Normalization Method of Building's Actual Energy Consumption for Normalized Building Energy Benchmarking

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Abstract

Energy use intensity (EUI, kWh/m²·yr) has been widely used in the building industry for building energy benchmarking. However, this EUI-based building energy benchmarking could lead to a biased assessment because it overlooks other influential factors such as operational schedule, occupancy, plug-load, setpoint temperature, and weather (hereafter referred to as operational factors). To overcome the issue, the authors propose a normalization process for the building's actual energy consumption considering the aforementioned factors. In this study, a concept of normalization coefficients was introduced based on the relationship between the operational factors and the change in energy consumption. The eXtreme Gradient Boost regression (XGBoost) models were used for deriving normalization coefficients that can convert the actual heating and cooling EUIs into the normalized EUIs per building under the operational factors. Validation studies demonstrated that the conversion of actual EUIs into normalized EUIs using these coefficients can contribute to fair building energy benchmarking. In other words, the proposed normalization approach holds promise for achieving more objective building energy performance benchmarking.

1. Introduction

Objective building energy benchmarking can play an important role in making decisions to improve building energy efficiency and supporting government agencies and policymakers in their efforts to reduce greenhouse gas emissions (Piscitelli et al., 2024). Building energy benchmarking is a process that diagnoses the energy performance of a building compared to peer groups generally established by building types or climate zones. In conventional energy benchmarking systems, energy use intensity (EUI, kWh/m²·yr) defined as energy use per unit floor area has been widely utilized as a performance indicator for building energy benchmarking. However, it has been acknowledged that EUI can be an 'unfair' metric because it overlooks other influential factors such as operational schedule, occupancy, plug-load, setpoint temperature, and weather (Bogin et al., 2024). Thus, this EUI-based building energy benchmarking could lead to a biased assessment regarding distinguishing energy-efficient from energy-inefficient buildings. Other trials have been undertaken to develop energy use per worker in office buildings, and energy use per bed in hotels, but they have proved to be unsatisfactory (Arjunan et al., 2022). Therefore, for more objective building energy benchmarking, it is imperative to normalize actual energy consumption over operational schedule, occupancy, plug-load, setpoint temperature, weather (hereafter referred to as operational factors).

As part of the building energy benchmarking, many efforts have been made to define 'peer build-

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ing group'. Recently, data-driven models considering multiple influential factors have been introduced. For example, by the use of multiple linear regression (MLR) models, actual energy consumption is *neutralized* depending on building type, climate, or building's thermal attributes, etc. (Dahlan et al., 2022; Kükrer et al., 2023; Gupta et al., 2023). Unsupervised clustering methods are adopted to define peer groups according to building types, climate zones, or building energy usage patterns and attributes (Gao & Malkawi, 2014; Zhan et al., 2020). The aforementioned studies are focused on developing a 'peer building group' and then comparing my target building to the peers.

Rather than taking that approach, this study introduces an EUI normalization process. The normalization methodology considers the combined influences of diverse operational factors such as the operational factors as well as a combination of them. With the introduction of the normalization, we aim to assess the 'pure energy performance level' of buildings.

With this in mind, this study proposes a benchmarking approach utilizing normalization coefficients established by the relationship between operational factors and EUI. The eXtreme Gradient Boost regression (XGBoost) models were used for deriving normalization coefficients for heating and cooling EUIs. The normalization coefficients can convert the actual heating and cooling EUIs into the normalized EUIs per building under the operational factors.

As validation studies, comparative analyses between actual EUIs and normalized EUIs were carried out. It was substantiated that buildings with an identical design exhibit similar normalized energy consumption. The proposed normalization method is expected to reduce the so-called performance gap. In other words, the results indicate that normalized EUI can be a promising candidate for more objective benchmarking of building energy performance.

