

Article

Development of Energy Benchmarks for Office Buildings Using the National Energy Consumption Database

Hye Gi Kim and Sun Sook Kim *

Department of Architecture, Ajou University, Suwon 16499, Korea; kimhyegi@ajou.ac.kr

* Correspondence: kss@ajou.ac.kr; Tel.: +82-31-219-3571

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Abstract: In an effort to improve the energy efficiency of existing buildings, it is necessary to first evaluate the energy performance of those buildings. Since it is difficult to obtain detailed information on existing buildings, the challenge is how to conduct reliable energy performance assessments with this limited information. As a result, many countries have adopted evaluation systems based on measured energy consumption data for existing buildings. This study aims to analyze the building energy consumption and characteristics using Korea's national building database and provide an energy performance benchmark for continuous management of the energy performance of existing buildings. We analyzed the relationship between the basic statistical characteristics of the information collected from the national integrated energy database and energy consumption. The total floor area was found to be closely related to energy consumption, and various regression analysis methods were applied and compared to develop a benchmark to explain the trends of energy consumption according to the increase in total floor area. Finally, the developed benchmarks were used to evaluate energy consumption and examine the feasibility of the benchmarks.

Keywords: building energy benchmarking; energy performance benchmark; existing building; office building

1. Introduction

Building energy benchmarking is a mechanism to evaluate and compare the energy performance of a building, relative to other similar buildings or a reference building in order to give stakeholders information and motivate energy retrofits [1–3]. The energy benchmark can be defined as a representative value of the energy performance of a peer group with similar properties to a given building. It is used as a comparison criterion for evaluating whether the building performs well in terms of energy consumption. Comparing energy consumption with a benchmark can help determine whether a given building consumes more or less energy compared to its physical performance. An ideal building energy benchmarking condition is the availability of a database which consists of the physical and energy performance of peer groups with numerous existing buildings. However, collecting and managing an array of data for many buildings could prove to be problematic. Actually, it is an issue facing many countries that are performing benchmarking [3–5]. Thus, to develop a usable benchmark, it is important to check the state of the collected data [3,6–9]. In addition, the benchmarking information must be communicated to stakeholders in an appropriate way [10]. For example, energy consumers may be more interested in using electricity or gas than greenhouse gas (GHG) emissions. Meanwhile, policymakers may be more interested in national GHG mitigation. In addition, energy performance must be fairly evaluated. A building that operates 12 hours a day should not be penalized for consuming more energy than another building that operates only 8 hours a day. Therefore, the fair

energy performance evaluation that considers the business constraints or operational requirements of each of these buildings is required. With advanced information technologies, many countries have provided database (DB), tools, and evaluation frameworks to assess energy performance as well as to compare buildings to standards or their peer group based on the real energy data collection. The U.S. Energy Star [11,12] is one of the leading energy benchmarking schemes, and many states and cities including Minnesota [13], Seattle [14], and New York City [15] have adopted mandatory or voluntary energy benchmarking policies based on it. The Building Performance Database (BPD) [16] also provides data sets and statistical information that collect characteristic information related to energy consumption in commercial and residential buildings in the U.S. The U.K. [17] and Ireland [18] are also developed CO₂ emission benchmarking systems to disclose the energy performance of public buildings.

As a way to improve energy efficiency of buildings, the Korean government compiled a nationwide integrated energy consumption DB with information on about 6.9 million buildings and energy records and has operated an energy benchmarking system based on this DB [19,20]. The energy data consists of the addresses and the monthly usage data of electricity, gas, and district heating, while building records comprise the addresses and building energy features such as floor area and building height, among others. The integrated database is based on monthly energy billing data of real buildings, so it is meaningful in that it is demand-side data, not supply-side data. In other words, since the database represents the energy consumption in buildings and household units, it is useful for comparing or evaluating the energy consumption of buildings to encourage voluntary energy saving by the public or to make decisions on property trading or renting. The current energy performance benchmarking system utilizes the annual primary energy consumption of electricity and heat energy as a benchmark. Primary energy or GHG emissions are appropriate to compare national consumption of natural resources such as petroleum and coal, or to check the implementation status on GHG reduction targets. However, since stakeholders, such as building owners and facility managers in individual buildings, are less aware of the concept of primary energy, there is a need to provide them information on final energy that is more intuitive to understand in relation to energy costs.

The purpose of this study is to prepare a benchmark for energy consumers that can identify the energy consumption level of buildings using only the available information using Korea's national building database. First, we examined the purpose of energy performance benchmarking, the types of target audiences, and how to develop these benchmarks. Depending on whether the energy consumer who consumes energy directly or the government who must manage energy at the national level, it may have different purposes such as reducing the amount of electricity and gas consumed in buildings or reducing the source energy consumed in a country. Therefore, two types of target audience were set for using the benchmarking, and the purpose and requirements of using each type of benchmarking were analyzed. The benchmark development methods were classified based on the type and volume of information that could be collected, as well as the purpose and requirements of benchmarking. Next, various benchmark development methods were investigated for suitable benchmark development. Then, data on energy consumption and the basic building characteristics of office buildings were collected and analyzed from the DB system in Korea. Descriptive statistics of energy consumption and building features were performed, and the number of buildings in the collected dataset and the characteristics describing each building were verified to identify those that can provide the required information for energy consumers. Based on the requirements for energy consumers and the analyzed results of the nationwide database, the benchmark was developed, and energy performance was evaluated. Various regression analysis methods were applied and compared to develop appropriate benchmarks for the type and level of information that can be collected. We found energy influence factors that can be considered to evaluate the energy performance of office buildings. Finally, the performance of nationwide office buildings was evaluated using the developed benchmarks, and the results discussed.

2. Overview of Energy Benchmarking

2.1. Purpose and Requirements of Benchmarking

Setting the target audience is an important development procedure given that it is a fundamental factor to establish appropriate energy benchmarks and performance assessment methods [10]. The target audience can be classified into two broad categories, depending on whether they have a direct interest in the actionable strategies to improve building efficiency or they want to establish a national standard and manage numerous buildings. Table 1 shows the purpose and requirements of the energy benchmarking taking into consideration each target audience.

Table 1. Purpose and requirements of energy benchmarking according to target audience.

