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[2II06-01] A method for data-driven energy conservation diagnosis on each floor for buildings

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This study examines to comprehend the energy consumption patterns by floor in large-scale buildings and examine a method for taking energy-saving measures based on the analytical results. In this paper, we show how to classify the floors of large-scale buildings based on their hourly energy consumption time-series data and how to build a model for interpreting the classification results. The paper also discusses whether the patterns of floors classified by the model can be used to identify energy-saving measures for those floors.This analysis used mixed hourly energy consumption data for each floor of three large office buildings. First, we clustered the floor energy consumption pattern data to classify the floors. Next, we constructed a random forest prediction model with the clustering results as the target variable and various quantities related to energy consumption characteristics as the explanatory variables. Then, we quantified the energy consumption characteristics of each cluster based on the information obtained in the process of building a prediction model using random forests, and showed that it is possible to identify energy-saving measures by interpreting the energy usage trends of the floors. Finally, we analyzed small and medium-scale buildings by floor in the same way as an analysis of large-scale buildings and confirmed that it is possible to comprehend their energy consumption patterns and identify energy-saving measures. In addition, we examined the explanatory variables used to build the random forest prediction and selected explanatory variables that can be more effectively extract energy-saving measures.

A method for data-driven energy-conservation diagnosis on single floors in buildings

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Abstract. This study proposes a data-driven energy-saving diagnostic method that analyzes hourly energy consumption data at the building, the floor, or equipment scale. This paper focuses specifically on floor analysis. We first classified floor groups by clustering based on the similarities of their time-based pattern data. After the clustering process, we performed feature importance analysis and identified key factors influencing the energy consumption of each cluster using the random forest algorithm, from which we then proposed specific energy conservation measures. This method was tested on the energy consumption data from three large and five small-medium buildings. The analysis revealed distinct energy usage characteristics for each cluster, and specific energy conservation measures were devised artificially based on the results. In conclusion, we confirmed that it is possible to develop specific energy conservation measures tailored to actual energy usage by analyzing floor-specific energy consumption characteristics according to the building size.

1 Introduction

Thorough energy management in existing buildings is important for realizing a sustainable society. To implement appropriate energy management, it is therefore essential to understand and evaluate the actual status of building operations based on operational data, as well as identify areas for improvement.

In Japan, devices that collect data related to energy usage, such as the Building Energy Management System (BEMS), have become widespread. However, the data collected by these devices are not being fully utilized owing to various factors, including, high analytical workload, analytical cost, and the fact that their use was not anticipated in advance. However, machine learning methods can be used to streamline and accelerate energy conservation diagnostics based on data accumulated by these devices and applying these methods to buildings can support operational improvements and equipment upgrades, enabling energy savings that do not rely on conventional experience. On the other hand, among the large number of existing buildings, detailed data is actually measured in only a small fraction. Generally, only the total electricity consumption data for the entire building or energy consumption per floor is typically measured.

In this study, we developed a data-driven energy-saving diagnostic method that analyzed hourly energy consumption data from three large and five small–medium buildings to understand energy consumption at both building and floor scales. Energy conservation measures were then proposed based on the results. Furthermore, when conducting detailed diagnostics for specific buildings based on this diagnosis, the application of additional analytical methods is anticipated.

2 Data-driven energy-saving diagnosis

2.1 Analysis and application of measures

We first classified buildings into types based on their energy consumption patterns using clustering. After the clustering process, a prediction model was created using the random forest machine learning algorithm to perform feature importance analysis and identify the energy consumption trends of each cluster. Next, model buildings for which detailed information was available at the floor or equipment scale were selected from the clusters. Energy consumption patterns at the floor or equipment scale were analyzed using the same clustering and random forest methodology to identify energy consumption trends, from which specific energy conservation measures were then proposed.

Energy conservation measures that have been recognized as effective were expected to be applied to other buildings within the same cluster (including buildings for which detailed data were not available) to achieve energy conservation in a large number of buildings.

