sustainability

MDPI

Article

Temporal Segmentation for the Estimation and Benchmarking of Heating and Cooling Energy in Commercial Buildings in Seoul, South Korea

Ki Uhn Ahn [1,*], Deuk-Woo Kim [2], Seung-Eon Lee [2], Chang-U Chae [3] and Hyun Mi Cho [1]

1 Department of Building Research, Korea Institute of Civil Engineering and Building Technology, Goyang-si 10223, Korea
2 Department of Building Energy Research, Korea Institute of Civil Engineering and Building Technology, Goyang-si 10223, Korea
3 Research Strategic Planning Department, Korea Institute of Civil Engineering and Building Technology, Goyang-si 10223, Korea
* Correspondence: ahnkiuhn@kict.re.kr

check for updates

Citation: Ahn, K.U.; Kim, D.-W.; Lee, S.-E.; Chae, C.-U.; Cho, H.M. Temporal Segmentation for the Estimation and Benchmarking of Heating and Cooling Energy in Commercial Buildings in Seoul, South Korea. *Sustainability* **2022**, *14*, 11095. https://doi.org/10.3390/su141711095

Academic Editors: John Gardner, Seongjin Lee, Kee Han Kim and Sukjoon Oh

Received: 24 June 2022
Accepted: 2 September 2022
Published: 5 September 2022

Abstract: The building sector is responsible for more than one-third of total global energy consumption; hence, increasingly efficient energy use in this sector will contribute to achieving carbon neutrality. Most existing building-energy-benchmarking methods evaluate building energy performance based on total energy use intensity; however, energy usage in buildings varies with the seasons, and as such, this approach renders the evaluation of cooling and heating energy difficult. In this study, an information gain-based temporal segmentation (IGTS) method was used to identify the seasonal transition times based on patterns of hourly weather and corresponding building energy use. Twelve commercial buildings were considered for the study and four seasons were identified using IGTS; base-load, cooling energy, and heating energy data were gathered. For the 12 buildings, the estimated and measured heating and cooling energy during the summer and winter periods showed a linear relationship (R^2 = 0.976), and the average of those differences was 9.07 kWh/m^2. In addition, differences in the benchmarking results based on these energies were marginal. The results indicated that the IGTS approach can be effectively used for determining the actual heating and cooling energy consumption in buildings, as well as for energy benchmarking. This can, in turn, improve building energy use, with positive implications for achieving carbon neutrality.

Keywords: energy use intensity; temporal segmentation; commercial building; benchmarking; energy disaggregation

1. Introduction

The building sector accounts for over one-third of total global energy consumption and is a major source of carbon emissions [1]. In 2019, the South Korean government announced an increase in the greenhouse gas reduction target from 26.3% to 40% by 2030, compared to the 2018 levels, as a part of the efforts to achieve carbon neutrality by 2050 [2]. In particular, the carbon emissions of the building sector in 2030 must be reduced by 32.8% by designing energy-efficient buildings and using energy-saving/-efficient equipment [3].

Energy efficiency can be defined as the use of less energy to produce the same output; hence, energy-efficiency indicators are used to indicate the energy consumption performance level of energy-consuming systems [4]. Energy benchmarking can be effective in promoting efficient energy use by comparing buildings with similar characteristics [5,6]. Energy use intensity (EUI), which can be defined in simple terms as normalized energy use based on gross floor area, is commonly used as an energy-efficiency indicator in benchmarking building energy [1,6]. For example, the Chartered Institution of Building Services Engineers (CIBSE) uses EUI to benchmark the energy performance of similar buildings and performs a comparative assessment to rate the energy efficiency of the buildings [1,7,8]. Although EUI a straightforward parameter for determining building energy efficiency [9], its meaning is ambiguous, and as such, it is not helpful for identifying opportunities and prioritizing potential actions for more detailed analyses and full-scale audits [1,10,11].

Based on the data source and application, benchmarking approaches can be classified into two types: empirical or simulation-based [1]. Empirical benchmarking, which uses empirical data, is actively applied for operational rating, whereas simulation-based benchmarking, which uses theoretical data, is utilized for asset rating, tailored benchmarking, and scenario analysis [12,13]. Empirical benchmarking utilizes statistical techniques such as ordinary least squares (OLS), stochastic frontier analysis (SFA), or data envelopment analysis (DEA). OLS determines the best-fit regression curve based on factors including building age, energy system, and floor area. The residual between the actual EUI and the OLS-predicted EUI is a measure of the inefficiency of building energy use [4,5,14]. A limitation of the OLS approach is that it calculates a fitted average function that provides no direct quantitative information on energy inefficiency of the target building [5]. SFA separates random error components from inefficiency components to achieve accurate measures of relative efficiency [15–17]. However, SFA may not be appropriate for determining the efficiency of energy data in which outliers exist [5]. DEA is a multi-factor productivity analysis method for assessing the relative efficiency of decision-making units (DMUs) [18]. For building efficiency benchmarking, a building is defined as a DMU when the aim is to obtain an objective energy-efficiency score of that entire building [9]. While DEA is good at estimating relative efficiency within a sample, it cannot explain some of the actual energy use because certain factors are not testable in DEA [5].

Simulation-based benchmarking can be used to conduct detailed comparisons and assessments through the use of end-use results from simulations; however, it may not be practical in terms of benchmarking owing to the requirements of significant time, cost, and efforts to develop a simulation model. In addition, in building energy simulations, inevitable discrepancies exist between predicted and actual energy performance [19,20], which reduces the reliability of the simulation-based benchmarking results. Therefore, for existing buildings, using empirical data to quantify energy efficiencies is preferable [19,21]. In particular, end-use metering or sub-metering technology is a better solution for determining the energy use of individual loads [19]. End-use metering provides highly useful, detailed energy information; however, it is not cost-effective or technically practical because of the use of mixed circuits for different end-users.

In this study, an information gain-based temporal segmentation (IGTS) method [22] (an unsupervised segmentation technique) was applied to identify seasonal transition times based on patterns of hourly weather and corresponding building energy use. Data from 12 commercial buildings were separately measured for eight end-uses of electric energy (cooling, heating, hot water supply, lighting, fan-generated air movement, appliances, indoor transportation, and auxiliary devices) and three end-uses of gas energy (cooling, heating, and hot water supply). The data for each building and end-use were measured hourly for over one year.

