medium-size office building. The result of the sensitivity analysis on annual heating and cooling EUI showed that fenestration SHGC, lighting power density, and window-wall ratio tended to be relatively sensitive. The uncertainty in sensitivity of these variables tended to be large. In addition, it could be observed that the ranking of sensitivity among these three variables changed depending on the cases of building usage scenarios. This can be inferred that it has limitation to define the superiority between design variables due to the assumptions of building usage scenarios accompanying the sensitivity analysis.

Therefore, it is necessary to consider uncertainty about building usage scenarios in the sensitivity analysis process, and provide the results to decision makers in stochastic form rather than deterministic form. Furthermore, the sensitivity analysis based on stochastic approaches is expected to help decision makers reach reasonable decision making since it is possible to consider changes in the building use in the building's use process.

As a follow-up study, the author will analyze the correlation between indoor environmental factors and sensitivity indicators. Also, the case study has been conducted on specific buildings and specific conditions (Ideal Load Air System, new construction, variable range), but further studies will reflect real-world buildings to secure the versatility of the study.

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# 국문초록

# 건물 사용 시나리오에 따른 건물 설계변수 민감도의 불확실성

유영서

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건물 생애 주기 동안의 지속 가능한 건물에너지 소비를 위해서는 건물 초기 설계 단계의 의사결정이 매우 중요하다. 합리적인 의사결정은 건물의 전체 관점에서 설계변수와 건물 성능 간 관계를 고려할 수 있는 과학적 방법을 수반해야 한다. 이에 대한 수단으로써, 전역 민감도 분석을 활용할 수 있다. 민감도 분석은 개별 입력변수의 단위 변화량에 대한 출력변수의 변화량을 추정하는 기법으로, 이를 통해 건물 에너지사용량에 대한 설계변수들의 영향력을 정량화 할 수 있다.

그러나 민감도 분석 수행 시, 설계변수 이외의 건물의 사용 시나리오는 분석가의 주관적 판단에 따른 결정적인 값으로 설정된다. 이로 인해, 동일한 건물 및 설계변수를 대상으로 하였음에도 불구하고, 분석가마다

결과가 달라질 수 있는 객관성 문제가 발생할 수 있다. 이런 관점에서, 본 연구에서는 건물 사용 시나리오 가정에 따른 불확실성을 고려한 건물에너지 설계변수의 민감도 분석 프로세스를 제시한다.

사례연구에서는 5개의 건물 사용 시나리오 (재실밀도, 기기밀도, 침기율, 냉방 및 난방 설정온도)를 고려하고, 5개의 설계변수 (외벽 열관류율, 유리 SHGC, 조명밀도, 창호 열관류율, 창면적비)에 대한 Sobol 민감도 분석을 수행한다. 그리고 냉난방 에너지 사용량에 대한 전역 민감도 분석 수행 결과로써, 설계변수 민감도의 불확실성이 존재할 뿐만 아니라, 이들 간 민감도 순위도 달라질 수 있음을 보인다. 이를 통해, 민감도 분석 과정에서 다양한 건물 사용 시나리오에 대한 불확실성을 고려하는 것이 중요하며, 합리적인 의사결정에 도달하기 위해서는 확률적 접근의 민감도 분석이 필요함을 논한다.

**주요어** : 건물 에너지, 전역 민감도 분석, 불확실성 분석, 의사결정

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