Feature	Target Audience	
	Energy Consumers	Policymakers
Definition	Those who have a direct interest in the actionable strategies to improve building efficiency and to manage energy costs.	Those who want to establish a national standard and regulate numerous buildings.
Examples	Building owners Operators/Managers, etc.	Local government National government, etc.
Want to	Reduce energy costs Improve energy efficiency of their buildings	Reduce the amount of raw fuel needed to operate buildings Identify the energy consumption status for reduction and management of GHG
Interested in	Demand-side (Site) energy: - Final energy (e.g., electricity, gas) - End-use energy (e.g., heating, cooling)	Supply-side energy: - Source energy - Primary energy
Uses to	- Identify own building level among similar buildings - Identify energy type to improve - Establish strategies of investment priorities among building energy improvement opportunities.	- Encourage or require benchmarking to public - Performance information disclosure - Strengthen the regulation or extend support to poorly performing buildings - Provide incentives to low-energy use buildings

The reason for considering the target audience is that the requirements to be taken into account for developing energy benchmarking are different. Since the information which should be provided is different based on the target audiences, it is necessary to appropriately establish the type of energy performance to be compared and evaluated. Similarly, energy consumers aim to reduce energy costs and improve energy efficiency of their building through benchmarking. Thus, the comparison target should be selected to determine whether the current energy consumption level of a given building is good or bad, when compared to other similar buildings. Also, the change of measured performance over time can be compared by selecting an individual building as a comparison target. On the contrary, the main objective of policymakers is not detailed management of individual buildings, but to consider the comparison and ongoing management of energy performance for numerous buildings to analyze the realization of national GHG reduction targets. Therefore, policymakers want to identify the poorly performing group of buildings among large-scale buildings or analyze the performance tendency. Therefore, to make it easier to manage at the national level, buildings are grouped on the basis of building type and region.

2.2. Benchmark Development Methods

The benchmark is derived from a comprehensive consideration of the purpose of benchmarking and the characteristics of the building. Benchmark types are classified as absolute and relative reference points. The absolute reference point is a good criterion to emphasize the final goal, and the relative reference point is suitable for benchmarking since it can effectively compare measured performance market-wide [21]. A benchmark can be derived using statistical techniques, data mining, simulation, etc. In this study, we analyzed the method for developing the benchmark of relative reference points.

2.2.1. Statistical Techniques

Regression Analysis

Regression analysis is widely used to develop energy benchmarks for explaining the relationship between the various dependent variables and energy consumption. For example, in the U.S. Energy Star benchmarking system [11,21], the predicted energy use intensity (EUI) is calculated by a simple linear regression model which can explain relationship between building operational characteristics and primary energy consumption. Lee et al [22] derived multiple regression for predicting end-use energy consumption such as heating and cooling energy use, etc., based on the survey of 71 residential buildings in Korea. Next, Hong et al. [23] analyzed and reviewed various benchmark development methods and gave examples of analyzing relationships through complex top-down methods such as regression analysis. Chung [24] described the benchmarking process for energy efficiency through multiple regression analysis, in which the relationship between EUI and explanatory elements was developed.

To create benchmarks through regression analysis, building operating characteristics such as climate, occupancy density, etc., and energy consumption data of many buildings are required. Later, by analyzing the relationship between operating characteristics and energy consumption, key characteristics that affect energy consumption are found and regression equations to predict energy consumption are derived. Function can be expressed in a variety of ways, including linear, polynomial, and exponential. Specifically, the energy performance benchmark values for each building are derived differently. For example, if gross area is a key variable affecting energy consumption, the larger the area, the greater the expected energy consumption. That is to say, knowing the values of key variables allows to instantly normalize benchmarks for an objective comparison of energy performance. This has the advantage of allowing flexible benchmark normalization even if the variable value changes. However, if there are not many kinds of variables to be used as independent variables, it is difficult to prepare a model with high explanatory power. Also, if there is no information on the values of key variables, the predicted energy consumption cannot be calculated even with the regression equation. All regression methods require regular expert evaluation and updates to validate the developed model.

Types of regression are divided into simple linear, polynomial, segmented regression, etc. Linear equations have the advantage of being simple to develop and easy to interpret, but they require extra data preprocessing or transformation to analyze nonlinear relationships. On the other hand, polynomials and exponential equations have the advantage of being more explanatory about nonlinear relationships, but they are difficult to interpret. The segmented regression is a method to make up for the shortcomings of linear and nonlinear models, and it is a method to create a linear equation for each section by dividing the line into several points based on the point where the variable amount of change varies. That is, segmented regression is a method in which independent variables are divided into intervals and separate line segments are developed for each interval. A detailed analysis is required to find the point of change in the relationship between variables.

Calculation of Central Tendency

Central tendency is a method to represent the tendency of data as a specific numerical value, indicating its nature as a measure of the center of distribution. That is, it can be used as a reference value for evaluating the energy performance of a building. The types of central tendency are mean, median, and it generally uses mean as a central tendency for a group or sample. The DEC [17] is a UK benchmarking system that compares CO₂ emissions based on the actual energy use with benchmark CO₂ emissions. The benchmark CO₂ emission, the electricity and heat energy usage for 29 building properties proposed by CIBSE were developed using median based on standard operating hours and heating degree days which is based on the balance point temperature of 15.5 °C. Mathew et al. [25] explained trends of building energy performance through central tendency analysis of more than 750,000 building energy data in the United States. Mims et al. [26] suggested averages, medians, etc., of energy consumption for each state are calculated and provided.

However, the mean is sometimes distorted due to the influence of extreme data values. Particularly, since it is often the case that energy is used excessively in a certain building or household, it is necessary to carefully examine the distribution of the data to apply the mean. In this case, the median is applied, which is not affected by extreme values. The central tendency should also be calculated considering conditions such as occupancy, climate, etc. for a fair comparison. However, unlike the regression equation where the benchmark value is calculated according to the input values, central tendency is a single value. Therefore, it is necessary to calculate the central tendency of energy consumption normalized to standard conditions, or to classify peer groups with similar conditions and calculate benchmarks for each group. If the central trend of energy usage normalized to standard conditions is used as the benchmark, the energy consumption of the evaluation building is normalized for the standard condition, or the benchmark is corrected in consonance with the condition of the evaluation building. Contrarily, when using peer group benchmarks, the evaluation building is compared against the benchmark of the group that most closely resembles its characteristics. Unlike the regression model, central tendency is intuitive with a single value. In addition, statistical processing is simpler than regression analysis. Unlike a regression equation that requires a lot of feature information, statistical processing does not require any information, which is convenient for the user. However, if the energy consumption is normalized to standard conditions, the energy trend due to that variable remains unknown.

