Master’s Thesis of Engineering

Issues and improvements of Building Energy Codes in South Korea

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Abstract

A rational building energy performance assessment is important for energy efficient building design. Therefore, the results of building energy performance assessment should be sufficiently objective and transparent. Additionally, a performance-based approach is considered more reasonable in building energy performance evaluation than a prescriptive approach. However, in the case of ECO2 used in the Korean Building Energy Assessment, it was developed with a focus on simplicity of evaluation, even at the expense of accuracy, by specifying operational factors as single values and not reflecting uncertainty. This has led to controversial regarding accuracy, usability, and the reliability of assessment results. The evaluation criteria for the Energy Performance Index (EPI), which is mandatory for buildings larger than 500m^2, also lack an objective methodology. To establish a rational evaluation system, a scientific method that considers the thermal behavior of buildings should be employed. In this context, this study presents a process for quantifying the uncertainty of energy demand based on changes in building usage scenarios and an improvement process for the EPI scoring system through a scientific approach.

In Case Study #1, an analysis of the uncertainty of building energy demand is performed based on variations in five factors of the usage profile: occupancy density, plug load density, light power density, infiltration rate, and ventilation rate. The study argues for the necessity of a stochastic approach, the stochastic usage profile based on the quantification of uncertainty in building energy demand.

In Case Study #2, Sobol sensitivity analysis and polynomial regression between seven building design factors (wall U-value, window U-value, roof U-value, floor U-value, Fenestration SHGC, light power density, and infiltration rate) and energy demand are conducted. By replacing sensitivity indices with the base score (a) of the EPI and using the polynomial regression equation as the weighting (b), a scoring system that partially reflects the thermal behavior of buildings is proposed. The correlation analysis between EPI and EPI*, ECO2 and EnergyPlus energy demand demonstrates the difficulty of ECO2 in reflecting the thermal behavior of buildings, emphasizing the need for a transition to a performance-based approach.

Keyword: Building Energy Assessment, Energy Performance Index, Sensitivity analysis, Uncertainty analysis, Stochastic Approach

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Chapter 1. Introduction

1.1 Problem statement and objectives

Buildings are regarded as significant contributors to national energy consumption, and efforts are being made worldwide to reduce building energy usage through building energy efficiency assessments such as BREEAM in the UK, LEED in the US, and G-SEED in South Korea (Amiri, Ottelin & Sirvari, 2019). In South Korea, the energy-saving design standards for buildings specify minimum performance requirements for various building components, and buildings are required to obtain a certain score (65 points) through an Energy Performance Index (EPI). Additionally, the ECO2 program is specified for predicting building energy usage.

However, there have been criticisms regarding the building energy code. Buildings that have obtained the highest rating through the ECO2 calculation have received low scores in evaluations based on actual energy consumption, indicating a performance gap. This raises the need for a reassessment of the building energy code (Yun, 2021). In other words, performance gap can occur between the results obtained from ECO2 calculations and the actual energy usage, leading to potential errors in the evaluation of building energy efficiency based on the ECO2 calculation.

To achieve an objective assessment of building energy performance, two key aspects should be ensured: (1) the evaluated system's performance should accurately reflect reality, and (2) the reliability of the results, considering the uncertainty of input variables, should be secured to prevent potential manipulation by evaluators (Park, 2006). Moreover, it is preferable for building energy performance evaluations to adopt a performance-based approach (e.g., $kWh/m^2 \cdot yr$) rather than a prescriptive approach (e.g., minimum performance requirements) as it is more rational (Park, 2006).

Models used for energy usage prediction in buildings should be capable of sufficiently predicting the thermal behavior of buildings and allow users to input relevant variables (Hopfe, 2009). Furthermore, it is advantageous for simulation tools and the models created using them to have open-source availability (Malkawi & Augenbroe, 2004). However, ECO2, which is widely used in South Korea, has been subject to controversies regarding the accuracy of its algorithm, inconvenience in inputting variables, and the reliability of its results (Kim, Kwak & Kim, 2018). ECO2 is developed based on ISO13790 and DIN V 52016, and the original intention of ISO13790 was to prioritize 'simplicity of evaluation' even at the expense of 'accuracy'. Moreover, the evaluation criteria for the Energy Performance Index (EPI), which is mandatory for buildings with a floor area of over $500m^2$, focusing on heating energy and lack sufficient evaluation of cooling energy, while the evaluation criteria themselves are not based on objective methods (Yoo et al., 2020).

This study aims to identify and propose solutions for the academic and technical issues that may arise during the process of analyzing building energy using a quasi-steady state simulation program (ECO2) and presenting the results. Additionally, an analysis of the EPI, which is applied to building energy evaluations, will be conducted.

1.2 Research process

This study is divided into two main processes. The first process aims to quantify the uncertainty of energy demand based on the uncertainty of the usage profile. Through this process, the need for introducing a probabilistic approach in the evaluation framework of building energy efficiency rating certification is proposed. The second process analyzes the correlation between the existing Energy Performance Index (EPI) system and energy demand and compares the extent to which it can be improved. The detailed procedures are as follows.

The quantification process of energy demand variation based on the uncertainty of the usage profile is conducted as a case study. The uncertain factors considered in the usage profile include the minimum outdoor air intake rate (ventilation), infiltration rate, light power density, occupancy density, and plug load density. Uncertainty analysis (UA) of heating and cooling energy demand is performed. Since ECO2 specifies the usage profile and does not allow direct input of values for these factors, UA cannot be performed. Therefore, EnergyPlus, which allows easy modification of variable values, is used to conduct the uncertainty analysis. The overall process is as follows (Figure 1.1): (1) Building energy modeling (ECO2 and EnergyPlus), (2) Latin Hypercube Sampling (LHS) for probabilistic sampling of the usage profile, (3) Simulation, (4) Uncertainty analysis.

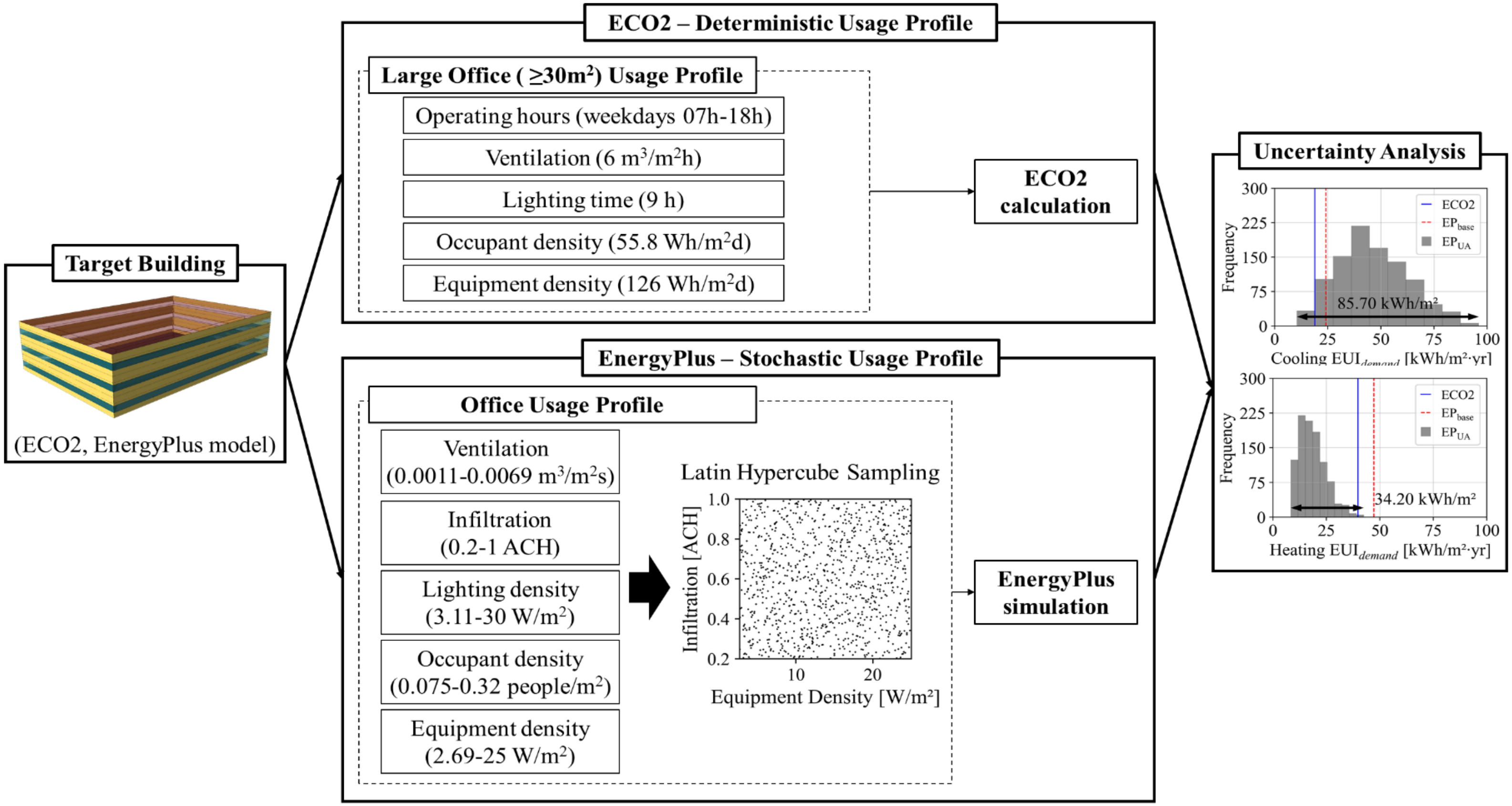


Figure 1.1 Uncertainty analysis process

The second part involves the analysis of two evaluation methods (EPI and ECO2) applied to building energy assessment in South Korea. To perform this analysis, a cross-comparison with EnergyPlus, one of the high-fidelity tools, was conducted. Firstly, the level of correlation between EPI and simulation programs (ECO2 and EnergyPlus) was compared, and the potential improvement of EPI was analyzed. It should be noted that ECO2's source code is not available, which limited the ability to propose improvement directions in this study. Additionally, when analyzing annual energy demand as the sum of heating and cooling, it becomes challenging to separate the effects of design factors on heating and cooling, making a clear analysis difficult. Therefore, this study focused on analyzing cooling only, with plans to address heating and total energy demand in future research.

