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Analysis of factors affecting energy flexibility in preheating residential buildings based on cluster analysis

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ABSTRACT

Demand response is an effective method for achieving energy flexibility. By utilizing the thermal properties of the building envelope, energy shifting can be achieved by preheating. In this study, a simulation-based method was used to quantify the energy flexibility of residential buildings in Kitakyushu City, Japan. A rule-based control method was used to control the heating systems, resulting in different heat energy reduction ratio after preheating at different start time during the day. Then, k-means clustering analysis was performed on the energy reduction of different buildings during January. The optimal number of clusters was determined to be two based on the Calinski-Harabasz and Davies-Bouldin indices. The results of the clustering analysis showed that the energy reduction was significantly affected by the thermal insulation properties of the building envelope compared to the thermal mass. In addition, weather conditions also had a significant impact on energy reduction, with higher solar radiation and lower humidity contributing to a significant enhancement of energy reduction effects.

Keywords: Demand response, Heating system, Building envelope, Clustering analysis, Weather condition

1. INTRODUCTION

With the increasing integration of renewable energy sources, generation-side energy supply is becoming increasingly uncertain. Therefore, user-side energy consumption needs to be managed to ensure grid stability [1]. As a result, buildings need to adjust their energy consumption in response to grid supply and electricity prices. This strategy, known as "demand-following-supply" [2], involves demand response (DR), where buildings modify their energy consumption based on local climate, weather conditions, and user comfort considerations to meet the requirements of the energy grid [3].

The capability to reduce, shed, shift, modulate, or generate electricity provided by DR is often referred to as energy flexibility [4]. The building envelope plays a crucial role in facilitating energy shifting by preheating, and effectively reducing the heat load after preheating [5]. During the heating season, building energy flexibility is primarily determined by its thermal performance and the outdoor environment. Wei et al. [6] investigated the impact of dynamic electricity pricing and found that improved insulation performance of external walls leads to greater cost savings on electricity. It also enables shorter preheating durations during low-price periods, thereby covering longer periods of high-price peaks. Foteinaki et al. [7] implemented temperature control within the range of human comfort for HVAC systems and quantified the changes in building loads during the control period. Their study revealed a strong correlation between energy flexibility and solar radiation, highlighting the significance of thermal insulation properties in the building envelope. However, the thermal performance of the building envelope can be evaluated based on two aspects: U-value and thermal mass. Thus, it is crucial to identify key thermal performance indicators that affect energy flexibility. Currently, most studies only focus on typical daily scenarios and analyze the influence of the outdoor environment on energy flexibility, which limits the derivation of more generalized conclusions.

A simulation-based method was used to analyze the factors affecting energy flexibility. Residential buildings are classified based on the thermal performance of their envelopes. Rule-based control (RBC) strategies are adopted for DR. Cluster analysis was performed by k-means algorithm to analyze the impact of the thermal performance of the building envelope and the outdoor environment on the energy flexibility.

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2. METHODOLOGY

2.1 Control strategy of preheating

Marina Takasu et al [8] experimented that a temperature maintained in the range of 23±2°C can maintain 80% of the thermal comfort zone. This study compares the reference case and the flexibility case to explore the energy reduction after preheating. In the reference case, the indoor setting temperature will be maintained at 23°C as shown in Table 1. In the flexibility case, the preheating strategy is implemented. Fig. 1 shows the difference between the reference case and the flexibility case. In the flexibility case, the preheating time is from t_0 to t_1, the setting temperature is 25°C, and the heat load is significantly increased during the preheating period (Δt_0). After preheating, the setting temperature is 23°C and the heat load is reduced to achieve energy shifting. Since preheating provides short-term energy flexibility, the heat load is significantly reduced within Δt_1 after preheating.