2.2.2. Development of Simulation Model

Simulation models are a method for benchmarking a reference or normative model that standardizes the building's geometry, operational characteristics, etc. EnergyPlus, the simulation engine, is one of the many energy modeling tools used for this approach. ASHRAE [27] provides 53 standard U.S. buildings based on CBECS data and provides a way to analyze energy savings through improving the performance of buildings. Bannister and Hinge [28] selected reference building that could be the basis of simulation to analyze the performance of buildings. Simulation models have the advantage of being able to account for the various characteristics influencing the changes in energy use. In addition, simulation can input various energy conservation measures (ECMs) and compare the results. However, a disadvantage for many users is that benchmarks based on simulation modeling may not be well normalized against an actual building stock.

2.2.3. Data Mining

This method is used to offset the absence of data and to improve the accuracy and reliability of calculating the estimated energy consumption. Unlike simulation models that use thermodynamic equations to calculate the physical behavior of buildings and their interactions with the external environment based on physical descriptions, this method derives an optimal model that describes the output value by empirical training, based on only minimal input variables without physical knowledge. Generally, genetic algorithms or artificial neural network techniques are widely used. Park et al. [29] developed six types of benchmarks using various data mining techniques based on 1072 office building data to develop new benchmarks for Korean office buildings. Liu et al. [30] used data mining technologies to derive nine energy consumption patterns and develop benchmark for quantitative energy evaluation by pattern for dynamic energy performance evaluation.

Unlike regression analysis, which explains the direct causal relationship between input and output variables, various mediated or nonlinear effects are estimated based on the output value, assuming a hidden layer that cannot be explained solely by input variables. The resulting model represents a complex network of relationships between input variables, hidden layers, and output values. In other words, if a nonlinear relationship or irregular pattern appears between variables, it is possible to calculate more accurately than the regression equation. However, since it is impossible to explain the relationship between input and output, unlike a regression equation which explains how an input value affects an output value, it is difficult to adopt these models in public policy.

2.3. Energy Performance Evaluation

If the energy consumption is compared as is, it is impossible to evaluate energy performance fairly considering various conditions that may affect energy consumption besides the performance of the building. In other words, in order to determine the level of energy consumption of a building in the entire market, the same conditions must be made so that they can be compared with each other. The Energy Star's Energy Efficiency Ratio (EER) is a representative index that allows the comparison of energy performance between the buildings to be compared. EER is 1 when the expected energy consumption is the same as actual consumption, and less than 1 suggests that it uses less energy and more than 1 means that it uses a lot of energy:

$$\text{Energy Efficiency Ratio (EER)} = \frac{\text{Actual Energy Consumption (MWh)}}{\text{Benchmark (MWh)}} \quad (1)$$

However, by simply comparing the EER values of buildings, it is difficult to identify how much or how little energy is consumed. Therefore, in order to enable objective comparison with buildings, it is necessary to build a rating or scoring system to intuitively understand the evaluation results. For example, the Energy Star describes these EER values in terms of 1–100 points, and the DEC are designed to show the evaluation results with a seven-level grade from A to G [17].

3. Development of Benchmark

Korea's current energy performance benchmarking system is still developing, and the operating benchmarks are based on annual primary energy consumption of electrical and thermal energy. Therefore, this study aims to develop a benchmark based on secondary energy consumption to provide information to energy consumers. Initially, the national database was analyzed to determine the type and amount of data constructed, and the relationship with energy consumption. Next, the benchmark development method was applied, and the most appropriate benchmark was derived based on the analysis results.

3.1. Data Description

In this study, we selected the office building stock with an area of more than 3000 m², which are the target buildings of the energy consumption disclosure system in Korea. To obtain measured data for office buildings, a nationwide integrated energy consumption database, which includes information on approximately 6.9 million buildings, was used. The information in the Korea database comprises information on all buildings. Despite errors associated with missing or erroneous data, it is possible to reflect the most accurate information. The national databased contains 7078 buildings registered for office use. Of these, 4304 single-use office buildings were selected, excluding 2774 multi-use buildings that do not consistently reflect the characteristics of office buildings. Building characteristics and monthly energy consumption data for 2013 to 2015 were compiled. Subsequently, 589 office buildings were excluded where at least one of the 36 months has no energy data or zero electrical energy consumption, and finally 3715 offices were selected. Table 2 and Figure 1 show the overview and distribution of the 3715 collected office buildings. Although total energy consumption and area data existed for all the 3715 buildings, some data on building characteristics were missing. Total energy consumption is calculated by adding electricity, gas and heat consumption for heating, cooling, ventilating, lighting, domestic hot water, and equipment. Average total energy consumption per building was about 1500 MWh in three years, and average final energy use intensity (EUI) was 149.6 kWh/m². The average of EUI (149.6 kWh/m²) over the three years was lower than the average EUI (160 kWh/m²) of office buildings assessed by the Energy Star program in 2018 [12] and the benchmark EUI (215 kWh/m²) for office buildings in CIBSE Energy Benchmark TM46 [31]. It was also much lower than the average EUI (245.7 kWh/m²) of 56,177 office buildings in the BPD [16]. Since the offices

defined in the BPD includes building types with very high EUI, such as medical offices and banks, their average EUI seemed to be much higher than other values.

Table 2. Basic statistical analysis of collected office building data in Korea.