This study is outlined in Figure 1.2: (1) Selection of target buildings, (2) Selection of seven design variables and creation of 500 samples based on input ranges, followed by EnergyPlus simulations, (3) Development of an Artificial Neural Network (ANN) surrogate model based on EnergyPlus results, (4) Perform Sobol global sensitivity analysis on cooling energy demand using the surrogate model, (5) Build regression models for cooling energy demand based on the variations of each design variable, (6) Quantification of the influence of design variables and transformation of regression equations into continuous functions, (7) Adjustment of the scoring system for improvement in EPI based on step (6), (8) Analysis of the correlation between the scores obtained from the original EPI and new EPI* and cooling energy demand.

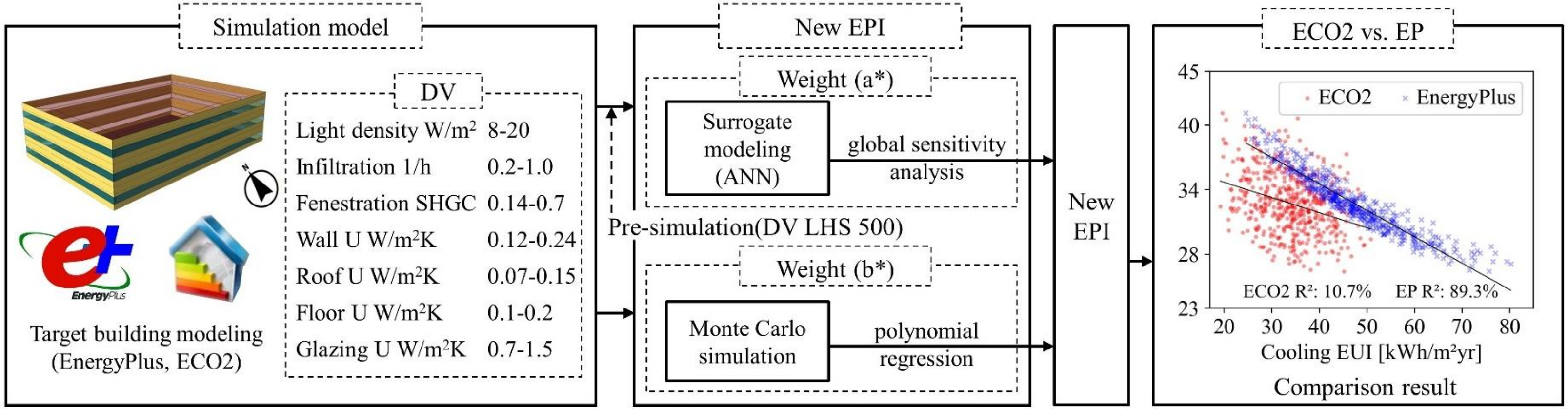


Figure 1.2 New EPI* research process

(DV: design variable, EP: EnergyPlus, LHS: Latin Hypercube Sampling)

1.3 Thesis outline

Chapter 1 describes the issues to use Korean building energy code for building energy use assessment, and introduces the research process. The outline of the thesis is also described.

Chapter 2 explains the limitation of Korean building energy code which is the backgrounds of the thesis.

Chapter 3 explains a description of the methodology used in this case study of this research. The uncertainty analysis section focuses on Latin Hypercube Sampling. The sensitivity analysis section introduces the Sobol method, and an overview of polynomial regression.

Chapter 4 introduces simulation model (building energy model) for case study. A target building and list of design variables are described. Also, the building usage scenarios are explained. Moreover, the accuracy of the surrogate model built to reduce computational time is illustrated.

Chapter 5 presents the results of the case study conducted in this study. The author discusses the need for a stochastic approach to the usage profile based on the results of uncertainty analysis. The results of sensitivity analysis and polynomial regression lead the author to propose a new Energy Performance Index* (EPI*), and correlation analysis is performed to analyze the results. This analysis highlights the limitations of the current EPI.

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

Chapter 2. Issues of Existing Building Energy Codes

2.1 Energy Performance Index (EPI)

In the case of domestic buildings, newly constructed buildings with a floor area of 500m^2 or more must satisfy requirements of the building energy standard and achieve an EPI (Energy Performance Index) score of 65 or higher (74 for public institutions) (KEA, 2016). EPI is a prescriptive approach divided into four sectors: building, mechanical facilities, electrical facilities, and renewable energy facilities. Each sector consists of a base score (a) and a scoring factor (b) based on the range of each design variable. The score for each design variable is calculated by multiplying the base score (a) and the scoring factor (b), and the sum of the scores for all items is used to determine the total score for building permit approval.

Table 2.1 represents a partial list of the base scores (a) for non-residential large buildings (3,000m^2 or more). The total base score (a) for the six evaluation items is 43 points, with the thermal transmittance of the building envelope (walls, roofs, floors) accounting for approximately 77% of the total score. This indicates the emphasis of thermal transmittance in the Korean building energy codes. On the other hand, the infiltration, solar heat gain through glazing, and lighting density are less emphasized. The scoring factor (b) is presented discretely, with values of 0.6 and 1.0 in increments of 0.1 (Table 2.2). To achieve a more rational representation, it is necessary to change the scoring factor (b) continuously. However, in this study, we adjust the current EPI scoring system for the items in Tables 2.1 and 2.2, focusing on cooling energy, and present examples of new EPI

Table 2.1 Weight (a) in EPI

Category	Design variables	weight(a)
Architecture-1	Exterior Wall U-value [W/m^2·K]	21
Architecture-2	Roof U-value [W/m^2·K]	7
Architecture-3	Floor U-value [W/m^2·K]	5
Architecture-5	Infiltration [m^3/h·m^2]	5
Architecture-9	Solar heat gain [W/m^2]	2
Electric system-1	Lighting power density [W/m^2]	3
	Total	43

Table 2.2 Weight (b) in EPI

Category	Design variables	weight(b)				
		1	0.9	0.8	0.7	0.6
Architecture - 1	Exterior Wall U-value [W/m^2·K]	less than 0.49	0.49 - 0.56	0.56 - 0.62	0.62 - 0.68	0.68 - less than 0.74
Architecture - 2	Roof U-value [W/m^2·K]	less than 0.09	0.09 - 0.10	0.10 - 0.11	0.11 - 0.13	0.13 - less than 0.15
Architecture - 3	Floor U-value [W/m^2·K]	less than 0.12	0.12 - 0.13	0.13 - 0.15	0.15 - 0.17	0.17 - less than 0.21
Architecture - 5	Infiltration [m^3/h·m^2]	less than 1.00	1.0 - 2.0	2.0 - 3.0	3.0 - 4.0	4.0 - 5.0
Architecture - 9	Solar heat gain [W/m^2]	less than 14.0	14 - 19	19 - 24	24 - 29	29 - 34
Electric system - 1	Light power density [W/m^2]	less than 8.00	8 - 11	11 - 14	14 - 17	17 - 20

2.2 ECO2

2.2.1 Overview

The analysis of building energy usage can be categorized into two methods: steady-state analysis and dynamic analysis. Steady-state analysis assumes indoor and outdoor conditions to be in a steady state, offering the advantages of simplified input variables and shorter computation time (Lee, Yu & Cho, 2009).

On the other hand, dynamic analysis simulates the time-varying thermal behavior of buildings using analytical/exact methods such as state-space equations or numerical/approximate methods like finite difference methods. Representative dynamic simulation software, such as EnergyPlus, can calculate time-dependent heat transfer between individual components based on detailed input variables. Dynamic simulation tools require extensive information on input variables and inevitably involve engineering assumptions and simplifications during the modeling process to reflect reality.

A method that combines the advantages of steady-state and dynamic analysis is quasi-steady state analysis. In this approach, energy analysis equations take the form of algebraic equations with regression coefficients incorporated to approximate dynamic behavior (ISO 13790, 2008; DIN V 18599, 2007).

While the United States and Canada allow dynamic simulation as an energy-saving criterion, in Korea, ECO2 based on DIN V 18599, which adopts quasi-steady state analysis, is mandated and monthly calculations are used to evaluate primary energy consumption per unit area (Korea Institute of Construction Technology, 2014). This method offers the advantage of simplicity compared to dynamic simulation tools. However, it has limitations in modeling realistic building shapes and systems, limited input variables, and the inability to account for uncertainties in thermal behavior (Jo, 2017).

2.2.2 Energy Modeling

Shape modeling is divided into building shape, the physical positions and thermal properties of each material (walls, roofs, floors, windows), and thermal zoning. Generally, it is modeled by referring to drawings and specifications (Ahn, Kim, & Park, 2012).

In the case of EnergyPlus, the shape model is built in three dimensions using tools such as DesignBuilder or SketchUp. It allows direct visualization of the 3D shape. However, in ECO2, information related to rooms (orientation, area, etc.) is entered as text, and the visualized shape is not provided. Additionally, it is not possible to define relationships with adjacent spaces, and therefore, heat transfer with adjacent spaces is not considered (Figure 2.1). This discrepancy can lead to a difference from the reality.