2. Methodology

2.1 Data Collection

For a reference building, a three-story medium office building developed by the US DOE (Deru et al., 2011) was selected (Fig. 1). The gross floor area of the building is 4,500 m^2 with a window-to-wall ratio (WWR) of approximately 33.3%. The aspect ratio of the building is 0.6. Based on the building energy code compliance in South Korea (MOTIE, 2023), the thermal insulation values for the external walls, floor, and roof of the building were set as 0.48 W/(m^2·K), 1.81 W/(m^2·K), and 1.81 W/(m^2·K), respectively. The window U-value and SHGC were set to 2.0 W/(m^2·K) and 0.38, respectively. Lighting power density was set to 8.1 W/m^2, and the infiltration rate was set to 0.5 ACH. Also, the building was modelled with an 'Ideal Loads Air System' instead of detailed HVAC systems.

After developing the reference building model as a 'baseline', the authors used Latin hypercube sampling (LHS) in order to generate 200 medium office buildings with different operating conditions (Mckay et al., 2000). The operating conditions were regarded as the key factors affecting the building's operational energy consumption, independent of the building's thermal properties. The factors included operational schedule (starting hour, operation hours), occupant and appliance densities, heating and cooling setpoint temperatures. Additionally, weather data from 90 locations in South Korea, were collected (KMA, 2022), and the meteorological characteristics of each location were analysed in terms of heating and cooling degree-days (HDD, CDD). A total of 18,000 simulation runs were conducted (=200 operation conditions times 90 locations). The details of the factors are tabulated in Table 1.

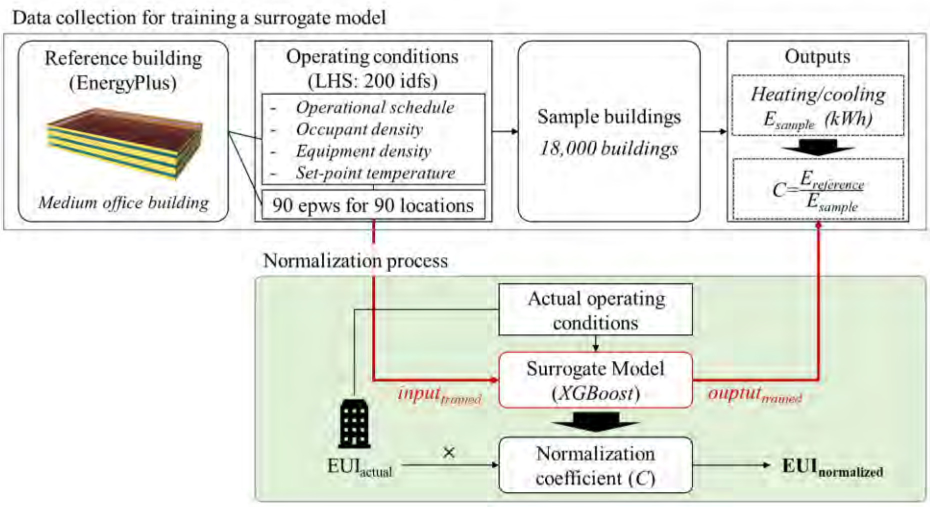

Fig. 1 – Building energy normalization process (E_{sample}: Energy consumption of a sample building, $E_{reference}$: Energy consumption of a reference building, EUI_{actual}: actual EUI of a building, $EUI_{normalized}$: normalized EUI by a normalization coefficient)

As the output variables of the sample buildings, we collected the annual heating and cooling energy consumptions (kWh/m²·yr) exclusive of domestic hot water because heating and cooling energy are closely correlated with building thermal performance. In addition, the reference building's energy consumption was calculated based on the reference operating conditions that are referred to ASHRAE standard 90.1 (2022) and Seoul weather data. These conditions include a starting time of 9:00 AM, 8 hours of operation, an occupant density of 0.16 person/m², appliance density of 8.61 W/m², and heating and cooling setpoint temperatures of 20 °C and 26 °C, respectively. Additionally, Seoul weather data exhibits HDD of 2,730 K d and CDD of 903 K d. Note that we used the reference building's energy consumption as the numerator and the sample energy consumption as the denominator (Fig. 1).