	Data	Code	N	Percentile					Mean	Std.	Skew-Ness
				0%	25%	50%	75%	100%			
Final Energy	2013 [MWh]	E13	3715	164	531	848	1558	58,204	1658	3246	9.11
	2014 [MWh]	E14	3715	134	494	790	1436	54,835	1548	2936	8.46
	2015 [MWh]	E15	3715	123	495	790	1426	55,298	1534	2927	8.64
	2013 [kWh/m ²]	EUI13	3715	52.0	110.0	150.0	195.8	453.0	157.1	63.4	0.78
	2014 [kWh/m ²]	EUI14	3715	37.5	103.3	140.0	180.4	376.2	146.4	57.6	0.69
	2015 [kWh/m ²]	EUI15	3715	37.5	103.0	139.2	180.5	331.9	145.2	56.3	0.56
Building features	Total floor area (TFA) [m ²]	X1	3715	3001	3975	5381	9521	212,615	9664	13,786	6.36
	TFA above the ground [m ²]	X2	3715	1245	3010	4072	6650	139,896	6759	9171	6.68
	Building age [years]	X3	3668	3	15	22	26	81	21	10	0.47
	Num. of floors above the ground	X4	3710	1	5	7	10	60	8	5	2.16
	Num. of basement floors	X5	3710	0	1	2	3	10	2	2	1.25
	Total num. of floors	X6	3710	1	7	9	13	63	11	6	1.81
	Building height [m]	X7	3024	3	23	31	44	250	37	22	2.43

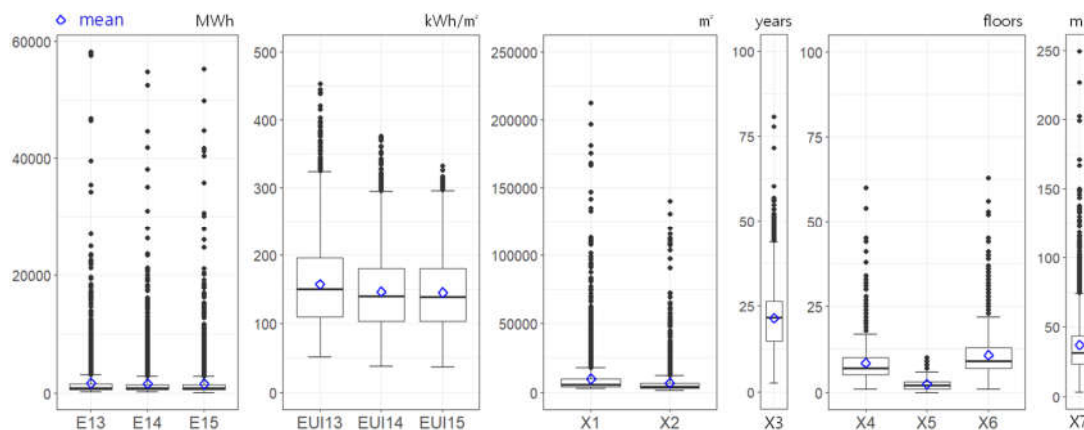


Figure 1. Distribution of collected office building data in Korea.

The larger the difference between the median (50% percentile) and the mean, the larger the skewness value, and the more asymmetric the distinction becomes, as shown in Figure 1. The total energy consumption every three years showed very large positive skewness. Very high energy consumption is not an outlier, but rather a reflection of information from buildings that actually show very high energy consumption. In addition, area and building height appeared to have positive skewness. The number of floors did not exceed two but appeared to be close to two. That is, the variables relative to building size may be considered to have asymmetry. This can be seen as a result of reflecting the information of large office buildings, not outliers or data errors. This asymmetric distribution can be confirmed not only by the skewness but also by the difference between the mean and the median. However, all EUI appeared as a normal distribution. This is because there is a very high proportional correlation of 0.8 or more between the annual total energy consumption and total floor area, as shown in Table 3. This is a different trend from residential buildings whose energy consumption does not increase significantly since the number of residents is constant even though the area is larger. In the case of workplaces, the area and energy consumption are proportional to each other because the number of employees and work equipment increases in proportion to the size of the company.

Table 3. Result of correlation analysis between variables.

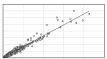
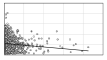
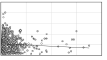
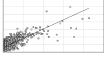
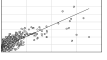
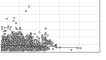
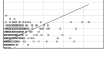
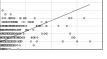
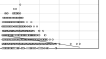
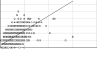
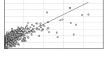
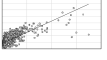
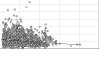
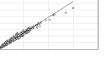
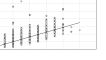
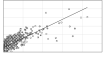
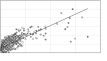
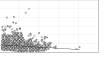
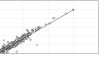
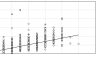
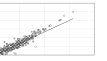
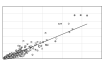
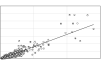
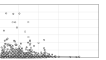
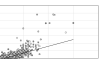
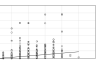
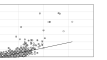
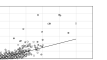
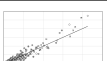
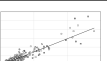

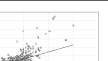
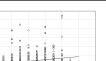
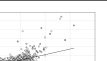
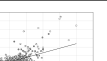
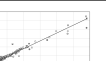
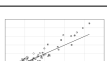
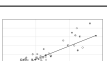

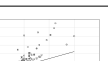
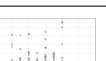
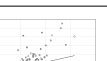
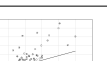
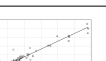
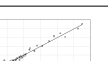
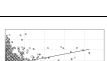


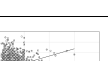




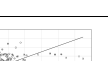












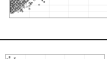
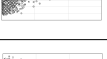





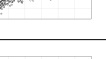
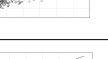
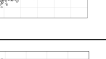


Code	X1	X2	X3	X4	X5	X6	X7	E13	E14	E15	EUI13	EUI14	EUI15
X1	1												
X2	0.94 **	1											
X3	−0.12 **	−0.09 **	1										
X4	0.53 **	0.52 **	−0.13 **	1									
X5	0.51 **	0.34 **	−0.19 **	0.65 **	1								
X6	0.56 **	0.51 **	−0.15 **	0.98 **	0.79 **	1							
X7	0.59 **	0.59 **	−0.17 **	0.94 **	0.65 **	0.93 **	1						
E13	0.82 **	0.79 **	−0.05 **	0.57 **	0.50 **	0.60 **	0.61 **	1					
E14	0.83 **	0.79 **	−0.08 **	0.56 **	0.50 **	0.58 **	0.60 **	0.98 **	1				
E15	0.89 **	0.80 **	−0.08 **	0.55 **	0.49 **	0.57 **	0.60 **	0.97 **	0.99 **	1			
EUI13	0.16 **	0.16 **	0.10 **	0.29 **	0.19 **	0.28 **	0.26 **	0.64 **	0.61 **	0.59 **	1		
EUI14	0.17 **	0.17 **	0.05 **	0.27 **	0.18 **	0.27 **	0.26 **	0.63 **	0.65 **	0.63 **	0.95 **	1	
EUI15	0.17 **	0.17 **	0.04 *	0.26 **	0.17 **	0.25 **	0.25 **	0.60 **	0.63 **	0.65 **	0.90 **	0.95 **	1

* means p -value ≤ 0.05 ; ** means p -value ≤ 0.01 .