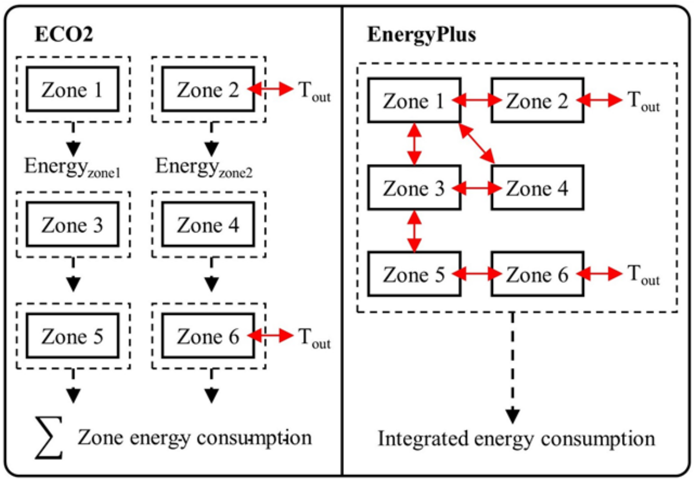
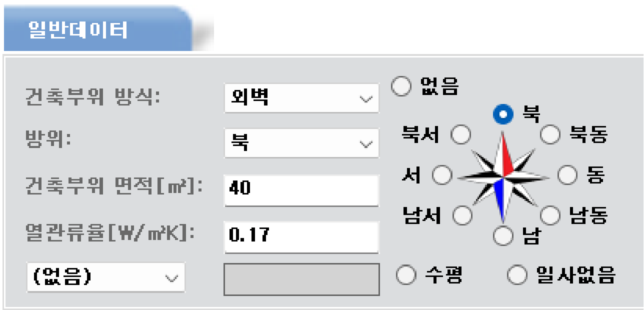


Figure 2.1 Thermal zoning between adjacent zones (ECO2 vs. EnergyPlus)

Furthermore, in ECO2, all zones are represented as a rectangular space (floor area × height), making it difficult to reflect polygonal surfaces, for example (Figure 2.2(a)). Additionally, it is limited to eight orientations (east, west, south, north, southeast, northeast, northwest, southwest) (Figure 2.2(b)). Building shape and orientation are important variables in building energy-saving design, but ECO2 has limitations in reflecting these aspects, and they need to be determined based on the subjective judgment of the modeler.

(a) Zone



(b) Wall surface

Figure 2.2 Information entry in ECO2

ECO2, which takes a quasi-steady state approach, simplifies the HVAC system modeling. Consequently, it is challenging to simulate HVAC systems that closely resemble the reality using ECO2, leading to the following issues:

- Difficulty in reflecting VAV system control:

The reheat energy and fan power consumption of terminal boxes can vary significantly depending on the minimum and maximum airflows of VAV systems. EnergyPlus considers these as system input variables (Cho, Kang & Seong, 2012). However, ECO2 only allows selecting control options (control on or off), making it difficult to analyze the dynamic behavior of VAV systems. Modelers also face difficulties in accurately representing the system dynamics.

- Difficulty in simulating the dynamic behavior of radiant floor heating systems:

To simulate the dynamic behavior of radiant floor heating systems, information about surface finishes, mortar, insulation materials, and properties of the concrete (thermal conductivity, thickness) is required, along with information about the hot water pipes (diameter, spacing, burial depth) (Wu et al., 2015; Liang, 2021). On the contrary, ECO2 lacks input fields for hot water pipes (diameter, spacing, burial depth), and it does not require information about hot water flow rate and control. Therefore, it is challenging to simulate time-varying heat transfer phenomena accurately in the floor panels (Kim, Choi, & Park, 2020).

• Difficulty in reflecting partial load characteristics:

Each heating and cooling equipment has its own partial load performance curve, which can be considered in dynamic simulation tools. Moreover, in cases where multiple devices are connected in parallel, it is possible to input the minimum and maximum partial load ratios for each device. However, in ECO2, only refrigerant type, inlet and outlet water temperatures, and control mode can be inputted, making it difficult to reflect the partial load characteristics and the resulting operational efficiency of cooling and heating equipment (DIN V 18599-7, 2007).

• Others:

In ECO2, it is not possible to set the efficiency and flow rate of pump motors, making it challenging to accurately reflect the operational characteristics of pumps. Additionally, even if the supply and return temperatures of heat-producing devices are changed, there is no change in the calculated monthly energy usage results (Li, Wu & Yu, 2015).

2.3 Usage Profile

2.3.1 Standard usage profile (ECO2)

The ECO2 program is a building energy assessment standard and based on ISO 13790 and DIN V 18599. It has been used to predict the energy consumption of buildings during the certification process for domestic building energy efficiency ratings. Based on monthly calculations, it interprets the thermal behavior of the building under quasi-steady state conditions and calculates the energy consumption using monthly average weather data. In this case, the monthly mean weather data utilizes Typical Meteorological Year (TMY) data, which includes outdoor temperature and monthly mean solar radiation based on incident angles by direction. In the ECO2 modeling process, the usage profiles of each space need to be specified. Among the 20 predetermined usage profiles (e.g., residential space, office, auditorium, etc), the relevant profile corresponding to the space's purpose is selected and inputted. The usage profiles contain information regarding (1) start and end times of use, (2) start and end times of operation, (3) specified demand (minimum outdoor air intake, hot water demand, lighting hours), (4) internal heat gain (occupancy density, plug load density), (5) heating and cooling set point temperature and (6) monthly usage days (Table 2.3). These values are predetermined and cannot be modified by the user. The user can freely input values for infiltration rate [1/h] and light power density [W/m^2] related to space operation. However, other operational variables cannot reflect probabilistic states, which may lead to discrepancies between the actual building's energy consumption and ECO2 calculations. Unlike ECO2, EnergyPlus allows users to input usage profile values freely according to the building's operation mode.

Table 2.3 Large Office usage profiles of ECO2

Category	Unit	Value
Hours of Use and operation		
Start time of use	[hh:mm]	09:00
End time of use	[hh:mm]	18:00
Start time of operation	[hh:mm]	07:00
End time of operation	[hh:mm]	18:00
Set demands		
Ventilation	[m3/(m^2h)]	6
Domestic hot water	[Wh/(m^2d)]	30
Lighting time	[h]	9
Internal heat gain		
Occupant density	[Wh/(m^2d)]	55.8
Plug load density	[Wh/(m^2d)]	126
Indoor air temperature		
Heating set point temperature	[℃]	20
Cooling set point temperature	[℃]	26
Number of operation days		
January	[d/mth]	22
February	[d/mth]	19
March	[d/mth]	21
April	[d/mth]	22
May	[d/mth]	22
June	[d/mth]	20
July	[d/mth]	22
August	[d/mth]	21
September	[d/mth]	18
October	[d/mth]	21
November	[d/mth]	21
December	[d/mth]	21
Correction factor by usage profile		
Heating	-	1
Cooling	-	1
Domestic hot water	-	1
Lighting	-	1
Ventilation	-	1

2.3.2 How to define ECO2 usage profile in EnergyPlus

EnergyPlus is a well-known, high-fidelity dynamic building energy simulation program used to calculate the hourly energy consumption of a building based on input information for various objects, including building envelope and HVAC systems. Unlike ECO2, EnergyPlus allows users to input variables in more detail, enabling more precise modeling of the dynamic behavior of building systems (Ahn, Kim & Park, 2012).

In EnergyPlus, users can directly specify most of the variables related to objects that make up the building energy model. Regarding the minimum outdoor air intake rate and ventilation rate in the usage profile, there are three and two interpretation options, respectively, and the modeling approach can be specified based on the user's settings. For light power density, plug load density, and occupancy density, there is only one interpretation option. If users want to input these parameters in the building energy model, they can input detailed values during the modeling process. The minimum outdoor air intake rate and ventilation rate can be input in three different units, commonly as air flow rate per floor are ($m^3/s{\cdot}m^2$) and air changes per hour (ACH), or as air flow rate per surface are ($m^3/s{\cdot}m^2$) and air flow rate per person ($m^3/s{\cdot}$person) for each envelope area. The heat gains for light power density, plug load density, and occupancy density can be input in two different units. For light power density and plug load heat gains, users can input heat gains per floor area (W/m^2) and heat gains per person (W/person). For human occupancy heat gain, users can input occupancy level per area (people/m^2) and occupancy area per person (m^2/person). Unlike ECO2, EnergyPlus allows for easy application of stochastic usage profiles by allowing changes in detailed input values. Therefore, in this study, EnergyPlus was used as a tool for uncertainty analysis.

Chapter 3. Methodology

3.1 Uncertainty Analysis

The factors that affect building energy include climate, operating conditions, and envelope properties, among others. These factors continuously and randomly change, it is difficult to define a single value for building energy analysis. Nonetheless, ventilation rate is assumed as a single value for zone usages, and occupancy density and plug load density is assumed as deterministic value. Additionally, 24-hour weather data is sometimes used to represent a month. Uncertainties in building energy simulation can be categorized into three types: (1) Uncertainty in property values, such as material properties and equipment performance (capacity, COP), (2) Model uncertainty, which involves simplifications in the model (metabolic rate, clothing insulation), and (3) Scenario uncertainty, which includes variations in weather conditions and operational characteristics. These factors are values that necessarily change during the operation of a building and cannot be determined as single(deterministic) values.