Figure 1 shows the relationship between the total energy (*Total*) and cooling and heating energy (*CoolHeat*) during 2018 for the 12 target buildings. The coefficient of determination (R^2 = 0.271) showed that *CoolHeat* was weakly correlated with *Total*. This indicated that measuring the efficiency of *CoolHeat* use based on total energy consumption as a benchmark for determining EUI is not suitable. In terms of the thermal energy performance of buildings, this study considered that *CoolHeat* is reducible, while others (*Others*) including hot water supply (*Shw*), lighting (*Light*), air movement by fan (*Vent*), appliances (*App*), indoor transportation (*Trans*), and auxiliary devices (*Aux*) are unreducible. Therefore, in this study, benchmarking was conducted with respect to the total amount of *CoolHeat*, which has the potential to be reduced.

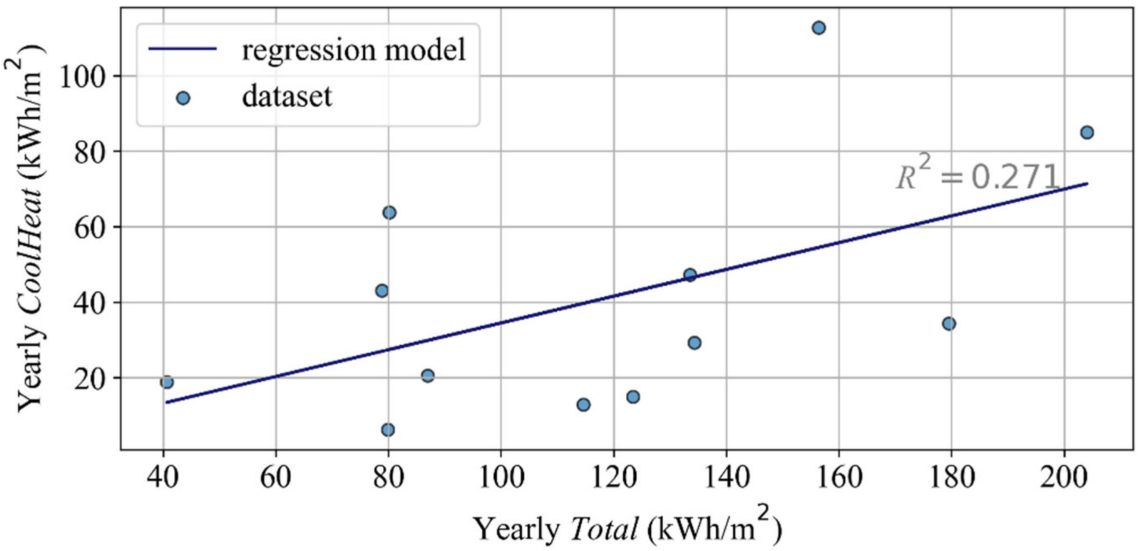


Figure 1. Scatter plot between energy use intensity (EUI) for *Total* and *CoolHeat* in 2018 for 12 target buildings.

The temporal segmentation results of IGTS were used to disaggregate *CoolHeat* without installing any sub-metering devices. The authors estimated the heating/cooling energy and base-load energy for the four seasons using IGTS; the estimated values were compared with the actual cooling/heating energy values. In addition, energy benchmarking was conducted based on the estimated heating/cooling energy. This was then compared with the actual data to verify the efficiency of seasonal segmentation-based heating/cooling energy estimation and benchmarking.

2. Data

A dataset comprising data from 12 commercial buildings in Seoul, South Korea, was used (Figure 2). Table 1 shows descriptions of the 12 buildings, including year built, total floor area, number of floors, and types of heating, ventilation, and air conditioning (HVAC) systems. In particular, the 12 buildings mainly comprised office spaces; other commercial facilities are described in Table 1. The data measurement period for each building ranged from a minimum of 1 year and 10 months to a maximum of 2 years. The dataset included sub-metered data for eight end-uses that were measured based on the Korean Institute of Architectural Sustainable Environment and Building Systems (KIAEBS) S-7 protocol [23], which was developed by referring to ISO12655 [24]. In particular, watt-hour meters, gas flow meters, and calorimeters were installed in the 12 buildings in accordance with the KIAEBS S-7 protocol. In this study, these eight end-uses consumed electric (*Elec*) energy and the three end-uses considered (*Cool*, *Heat*, *Aux*) consumed gas (*Gas*); the different end-uses of energy are described below.

- Cooling energy (*Cool*): energy used for space cooling in the building through central cooling sources (e.g., chiller, cooling tower), pumps involved in cooling, individual cooling systems (e.g., electric heat pumps, gas heat pumps), and their operation and control.
- Heating energy (*Heat*): energy used for space heating in the building through central heating sources (e.g., boiler), pumps involved in heating, individual heating systems (e.g., electric heat pumps, gas heat pumps), and their operation and control.
- Hot water supply (*Shw*): energy used to produce and transport hot water for building domestic water services by central hot water sources (e.g., boilers) and pumps carrying hot water.

- Lighting (*Light*): Energy used by the main lighting equipment composed of separated branch circuits.
- Air movement by fan (*Vent*): energy used for cooling, heating, ventilation, and air circulation by fans in mechanical systems (e.g., air handling unit, outdoor unit, fan coil unit).
- Appliances (*App*): energy used by office appliances, auxiliary heaters, electric fans, water purifiers, and non-identifiable energy use in circuits.
- Indoor transportation (*Trans*): energy used by indoor transportation devices (e.g., escalators, lifts, etc.)
- Auxiliary devices (*Aux*): energy used by main pumps for water supply.

Table 1. Descriptions of the 12 target buildings.