Table 3 shows the correlation between energy consumption and building characteristic variables. The Spearman's correlation was used for considering the asymmetry of some variables. There was a high correlation close to 1 between the total energy consumption from 2013 to 2015. A similar minimum, average, and maximum value of energy use and a close correlation of 1 indicate that energy was used similarly over three years. EUI also appeared to be similar. Except for building age, all building characteristic variables are related to building size and have a significant positive correlation with each other as well as energy consumption. The same is true of the simple linear regression analysis in Table 4. It shows the trends and determination coefficients for the columns on the X axis and the rows on the Y axis. The directionality according to the sign in the correlation coefficient of Table 3 can be seen from the figures in Table 4. In addition, the closer the linear density, the higher the coefficient of determination. That is, it can be understood that the deviation with respect to the predicted value is small, indicating high explanatory power.

An ideal database would be composed of many buildings and numerous features describing each building. However, there were many samples in the collected data, but not various kinds of building characteristic information. Most variables related to the building size, which suggests that errors can occur due to mutual collinearity when used for regression analysis. Furthermore, although the collected data of building characteristics affect energy performance, these features are difficult to regard as factors that can be changed to improve the energy performance of a building. It suggests that it is suitable for analyzing the simple trend of the large-scale data set, but difficult to use for complicated simulation or detailed diagnosis. In other words, it is possible to simply compare energy consumption levels using information from the national database, but it is difficult to explain the reason.

Table 4. Graphs and determination coefficients of simple linear regression analysis between variables.

$\begin{matrix} Y \\ \backslash \\ X \end{matrix}$	X1	X2	X3	X4	X5	X6	X7	E13	E14	E15	EUI13	EUI14	EUI15
X1		0.96	0.01	0.49	0.25	0.48	0.56	0.88	0.91	0.91	0.03	0.03	0.03
X2			0.002	0.49	0.18	0.15	0.54	0.86	0.89	0.89	0.03	0.03	0.03
X3				0.01	0.05	0.02	0.02	0.002	0.003	0.004	0.015	0.006	0.004
X4					0.44	0.96	0.92	0.45	0.46	0.45	0.07	0.07	0.06
X5						0.63	0.46	0.18	0.19	0.19	0.02	0.03	0.02
X6							0.90	0.42	0.44	0.43	0.17	0.06	0.06
X7								0.50	0.52	0.51	0.06	0.06	0.06
E13									0.98	0.96	0.11	0.10	0.09
E14										0.99	0.10	0.10	0.10
E15											0.09	0.10	0.10
EUI13												0.88	0.78
EUI14													0.90
EUI15													

3.2. Development of Benchmark Using Regression Analysis

The national data do not include operational information such as operating hours and occupancy, although energy consumption has been found to be closely related to variables related to building size. In addition, most building size variables have a high R-squared value of about 0.4 to 0.9, which indicates that energy consumption can be well explained by a small number of variable types. In addition, regression has the advantage that the function calculation can calculate the benchmark considering the characteristics of individual buildings rather than the representative values such as the mean or median. Therefore, the benchmark was developed using a regression method that can flexibly reflect the variability of variables when it has high explanatory power. To find the most suitable type of regression analysis, a benchmark by type was developed and compared the analysis results. The coefficient of determination of models were compared to identify the fit of model.

A regression analysis was conducted on energy consumption and building information variables for each year and all three years from 2013 to 2015. Since we did not compare the energy consumption of each year, normalization to standard climate condition was not performed. The coefficients of the three-year equations for all types were found to be almost similar. Of the independent variables X1–X7, all variables except building age (X3) were so highly interrelated that they cannot be used in multilinear regression analysis. In addition, building age is a variable that reflects information on factors related to energy performance of a building, such as U-value, so it may be difficult to make a fair assessment. If building age is included as a variable in the regression equation, it means that the poor energy performance of old deteriorated building can be allowed considering its age.

A simple regression analysis was performed to analyze the change in dependent variables due to the change in one variable. Simultaneously, the total floor area (TFA) most relevant to energy consumption was selected as an independent variable. The coefficient of determination between TFA and total energy consumption is higher, in the quadratic equation than in the linear one, as shown in Figure 2. In small buildings, the linear equations are above the quadratic equations and the opposite trend is observed if the TFA is above a certain value. It indicates that if the office building increases above a certain scale, energy consumption increases rapidly. If linear equation is used as a benchmark, the larger the building, the lower the estimated energy consumption than if a quadratic polynomial is used as a benchmark. This can be interpreted as consuming more energy when comparing the actual energy against benchmarks. In other words, evaluating a large building with a linear equation and a lower R-square value than a second-order polynomial suggests that it can be evaluated more disadvantageously than smaller buildings.

To develop an appropriate benchmark, a model is usually chosen that best describes the relationship between the variable and energy usage. It may be reasonable to choose the quadratic model as a benchmark because it has a higher determination coefficient than linear equations. However, the quadratic model using a single variable not only makes it difficult to interpret the increase in energy consumption due to the increase in area, but also the utility of the equation is lower than that of the linear model. Therefore, to develop a fair and reasonable energy performance assessment and easy-to-understand benchmarks, we applied the segmented regression which makes two or more models by separating linear equations, according to the section of the independent variable.

Segmented regression is useful when independent variables that are categorized into various groups represent different relationships among variables by region. Two separated linear equations divided by breakpoints are suitable for quantifying the rapid change in response y due to various variables x . A breakpoint is the value at which a sudden change occurs. Segment regression is based on the dependent variable y and the independent variable x . The segments in each interval are derived by the least squares method. In other words, the sum of the squared (SSD) between the observed y and the calculated \hat{y} is minimized.