In recent years, the field of building energy simulation has been acknowledging and attempting to quantify the uncertainty of building energy through stochastic approaches, rather than specifying input parameters as deterministic values. Deterministic approaches define input values as single values and produce deterministic results. However, stochastic approaches that consider uncertainty allow input values to be defined as ranges, resulting in stochastic outcomes, which can provide more objective information.

However, the ECO2 assumes some of the input variables with stochastic characteristics, such as variations in weather conditions and operational characteristics, metabolic rate, and clothing insulation, as single values, and the user cannot modify them, making it difficult to analyze uncertainty based on operation. While it is possible to modify some variables (material properties, equipment capacity, and COP), the limitations of the input system make it difficult to effectively apply them for analyzing actual uncertainty. The uncertainty analysis is performed through the following steps: (1) Building energy modeling, (2) Selection of uncertainty range for input parameters, (3) Modification of input parameter values in the model from step (1), (4) Simulation. The EnergyPlus energy model can be edited as a text file (.txt) and can be automated using tools like Python, allowing the creation of a new energy model in a short time (within 5 minutes for 1000 inputs). However, with the ECO2 model, the user needs to manually edit information and go through the calculation process, which takes several hours for model generation (as shown in the red box in Figure 3.1). This can exponentially increase with the size of the building, posing a significant burden on the user depending on the scale.

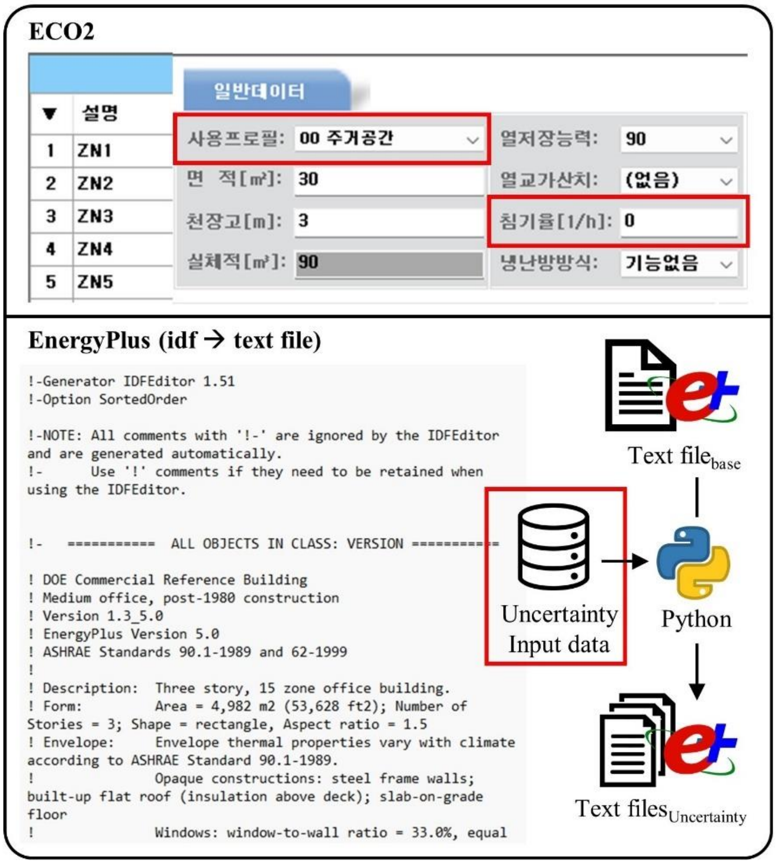


Figure 3.1 Comparison of the process for uncertainty analysis (ECO2 vs. EnergyPlus)

Due to normative approaches and limitations of the input system, ECO2 cannot perform uncertainty analysis of building energy, which can have disadvantages in terms of providing objective information and ensuring reliability. This can also affect its role as a decision support tool. Despite being recognized as a domestic building energy simulation program, ECO2 is not effectively applied in actual design stages. Therefore, in this study, EnergyPlus was considered as a tool for uncertainty analysis, and the Latin Hypercube Sampling method was used for sampling the input values.

One of the most well-known sampling methods, in this study, Latin Hypercube Sampling (LHS) method was selected to achieve more precise distribution estimation of the outcome values (McKay, Beckman & Conover, 1979). LHS is one of the most widely used methods in building simulation for uncertainty analysis and has been sufficiently validated through previous research (Kim & Park, 2008). LHS allows for uniform sampling of samples, avoiding overlapping of input samples. The procedure is as follows: 1) Divide the range of 0-1 into N equal intervals, 2) Randomly extract one sample per interval, 3) Calculate the inverse cumulative distribution function for the extracted samples to derive samples of input variables. For example, when two input variables follow a uniform distribution of 0-1, if a sample of size 8 is extracted using LHS, a random permutation of the set {1, 2, …, 7, 8} will yield a result such as {5, 3, 6, 7, 1, 8, 2, 4}. The numbers indicated in Figure 3.2 represent the order of extraction, and it can be observed that exactly one sample is selected in each row and column (Im, Kwon & Lee, 1995). In this study, this method was used to derive 1,000 samples for five variables (minimum outdoor air intake rate, occupancy rate, light power density, occupancy density, plug load density), and uncertainty analysis was performed.

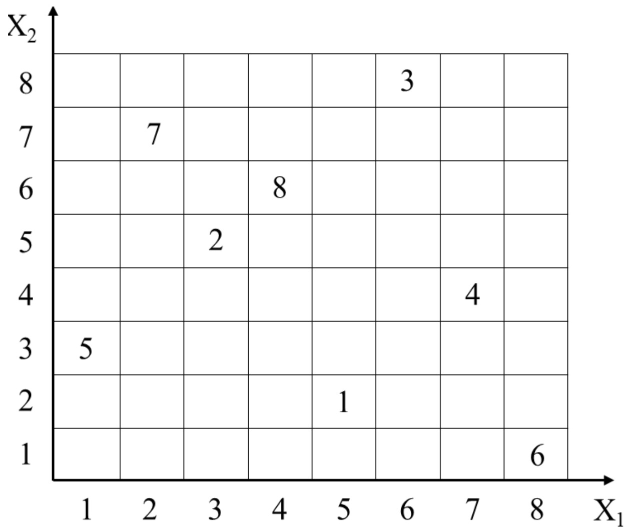


Figure 3.2 Latin Hypercube Sampling example
(modified from Im, Kwon & Lee, 1995)

3.2 Sensitivity Analysis

Sensitivity analysis can be divided into local and global sensitivity analyses (Tian, 2013). Local sensitivity analysis observes the influence of output variables on selected input variables, while global sensitivity analysis quantifies the impact on output variables by simultaneously varying all input variables. Global sensitivity analysis can be performed using three main methods, as described below (Tian, 2013 & Yoo, et al., 2020).

(1) Regression: This method is widely used because it is computationally efficient, easy to understand using metrics such as Standard Regression Coefficients (SRC) and Partial Correlation Coefficients (PCC). However, it has the drawback of only measuring sensitivity for linear relationships between input and output variables or monotonically related functions with one output and one input variable.

(2) Screening-based: This method requires less computation compared to other global sensitivity analysis methods, but it cannot quantify the sensitivity of input variables. One prominent method is the Morris method, which estimates the effects of input variables on the output value using the mean (μ), evaluates interactions using standard deviation (σ), and estimates the final impact of input variables with μ^* (Saltelli, et al., 2004).

(3) Variance-based: This method allows for quantifying the sensitivity of input variables without building a model and is applicable even for complex nonlinear relationships. Sensitivity is composed of the sensitivity of input variables to the output variable and n-th order interactions between input variables. A representative method is Sobol, although it requires a large amount of computation. Recently, meta-

modeling methods have been proposed as an extension of variance-based methods, which use machine learning models to quantify the sensitivity of input variables as a variance-based approach (Saltelli, et al., 2006).

In this study, we adopted the Sobol method, which enables analysis over the entire range of input variables and quantifies interactions. Equation 3.1 shows the sensitivity index (S_i) calculated through the Sobol method. In this equation, $E(V(Y|X_i))$ represents the expected variance of the output variable with respect to the input variables, and $V(Y)$represents the total variance of the output variable. The sensitivity index takes values between 0 and 1. The calculated sensitivity index (S_i) indicates the influence on the output variable (e.g., building energy usage), and it was applied in this study to improve the base scores (a).

$$S_i = \frac{E(V(Y|\, X_i))}{V(Y)} \tag{3.1}$$

where,

S_i : Sensitivity Index

E : Expected value

V: Variance

Y: Output variable

X_i: Input variable

3.3 Polynomial Regression

Regression analysis is a methodology employed to represent the correlation between the explanatory variable(s), also known as the independent variable(s), and the response variable using a regression model. In the case where there is only one explanatory variable, it is categorized as a simple linear regression, while if there are two or more explanatory variables, it is classified as multiple regression. The regression equation can be formulated as a polynomial equation of degree 0 to n (where n is an integer), depending on the chosen regression model. In situations where the regression equation is constructed in multiple dimensions, it is referred to as multidimensional regression or polynomial regression. Equation 3.2 illustrates a polynomial regression equation when dealing with a simple regression that has one independent variable.