2.2 Surrogate Model

Based on the EnergyPlus simulation runs, we trained an XGBoost regression model as a surrogate model for obtaining the normalization coefficients. XGBoost is an efficient implementation of gradient boosting based on decision trees (Chen & Guestrin, 2016). XGBoost builds a series of decision trees iteratively, where each tree corrects the errors of the previous one, thereby improving the overall model's prediction accuracy.
The input variables of the XGBoost regression models are shown in Table 1. Two XGBoost models were constructed to derive heating and cooling normalization coefficients, respectively. A total of 18,000 input-output pairs obtained from the pre-simulated EnergyPlus samples were partitioned into training and testing sets, or 7:3 (12,600:5,400). In other words, the models were trained with 12,600 training datasets, and the models' accuracies were tested against 5,400 testing datasets.

Table 1 – List of influential factors used in the normalization process

Factors	**Unit**	**Range**	**Reference**
Starting hour	h	[7, 10]	Building audit reports
Operation hours	h	[8, 14]	Building audit reports
Occupant density	people/m²	[0.075, 0.25]	ASHRAE (2021)
Appliance density	W/m²	[2.7, 16.1]	ASHRAE (2021)
Heating setpoint temperature	℃	[18.5, 21.5]	Building audit reports
Cooling setpoint temperature	℃	[24.5, 27.5]	Building audit reports
Heating degree-days	-	[1,393, 3,492]	KMA (2022)
Cooling degree-days	-	[452, 1,118]	KMA (2022)

2.3 Normalization Process

As illustrated in Fig. 1, the proposed normalization coefficient is defined as Eq. (1).

$$C = E_{reference} / E_{sample} \quad (1)$$

where $E_{reference}$ denotes the energy consumption of a reference building under the reference operating and weather conditions (Section 2.1), while E_{sample} represents the energy consumption of a sample building under different operating and weather conditions.

The coefficients can be regarded as a lumped number that can account for dynamically interwoven effects of the aforementioned operational factors. Thus, a normalization coefficient greater than 1.0 means that the sample building whose thermal performance is equal to the reference building consumes less energy than that of the reference building because of the aforementioned factors, e.g. operation hours, occupant density, setpoint temperatures, weather, etc.

Then, EUI_{actual}, the actual energy use of a target building, can be converted into $EUI_{normalized}$, normalized energy use as shown in Eq. (2).

$$EUI_{normalized} = EUI_{actual} \times C \quad (2)$$

This normalization process can be exemplified as shown in Table 2. The normalization coefficients are likely to contribute to objective building energy benchmarking.

Table 2 – Normalization example

	EUI (kWh/m²·yr)
$E_{reference}$	100
E_{sample}	120
C	0.83
EUI_{actual}	150
$EUI_{normalized}$	125.0

2.4 Two Validation Studies

In order to ascertain the validity of the normalization coefficients proposed in this study, it is necessary to collect measured energy data from a variety of existing buildings. However, collecting such data demands significant costs and time. Therefore, the authors conducted two validation studies using a series of simulation results.

- Validation study #1 (*buildings' identical thermal performance under different operations*)

We derived the normalization coefficients for 18,000 buildings with identical architectural designs ('can be regarded as identical thermal performance') but varying operation hours and plug-loads in different locations. Then, three types of EUIs were calculated from 18,000 buildings.

The first EUIs are obtained from the reference operating conditions and defined as the true EUI (EUI_{true}). The second EUIs are calculated according to the building's actual operating conditions and defined as the actual EUI (EUI_{actual}). Finally, the third EUIs were calculated based on the normalization coefficients and defined as the normalized EUI ($EUI_{normalized}$). Then, two differences in EUIs were calculated: one is ε_{actual} between the EUI_{true} and EUI_{actual}, and the other is $\varepsilon_{normalized}$ between the EUI_{true} and the $EUI_{normalized}$.

- Validation study #2 (*buildings' different thermal performance under different operations*)

We generated 1,000 buildings with different architectural designs under varying operating conditions. In order to generate 1,000 different buildings, the authors conducted LHS with seven architectural design variables as tabulated in Table 3. Similar to the validation study #1, a comparative analysis was performed using three types of EUIs (EUI_{true}, EUI_{actual}, $EUI_{normalized}$) and two mean absolute percentage errors (MAPE) as the evaluation metrics. The first is MAPE between the EUI_{true} and EUI_{actual}, while the second is MAPE between the EUI_{true} and the $EUI_{normalized}$. Then, a correlation analysis was conducted between the EUI_{true} and the EUI_{actual}, as well as between the EUI_{true} and the $EUI_{normalized}$, using the coefficient of determination (R^2).