Index	Year Built	Total Floor Area (m^2)	No. of Above-ground/Underground Floors	HVAC System	Service Water System	Commercial Facilities
bldg.#01	1995	22,471	19F/B7	• Absorption chiller-heater • CAV, FCU	• Electric water heater	• Coffee shop (1F)
bldg.#02	1983	10,517	10F/B2	• Steam boiler, turbo chiller • CAV, FCU	• Steam boiler	• Gym, exhibition hall (B1) • Bank, retail store (1F)
bldg.#03	1968	2482	7F/B1	• Absorption chiller-heater • PAC, FCU	• Electric water heater	• Sauna (B1) • Printing house (1F)
bldg.#04	2008	31,787	20F/B6	• Absorption chiller-heater • VAV, FPU	• Steam boiler	• Cafeteria (5F)
bldg.#05	1990	1265	5F/B1	• Hot water boiler, compression chiller	• Hot water boiler	• Retail store (1F)
bldg.#06	1971	4034	4F/B1	• EHP	• Electric water heater	• Gym (4F)
bldg.#07	2006	29,547	21F/B5	• Absorption chiller-heater • CAV, FCU	• Steam boiler	• Restaurant, hospital (B1)
bldg.#08	2012	2544	6F/B2	• EHP	• Hot water boiler, solar water heating	• Cafeteria (1F)
bldg.#09	2008	1633	5F/B1	• EHP, Hot water boiler, PAC	• Hot water boiler	• Office only
bldg.#10	1967	2408	4F/B2	• Steam boiler, EHP	• Electric water heater	• Retail store (1F)
bldg.#11	1995	7124	11F/B4	• EHP	• Electric water heater	• Billiard rooms, restaurant (B1) • Restaurant (1F)
bldg.#12	2007	19,973	12F/B5	• District heating and cooling, EHP • CAV, FCU	• District heating	• Billiard rooms, gym (B1) • Bank (1F)

CAV: constant air volume system; FCU: fan coil unit system; PAC: packaged air conditioner; VAV: variable air volume system; FPU: fan powered unit; EHP: electric heat pump system.

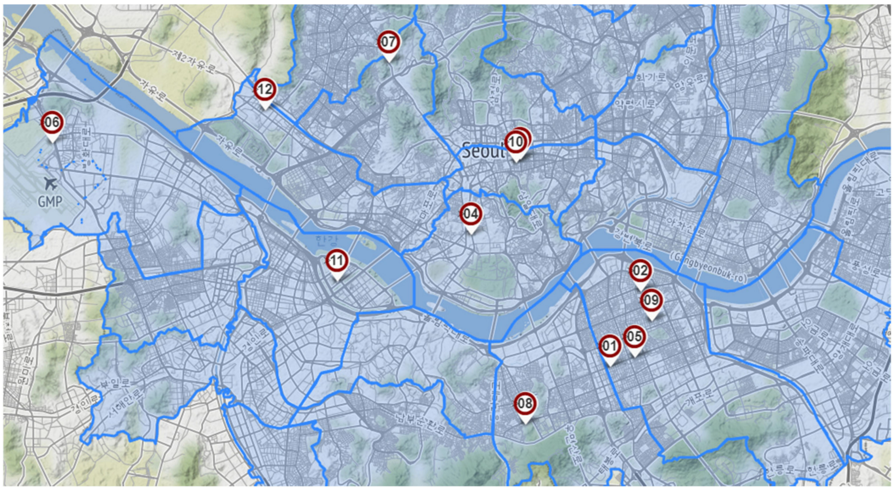
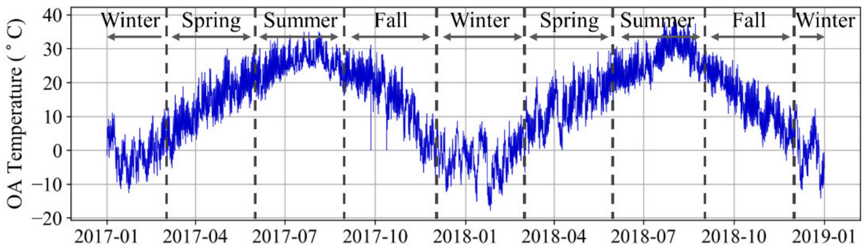
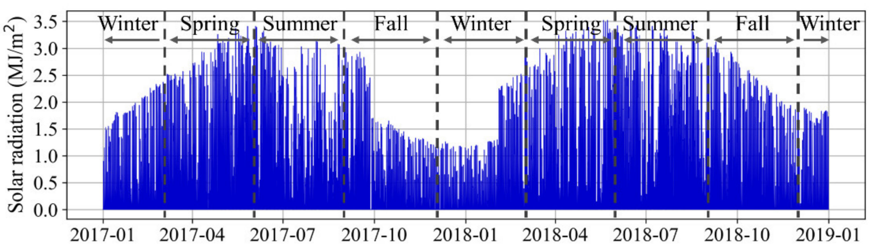


Figure 2. Location of the 12 commercial buildings in Seoul, South Korea. Numbers in the circular markers are the indexes of the target buildings (Table 1). NB. the marker of bldg.#03 is overlapped with that of bldg.#10.

In South Korea, the seasons have distinct characteristics and are generally divided into four categories, each with a fixed three-month interval, regardless of region: spring (March–May), summer (June–August), fall (September–November), and winter (December–February). The hourly weather data of Seoul were provided by the OpenAPI of the Korea Metrological Administration [25] (Figure 3). These data were merged with the dataset of the 12 buildings. The cooling and heating systems are operated in summer and winter (*SW*); however, the actual periods of cooling and heating energy use depend on the operation policy of each building and are different from those based on general seasonal classification. For example, Figure 4 shows the total electric and gas energy use of bldg.#01 and bldg.#02 (which were randomly selected), indicating that the energy use generally increased for cooling in summer and heating in winter, but also that periods of increase or decrease in energy use differed between the two buildings. In other words, inferring the use of cooling and heating energy based solely on the simplistic classification of seasons would be problematic.

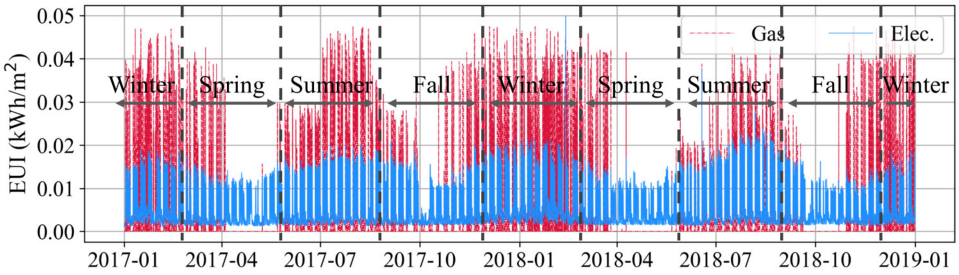


(**a**)

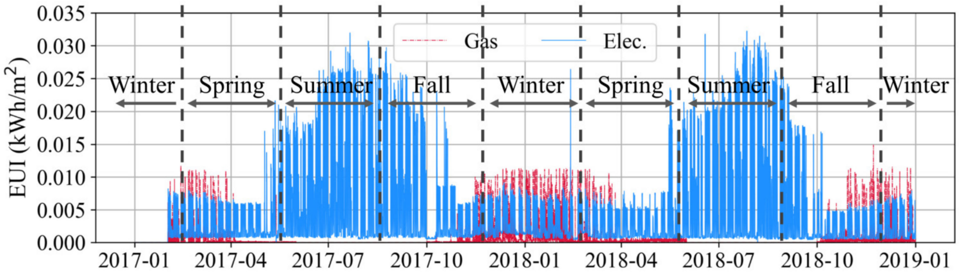


(**b**)

Figure 3. Hourly (**a**) outdoor air (OA) temperature and (**b**) solar radiation in Seoul.