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2.2 Floor clustering method

We focused specifically on floor analysis. The floor clustering procedure was divided into three steps, as shown in Figure 1. In the data preprocessing stage, the hourly averages for the period shown in Table 1 were calculated based on the floor-specific energy consumption data for all selected buildings, from which energy consumption pattern data were created. These pattern data were normalized to create time-based hourly energy consumption pattern data, which were then used as the input dataset for clustering.

In the classification stage, floor groups were classified by clustering based on the similarities of their time-based pattern data (i.e., initial clustering). If clusters with a certain number of floors were generated, the process proceeded to the cluster refinement stage, in which clustering was performed again on the clusters (i.e., "re-clustering"). The re-clustering was performed on clusters containing a relatively large number of the analyzed floors to more clearly classify and understand the energy consumption characteristics of each floor. We used k-means++ as the clustering algorithm, while the elbow method, which uses the sum of squared errors (SSE), was used to determine the number of clusters.

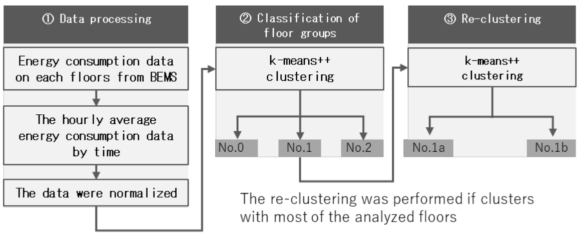

Fig. 1. Flow chart of the floor clustering procedure

2.3 Random forest feature analysis

Figure 2 shows a conceptual diagram of the feature importance analysis using the random forest algorithm. The clustering results from Section 2.1 were used as the target variables, while various energy consumption characteristics derived from the time-based energy consumption data were set as explanatory variables. A floor-classification prediction model was then constructed using the random forest algorithm. Based on the information gain obtained during model creation, the extent to which each explanatory variable contributed to the classification was indicated as a ratio between 0 and 1. Based on these results, the energy consumption trends of each cluster were quantified to understand the energy consumption status of each floor and determine appropriate energy conservation measures.

3 Case studies

The buildings analyzed using the method developed herein are listed in Tables 2 and 3. Large buildings A, B, and C, which contained a total of 62 floors, were analyzed. The data was measured hourly over one year for each floor of the buildings and categorized into lighting power consumption, air conditioning fan power consumption, and cooling/heating. For clustering, the total primary energy consumption, which was calculated by summing these data, was used.

The small–medium buildings included 44 floors in buildings D, E, F, G, and H. The data consisted of the total primary energy consumption, which was calculated by summing the hourly electricity consumption for lighting and air conditioning on each floor over one year. The explanatory variables created from the measurement data and used in the feature importance analysis are presented in Tables 4 and 5.

3.1 Analysis of large buildings

The initial clustering categorized the floor groups into four clusters (numbered 0–3). For clusters No. 0 and No. 1, each of which contained more than 25% of the total number of floors, a re-clustering was performed that divided them into subclusters No. 0_A, No. 0_B, No. 1_A, and No. 1_B. Table 6 presents the number of floors associated with each cluster and Figure 3 shows the time-based pattern and feature analysis results.

Cluster No. 0_A had air handling unit (AHU) fan power ratios, summer cooling energy consumption, lighting power and AHU fan power during overtime hours, and early-morning AHU fan power that were all greater than the average values. As a result, this floor group was considered to have a high cooling demand, high operating rates during overtime hours, and high thermal loads when air conditioning operation began.