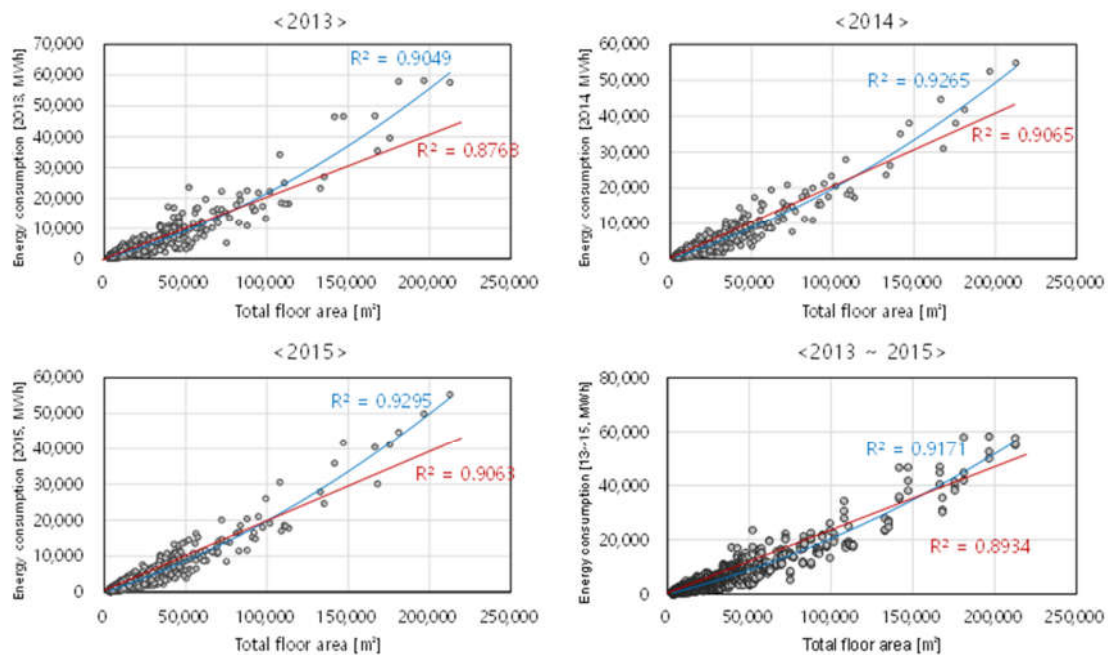


Figure 2. Difference of coefficient of determination between second-order polynomial regression and simple linear regression by year.

The dependent variable is represented by the following equation:

$$Y_r = \beta_1 \cdot x + C_1 \text{ for } x < BP \text{ (breakpoint)} \quad (2)$$

$$Y_r = \beta_2 \cdot x + C_2 \text{ for } x > BP \text{ (breakpoint)} \quad (3)$$

where Y_r the predicted value of y for value of x ; β_i regression coefficients (the slope of the line segments) and C_i regression constants (the intercept at the y -axis).

In this study, we used the SegReg program developed by the Institute for Land Reclamation and Improvement (ILRI) to derive significant breakpoint and segmented equations [32]. The program finds the most appropriate BP for classifying data into two groups for one group. In addition, the appropriate model was derived among the seven types of regression equations such as single horizontal line and two disconnected segments, etc.

Explanation coefficient (EC) means the total explanation by segmented linear regression with BP, like the determination coefficient which means total explanation by single linear regression. Figure 3 shows the procedure and method of data classification using the SegReg program to derive segmented regression. First, two groups having the highest EC of the entire data are divided. Subsequently, we performed segmental regression analysis on each of the two groups that were classified to identify whether there is a BP that may have a higher EC value. Check the number of groups, BP, and regression equation for each group when no more classification is possible.

Tables 5–7 below show the results of linear, quadratic polynomials, and segmented regression analysis (1–3) for four cases according to energy use years (A–D). Table 8 compares the analysis results for each regression method (1–3) for case D. All cases were found to have high explanatory power in the order of 2-order polynomials, segmented regression, and single linear equations. As a result of the segmentation regression analysis, two disconnected segments were modeled.

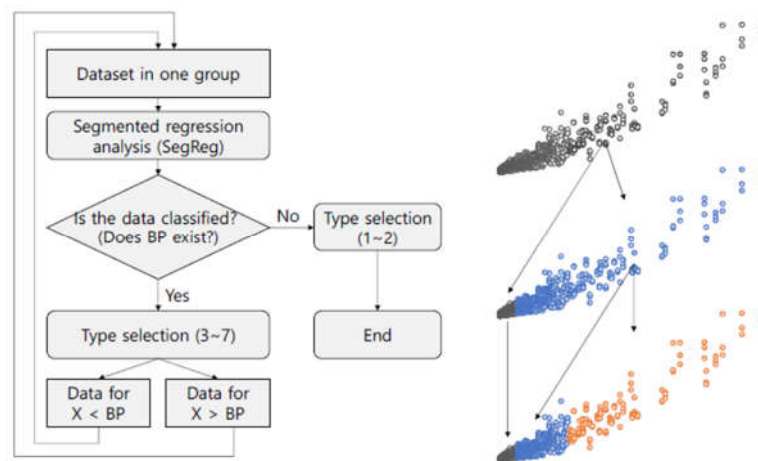


Figure 3. The procedure and method of data classification using SegReg program.

Table 5. Linear regression analysis result.

Case	Data	Break Point (BPx)	Number of Data	Regression Coefficient (RC)	Constant	Determination Coefficient (R ²)	
1	A	2013	None	3715	0.208	−435	0.877
1	B	2014	None	3715	0.203	−411	0.906
1	C	2015	None	3715	0.202	−420	0.906
1	D	2013~2015	None	11145	0.208	−435	0.893

Table 6. Quadratic regression analysis result.