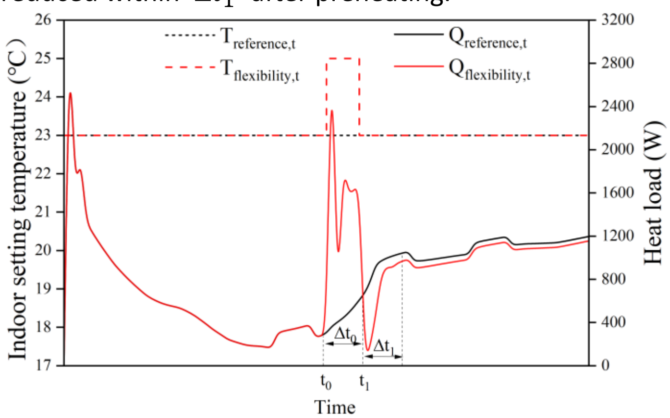

Fig. 1. Setting temperature and heat load in reference and flexibility cases.

Table 1. Control strategies of reference case.

Type	Duration	Setting temperature
Reference case	8:00-24:00	23°C

2.2. Energy flexibility indicators

Preheating can provide short-term heat load reduction. To quantify the potential for short-term energy flexibility, the heat energy reduction ratio (γ_E) is developed. γ_E is defined as the ratio of the energy reduced during a period after preheating to the energy in the reference case. The equation is as follows.

$$\gamma_E = \frac{\int_{t_1}^{t_1+\Delta t_1} Q_{reference,t} - Q_{flexibility,t}\, dt}{\int_{t_1}^{t_1+\Delta t_1} Q_{reference,t}\, dt} \quad (1)$$

where $Q_{flexibility,t}$ indicates the heat load of the building under the flexibility case, $Q_{reference,t}$ indicates the heat load of the building under the reference case, t_1 is the time when preheating ends, and Δt_1 is the period after preheating. To study the impact of DR events at different start times on energy flexibility, this study sets Δt_1 to 1 h.

3. DESCRIPTION OF THE BUILDING MODEL

3.1. Building information

A residential building in Kitakyushu was selected as the research object. A physical model of the building was created based on the actual size of the building. Actual building and the building model are shown in Fig. 2. Table 2 lists the detailed thermal performance of the building.

Table 2. Thermal performance of building components.

Building components	U-value $(w/(k \cdot m^2))$	Thermal mass $(kJ/(k \cdot m^2))$
External wall	0.205	504.6
Internal wall	1.747	493.1
Roof	0.207	67.1
Window	1.0	\

Fig. 2. Residential Buildings (left) and building model in SketchUp (right).

3.2. Weather conditions

To investigate the impact of weather conditions on energy flexibility, outdoor weather data from Kitakyushu, Japan in January 2020 are analyzed as shown in Fig.3 and Fig.4. Due to the mostly cloudy and rainy weather, the overall global horizontal radiation was relatively weak, and most days showed a low level of solar radiation. The average relative humidity was 70%, indicating high air humidity, and the average wind speed was relatively mild at 4.1m/s.

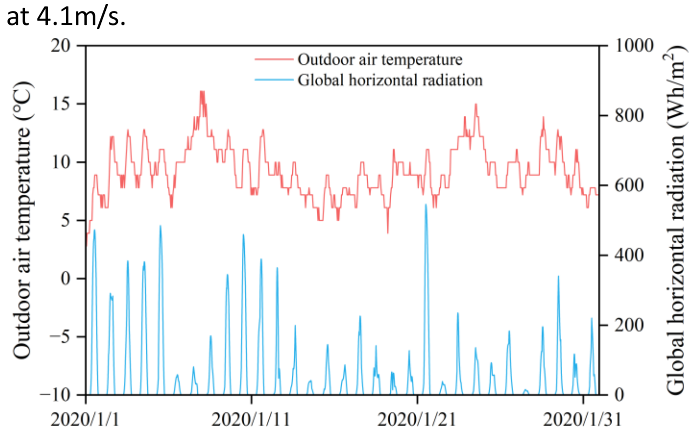

Fig. 3. Global horizontal radiation and outdoor temperature in January.