2.5 Benchmarking Case Study

In contrast to the validation studies (Section 2.4), we developed a benchmarking case study. For this purpose, we developed four different buildings (denoted by Blds. #1-#4) having different WWR and window U-values. The four buildings have different operating conditions. Bld. #1 represents far superior thermal performance having a WWR of 0.2 and a window U-value of 1.5 W/(m²·K). Blds. #2-#4 were designed to have proportionally higher WWR and window U-values than Bld. #1. In other words, Blds. #2-#4 represent far inferior thermal performance. The details of the four buildings and benchmarking results will be addressed in Section 3.4.

Table 3 – List of design variables and ranges

Variable	Unit	Range	Reference
Gross floor area	m^2	[450, 22,500]	0.1-5 ratio of the reference building
Aspect ratio	-	[0.06, 3]	0.1-5 ratio of the reference building
Number of floors	-	[2, 10]	Building audit reports
Wall U-value	$W/m^2{\cdot}K$	[0.15, 0.6]	Building audit reports; MOLIT (2023)
Window U-value	$W/m^2{\cdot}K$	[1.5, 3.5]	Building audit reports; MOLIT (2023)
Window-to-wall ratio	-	[0.2, 0.8]	Building audit reports
Window SHGC	-	[0.3, 0.7]	Building audit reports; ASHRAE (2021)

3. Results

3.1 Surrogate Model Accuracies

In order to evaluate the accuracies of the surrogate models, three metrics including the root mean squared error (RMSE), the coefficient of variation of root mean squared errors (CVRMSE), and the coefficient of determination (R^2) were used on the testing datasets (Table 4). The calculated RMSE, CVRMSE and R^2 scores are 0.03, 2.5% and 0.99 for heating normalization coefficients (C_{heat}), and 0.09, 8.3% and 0.98 for cooling normalization coefficients (C_{cool}), respectively. In addition, Fig. 2 shows the comparison between the simulation and prediction results. These results indicate high accuracies of the models in predicting normalization coefficients for heating and cooling EUIs.

Table 4 – Surrogate model accuracies

Output	RMSE (-)	CVRMSE (%)	R^2 (-)
C_{heat}	0.03	2.5	0.99
C_{cool}	0.09	8.3	0.98

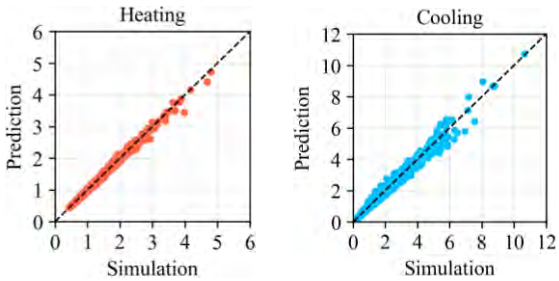

Fig. 2 – Simulation vs. surrogate model predictions (left: heating, right: cooling)

3.2 Calculated C_{heat} and C_{cool} vs. EUI

Fig. 3 shows the comparison results between the normalization coefficient and EUI_{actual} using the training datasets of the surrogate models. The relationship between the two variables appears to be inversely proportional. The variability in EUI_{actual} demonstrates that even buildings with identical thermal performance can exhibit a significant difference depending on the operating conditions. The range of cooling normalization coefficients is wider compared to that of heating, suggesting that cooling EUI is more sensitive to variations in operating conditions.

As exemplified in Table 2, the buildings with the normalization coefficients of less than 1.0 fulfil demanding operating conditions such as long operation hours, low indoor temperature in summer, severe weather locations, etc. Thus, these buildings are likely to be wrongly assessed as poor energy performance buildings, and vice versa for the buildings with normalization coefficients greater than 1.0.