Case		Data	BPx	Number of Data	RC		Constant	R ²
					x ²	x		
2	A	2013	None	3715	6 × 10 ^{−7}	0.15	−5.92	0.905
2	B	2014	None	3715	5 × 10 ^{−7}	0.15	−54.0	0.927
2	C	2015	None	3715	5 × 10 ^{−7}	0.15	−36.9	0.930
2	D	2013~2015	None	11,145	5 × 10 ^{−7}	0.15	−32.3	0.917

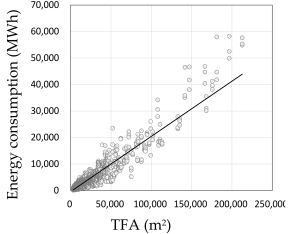
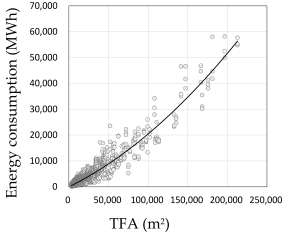
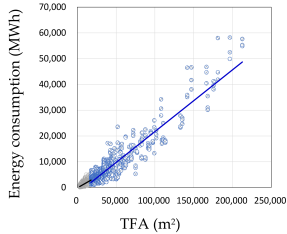
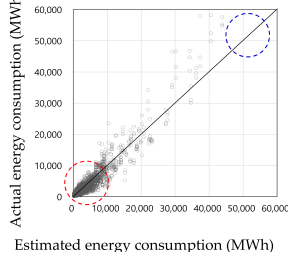
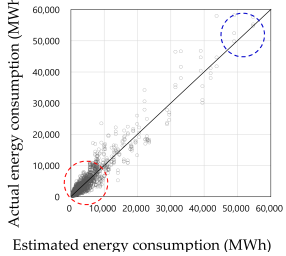
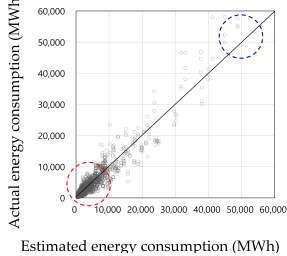
Table 7. Segmented regression analysis result.

Case	Data	BPx	Number of Data		RC		Constant		Explain Coefficient (EC)	
			X < BPx	X > BPx	A ₁	A ₂	K ₁	K ₂		
3	A	2013	17,674	3310	405	0.175	0.256	−105	−2520	0.894
3	B	2014	17,674	3310	405	0.165	0.231	−107	−2040	0.920
3	C	2015	17,674	3310	405	0.164	0.232	−106	−2180	0.922
3	D	2013–2015	17,674	9930	1215	0.168	0.240	−106	−2240	0.909

All cases were classified into two groups based on TFA 17,674 m², and all of them showed higher EC than the R-square of the linear regression model. All cases were found to have high explanatory power in the order of 2-order polynomials, segmented regression, and single linear equations.

Table 8 shows the comparison results by type of regression analysis for case D. The reason for the difference in the total description of the data according to the type of regression analysis method can be seen from the comparison between the actual and estimated energy consumption. If the actual and estimated energy usage match, the data will be located along the diagonal. On the diagonal, the red and blue sections correspond to the energy consumption levels at both extremes. That is, the red line corresponds to a small office and the blue line corresponds to a large office.

Table 8. Comparison results by type of regression analysis for case D.

	1. Linear Regression	2. Quadratic Regression	3. Segmented Regression
R^2	0.893	0.917	0.909
Model			
Estimated vs. Actual			

The ideal model is to distribute the data evenly across the diagonal. Looking at the blue circle line in Table 9, there is a big difference between the actual and expected energy consumption. In the case of the linear model, there was no data in the blue line region. In the quadratic polynomial model, the data was placed close to the diagonal. Conversely, the data in the red section shows that the estimated value is higher than the actual value. The segmented regression has been shown to partially compensate for the problems of the linear model. The data in the red line were adjusted to be more evenly distributed than the linear model based on the diagonal line. Also, since the data in the blue line region is located at a shorter distance from the diagonal than the linear model, the distribution deviation was reduced. Therefore, the segmented regression model has explanatory power close to the polynomial, which is useful in terms of ease of interpretation and utilization of the benchmark.

Table 9. Look-up table based on EER calculation result.

Score	Cumulative Percent	EER		Score	Cumulative Percent	EER	
		\geq	$<$			\geq	$<$
100	0%	0	0.317	89	11%	0.559	0.573
99	1%	0.317	0.368	88	12%	0.573	0.586
98	2%	0.368	0.403	87	13%	0.586	0.599
97	3%	0.403	0.431	86	14%	0.599	0.611
96	4%	0.431	0.455	85	15%	0.611	0.623
95	5%	0.455	0.476	84	16%	0.623	0.635
94	6%	0.476	0.495	83	17%	0.635	0.646
93	7%	0.495	0.513	82	18%	0.646	0.657
92	8%	0.513	0.529	81	19%	0.657	0.668
91	9%	0.529	0.544	80	20%	0.668	0.679
90	10%	0.544	0.559	40	60%	1.057	1.067

Thus, we chose the partitioned regression analysis method and developed a partitioned regression model based on the combined energy consumption of three years. The following equation shows the result of the benchmark model applying segmented regression analysis:

$$Y_r = 0.168 \cdot x - 106 \text{ for } 3000 < x < 17,674 \quad (4)$$

$$Y_r = 0.240 \cdot x - 2240 \text{ for } x > 17,674 \quad (5)$$

4. Energy Performance Evaluation and Benchmark Validation

4.1. Energy Performance Evaluation

In this study, we adopted a method that converts energy performance into a score of 1–100 points with the help of the evaluation method used in the US Energy Star system. First, we drew a cumulative distribution of the energy efficiency ratios of the 3715 buildings analyzed as shown in Figure 4. Subsequently, we used the gamma distribution and minimized the sum of squared differences to identify the best gamma curve from the data. Smooth curves are mathematically defined by certain equations, so the curves can be used to calculate the EER at a given percentage. In other words, a look-up table was made that can be converted to a score of 1–100 points at a given percentage. Table 9 below shows a part of the score transformation look-up table derived based on the results of 3715 EER calculations.