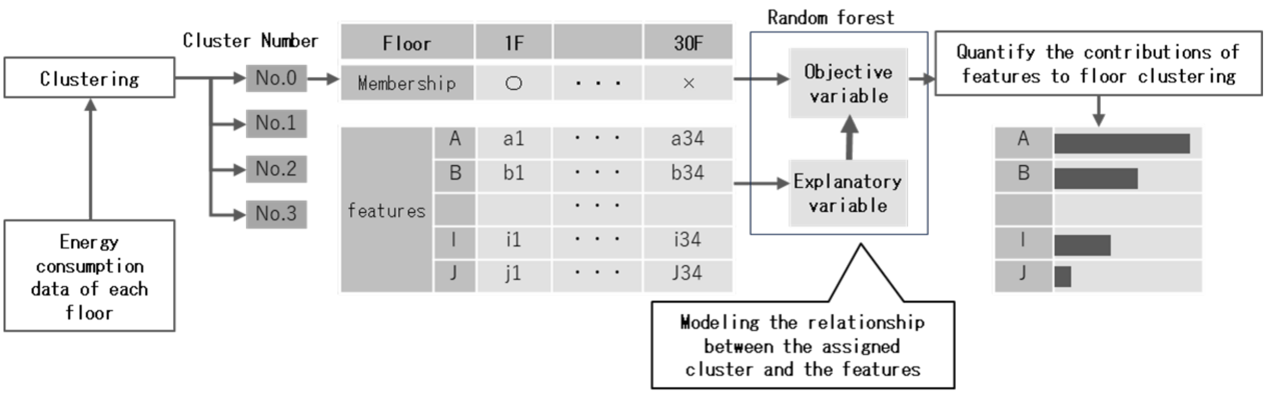

Fig. 2. Flow chart of the feature analysis steps using random forest.

Cluster No. 0_B had summer cooling energy consumption ratios, lighting power and AHU fan power during overtime hours, and winter AHU fan power and cooling energy consumption that were all greater than the average values. Consequently, these floors had high cooling demands and high operating rates during overtime hours. We also suspected that a mixing loss occurs during winter in these floors.

Cluster No. 1_A had winter AHU fan power ratios, winter heating energy consumption, and lighting power that were all greater than the average values. In contrast, the lighting power ratios between overtime and late-night hours were less than the average values. This indicates that this floor group has high heating demands and high daytime lighting usage.

Cluster No. 1_B had winter AHU fan power to heating energy consumption ratios, early-morning AHU fan power, and AHU fan power that were all greater than the average values, whereas the lighting power ratios were less than the average values. Therefore, this cluster of floors has high thermal loads when air conditioning operations began and low internal heat generation, which result in a high heating demand.

Cluster No. 2 had AHU fan power ratios during overtime hours, lighting power, late-night and early-morning AHU fan power, and winter cooling/heating energy consumption that were all greater than the average values. Therefore, this group of floors is suspected to experience mixing losses occur during the winter.

Cluster No. 3 had a load profile with a significantly higher base energy consumption than those of the other clusters. In addition, the cluster's AHU fan power ratios during late night and overtime hours, AHU fan power, and winter cooling energy consumption were all greater than the average values. This suggests that these floors may house a data center or other similar facility.

Based on the above considerations, the artificially devised specific energy conservation measures for the floor clusters are listed in Table 7. The energy conservation measures formulated here are intended to identify energy conservation measures that should be focused on based on energy consumption trends.

Table 1. Data categories used for clustering[1]

Category	Description
Holiday	Average energy consumption by time of day on holidays.
Intermediate	Average energy consumption by time during the intermediate period.
Summer	Average summer energy consumption by time of day.
Winter	Average winter energy consumption by time of day.
Peak day	Energy consumption on the peak day.
Maximum energy day	Energy consumption on the day with the highest daily energy consumption.
Minimum energy day	Energy consumption on the day with the lowest daily energy consumption.

Table 2. Summary of large buildings

Building	Building type	Number of floors	Total floor area (m^2)	Heating cooling plant system	Air conditioning system
A	Office + Data Center	30	137,000	DHC	AHU
B	Office	17	160,000	Central heat source system	AHU
C	Office	15	70,000	DHC	AHU

Abbreviations: DHC, district heating and cooling; AHU, air handling unit.

Table 3. Summary of small–medium buildings

Building	Building Type	Number of floors	Total floor area (m^2)	Heating cooling plant system	Air conditioning system
D	Office	9	12,000	PAC	Building multi air conditioner
E	Office	7	12,000	PAC	Building multi air conditioner
F	Office	16	15,000	PAC	Building multi air conditioner
G	Office	6	9,000	PAC	Building multi air conditioner
H	Office	6	9,000	PAC	Building multi air conditioner

Abbreviations: PAC, packaged air conditioner.