(**a**)



(**b**)

Figure 4. Energy use intensity (EUI) for total gas and electric energy use for (**a**) bldg.#01 and (**b**) bldg.#02.

3. Methods

3.1. Information Gain-Based Temporal Segmentation (IGTS)

Sadri et al. [22] reviewed temporal segmentation approaches (e.g., dynamic programming, heuristic approaches, probabilistic) to split time series into non-overlapping intervals, and proposed a new approach, the IGTS method, which considers multiple time series regardless of their heterogeneity and varying correlation between multiple sensor channels. In their study [22], the IGTS method was applied to determine transition times in human activities and daily routines based on heterogeneous sensor data (e.g., RFID tags, movement detection, daily life routine, smartphone logs). In the present study, the IGTS method was used to identify the transition time in seasonal operations from a dataset that included building energy use and weather data.

IGTS measures the amount of information in various segments of interest based on the concept of Shannon entropy. In particular, IGTS calculates the entropy of the distribution for each segment and then obtains the information gain to quantify the average reduction in entropy caused by splitting the time series for segmentation. The expected reduction in entropy ($\mathcal{L}$) caused by segmentation ($H(s_j)$) is calculated by the cumulative sum (F_i) of observations (c_i) as follows:

$$\mathcal{L} = H(\mathrm{S}) - \sum_{i=0}^{k} \frac{|s_i|}{|S|} H(s_i) \quad (1)$$

$$H(s_j) = -\sum_{i=0}^{m} p_{ji} \log p_{ji} \quad (2)$$

$$p_{ji} = \frac{F_i(t_j) - F_i(t_{j-1})}{\sum_{p=1}^{m} F_p(t_j) - F_p(t_{j-1})} \quad (3)$$

$$F_i(t) = \sum_{j=1}^{t} c_{i_j} \quad (4)$$

where $H(\mathrm{S})$ is the entropy of the entire time series; k is the number of segments; $|s_i|$ is the length of the ith segment; S is the entire time series as a segment; m is the number of time series; and c_{i_j} is the jth observation of the ith time series.

The best segmentation has the highest information gain. Dynamic programming (DP) optimization is applied to find a segmentation that maximizes the information gain (Equation (1)). DP minimizes the weighted entropy, i.e., $\sum_{i=0}^{k} \frac{|s_i|}{|S|} H(s_i)$, instead of maximizing information gain.

In this study, the IGTS method was used to determine the seasonal transition time for the four seasons, which reflects the seasonal patterns of building operations. The input data for IGTS were multivariate time series, including hourly outdoor air temperature, hourly solar radiation, hourly electric energy, and hourly total energy (i.e., the sum of total electric and gas energy). Only the dataset for the year 2018 was considered, because some target buildings did not collect data for the entire year of 2017. Estimating the optimal number of segments is still an ongoing problem, and Sadri et al. [22] determined the number of segments using information gain as an evaluation metric. In this study, the main aim was to classify the four seasons based on the seasonal patterns for annual energy use. Therefore, based on IGTS, the number of segments corresponded to the number of seasons in the dataset.

3.2. Estimation of Cooling and Heating Energy

CoolHeat was estimated as follows. First, for each of the 12 buildings, the IGTS determined the seasonal transition time during 2018 divided into four seasons in the given sequence: winter → spring → summer → fall → winter. Second, *Others* was determined based on the characteristics of seasonal energy use. The authors assumed that *CoolHeat* is season-dependent, while *Others* is season-independent and used at occupants' discretion throughout the year. For spring and fall, in which *CoolHeat* consumption is not significant, the statistical value of daily *Total* was regarded as daily *Others*. Specifically, daily *Others* was subjectively set to the 25th quantile for the set of daily *Total* during spring and fall, considering the intermittently used *CoolHeat*. Third, for *SW*, daily *CoolHeat* was estimated as daily *Total*, and daily *Others* was excluded. Finally, estimated *CoolHeat* in *SW* was compared with the actual measurements and benchmarking results.

4. Results

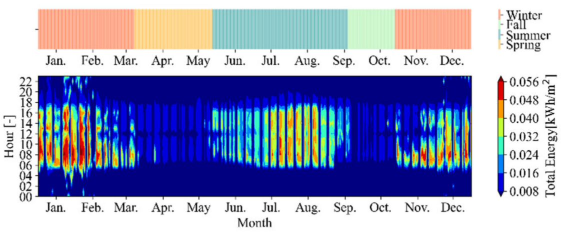
4.1. Temporal Segmentation for Estimation of Heating and Cooling Energy

Table 2 shows the temporal segmentation results of the IGTS that determines the seasonal transition times based on patterns of outdoor air temperature, solar radiation, electric energy, and total energy (sum of electric and gas energy). For bldg.#09, the winter–spring transition was the earliest; in other words, compared to the other buildings, the transition from a period of high energy use for *Heat* to low energy use occurred earlier in bldg.#09. For bldg.#07, the transition from spring to summer occurred earliest; that is, the transition period from the season of low energy use (*Others*) to that of high energy use (*Cool*) was the shortest. In addition, the building with the longest period of relatively high energy use in the summer was bldg.#10 (194 days), while those with the shortest periods were bldg.#5 and bldg.#6 (74 days each).

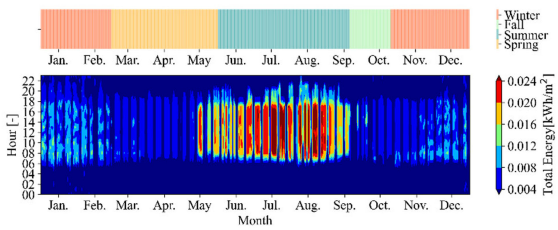
Table 2. Temporal segmentation results of the 12 target buildings.