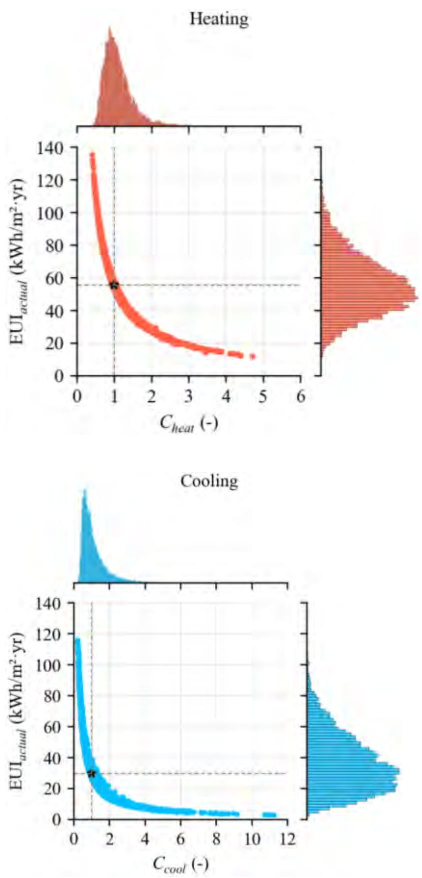

Fig. 3 – Normalization coefficients (*C*) vs. EUI_{actual} (above: heating, bottom: cooling)

3.3 Validation Study #1

Fig. 4 shows the distributions of ε_{actual} (the difference between EUI_{true} and EUI_{actual}) and $\varepsilon_{normalized}$ (the difference between EUI_{true} and $EUI_{normalized}$) for 18,000 buildings that have identical thermal performance under varying operational conditions. For heating ε_{actual}, the minimum and maximum values were -79.9 kWh/(m²·yr) and 43.8 kWh/(m²·yr), respectively. In contrast, for heating $\varepsilon_{normalized}$, the minimum and maximum values were -4.7 kWh/(m²·yr) and 6.4 kWh/(m²·yr), respectively. Regarding cooling ε_{actual}, the minimum and maximum values were -85.8 kWh/(m²·yr) and 27.5 kWh/(m²·yr), respectively. In contrast, for cooling $\varepsilon_{normalized}$, the minimum and maximum values were -9.1 kWh/(m²·yr) and 7.5 kWh/(m²·yr), respectively. As shown in Fig. 4, the distribution of $\varepsilon_{normalized}$ is quite marginal compared to ε_{actual}.

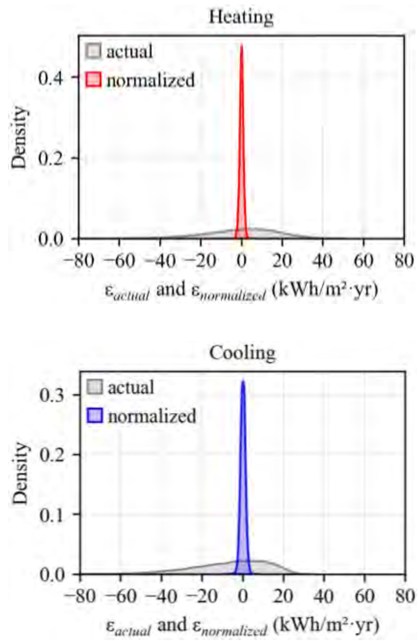

Fig. 4 – Distributions of ε_{actual} and $\varepsilon_{normalized}$ (above: heating, bottom: cooling)

3.4 Validation Study #2

As mentioned earlier in Section 2.4, Figs. 5-6 and Table 5 show the results of validation study #2. The MAPEs between EUI_{true} and EUI_{actual} are 25.4% and 45.4% for heating and cooling, respectively, while the MAPEs between EUI_{true} and $EUI_{normalized}$ are only 5.6% and 11.2% for heating and cooling, respectively. In addition, both relationships between EUI_{true} and EUI_{actual} for heating and cooling had lower R^2 scores of 0.35 and 0.22, respectively, while the relationships between EUI_{true} and $EUI_{normalized}$ for heating and cooling had far higher R^2 scores of 0.89 and 0.62, respectively. This means that the normalization coefficients can reduce any possible biased assessment of the actual EUIs.