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 {x_i}^2 + \beta_3 {x_i}^3 + \cdots + \beta_k {x_i}^k + e_i \qquad (3.2)$$

in here, $i = 1, 2, 3, \cdots, \mathrm{n}$

where,

β: Vector of regression parameter

k: Degree of the polynomial equation

In general, the least square method is commonly used to construct a regression model, and it was also applied in this study. The coefficient of determination, R^2, is widely used as a performance metric for multi-dimensional regression models

(Equation 3.3). R^2 is defined as the difference between 1 and the ratio of the sum of squared errors between the actual and predicted values to the total squared deviation of the actual values. R^2 ranges from 0 to 1, and a value above 0.8 is considered as indicative of a reliable regression model (Ostertagová, 2012).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.3}$$

where,

y_i : Actual values (=Ground truth value)

$\hat{y_i}$: Predicted values (=Estimated value)

$\bar{y}$: Arithmetic mean of the Y

In this study, the author performed the following processes: (1) sampling of input variables, (2) conducting EnergyPlus simulations, (3) building regression models for input and output variables, (4) deriving regression analysis to simulate the relationship between the model's input variables and output values. Figure 3.3 shows the process of improving weighting factors (b) using polynomial regression analysis through Monte Carlo simulations.

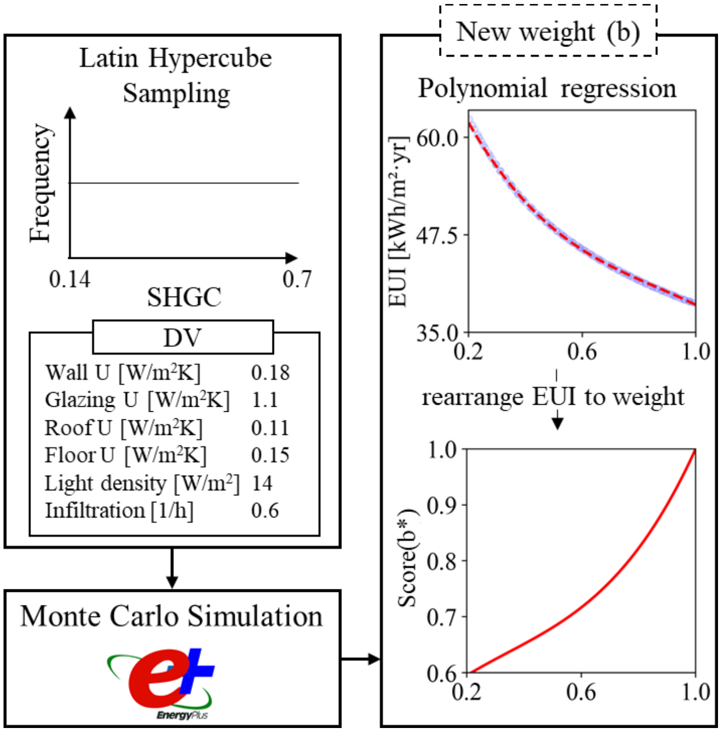


Figure 3.3 Converting weight (b) using polynomial regression

Chapter 4. Simulation model

4.1 Target building

The target building was selected as a medium-sized office building from the EnergyPlus reference building models provided by the DOE, due to the absence of domestic standard building models (Yoo, Yi & Park, 2021, Figure 4.1). The building has a total floor are of 4,981.8 m^2 and consists of three floors (width: 49.9m, length: 33.3m, height: 11.9m). Each floor is composed of four perimeter zones and one core zone, with a window-to-wall ratio of 33.01%. The output of the building energy analysis model was set as the monthly heating and cooling energy demand (kWh/m^2) of the target building. To achieve this, the heating source and air conditioning system of the target building were modeled as an “Ideal loads air system”, and the output of ECO2 was also set as the energy demand (kWh/m^2). Detailed information about the target building is provided in Table 4.1, and based on this information, the ECO2 model was built. For the EnergyPlus and ECO2 simulations, weather data for the Incheon region were used. EnergyPlus employed TMY2 (Typical Meteorological Year) data, while ECO2 utilized the embedded ISO TRY (Test Reference Years) Incheon standard weather data (Korea Institute of Construction Technology, 2017).

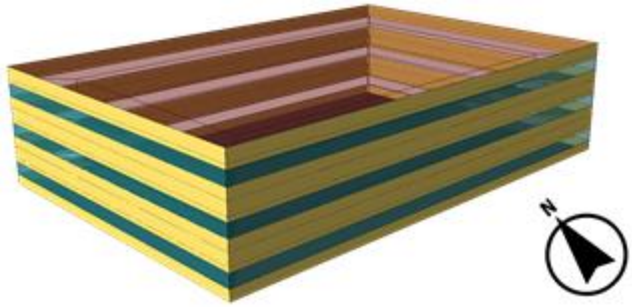


Figure 4.1. Target building

Table 4.1. Building parameters

Parameters		Values
Location		Inchon, South Korea
Total floor area [m^2]		4,981.8
Number of floors [-]		3
Ceiling height [mm]		2740
WWR [%]		33.01
U-value [$W/m^2 \cdot K$]	Wall	1.05
	Roof	0.28
	Floor	3.40
	Window	6.92
Fenestration SHGC [-]		0.25

All zones in the target building have floor areas exceeding $30m^2$, which corresponds to the 'Large Office (>$30m^2$)' category specified in the ECO2 usage profile. Therefore, the input values specified in the usage profile for 'Large Office (>$30m^2$)' (Table 2.3) were applied to the target building. For certain variables, excluding operating schedules (start and end times, operational start and end times), number of operation days, and cooling/heating set point temperatures, the input units of ECO2 and EnergyPlus differ from each other. Therefore, unit conversions were performed (Table 4.2). For example, in the case of occupancy density, the specified value in the occupancy profile is 55.8 Wh/m^2d. However, in EnergyPlus, the converted value of 0.075 people/m2 (55.8Wh/m^2 ÷ usage time of hours 9h ÷ human heat gain 70W) (Korea Institute of Construction Technology, 2014). It should be noted that while ECO2 considers sensible heat only for human heat release, EnergyPlus considers both sensible and latent heat.

In this study, uncertain variables in the usage profile, including minimum outdoor air intake, infiltration rate, light power density, occupancy density, and plug load density were considered. The ranges for these parameters were set based on references from domestic and international literature that conducted simulations on office building (Table 4.3). Furthermore, using the Latin Hypercube Sampling (LHS) method, 1,000 samples were generated, and uncertainty analysis was performed on these samples.

Table 4.2 Input variables of usage profile for large office

<table>
<tr><th colspan="2">Variables</th><th>ECO2</th><th>EnergyPlus</th></tr>
<tr><td colspan="2">Usage hour</td><td>09:00 – 18:00</td><td>09:00 – 18:00</td></tr>
<tr><td colspan="2">Operating hour</td><td>07:00 – 18:00</td><td>07:00 – 18:00</td></tr>
<tr><td colspan="2">Ventilation</td><td>6 $m^3/m^2{\cdot}h$</td><td>0.0016 $m^3/m^2{\cdot}s$</td></tr>
<tr><td colspan="2">Lighting time</td><td>9 h</td><td>09:00 – 18:00</td></tr>
<tr><td colspan="2">Occupant density</td><td>55.8 $Wh/m^2{\cdot}d$</td><td>0.89 people/m^2</td></tr>
<tr><td colspan="2">Plug load density</td><td>126 $Wh/m^2{\cdot}d$</td><td>11.455 W/m^2</td></tr>
<tr><td rowspan="2">Set point temperature</td><td>Heating</td><td>20℃</td><td>20℃</td></tr>
<tr><td>Cooling</td><td>26℃</td><td>26℃</td></tr>
</table>

Table 4.3 List of the building usage scenarios

Parameter	Min	Max	Reference
Ventilation [m^3/m^2s]	0.0011	0.0069	KEA, 2016 Yoon, Park, & Sohn,2008
Infiltration [ACH]	0.2	1	CIBSE, 2006 Hwang & Kim, 2009
Lighting density [W/m^2]	3.11	30	Yoo et al, 2020 Pan, Huang & Wu, 2007
Occupant density [$people/m^2$]	0.075	0.32	KEA, 2016 Hopfe, 2009
Plug load density [W/m^2]	2.69	25	ASHRAE, 2013 Yoon et al, 2008

4.2 Surrogate model (ANN)

The author developed an ANN surrogate model for Sobol sensitivity analysis due to the requirement of a large number of simulations. Firstly, the author performed Latin Hypercube Sampling (LHS) on the ranges of seven design variables. The author selected a subset of evaluation criteria from the existing Energy Performance Index (EPI) for the analysis, which included seven design factors: wall U-value (exterior wall), window U-value, roof U-value, floor U-value, window Solar Heat Gain Coefficient (SHGC), light power density, infiltration rate. The ranges for each factor were determined based on the energy-saving design criteria for domestic buildings and references from domestic literature, as shown in Table 4.4. It is important to note that the wall U-value [ID 1] represents the range of wall U-value without considering windows, and when adjusting the weighting factors (score (a) and (b)), the value of the wall U-value of the external wall derived from the area weighted value with the U-value of the window [ID 2] is the standard.

Table 4.4 Ranges of target parameters

ID	Design variables	Range	Reference
(1)	Wall U-value [W/m2·K]	0.12 – 0.24	KEA, 2016
(2)	Glazing U-value [W/m2·K]	0.7 – 1.5	
(3)	Roof U-value [W/m2·K]	0.07 – 0.15	
(4)	Floor U-value [W/m2·K]	0.1 – 0.2	
(5)	Fenestration SHGC	0.14 – 0.7	-
(6)	Light density [W/m2]	8.0 – 20.0	KEA, 2016
(7)	Infiltration [1/h]	0.2 – 1.0	

The training data was collected by conducting 500 pre-simulations using EnergyPlus. The artificial neural network (ANN) was built using the Scikit-Learn package in Python, and the CVRMSE value between EnergyPlus and the surrogate model was 2.2%, indicating that the surrogate model performs sufficiently well (Figure 4.2).