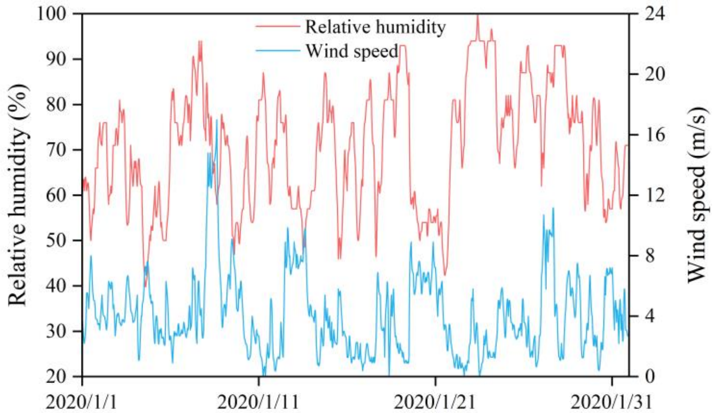

Fig. 4. Relative humidity and wind speed in January

3.3. Simulation model and validation

To validate the accuracy of the model in predicting building energy consumption, the simulation data were compared with the actual measured data. Fig. 5 shows the comparison results for three consecutive days.

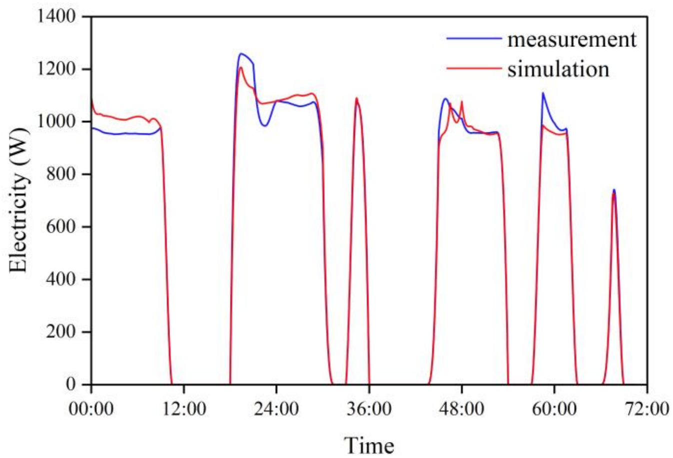

Fig. 5. Comparison of simulated and measured electricity.

The coefficient of variation of the root mean square error ($CV(RMSE)$) provided by ASHRAE Guideline 14 [9] was used to evaluate the accuracy of the model. The equation for $CV(RMSE)$ is presented below.

$$CV(RMSE) = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_{m,i} - E_{s,i})^2}}{\frac{1}{N}\sum_{i=1}^{N}E_{m,i}} \qquad (2)$$

Where $E_{m,i}$ and $E_{s,i}$ represent the measured and simulated electricity. $CV(RMSE)$ during the simulation time (January) 10.2%. ASHRAE Guideline 14 states that a model is considered effective when $CV(RMSE)$ is less than 15%. Therefore, this model is acceptable.

4. CASE STUDY

Chapters 2 and 3 introduce the quantitative indicator and the building model, respectively. The clustering analysis will be based on the indicator and model. The overall diagram of the clustering results analysis is shown in Fig.6.

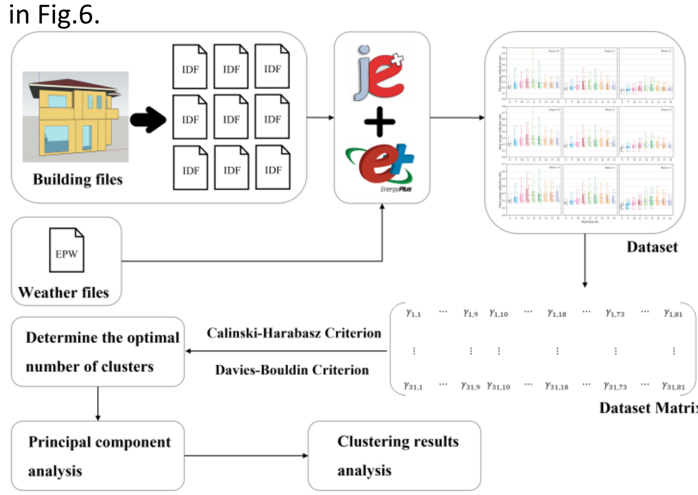

Fig.6. The overall diagram of the clustering results analysis.