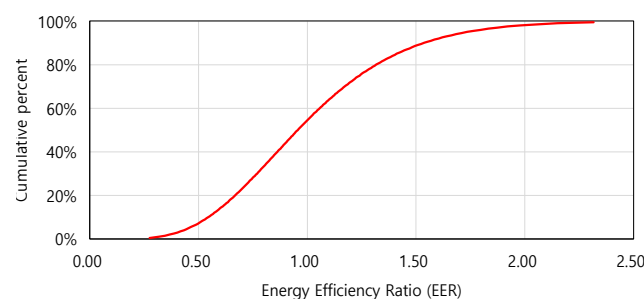
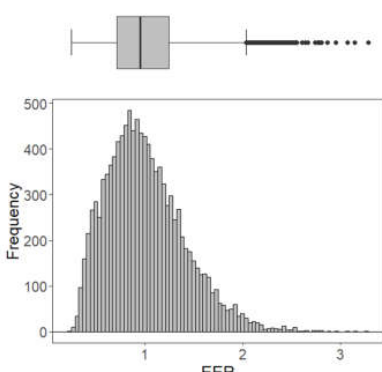


Figure 4. Gamma distribution according to the EER calculation result of office buildings.

4.2. Analysis of Energy Performance Evaluation Result and Validation of Benchmark

Table 10 shows the distribution of energy performance scores according to the EER of 3715 office buildings. Figure 5 reveals the results of comparing the energy performance score converted through the look-up table with the EUI. At 50% cumulative percentile, the EER score was 0.95, close to 1, representing a certain level of energy consumption. EER values appearing close to 1 in the 50% cumulative percentile indicate that buildings with typical energy usage levels are located at the middle level across the market. Therefore, the distribution of EER has been judged to be appropriately derived, and the benchmark can be considered to show the general tendency of using the office building.

Table 10. Energy performance evaluation result of office building.

	Cumulative Percent	EER
	0%	0.25
	25%	0.72
	50%	0.95
	75%	1.24
	100%	3.28

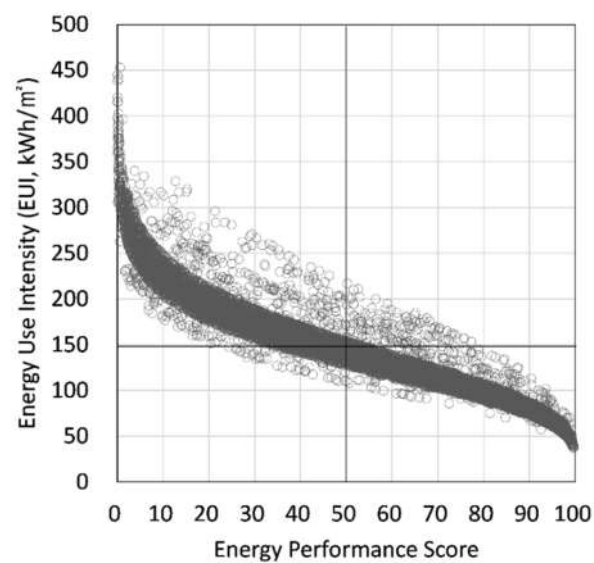


Figure 5. Energy performance score and EUI comparison.

As a result of comparing the energy performance score with the EUI in Figure 5, the higher the energy performance score, the lower the EUI. Concurrently, when the performance score was very low, the EUI showed a wide distribution of about 300–450 kWh/m², and when the score was very high, the EUI converged to about 40 kWh/m² value. The convergence of EUI by the energy performance score increases as a result of both energy-saving behavior and energy-performance improvements. Contrarily, the various distributional phenomena of EUI by the reduction of energy performance scores can be attributed to various causes such as low physical performance or energy-consuming behavior.

The lower the energy performance score, the wider the difference of the EUI distribution. This indicates that it is necessary to investigate and analyze additional variables that can explain the way the building operates. However, the energy performance score and EUI evaluated by the model developed in this study also show a significant correlation, which can help identify poor performance buildings. The benchmark can be used to identify low-score buildings and to determine the need for improved energy performance. The benchmark developed in this study can assess energy performance levels and identify problematic buildings, but the cause is unknown. However, it is very important to identify buildings that require further investigation, and this is likely to be possible through the developed benchmarks.

5. Conclusions

In order to improve the physical performance of existing buildings, it is necessary to first evaluate the current energy consumption level by considering the factors that affect energy consumption, in addition to physical performance. However, existing buildings often lack the data required for this analysis due to problems related to poor performance and data loss, among others. This study analyzed the purpose and requirements of energy performance assessment and developed a method for a reliable energy performance benchmark based on data available from national data.

The national data shows energy usage and building information for all buildings in Korea, but the building information only includes data on size and year, and no physical performance information. There was also no operational information. This study derived the factors influencing energy consumption in the information that can be collected for office buildings and analyzed how closely it is related to energy consumption. As a result, gross area had a causal relationship with energy consumption of over 0.9. This is an indicator that the area of the building is closely related to the increase in the number of workers or equipment, since the characteristics of the office buildings where there is no significant change in the number of people in the building or the number of equipment.

This suggests that although there is no data related to the operation of the building, there is adequate data on the number of buildings close to the total population, and suggests that benchmarks can be developed with data that can account for most of the energy use.

Based on this high explanatory power and a large number of data constructs, the benchmark was developed by regression analysis. In this case, we applied linear regression analysis, quadratic polynomial model, and segmented regression method to better elucidate the data. Finally, segment regression was selected that can enunciate and easily explain changes in energy consumption due to variable changes. Next, in order to fairly evaluate the building's energy performance level in the entire market, the EER was calculated by comparing the actual usage against the benchmark, and the energy performance score was used to determine the intuitive current energy consumption level.

As a result of comparing the energy performance score with the EUI, the higher the energy performance score, the lower the EUI. Concomitantly, when the performance score was very low, the EUI showed a wide distribution of about 300–450 kWh/m², and when the score was very high, the EUI converged to a certain value. The convergence of EUI by the energy performance score increases as the result of both energy-saving behavior and energy-performance improvements. On the contrary, the various distributional phenomena of EUI by the reduction of energy performance scores are due to various causes such as low physical performance or energy-consuming behavior. Therefore, in order to appropriately analyze the cause, additional investigation is needed for buildings with low scores, and the benchmark developed in this study can be used to find the buildings that need to be improved.

This study developed an energy performance benchmark for an office building in Korea. According to the characteristics of the building, even if there is meager information, a reasonable benchmark can be developed, and energy performance assessed. As buildings are used for a long time, it is imperative to make continuous energy performance assessments and improvements. This essentially requires a fair and reliable method of assessment. The results of this study can be used to identify buildings for energy performance improvement and the management of existing buildings in the future, and further studies will be conducted to derive the cause analysis and improvement directions of buildings with low-energy performance scores.

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