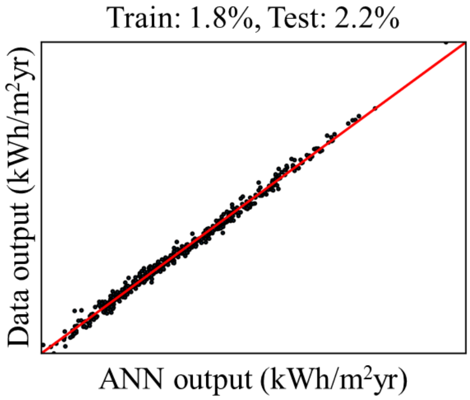


Figure 4.2 Comparison between EnergyPlus and surrogate model (ANN)

Chapter 5. Results

5.1 Uncertainty analysis

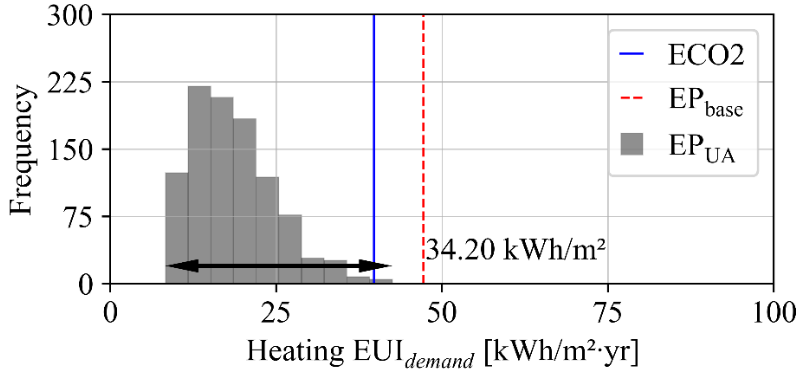
Figure 5.1-(a) and (b) show histograms of the distribution of annual cooling and heating energy demands simulated by EnergyPlus, considering the uncertainty in the usage profile variables. The histograms shows the EnergyPlus Uncertainty Analysis (EP_{UA}) results (gray area), the EnergyPlus simulations with the base usage profile values (EP_{base}, red dashed line), and the calculated results from the ECO2 (ECO2, blue solid line). The X-axis represents the annual energy demand in kWh/m^2·yr, and the y-axis represents the frequency. As mentioned in Section2, since ECO2 and EnergyPlus use different building energy calculation methods, it is difficult to quantitatively compare the building energy demands (EP_{base}, ECO2). Therefore, the analysis was conducted with the aim of demonstrating the need for a probabilistic approach to usage profile, rather than examining the differences between ECO2, EnergyPlus calculations, and actual building energy consumption.

As shown in Figure 5.1-(a), the annual heating energy demand is 47.2 kWh/m^2·yr when the base usage profile (EP_{base}) is used. The heating energy demand ranges from a minimum of 8.3 kWh/m^2·yr to a maximum of 42.5 kWh/m^2·yr, depending on the operation of the target building. The variation in energy demand due to the uncertainty in the usage profile amounts to 34.2 kWh/m^2·yr (range on the x-axis of the gray area, the difference between the maximum and minimum values in EP_{UA}). Furthermore, compared to EP_{base}, the heating energy demand shows a minimum difference of 4.7 kWh/m^2·yr ($|EP_{base}$-maximum value in $EP_{UA}|$ in Figure 5.1-(a)) and a maximum difference of 38.9 kWh/m^2·yr ($|EP_{base}$-minimum value in $EP_{UA}|$ in

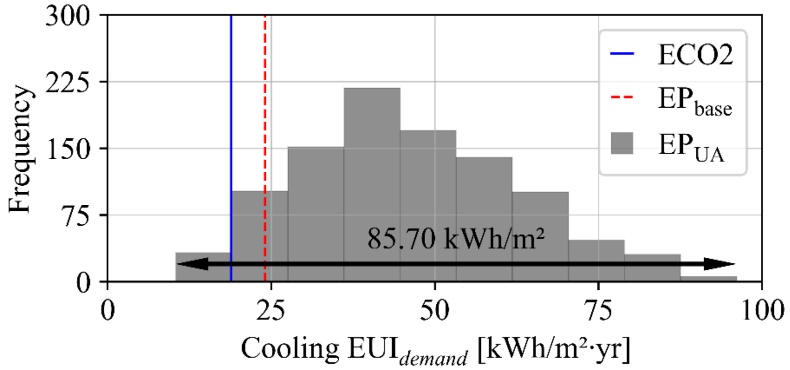
Figure 5.1-(a)), corresponding to 10% and 82% of EP_{base}, respectively. This indicates that the deterministically assessed heating energy demand can differ significantly from the actual performance during operation.

Figure 5.1-(b) presents the annual cooling energy demand. When the base usage profile is applied (EP_{base}), the demand is 24.1 kWh/m^2·yr. The cooling energy demand ranges from a minimum of 10.4 kWh/m^2·yr to a maximum of 96.1 kWh/m^2·yr, depending on the operation of the target building. The variation in energy demand due to the uncertainty in the usage profile amounts to 85.7 kWh/m^2·yr (difference between the maximum and minimum values in EP_{UA}). Furthermore, compared to EP_{base}, the cooling energy demand shows a minimum difference of 13.7 kWh/m^2·yr ($|EP_{base}$-maximum value in $EP_{UA}|$ in Figure 5.1-(b)) and a maximum difference of 72.0 kWh/m^2·yr ($|EP_{base}$-minimum value in $EP_{UA}|$ in Figure 5.1-(b)), corresponding to 56% and 298% of EP_{base}, respectively. This indicates that the deterministically assessed cooling energy demand can differ significantly from the actual energy demand during operation, and this difference is greater than that observed in the heating energy demand. This implies that when performing deterministic assessments in buildings dominated by internal heat gains, there is a high possibility of evaluation errors and biased decision-making.

In summary, the uncertainty analysis of annual heating and cooling loads revealed significant uncertainties in both demands. This indicates that the deterministic assessment of usage profile input parameters may not provide an objective evaluation since it does not reflect the actual conditions under which zones and systems are operated. In actual buildings, larger uncertainties may exist, and when considering ventilation loads, lighting loads, and domestic hot water loads, larger performance differences can occur. Therefore, it is expected that considerable discrepancies may arise between the obtained assessment grades and those based on actual energy consumption.



(a) Heating energy demands



(b) Cooling energy demands

Figure 5.1 Distribution of annual heating and cooling energy demand according to stochastic usage profiles

Figure 5.2 shows the monthly distribution of total energy demand (Total EUI demand, black), heating energy demand (Heating EUI demand, red), and cooling energy demand (Cooling EUI demand, blue) according to the uncertainty of the usage profile variables. The data is represented using a box and whisker plot, which provides an intuitive visualization of the distribution. The plot consists of (1) the first quartile (Q1) and the third quartile (Q3), which divide the data into the lower 25% and upper 75% ranges respectively, and (2) the interquartile range (IQR), which represents the range between the 25th and 75th percentiles. In this study, $|$upper whisker – lower whisker$|$ was considered as a measure of uncertainty associated with the usage profile.

The energy demand variation due to changes in the building operation (usage profile variables) showed uncertainties of up to 9.38 kWh/m^2 during the winter period (based on January, 11.94-2.56 kWh/m^2) and up to 13.08 kWh/m^2 during the summer period (based on August, 17.58-4.5 kWh/m^2). For the transitional seasons (March-May and September-October), the minimum cooling energy demand reached approximately 0 kWh/m^2, indicating scenarios where air conditioning was not required.

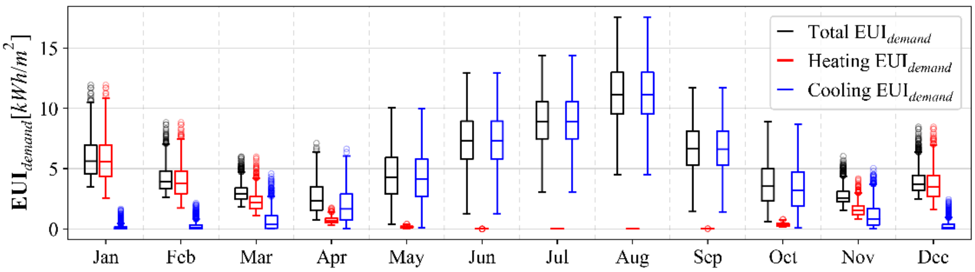


Figure 5.2 Monthly total, heating and cooling energy demand distribution

However, the maximum cooling energy demand could reach up to 11.71 kWh/m^2 (based on September). Therefore, it is evident that the need for cooling operation during transitional seasons depends on factors such as occupant preferences and operational conditions, which may not be captured in a single-point evaluation. This highlights the need to consider a stochastic approach for a more objective and realistic assessment of building energy, particularly during the transitional periods encompassing both heating and cooling seasons.

5.2 Sensitivity analysis

As mentioned in Section 3, in this study, a global sensitivity analysis of seven design variables for cooling energy demand was conducted to improve the base score (a). The results are presented in Table 5.1. Among the variables, the infiltration rate [ID 7] showed the highest sensitivity with a value of 0.352, indicating its significant impact on cooling energy demand. Window-related variables, such as Fenestration U-value [ID 2] with a sensitivity of 0.041 and Fenestration solar heat gain coefficient (SHGC) [ID 5] with a sensitivity of 0.35, were also found to be sensitive to cooling energy demand. Additionally, light power density [ID 6] exhibited a sensitivity of 0.257, indicating its substantial influence on cooling energy demand. On the other hand, the thermal transmittance of the building envelope had minimal impact on cooling energy demand (Wall U-value [ID 1]:0.0005, roof U-value [ID 3]: 0.0002, floor U-value [ID 4]: 0.0001). The sensitivity analysis results suggest the following implications:

(1) Building Envelope U-value: The building envelope U-value showed relatively low sensitivity to cooling energy demand compared to the base score (a) in the current Energy Performance Index (EPI). Considering that cooling energy constitutes a significant portion in modern office buildings, it is necessary to consider changes in the base score to address this issue.