4.1. Building cases setting

To further investigate the contribution of U-value and the thermal mass to the energy reduction, nine different building types were generated by modifying the envelope based on the original building model, and the buildings were classified into light, medium, and heavy types according to the building thermal mass, and then into high, medium, and low performance buildings according to the U-value of the building envelope. Table 3 shows the detailed parameters of the thermal physical properties of each building.

Table 3. Thermal performance of the building cases.

Thermal mass category	Light structure			Medium structure			Heavy structure		
Insulation performance	High	Medium	Low	High	Medium	Low	High	Medium	Low
Building name	House 1.0	House 1.1	House 1.2	House 2.0	House 2.1	House 2.2	House 3.0	House 3.1	House 3.2
External wall thermal mass ($kJ/k \cdot m^2$)	274.6	272.3	270.6	389.6	387.3	385.6	504.6	502.3	500.6
Internal wall thermal mass ($kJ/k \cdot m^2$)	263.1	263.1	263.1	378.1	378.1	378.1	493.1	493.1	493.1
External wall U-value ($w/k \cdot m^2$)	0.207	0.403	0.713	0.206	0.398	0.699	0.205	0.394	0.685

Internal wall U-value $(w/k \cdot m^2)$	1.942	1.942	1.942	1.839	1.839	1.839	1.747	1.747	1.747

4.2. Types of control strategies

To study the impact of preheating start times within a day on energy flexibility, the RBC strategy was proposed to the heating system. The control strategies of flexibility cases were set as shown in Table 4.

Table 4. Control strategies of second flexibility cases.

Type	Duration	Setting temperature
	8:00-9:00	
	9:00-10:00	
	10:00-11:00	
	11:00-12:00	
Flexibility cases	12:00-13:00	25°C
	13:00-14:00	
	14:00-15:00	
	15:00-16:00	
	16:00-17:00	

4.3. Description of dataset matrix

γ_E of each building under different control strategies are analyzed and made into a clustering matrix as in Fig. 7. The matrix is a 31 × 81 determinant. The number of rows is 31, which represents 31 days in January. The number of columns is 81, representing the various types of buildings preheating at different start times. Since there are 9 types of buildings with 9 different preheating start times, the number of columns is 81. Finally, the dataset matrix was imported into MATLAB for K-means clustering analysis.

$$\begin{pmatrix} \gamma_{1,1} & \cdots & \gamma_{1,9} & \cdots\cdots & \gamma_{1,81} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \gamma_{31,1} & \cdots & \gamma_{31,9} & \cdots\cdots & \gamma_{31,81} \end{pmatrix}$$

Fig. 7. γ_E dataset matrix for clustering.

4.4. K-means clustering analysis

The Calinski-Harabasz (CH) and Davies-Bouldin (DB) evaluation are effective in assessing the optimal number of clusters. The CH value represents the separation between clusters, and the global inter-cluster distance is much larger than the intra-cluster distance, i.e., the larger the separation between clusters the better the clustering result. The CH value represents the similarity between each cluster and its most similar cluster, the intra-cluster distance is much smaller than the inter-cluster distance, i.e., the smaller the similarity between classes the better the clustering result. As shown in Fig. 8, the optimal number of clusters is 2.

Principal component analysis evaluates the results of clustering from a visualization point of view. After principal component analysis, the data is dimensionally reduced to 2-dimensional data. As shown in Fig. 9, the two confidence ellipses have no intersecting parts, which indicates that the classification results are quite good.