3.2 Analysis of small–medium buildings

Initial clustering categorized the floor groups into four clusters. Table 8 lists the number of floors in each cluster by building and Figure 4 shows the time-based patterns and feature analysis results.

Cluster No. 0 had winter air conditioning (AC) power ratios that were greater than the average value; therefore, this floor group had high heating demands.

Cluster No. 1 had a load profile with a significantly higher baseload energy consumption than those of the other clusters. In addition, its ratio of lighting power to AC power during overtime hours, as well as late-night lighting power and AC power, were greater than the average values. Thus, this group of floors likely houses a data center.

Cluster No. 2 had late-night and overtime lighting power and AC power, as well as AC power during summer and intermediate hours, that were greater than the average values. This suggests high cooling demands, standby power consumption, and the presence of a server room on these floors.

Cluster No. 3 had a unique load profile on peak days, with peaks observed on 75% of the floors during early morning hours in the winter. In addition, the of lighting

Table 4. Features used for the feature analysis of large buildings[3]

Features	Descriptions
Lighting power ratio	Annual lighting power consumption / Annual total energy consumption
AHU fan power ratio	Annual AHU fan power consumption / Annual total energy consumption
AHU fan power ratio (Summer)	AHU fan power consumption during summer / Annual AHU fan power consumption
AHU fan power ratio (Winter)	AHU fan power consumption during winter / Annual AHU fan power consumption
Cooling energy consumption ratio (Summer)	Cooling energy consumption during summer / Annual heating and cooling energy consumption
Cooling energy consumption ratio (Winter)	Cooling energy consumption during winter / Annual heating and cooling energy consumption
Cooling energy consumption ratio (Intermediate)	Cooling energy consumption during Intermediate / Annual heating and cooling energy consumption
Heating energy consumption ratio (Summer)	Heating energy consumption during summer / Annual heating and cooling energy consumption
Heating energy consumption ratio (Winter)	Heating energy consumption during winter / Annual heating and cooling energy consumption
Overtime lighting power ratio	Overtime lighting power consumption / Annual lighting power consumption
Overtime AHU fan power ratio	Overtime AHU fan power consumption / Annual AHU fan power consumption
Late-night lighting power ratio	Late-night lighting power consumption / Annual lighting power consumption
Late-night AHU fan power ratio	Late-night AHU fan power consumption / Annual AHU fan power consumption
Early-morning AHU fan power ratio	Early-morning AHU fan power consumption / Annual AHU fan power consumption

Table 5. Features used for the feature analysis of small–medium buildings

Features	Descriptions
Lighting power ratio	Annual lighting power consumption / Annual total energy consumption
AC power ratio (Summer)	Air conditioning power consumption during summer / Annual air conditioning power consumption
AC power ratio (Winter)	Air conditioning power consumption during winter / Annual air conditioning power consumption
AC power ratio (Intermediate)	Air conditioning power consumption during Intermediate / Annual air conditioning power consumption
Overtime lighting power ratio	Overtime lighting power consumption / Annual lighting power consumption
Overtime AC power ratio	Overtime air conditioning power consumption / Annual air conditioning power consumption
Late-night lighting power ratio	Late-night lighting power consumption / Annual lighting power consumption
Late-night AC power ratio	Late-night air conditioning power consumption / Annual air conditioning power consumption
Early-morning AC power ratio	Early-morning fan power consumption / Annual fan power consumption

power ratios during overtime hours, early-morning AC power, and winter AC power were all greater than the average values. Therefore, this floor group can be characterized by high heating demands, significant heat demands when winter air conditioning operations begin, and high operating rates during overtime hours.

Based on the above considerations, the specific energy conservation measures devised artificially are listed in Table 9.