Index	Winter		Spring		Summer		Fall		Winter	
	Start	**End**	**Start**	**End**	**Start**	**End**	**Start**	**End**	**Start**	**End**
bldg.#01	1 January	22 March	23 March	27 May	28 May	18 September	19 September	28 October	29 October	31 December
bldg.#02	1 January	1 March	2 March	31 May	1 June	20 September	21 September	25 October	26 October	31 December
bldg.#03	1 January	22 March	23 March	17 June	18 June	18 September	19 September	30 October	31 October	31 December
bldg.#04	1 January	22 March	23 March	27 May	28 May	18 September	19 September	18 November	19 November	31 December
bldg.#05	1 January	22 March	23 March	24 June	25 June	6 September	7 September	04 November	05 November	31 December
bldg.#06	1 January	9 March	10 March	24 June	25 June	6 September	7 September	11 November	12 November	31 December
bldg.#07	1 January	14 February	15 February	13 May	14 May	20 September	21 September	4 November	5 November	31 December
bldg.#08	1 January	9 March	10 March	27 May	28 May	19 September	20 September	18 November	19 November	31 December
bldg.#09	1 January	12 February	13 February	27 May	28 May	19 September	20 September	28 October	29 October	31 December
bldg.#10	1 January	8 March	9 March	15 April	16 April	26 October	27 October	18 November	19 November	31 December
bldg.#11	1 January	28 February	1 March	27 May	28 May	18 September	19 September	18 November	19 November	31 December
bldg.#12	1 January	8 March	9 March	17 June	18 June	18 September	19 September	18 November	19 November	31 December

A carpet plot allows us to easily identify the patterns of energy use by visual inspection [26]. Figure 5 shows the carpet plots of the temporal segmentation results (orange: spring, dark cyan: summer, light green: fall, red: winter), allowing the reader to intuitively understand the patterns of energy use. The operating hours of most target buildings were similar, starting at 8:00 and ending at 18:00; however, the timings for some buildings varied (e.g., bldg.#04, bldg.#06, and bldg.#10 operated from 04:00 to 16:00, from 06:00 to 20:00, and from 07:00 to 16:00, respectively). In addition, as shown in the color legends of the carpet plots, each building had a different EUI. For some buildings, *Total* during winter was higher than that during summer (bldg.#06, bldg.#08, bldg.#10, and bldg.#12), while for others, the reverse was true (bldg.#02, bldg.#04, bldg.#05, and bldg.#07). In particular, in bldg.#04, the time at which energy use decreased became earlier during the transition from winter to spring, and the level of energy use became insignificant, regardless of the time during the day. During the transition from spring to summer, energy use in the afternoon started to increase gradually, and the time when energy use started shifted to the morning. Therefore, the results (Table 2, Figure 5) show that the IGTS can determine the temporal segments that reflects the characteristics of seasonal energy use through changes in energy use patterns in an entire year, even though the energy usage was intermittent during the day.



(**a**)



(**b**)