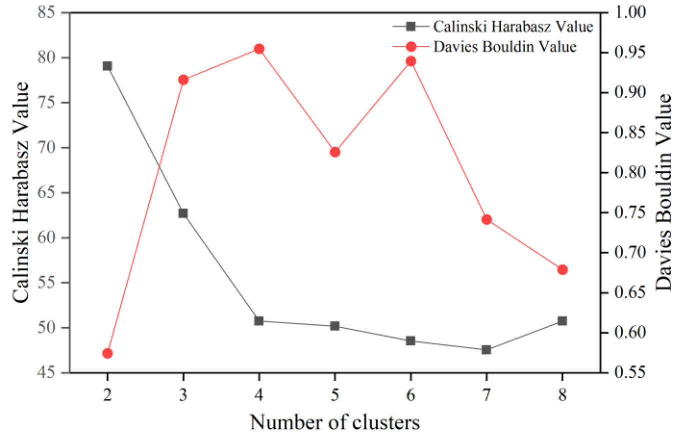

Fig. 8. Calinski-Harabasz (CH) and Davies-Bouldin (DB) evaluation.

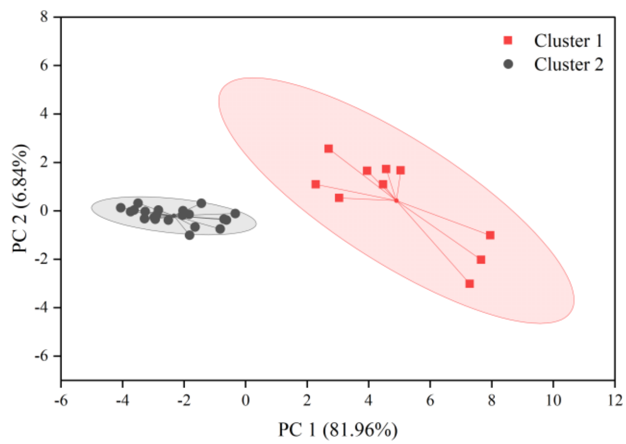

Fig. 9. Principal component analysis.

5. RESULT AND DISCUSSION

5.1. Weather condition in each cluster

As shown in Fig. 10 and 11, after clustering into 2 clusters, the differences between the clusters can be seen for each outdoor weather parameter. In general, humidity and solar radiation differ very significantly after the grouping. Thus, Cluster 1: Solar radiation varies more significantly during the day. Solar radiation is higher at noon and humidity is lower. Cluster 2: Solar radiation does not vary significantly during the day. The overall solar radiation is lower than in cluster 1 and the overall humidity is higher than in cluster 1. According to the classification, γ_E is more influenced by solar radiation and humidity.

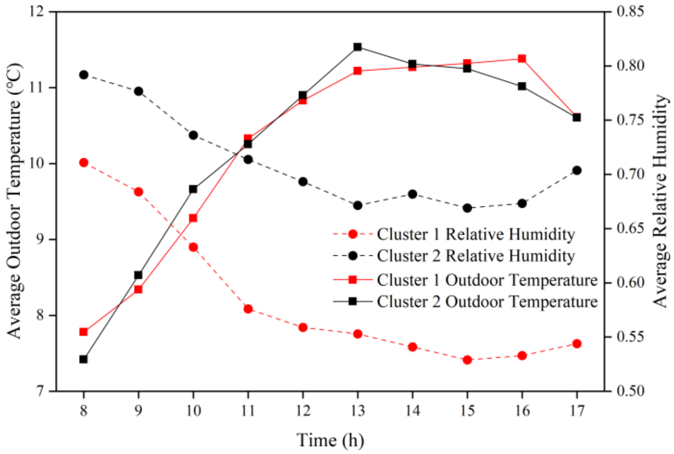

Fig. 10. Average values of outdoor temperature and relative humidity in each cluster.