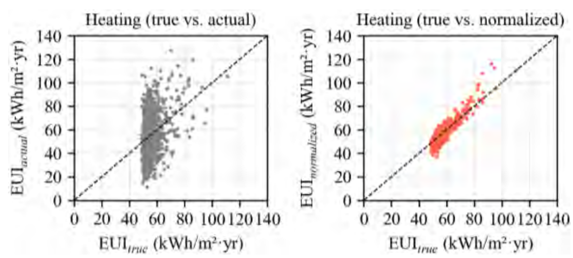

Fig. 5 – Comparison of heating EUI_{true} vs. EUI_{actual}, $EUI_{normalized}$

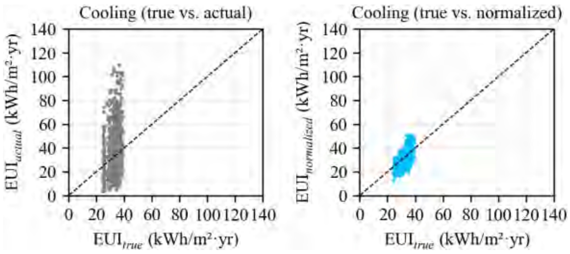

Fig. 6 – Comparison of cooling EUI_{true} vs. EUI_{actual}, $EUI_{normalized}$

Table 5 – Comparative analysis results

Dependent variable		**MAPE (%)**	**R^2 (-)**
Heating	EUI_{actual}	25.4	0.35
	$EUI_{normalized}$	5.6	0.89
Cooling	EUI_{actual}	45.4	0.22
	$EUI_{normalized}$	11.2	0.62

3.5 Benchmarking Results

As mentioned earlier in Section 2.5, Table 6 shows the four buildings and benchmarking results. EUI_{true} represents energy use under the reference operating conditions. heating EUI_{actual} reflects biased rankings. However, heating $EUI_{normalized}$ are close to EUI_{true}, and renders more objective benchmarking than EUI_{actual}.

Similarly, the variances in cooling EUI_{true} among the four buildings were negligible. Nevertheless, cooling EUI_{actual} shows substantial differences between the four buildings, while cooling $EUI_{normalized}$ shows significantly smaller differences. Based on Table 5, it can be highlighted that $EUI_{normalized}$ can serve as a promising candidate for a more objective benchmarking of building energy performance.

Table 6 – Benchmarking results

Building #		**#1**	**#2**	**#3**	**#4**
Architectural designs	WWR (-)	0.2	0.4	0.6	0.8
	Window U (W/(m²·K))	1.5	2.2	2.8	3.5
Heating	EUI_{true} (kWh/(m²·yr))	54.1	56.0	58.5	61.5
	EUI_{actual} (kWh/(m²·yr))	39.0	77.3	62.2	42.7
	$EUI_{normalized}$ (kWh/(m²·yr))	54.1	58.6	59.6	62.3
Cooling	EUI_{true} (kWh/(m²·yr))	30.0	29.5	28.8	28.1
	EUI_{actual} (kWh/(m²·yr))	22.1	77.8	77.0	71.0
	$EUI_{normalized}$ (kWh/(m²·yr))	28.0	30.2	28.3	26.6

4. Conclusion

This study introduced a normalized building energy benchmarking approach. The proposed normalization coefficients were established to account for the variation in EUI influenced by operational factors (starting time, operation hours, occupancy, plug-load, setpoint temperature, weather).

The heating and cooling normalization coefficients were generated using XGBoost models constructed based on a reference medium office building by US DOE. Two validation studies demonstrated the conversion of actual EUIs into normalized EUIs can enable more objective building energy benchmarking (Sections 3.3-3.4). Moreover, the approach proved effective for buildings with different thermal performance and architectural designs (Section 3.5).

Conclusively, the proposed normalization coefficients are likely to mitigate potential biases against actual EUIs and contribute to better building energy benchmarking. Additionally, the proposed normalization approach may be considered as an alternative for reducing the performance gap between measured and predicted energy use. As a further study, we aim to apply the concept of normalization coefficients to several existing buildings selected from Korean building energy database. The outcomes of this study will be beneficial for advancing objective building energy performance benchmarking methods and fostering performance-based thinking within the IBPSA community.

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