Figure 5. *Cont.*

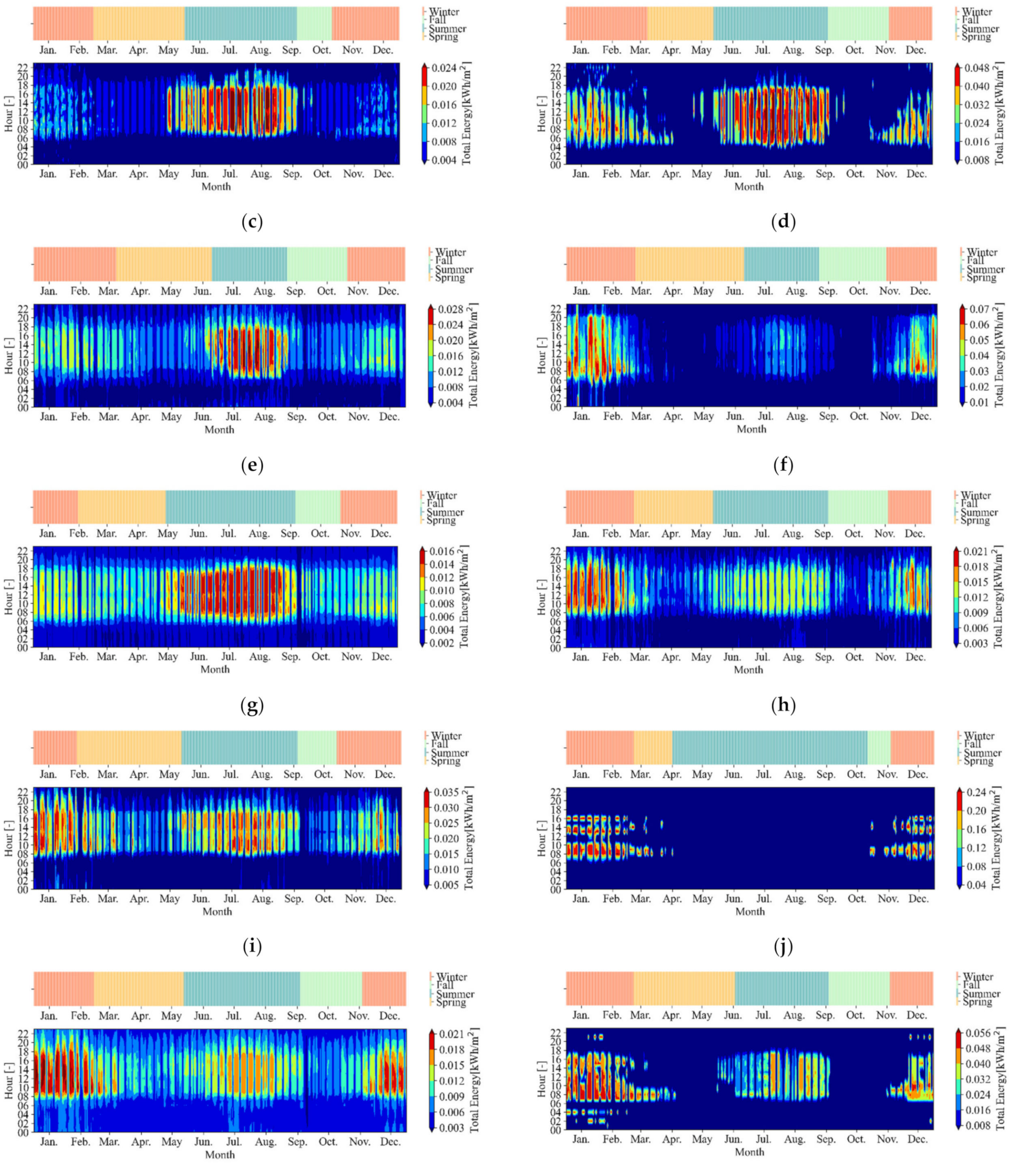
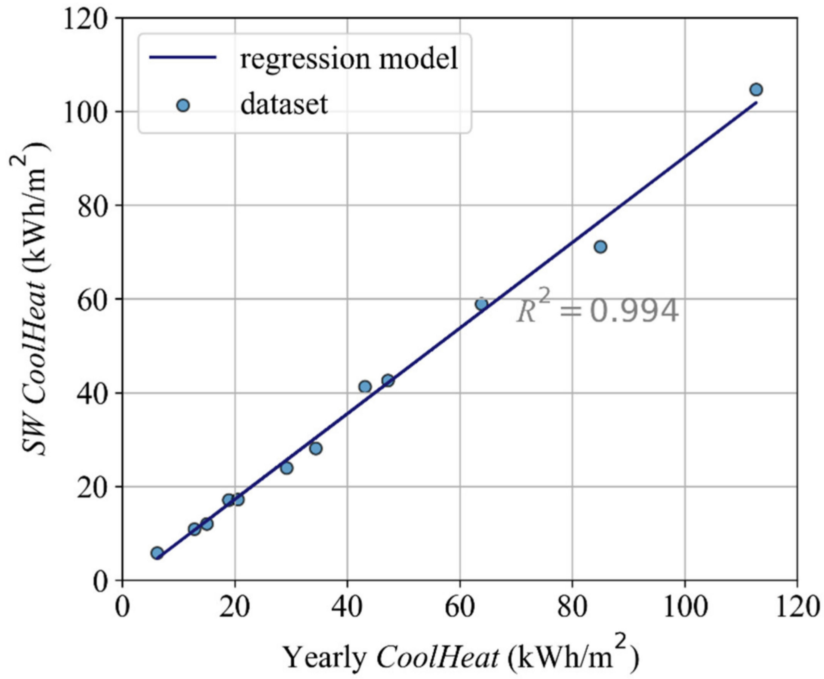
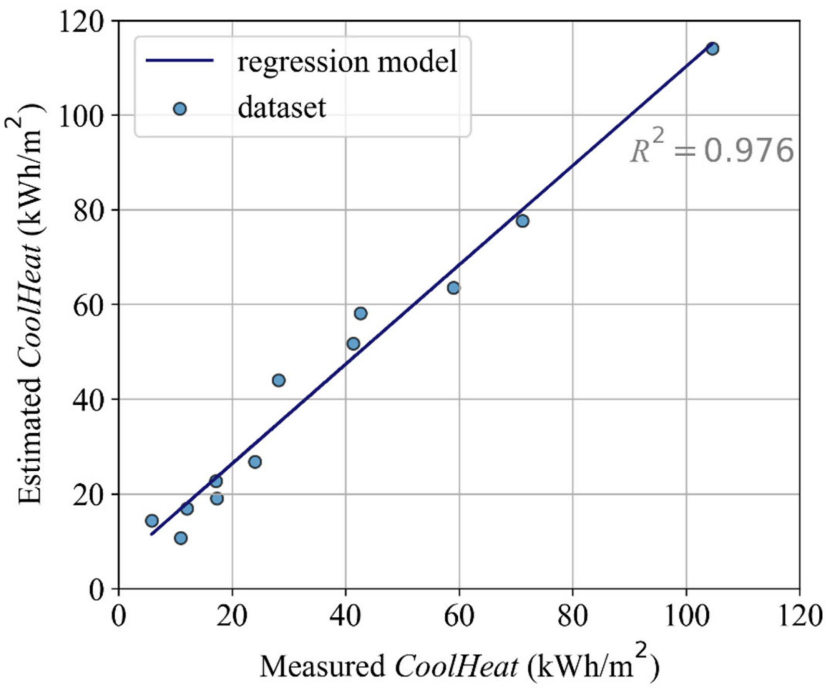


Figure 5. Carpet plots depicting temporal segmentation results of total energy for the 12 target buildings; (**a**–**l**) denote buildings 1–12, respectively.

Figure 6a shows the relationship between measured *CoolHeat* in 2018 and the *CoolHeat* during the *SW* periods determined through IGTS. With R^2 = 0.994, *CoolHeat* in the *SW* periods can be regarded as the total amount of *CoolHeat* use in buildings. Figure 6b shows a scatterplot of the measured and estimated *CoolHeat* during *SW* according to the procedure detailed in Section 3.2. Although there was a difference between the measured and estimated values, considering R^2 = 0.976, estimated *CoolHeat* based on the IGTS can be considered to sufficiently describe measured *CoolHeat*.



(**a**)



(**b**)

Figure 6. Scatterplots for *CoolHeat*. (**a**) Energy measured during 2018 and during summer and winter (*SW*) by information gain-based temporal segmentation. (**b**) Measured and estimated *CoolHeat* during *SW*.

4.2. Benchmarking Based on Estimated Heating and Cooling Energy

Table 3 shows the values and benchmarking rankings for *Total*, measured *CoolHeat*, and estimated *CoolHeat* for *SW* (which is the target period of this study), and for the entire year of 2018. While the ranks of *Total* were different for the whole year and the *SW* period in some buildings (e.g., bldg.#01, bldg.#02, bldg.#04, bldg.#05, bldg.#07, bldg.#08, bldg.#09, and bldg.#012), the ranks of *CoolHeat* were not. Hence, it can be inferred that *CoolHeat* exhibits seasonal variations. Therefore, it is necessary to independently compare and evaluate the *CoolHeat* rather than *Total* or EUI.

Table 3. Comparison of *Total*, measured *CoolHeat*, and estimated *CoolHeat*.