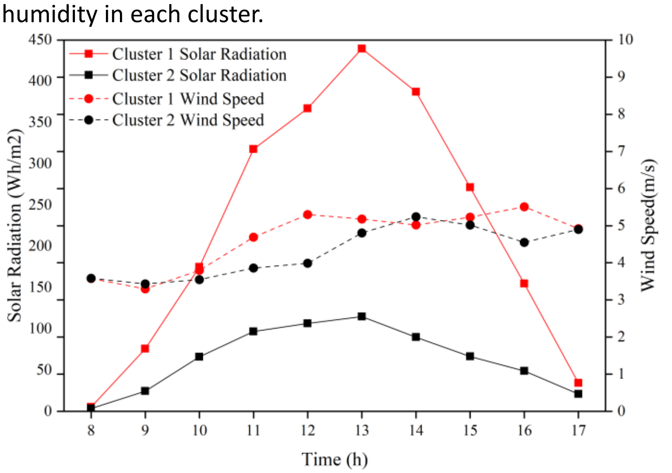

Fig. 11. Average values of solar radiation and wind speed in each cluster.

5.2. γ_E in each cluster

Based on the results of the clustering, average γ_E is calculated for different buildings in both clusters at each preheating start time. The results are shown in Fig. 12.

5.2.1. Impact of building thermal performance

The insulation of the building has a more significant effect on γ_E than the thermal mass. As shown in Fig. 12, the overall level of γ_E is higher for the high insulated building House 1.0 than for the rest of the buildings when preheating starts at 12:00. The average γ_E of the high insulation building House 1.0 is 39.35% above the low insulation building House 1.2. However, the distribution of γ_E is similar for buildings with different thermal mass. As shown in Fig. 13, the average γ_E for the heavy structure building House 3.0 is 4.53% above the light structure building House 1.0.

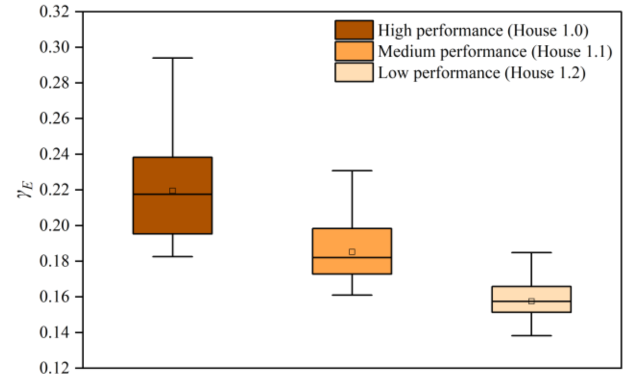

Fig. 12. Distribution of γ_E for buildings with different insulation performance (House 3.0 House 3.1 and House 3.2) in cluster 1 preheating applied for 1 h at 25°C.

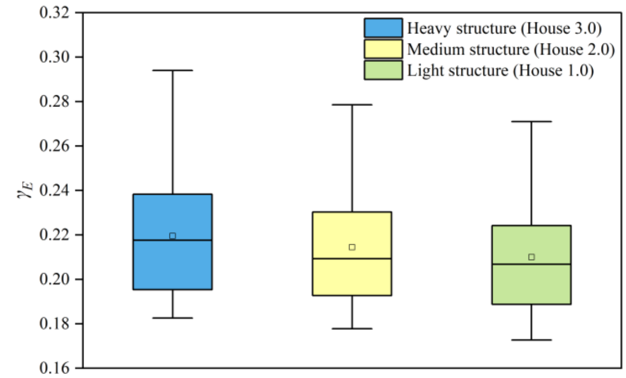

Fig.13. Distribution of γ_E for buildings with different thermal mass (House 3.0 House 2.0 and House 1.0) in cluster 1 preheating applied for 1 h at 25 °C.