3.3 Considerations

In this analysis, the classification of floor groups contained in different buildings was based on the seasonal energy consumption trends of each floor. This demonstrates that mixing floor-specific energy consumption data from multiple buildings is acceptable as inputs for modeling operational data. This suggests that a diagnostic model can be created based on the detailed analytical results of a representative building and can then be applied to other buildings to diagnose their energy usages.

4 Conclusions

We confirmed that it is possible to develop specific energy conservation measures tailored to actual energy usage by analyzing floor-specific energy consumption characteristics according to the building size. There are two potential methods for applying this analysis.

(1) If the floor energy consumption data at the same level as used in this study can be obtained for diagnosis, the same method can then be used to identify floor-specific energy consumption trends for that building and formulate energy conservation measures.

(2) If the floor-by-floor energy consumption patterns of the building are similar to those of any floor cluster in the results obtained herein, the energy conservation measures extracted from that cluster can be applied directly to the building.

To implement specific energy-saving measures, such as optimizing air conditioning systems, it is necessary to identify the actual causes of energy waste. This involves conducting detailed diagnoses on each piece of equipment in floors with potential for energy savings.

In the future, it will be necessary to increase the number of buildings analyzed to improve the diagnostic accuracy and propose methods for automating the development of energy-conserving measures.

Notes

1. The summer and winter periods were defined as June 1 to September 30 and December 1 to March 31, respectively, while the intermediate periods were April 1 to May 31 and October 1 to November 30.
2. To convert electricity and cooling/heating energy consumption to primary energy, conversion factors of 9.76 [MJ/kWh] and 1.36 [MJ/MJ], respectively, were used.
3. Early morning was defined as 6:00 AM to 9:00 AM, overtime hours were 8:00–10:00 PM, and late night hours were 12:00–6:00 AM.

Table 6. Number of floors in each cluster (large buildings)

No.	0 A	0 B	1 A	1 B	2	3
Building A	8	3	10	2	6	1
Building B	10	1	1	1	4	-
Building C	-	3	7	-	5	-
Total	18	7	18	3	15	1

Table 7. Energy conservation measures for large buildings

No.	Energy conservation measures
0_A	• Optimization of nighttime use areas and operating schedules for air conditioning and lighting • Optimization of air conditioning settings and outside air intakes during summer • Optimization of early-morning air conditioning operating schedules
0_B	• Optimization of nighttime use areas and operating schedules for air conditioning and lighting • Optimization of air conditioning settings and outside air intakes during summer • Optimization of air conditioning settings and utilization of economizer cycles during winter • Prevention of mixing loss
1_A	• Reduction in the standby power consumption of automated office equipment • Optimization of air conditioning settings and outside air intakes during winter
1_B	• Reduction in the standby power consumption of automated office equipment • Optimization of air conditioning settings and outside air intakes during winter • Optimization of early-morning air conditioning operation schedules
2	• Optimization of air conditioning settings and outside air intakes during winter • Prevention of mixing loss • Optimization of air conditioning settings in server rooms • Utilization of economizer cycles in server rooms during winter
3	• Optimization of air conditioning settings during winter • Utilization of economizer cycles during winter