(2) Windows: Window-related design variables shows significant sensitivity to cooling energy demand, making them crucial aspects to consider in energy-saving design. Therefore, improving the base score (a) while considering these influences is essential.

(3) Light power density and infiltration rate: Both factors showed considerable sensitivity to cooling energy demand, emphasizing the need to consider them in energy-saving design.

(4) By replacing the base score (a) with the sensitivity indices presented in Table 5.1, the EPI can align more closely with performance-oriented results, as discussed in the subsequent Section 5.4

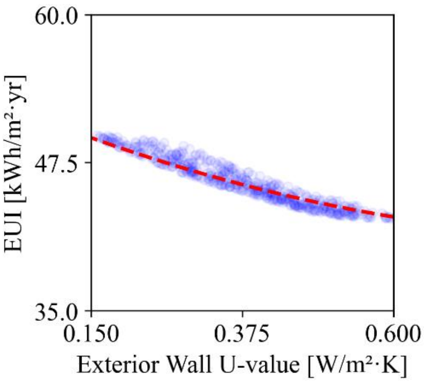
Table 5.1 New EPI* weight (a*) based on sensitivity

ID	Design variables	Sensitivity index (S_i)	New weight (a*)
(1), (2)	Exterior wall U-value [$W/m^2 \cdot K$]	0.0413	1.82
(3)	Roof U-value [$W/m^2 \cdot K$]	0.0002	0.01
(4)	Floor U-value [$W/m^2 \cdot K$]	0.0001	0.0
(5)	Fenestration SHGC	0.3498	15.0
(6)	Light density [W/m^2]	0.2565	11.0
(7)	Infiltration [1/h]	0.3519	15.1
	Total	0.9998	42.9

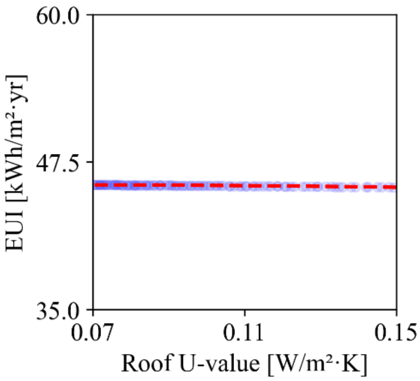
5.3 Results of Polynomial regression

Prior to regression analysis, the floor U-value among the seven design factors was excluded from consideration due to its very low sensitivity (ID 4, Table 5.1). Consistent with the evaluation criteria for energy-saving design in buildings, the thermal transmittance of exterior wall and fenestration were considered by converting them into external wall thermal transmittance using area-weighted calculations. Figure 5.3 shows the results of the polynomial regression analysis, where blue dots represent EnergyPlus simulation results, and the red dotted line represents the regression result.

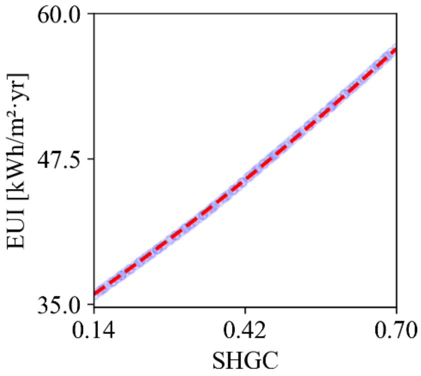
The roof U-value and light power density can be adequately explained by a first-order linear regression analysis, showing sufficient correlation with the results. The wall thermal transmittance and fenestration solar heat gain coefficient (SHGC) can be described by second-order regression equations, while infiltration can be represented by a third-order regression equation (Table 5.2). The results of the polynomial regression analysis enable the representation of variations in cooling energy demand based on the design variables through regression equations, which can replace the weighting (b*) in the improved Energy Performance Index (Section 5.4).



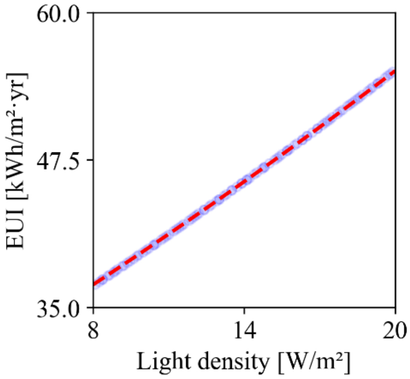
(a) Exterior wall



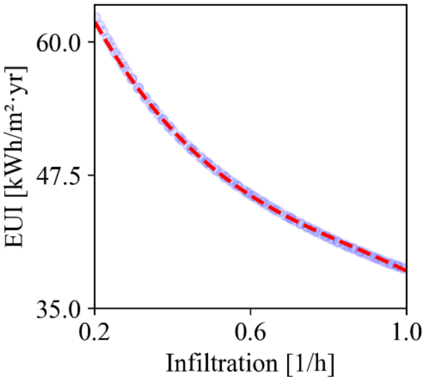
(b) Roof



(c) Fenestration SHGC



(d) Light power density



(e) Infiltration

Figure 5.3 Regression analysis results

(blue dots: EnergyPlus simulation results, red dotted line: regression result)

Table 5.2 New EPI* weight (b*) based on polynomial regression

ID	Design variables	Mathematical polynomial regression between design variables and cooling energy demands	R^2
(1), (2)	Exterior wall U-value [$W/m^2 \cdot K$]	$Y = 0.6723(X)^2 + 0.38(X) + 0.466$	0.93
(3)	Roof U-value [$W/m^2 \cdot K$]	$Y = 4.9723(X) + 0.246488$	0.99
(5)	Fenestration SHGC [-]	$Y = 0.000009(X)^2 - 0.007(X) + 1.085$	0.99
(6)	Light density [W/m^2]	$Y = -0.3333(X) + 1.2666$	0.99
(7)	Infiltration [1/h]	$Y = 0.6605(X)^3 - 0.6832(X)^2 + 0.5062(X) + 0.5155$	0.99

5.4 Results of new EPI*

In a previous study by Yoo et al. (2020) on the improvement of the weighting system for the Energy Performance Index (EPI), only the new EPI metric and EnergyPlus simulation results were compared to demonstrate the need for a scientific approach. In this study, sensitivity analysis was performed on eight selected factors for the weighting system improvement, and the sensitivity of each factor was substituted with the base score (a). For the weighting score (b), the correlation (+/-) was analyzed, and a first-order equation was used to represent the weighting (b). Similarly, to the previous study, the sensitivity of the selected factors was substituted with the base score (a), but in this study, the weighting score (b) was adjusted using linear regression equation that simulate the behavior of cooling energy demand for each factor. The detailed procedure for weighting adjustment in this study is as follows.

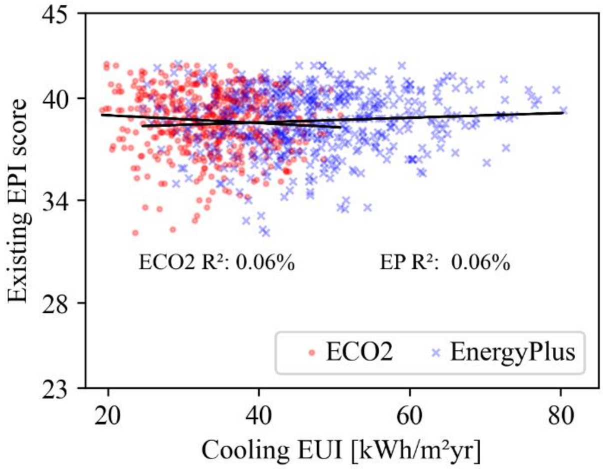
For the base score (a), the sensitivity of each design variable was converted into scores. Each sensitivity index was multiplied by 43 so that the sum of the sensitivity indices would be equal to the base score (a) for the design variables in the current EPI, which is 42.9 points (Table 2.1 in Section 2.1). The scoring conversion for the exterior wall involved simply summing the sensitivity indices of the wall thermal transmittance and the fenestration thermal transmittance to adjust the base score (a*). The solar heat gain coefficient (SHGC) was evaluated based on the SHGC value considering the shading device and window frame, assuming a base window without shading devices. Through the improvement of the base score (a*), the weighting for thermal transmittance significantly decreased. Particularly, the low sensitivity of the floor thermal transmittance was adjusted to 0 points in the improved base score (a*).

For the weighting score (b), the current EPI calculated the weighting discretely based on the values of the variables, as shown in Table 2.2 in Section 2.1. To reflect the thermal behavior of the building, the weighting (b*) was continuously adjusted based on the results of the regression analysis. For this purpose, the cooling energy demand of each design factor was normalized to have a value between 0.6 and 1.0. For example, in the case of the infiltration rate (Figure 5.3(e)), the maximum and minimum values of the cooling energy demand within the range were 62.3 kWh/m^2·yr and 38.7 kWh/m^2·yr, respectively. The difference between the maximum and minimum values was then normalized to be 0.4 (1.0-0.6), and the regression equation was adjusted to obtain lower scores for higher cooling energy demand. Table 5.2 shows the weighting (b*) for the new EPI* and the coefficient of determination (R^2) for each regression equation. It is worth noting that during the adjustment process for the base score (a), the base score (a) for the floor thermal transmittance was adjusted to 0 points, so no regression equation was developed for the weighting (b*) for the floor thermal transmittance.