5.2.2. Impact of weather condition

Cluster 1 Cluster 1 has higher solar radiation and a greater range of variability throughout the day. As shown in Fig. 14, for the same building, γ_E has a greater range of variation across time in Cluster 1 and a higher overall level. In addition, the trend of γ_E in Cluster 1 is more obvious throughout the day, with the average γ_E at 12:00 being 79.2% higher than that at 8:00. In cluster 2, the average γ_E at 14:00 was 17.1% higher than that at 8:00. At 8:00, the main difference between Cluster 1 and Cluster 2 is relative humidity, which is lower in Cluster 1. The overall level of γ_E is higher in Cluster 1 than in Cluster 2 at 8:00.

As shown in Fig. 15, at 8:00, the average γ_E of House 1.2 in Cluster 1 is 15.1% lower than that of House 1.0 in Cluster 2. And at 12:00, the average γ_E of House 1.2 in Cluster 1 is 32.2% higher than that of House 1.0 in Cluster 2. Thus, low insulation buildings can achieve higher energy reduction by preheating when solar radiation is higher.

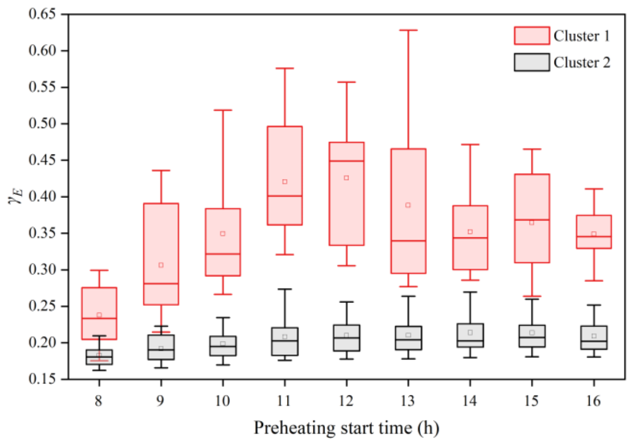

Fig. 14. Distribution of γ_E for House 1.0 preheating setting temperature is 25 °C, preheating duration is 1 h at different start times in cluster 1 and cluster 2.

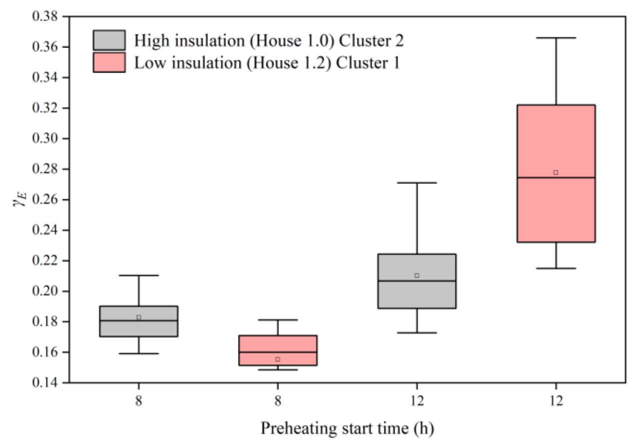

Fig.15. Comparison of House 1.0 in Cluster 2 and House 1.2 in Cluster 1, preheated for 1 h at 25 °C at 8:00 and 12:00.

6. CONCLUSION

In this paper, a simulation-based method was proposed to analyze the factors affecting energy flexibility. First, γ_E is used to quantify the energy flexibility of the preheating building. Then, γ_E for 9 building in different preheating start time was generated as a dataset matrix and cluster analysis was performed with an optimal number of clusters of 2. Cluster analysis was performed by the K-means algorithm and the performance after clustering was investigated by principal component analysis. Finally, based on the clustering results, the weather conditions and the γ_E were analyzed in two clusters. The conclusions are as follows:

1) The largest differences between the two clusters in the cluster analysis existed in solar radiation and relative humidity. Higher solar radiation and lower relative humidity would contribute to the energy reduction after preheating.
2) The insulation performance of the envelope significantly increases the γ_E compared to the thermal mass.
3) Compared to a high insulation building in a low radiation scenario, a low insulation building preheated in a high radiation scenario can achieve a higher γ_E.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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