Index	Segmentation	*Total*		*CoolHeat* (Measured)		*CoolHeat* (Estimated)	
		Energy (kWh/m^2)	Rank (-)	Energy (kWh/m^2)	Rank (-)	Energy (kWh/m^2)	Rank (-)
bldg.#01	*SW*	65.9	5	41.3	8	51.7	8
	Yearly	79.0	3	43.1	8	-	-
bldg.#02	*SW*	30.7	2	17.1	4	25.5	5
	Yearly	40.9	1	18.9	4	-	-
bldg.#03	*SW*	133.5	10	104.6	12	114.1	12
	Yearly	157.4	10	112.7	12	-	-
bldg.#04	*SW*	69.8	6	59.0	10	63.5	10
	Yearly	80.2	5	63.8	10	-	-
bldg.#05	*SW*	30.4	1	10.9	2	14.3	1
	Yearly	58.2	2	12.8	2	-	-
bldg.#06	*SW*	67.0	11	28.2	7	49.7	7
	Yearly	90.1	11	34.4	7	-	-
bldg.#07	*SW*	26.6	3	5.8	1	15.3	2
	Yearly	40.0	4	6.2	1	-	-
bldg.#08	*SW*	31.2	4	17.3	5	19.1	4
	Yearly	43.9	6	20.5	5	-	-
bldg.#09	*SW*	46.8	8	24.0	6	36.7	6
	Yearly	67.9	9	29.2	6	-	-
bldg.#10	*SW*	85.3	12	71.1	11	77.7	11
	Yearly	102.5	12	85.0	11	-	-
bldg.#11	*SW*	39.1	7	12.0	3	16.9	3
	Yearly	61.9	7	15.0	3	-	-
bldg.#12	*SW*	53.5	9	42.6	9	58.2	9
	Yearly	66.9	8	47.2	9	-	-

When comparing the rankings of estimated *CoolHeat* with those of measured *CoolHeat* for the *SW* period, rankings for bldg.#05 and bldg.#07 interchanged from 2 to 1 and 1 to 2, respectively. Similar observations were made for bldg.#02 and bldg.#08, for which the ranks changed from 4 to 5 and from 5 to 4, respectively. However, the estimated *CoolHeat* adequately described the measured *CoolHeat* (Figure 6b, Table 3), while the other benchmarking ranking results, based on estimated and measured *CoolHeat*, were the same (Figure 7). Therefore, the estimation method for *CoolHeat* based on IGTS sufficiently infers measured *CoolHeat* in a time- and cost-effective manner.

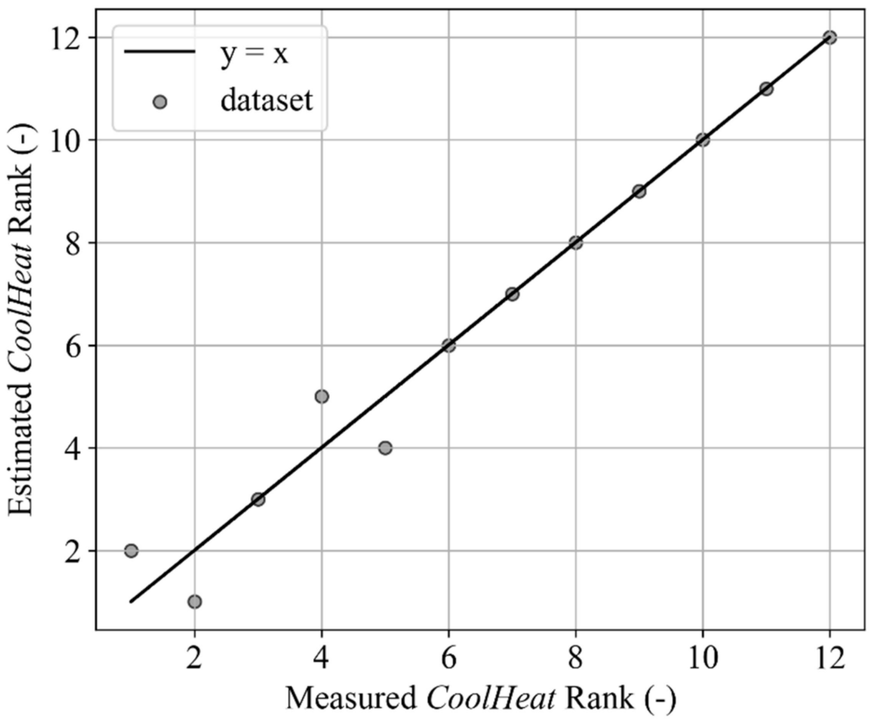


Figure 7. Benchmarking rank comparison between measured and estimated *CoolHeat*.

5. Limitations

The authors used hourly data obtained from 12 commercial buildings located in Seoul, South Korea. Less than 3% of the data for each building were missing (bldg.#06: 0.6%, bldg.#07 and bldg.#09: 0.1%, bldg.#08: 2.8%, bldg.#11: 0.4%, and others: 0.0%), and the missing values were interpolated. In addition, data that exceeded the 99.9% quantile were regarded as outliers and were replaced with interpolated values.

In South Korea, patterns in building energy use are distinct, based on seasonal changes. In this study, the IGTS determined the seasonal transition times based on the patterns of weather and building energy use. Therefore, the estimation method for *CoolHeat* applied in this study was limited to buildings with distinct changes in *CoolHeat* patterns depending on the seasons or weather conditions.

In addition, the estimation of *CoolHeat* by the IGTS at different temporal resolutions (such as daily or monthly intervals) needs to be further investigated. Finally, *Others* was defined as the 25th quantile for the set of daily *Total* during the spring and fall as determined by the IGTS, considering intermittently used *CoolHeat*. To improve the accuracy of estimated *CoolHeat*, it is necessary to improve the disaggregation algorithm used in the IGTS for *Others*.

6. Conclusions

Energy benchmarking of existing buildings is performed based on the annual total energy use; hence, it is difficult to evaluate relative energy efficiency with respect to cooling and heating that reflects the thermal characteristics of buildings. To overcome this problem, end-use metering has been considered for empirical benchmarking to quantify energy efficiency; however, it is not cost-effective or technically practical because of the use of mixed circuits for different end-users in existing buildings.