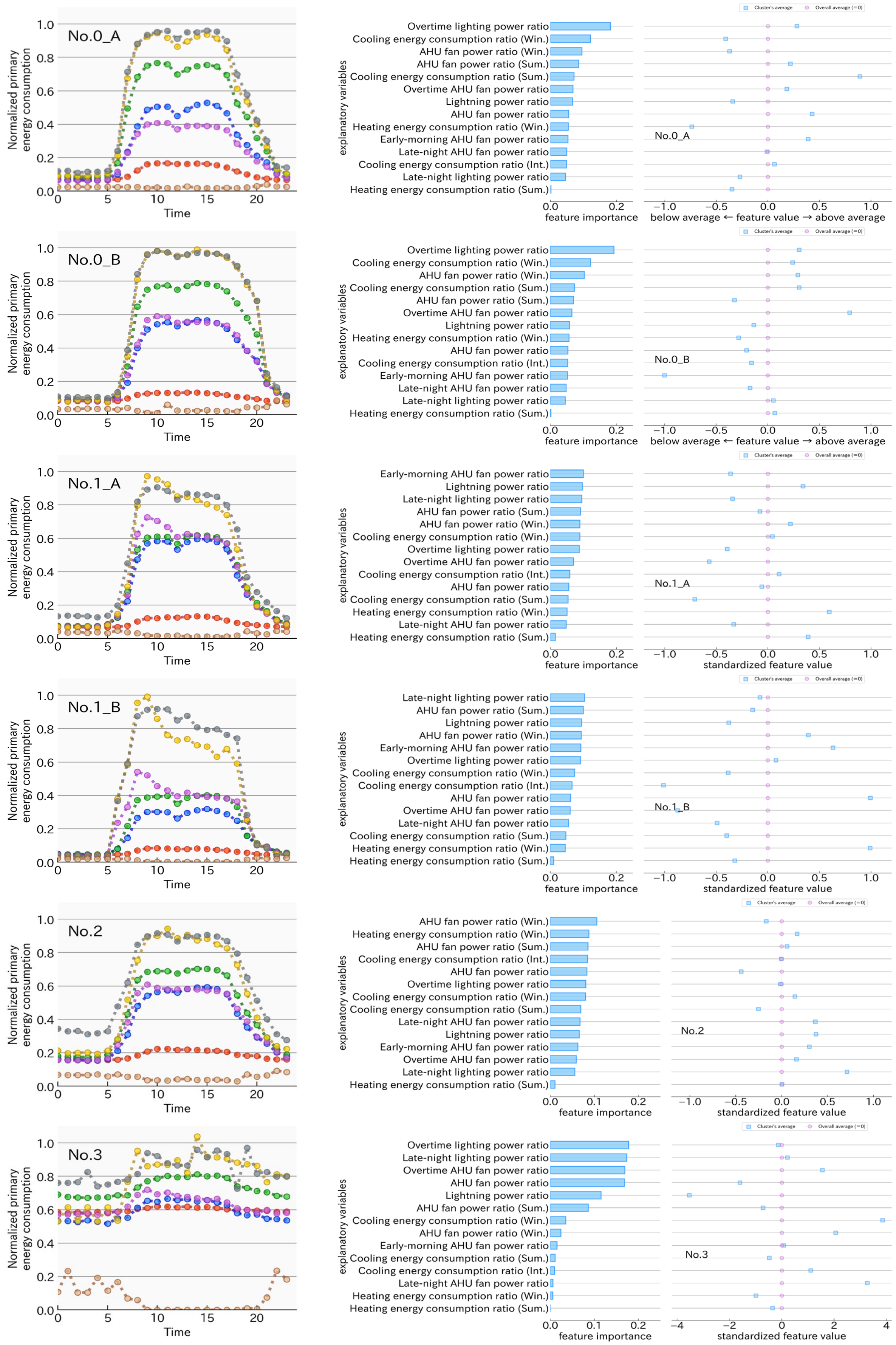

Fig. 3. Time-based pattern and feature analysis results for each cluster of large buildings. The waveforms on the left side represent the average energy consumption profile for each floor in each cluster over time. The graphs on the right display the results of the feature importance analysis using the random forest algorithm. The bar graph illustrates the feature importance of each explanatory variable, and the scatter plot shows the deviation between the cluster average and overall average of the standardized values for each explanatory variable.

Table 8. Number of floors in each cluster (small–medium buildings)

No.	0	1	2	3
Building D	5	1	-	3
Building E	5	-	2	-
Building F	5	1	10	-
Building G	3	-	2	1
Building H	2	1	3	-
Total	20	3	17	4

Table 9. Energy conservation measures for small–medium

No.	Energy conservation measures
0	• Optimization of air conditioning settings and outside air intakes during winter • Confirm whether air conditioning is used during winter
1	• Optimization of air conditioning settings during summer
2	• Optimization of air conditioning settings during summer • Optimization of nighttime use areas and operating schedules for air conditioning and lighting • Optimization of air conditioning settings in server rooms
3	• Optimization of air conditioning settings during winter • Optimization of early-morning air conditioning operation schedule