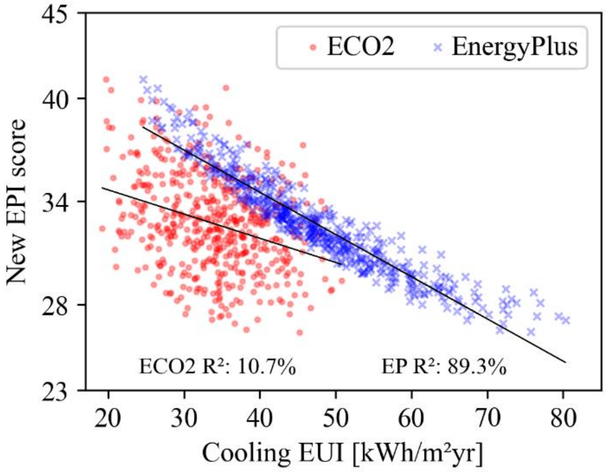
5.5 Results of Correlation analysis

Based on the ranges provided in Table 4.4, 500 samples were generated using the Latin Hypercube Sampling (LHS) method, and simulations were performed using the same samples in both ECO2 and EnergyPlus. Figure 5.4 shows the annual cooling energy demand calculated by ECO2 and EnergyPlus, along with the current and new EPI* scores. Each point in Figure 5.4 represents a building sample, and the y-axis represents the calculated EPI score for that sample (ranging from a maximum of 43 to minimum of 25.8). The negative slope of the regression model in Figure 5.4 indicates that as the cooling energy consumption increases, the EPI score decreases. Both the current EPI and the cooling energy demand show a poor correlation, with an R-squared value of 0.06% for both ECO2 and EnergyPlus (Figure 5.4(a)). This suggests that the current EPI does not effectively explain the cooling energy demand and similar analysis for heating will be conducted in future studies. The relationship between the new EPI* and the cooling energy demand shows a strong correlation with an R-squared value of 89.3% in EnergyPlus, while ECO2 still shows a poor correlation with an R-squared value of 10.7% (Figure 5.4(b)).

These findings indicate that the new EPI* based on the Sobol global sensitivity analysis and polynomial regression analysis conducted in tis study can reflect the thermal dynamics of buildings. Furthermore, the poor correlation between the results of ECO2 calculations and the new EPI* and EnergyPlus results suggests that ECO2 is lacking in evaluating cooling energy. This highlights the need for the new EPI* or alternative approaches to evaluate building energy consumption.



(a) existing EPI, ECO2 and EnergyPlus



(c) New EPI*, ECO2 and EnergyPlus

Figure 5.4 Correlation between EPI* and Cooling Energy demand EUI

(Red and blue dots represent 500 sampled buildings)

Chapter 6. Conclusion

The domestic building energy codes in South Korea can be broadly divided into two categories: ECO2 and Energy Performance Index (EPI). ECO2 was developed based on quasi-steady state for calculating building energy consumption. However, it has been the subject of constant controversy regarding the accuracy and reliability of its results, as it does not disclose the calculation algorithm and defines input variables as single(deterministic) values.

In this context, this study analyzed six issues that can arise when using the quasi-steady state calculation program ECO2: (1) inability to reflect building shape and absence of guidelines, (2) lack of support for attribute values required for system analysis, (3) difficulties in modeling new technologies, (4) standardization of input variables (usage profile and weather data), (5) lack of validation for simulation users and programs, (6) uncertainty, and (7) low usability of ECO2.

In particular, this study aimed to demonstrate the necessity of a stochastic approach to usage profiles by comparing the results of deterministic and stochastic approaches in terms of energy demand. The case study focused on a medium-sized office building consisting of large-scale office zones as the target building and performed an analysis of the uncertainty of energy demand according to the uncertainty of five factors in the usage profile (minimum outdoor air intake rate (ventilation), infiltration rate, light power density, occupancy density, plug load density). The results showed that the uncertainty levels (1st quartile range and 3rd quartile range, i.e., the range of 25% to 75%) for annual heating and cooling energy demand were 34.2 kWh/m^2·yr and 85.7 kWh/m^2·yr, respectively. This indicates that the building's energy consumption can vary depending on changes in the usage profile, making it difficult to objectively define the usage profile as a 'deterministic' assessment method. Such uncertainty can lead to significant differences between the energy efficiency grade obtained based on ECO2 calculation results (deterministic approach) and the grade obtained based on the actual measured energy consumption during operation in the energy efficiency certification system.

When evaluating building energy with a single value, objective assessment becomes difficult, and the building's energy consumption can be underestimated or overestimated, leading to biased building design (envelope, HVAC systems, etc). To achieve an objective 'performance-based evaluation', a stochastic approach that considers uncertainties arising during the operation stage of the building is necessary. Considering stochastic usage profiles can not only enhance objectivity and transparency in building energy assessors but also assist evaluators and designers in making rational and objective decisions. This study quantified the uncertainty of energy demand according to the uncertainty of the occupancy profile and is planned to conduct further research on the building energy evaluation process based on a stochastic approach.

Furthermore, in this study, an improved Energy Performance Index (EPI*) was proposed based on Sobol global sensitivity analysis and polynomial regression analysis. The correlation between the predicted cooling energy demand, current EPI scores, and new EPI* scores was analyzed. In the EPI improvement process, the importance of each design variable for cooling energy demand was quantified using global sensitivity analysis to adjust the base score (a). In the current EPI, the base score (a) for the thermal transmittance of the building envelope accounted for approximately 77%. However, in the improved baseline weight (a*) based on sensitivity analysis, it changed to approximately 4%, indicating that the thermal transmittance of the building envelope is not a significant variable from the cooling energy perspective. On the other hand, the light power density and window solar heat gain coefficient (SHGC), which had relatively low weights in the current EPI, increased by about five times in the improved baseline weight (a*) based on sensitivity analysis. The polynomial regression analysis was conducted to propose a continuous function form of the discrete weighting score (b) in the current EPI. The weighting score (b*) function represented the behavior of cooling energy demand according to each design variable as a regression equation and was incorporated into the scoring system.

Based on these analyses, the current and new EPI* were applied to a target building, and the correlation between the EPI scores and the cooling energy demand of two simulation programs (ECO2 and EnergyPlus) was analyzed. In the case of the current EPI, both ECO2 and EnergyPlus showed no correlation (ECO2 R^2: 0.06%, EnergyPlus R^2: 0.06%). However, in the case of the new EPI*, EnergyPlus exhibited a strong correlation (R^2: 89.3%), while ECO2 still showed no correlation (R^2: 10.7%).

ECO2 predicts building energy usage through a simplified algorithm for thermal behavior. Additionally, ECO2 cannot be connected to open-source programs, and the modeling method is difficult for users to understand, making it challenging to quantify the importance of each input variable. The results of this study indicate that ECO2 does not show a correlation with the new EPI* based on scientific evidence.

From this perspective, a transition to a performance-based energy saving standard must be mandated in Korea.

The limitation of this study is that it was conducted targeting a medium-sized office building (DOE reference building), and it is expected that the base score (a*) and weighting (b*) may differ for other types of buildings. Future research will be conducted to generalize and apply the findings to other building types.

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국문초록

건물에너지 성능평가는 최대한 실재(reality)와 근사해야 하며(정확성), 평가 결과가 충분히 객관적이고 투명해야 한다(객관성, 투명성). 그리고, 건물에너지 성능평가는 지시적 접근(prescriptive-approach)보다, 성능 중심 접근(performance-based approach)이 합리적이어서 좋다. 그러나, 국내 건축물에너지소비총량제에서 사용되는 ECO2의 경우, 정확성을 희생하더라도 평가의 단순함에 초점을 맞추어 개발되어, 운영인자를 단일 값으로 규정하여 불확실성을 반영하지 못한다. 이는, 정확성과 사용성 그리고 결과의 신뢰성에 대한 논란으로 이어지고 있다. 500m^2 이상의 긴축건물에 의무적으로 적용되는 에너지 성능지표(EPI)의 평가기준 또한 객관적인 방법으로 이루어지지 않고 있다. 합리적인 평가체계를 위해, 건물의 열적 거동을 고려할 수 있는 과학적 방법을 수반하여야 한다. 이러한 관점에서, 본 연구에서는 건물사용 시나리오의 변화에 따른 에너지요구량의 불확실성 정량화 프로세스와, 과학적 접근을 통한 EPI 배점체계 개선 프로세스를 제시한다.

사례연구 #1에서는 용도프로필 중 5개의 인자 (재실밀도, 기기밀도, 조명밀도, 침기율, 환기량)의 변화에 따른 건물에너지 요구량의 불확실성 분석을 수행한다. 그리고 건물에너지 요구량 불확실성 정량화를 통해, 용도프로필의 확률적 접근의 필요성을 논한다.

사례연구 #2에서는 7개의 건물 설계 인자 (벽체 열관류율, 창호 열관류율,

지붕 열관류율, 바닥 열관류율, 창호 SHGC, 조명밀도, 침기량)에 대한 Sobol 민감도 분석과 에너지요구량과의 다항회귀분석을 수행한다. 민감도 지수를 EPI의 기본 배점(a)으로 대체하고, 다항회귀식을 배점(b)로 대체함으로써 건물의 열적 거동을 일부 반영할 수 있는 배점체계를 제안하였다. 그리고, EPI와 EPI*, ECO2와 EnergyPlus 에너지요구량의 상관성 분석을 통해 ECO2는 건물의 열적 거동을 반영하기 어려움을 보이고, 성능 중심(performance-based)으로의 전환이 필요함을 논한다.

주요어 : 건축물에너지소비총량제, 에너지절약설계기준(EPI) , ECO2, 불확실성 분석, 민감도 분석

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