In contrast to energy benchmarking for existing buildings, this study sought to estimate and benchmark *CoolHeat*, using an energy dataset from 12 commercial buildings located in Seoul, South Korea. The buildings were sub-metered for eight end-uses (*Cool*, *Heat*, *Shw*, *Light*, *Vent*, *App*, *Trans*, and *Aux*). In particular, the IGTS was applied to identify seasonal transition times based on patterns of hourly weather and corresponding building energy use. The IGTS classified the four seasons using hourly time-series data for weather (e.g., outdoor air temperature, wind speed, and solar radiation) and energy use (e.g., electric energy and total energy). *Others* (that is energy except for *CoolHeat*) was defined based on the energy use in spring and fall, and finally, *CoolHeat* in *SW* was estimated. Although each building had different operation characteristics depending on the season (e.g., cooling dominant or heating dominant), as well as different periods for cooling and heating, the IGTS was able to distinguish the transition time of changes in the operating patterns of the buildings. For the 12 buildings, the estimated and measured *CoolHeat* in *SW* showed a linear relationship (R^2 0.976), and the average of those differences was 9.07 kWh/m^2. In addition, the differences in the benchmarking results based on estimated and measured *CoolHeat* were not significant.

This study showed that *CoolHeat* estimation based on the IGTS can efficiently represent actual *CoolHeat* without requiring any sub-metering devices. Additionally, it can be used for benchmarking to determine the relative thermal energy performance of a building. The target buildings were mixed-use buildings, i.e., offices and commercial facilities. It should be noted that the results of this study are limited to 12 target buildings for which hourly data were measured. As such, further verification for various types of buildings with unclear energy use patterns with respect to the seasons or weather conditions is required.

Author Contributions: K.U.A., D.-W.K., S.-E.L., C.-U.C. and H.M.C. analyzed the dataset and described the results presented in this paper. All authors have read and agreed to the published version of the manuscript.

Funding: Research for this paper was conducted under the KICT Research Program (project no. 436 20210204-001, Data-Centric Checkup Technique of Building Energy Performance) funded by the Ministry of Science and ICT.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data supporting the reported results in this study will be available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kim, D.W.; Kim, Y.M.; Lee, S.E. Development of an energy benchmarking database based on cost-effective energy performance indicators: Case study on public buildings in South Korea. *Energy Build* **2019**, *191*, 104–116. [CrossRef]
2. Korea.net. Available online: https://www.korea.net/NewsFocus/policies/view?articleId=205222 (accessed on 9 June 2022).
3. Korea.kr. Available online: https://www.korea.kr/news/policyNewsView.do?newsId=148894861 (accessed on 9 June 2022).
4. Chung, W.; Hui, Y.V.; Lam, M. Benchmarking the energy efficiency of commercial buildings. *Appl. Energy* **2006**, *83*, 1–14. [CrossRef]
5. Chung, W. Review of building energy-use performance benchmarking methodologies. *Appl. Energy* **2011**, *88*, 1470–1479. [CrossRef]
6. Pérez-Lombard, L.; Ortiz, J.; González, R.; Maestre, I.R. A review of benchmarking, rating and labelling concepts within the framework of building energy certification schemes. *Energy Build* **2009**, *41*, 272–278. [CrossRef]
7. *CIBSE, TM46*; Energy Benchmarks. The Chartered Institution of Building Services Engineers: London, UK, 2008.
8. *CIBSE, TM47*; Operational Ratings & Display Energy Certificates. The Chartered Institution of Building Services Engineers: London, UK, 2008.
9. Yoon, S.H.; Park, C.S. Objective building energy performance benchmarking using data envelopment analysis and Monte Carlo sampling. *Sustainability* **2017**, *9*, 780. [CrossRef]
10. Mathew, P.; Mills, E.; Bourassa, N.; Brook, M. Action-oriented benchmarking, using the CEUS database to benchmark commercial buildings in California. *Energy Eng.* **2008**, *105*, 6–18.
11. Mills, E.; Mathew, P.; Piette, M.A.; Bourassa, N.; Brook, M. Action-oriented benchmarking: Concepts and tools. *Energy Eng.* **2008**, *105*, 21–40. [CrossRef]
12. Borgstein, E.H.; Lamberts, R.; Hensen, J.L.M. Evaluating energy performance in non-domestic buildings: A review. *Energy Build* **2016**, *128*, 734–755. [CrossRef]
13. Bannister, P.; Hinge, A. Empirical benchmarking of building performance. In Proceedings of the American Council for an Energy Efficient Economy, Summer Study, Monterey, CA, USA, 25–31 August 2006.

14. Sharp, T. Energy benchmarking in commercial office buildings. In Proceedings of the American Council for an Energy Efficient Economy, Washington, DC, USA, 25 August 1996.
15. Aigner, D.J.; Lovell, C.A.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econometr.* **1977**, *6*, 21–37. [CrossRef]
16. Meeusen, W.; van den Broeck, J. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int. Econ. Rev.* **1997**, *18*, 435–444. [CrossRef]
17. Reifschneider, D.; Stevenson, R. Systematic departures from the Frontier: A framework for the analysis of firm inefficiency. *Int. Econ. Rev.* **1991**, *32*, 715–723. [CrossRef]
18. Talluri, S. Data envelopment analysis: Models and extensions. *Decis. Line* **2000**, *31*, 8–11.
19. Wang, S.; Yan, C.; Xiao, F. Quantitative energy performance assessment methods for existing buildings. *Energy Build* **2012**, *55*, 873–888.
20. De Wilde, P. The gap between predicted and measured energy performance of buildings: A framework for investigation. *Autom Constr.* **2014**, *41*, 40–49. [CrossRef]
21. Lee, W.L.; Yik, F.W.H.; Burnett, J. Assessing energy performance in the latest versions of Hong Kong Building Environmental Assessment Method (HK-BEAM). *Energy Build* **2007**, *39*, 343–354.
22. Sadri, A.; Ren, Y.; Salim, F.D. Information gain-based metric for recognizing transitions in human activities. *Pervasive Mob. Comput.* **2017**, *38*, 92–109.
23. Korean Institute of Architectural Sustainable Environment and Building Systems (KIAEBS), KIAEBS S-7. *Methods for Classification, Measurement and Normalization of Energy Consumption by End-Use in Office Buildings*; KIAEBS: Seoul, Korea, 2016.
24. *ISO12655*; Energy Performance of Buildings—Presentation of Measured Energy Use of Buildings. International Standard Organization (ISO): Geneva, Switzerland, 2013.
25. Open Government Data Portal. Available online: https://data.go.kr/data/15057210/openapi.do (accessed on 9 June 2022).
26. Meng, Q.; Xiong, C.; Mourshed, M.; Wu, M.; Ren, X.; Wang, W.; Li, Y.; Song, H. Change-point multivariable quantile regression to explore effect of weather variables on building energy consumption and estimate base temperature range. *Sustain. Cities Soc.* **2020**, *53*, 101900.