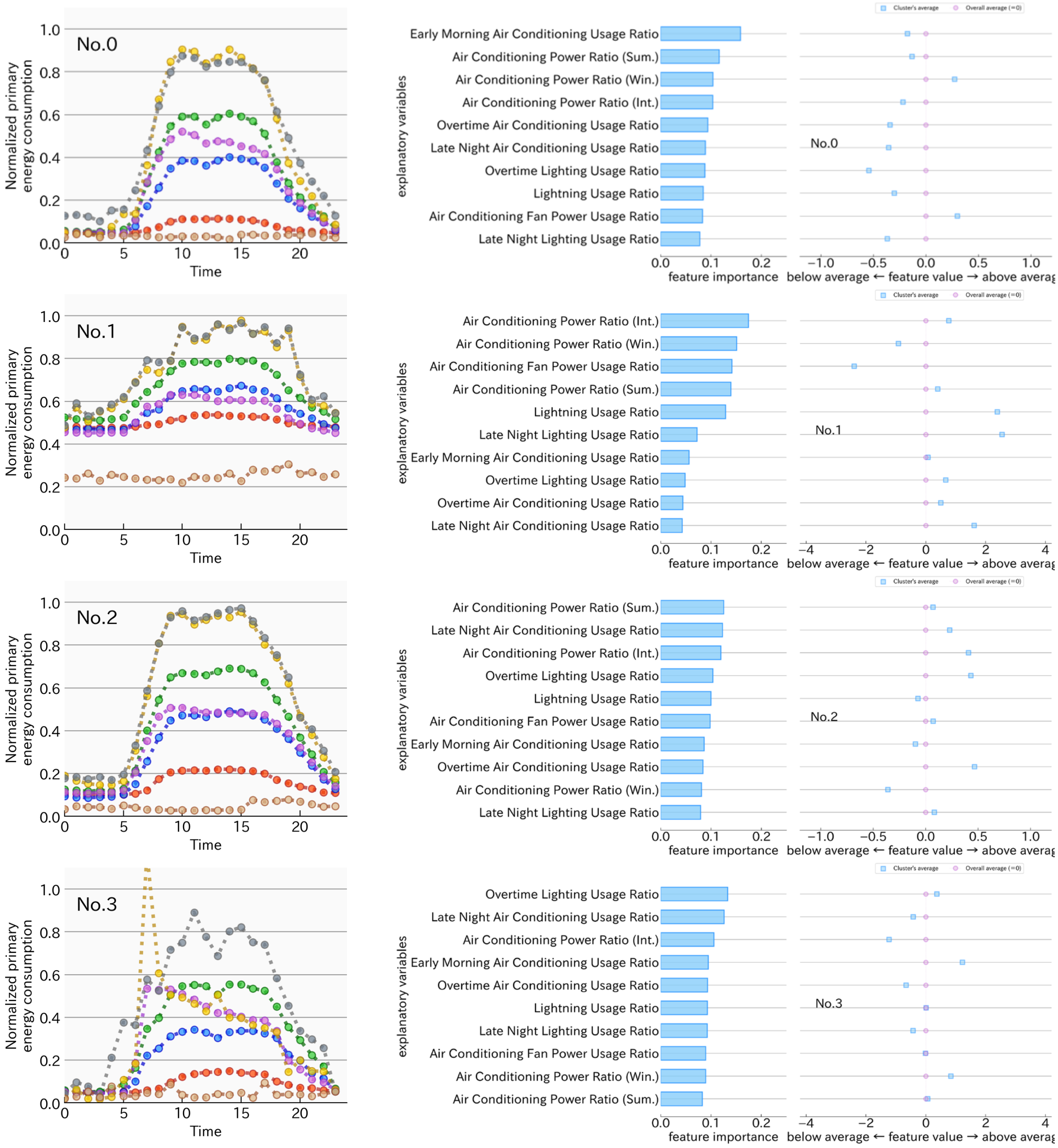

Fig. 4. Time-based pattern and feature analysis results for each cluster of small-medium buildings.