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Cooling strategies to reduce classroom overheating in future climates

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SUMMARY
In the context of climate change, classrooms are vulnerable spaces, prone to overheating and increased energy consumption due to their high occupancy rates. The aim of this work is to analyze the influence of passive cooling strategies on energy consumption and overheating in university classrooms under future climate conditions, including heat waves. Emphasis is given on passive cooling strategies to verify the limits of their application. Computational simulations were performed for a representative university classroom in São Paulo, Brazil, under both historic and future climate scenarios. The increase of window opening area was the most effective solution. Combining the latter with lower absorptance values and nighttime ventilation resulted in a slight improvement. However, during heat waves, passive strategies proved insufficient; nighttime ventilation was ineffective, and the use of mechanical cooling became crucial.

KEYWORDS
Passive strategies; climate change; heat wave; overheating; classrooms

1 INTRODUCTION

Climate change has become a constant topic of discussion and a worldwide concern, driving more frequent periods of intense heat and an increase in the quantity and intensity of heat waves (Taylor et al., 2023). The ever-increasing change in climate patterns presents risks to all life forms (IPCC, 2023).

Health risks to occupants, especially during heat waves, have become a major concern as the indoor environment is unable to maintain minimum adequate conditions in extreme situations (Liu et al., 2017). Such risks evidence the need to properly condition classrooms, given they are spaces prone to overheating and have high occupancy rates. However, in the context of climate change, it is necessary to consider the need to maintain a comfortable environment while reducing CO_2 emissions, thereby improving energy savings.

Mitigation and adaptation are key concepts to meet such needs. Passive cooling strategies can reduce energy consumption and overheating. Examples of passive strategies include shading, natural ventilation, and window opening times (Invidiata; Ghisi, 2016), night ventilation (Gratia; De Herde, 2004), and materials with lower absorptance values (Synnefa et al., 2007). However, the efficiency of the applied strategies greatly depends on location, and in some cases, better results are achieved when solutions are combined (Triana et al., 2018). In other cases, it may be necessary to combine passive and active strategies, as passive strategies alone may not be sufficient (Borghero et al., 2023), incorporating the concept of resilient cooling into the built environment (Attia et al., 2021).

In this context, this study aims to analyse the influence of passive cooling strategies in the energy consumption and resilience to overheating of university classrooms in future climates in a Brazilian city. Emphasis is given on retrofit measures and ventilation schedule changes to verify the limits of their application.

2 METHODS

Computer simulations using EnergyPlus v22.1 (EERE, 2021) were carried out to assess the impact of selected passive strategies in historic and future climates.

2.1 Reference case and input data

The classrooms were modelled based on data collected from buildings of three universities in the state of São Paulo, providing a reference case. The simulated building has two floors and a total of eight classrooms of 65 m^2 each, with four classrooms on each floor. The classrooms are connected by an open and shadowed hallway facing north. All classrooms have windows on the north and south façades, allowing cross-ventilation, and are shaded by elements from the building itself. The window-to-wall ratio on the north façade is 47.3%, and on the south façade, it is 10.8%, all with a maximum opening factor of 0.3 (30%). The windows are single glazed with 4 mm clear glass. The simulated model used is a section of the actual building; therefore, the east walls of the east classrooms were modelled as adiabatic. External walls were built with concrete blocks with a U-value of 2.5 W/m^2K, heat capacity of 166 kJ/m^2K and solar absorptance of 0.61. The roof was composed of metallic tiles and a perforated concrete slab, with a U-value of 1.6 W/m^2K, heat capacity of 181.4 kJ/m^2K and solar absorptance of 0.16. The classroom analysed in this study is the one on the west side of the upper floor, that is, with three exterior walls and roof.

Classrooms were considered always fully occupied with a total of 38 students and 1 professor, from 8 a.m. to 12 p.m., from 2 to 6 p.m., and from 7 to 11 p.m. during weekdays. Internal gains due to equipment and lighting were 4.5 W/m^2 and 8.8 W/m^2, respectively. They were defined according to Brazilian Standards (Eletrobrás, 2014; INMETRO, 2015) and the collected data.

The building was simulated in two scenarios: naturally ventilated and on mixed mode. Natural ventilation was modelled using the Airflow Network module from EnergyPlus. Windows were open during occupied hours if the indoor temperature was both greater than 20˚ C and higher than the outdoor temperature. For the mixed mode scenario, the air-conditioning was modelled as ideal at a setpoint of 25.9˚C (Grassi et al., 2022)

All models were simulated for the city of São Paulo, Brazil, at latitude -23˚63’, with a humid subtropical climate Cwa, for the Köppen classification (Alvares et al., 2013), characterized by a generally non-rigorous dry winter and moderately rainy and hot summer. The weather files were obtained from the Weather Data Task Force, from IEA EBC Annex 80 (IEA, 2024), which generated typical meteorological years (TMYs) and years containing heat waves (HWYs) considering the socio-economic worst-case scenario (RCP 8.5) based on the 5th IPCC report (IPCC, 2014). Because this study compares historic and future climates, it was crucial that all files were taken from the same database. Annex 80 is the one that provides a weather file for a future year containing heat waves for São Paulo. The heat wave period was taken from the information provided on the weather file header as the most intense, extreme and hot period for 2080, which ranged from November 5 to 11.

2.2 Retrofit passive cooling strategies

Passive strategies selected in this study were envelope retrofit measures and the implementation of night ventilation.
(a) Windows opening factor increase to 1 (100%).
(b) Night ventilation from 11 p.m. to 8 a.m. The opening factor was set at 0.5 (50%), except during May to August, when it was reduced to 0.3 (30%) to prevent morning discomfort caused by cold.
(c) Roof and walls U-value decrease to 0.8 W/m²K and 1.27 W/m²K due to the addition of insulation layers.
(d) Decrease in walls and roof solar absorptance to 0.1.

3 RESULTS AND DISCUSSION

Results are shown in Figures 1 and 2. As expected, there is a significant increase in the indoor overheating degree (IOD)[1], hours of discomfort and cooling demand in 2080, for all cases. Conversely, there is a decrease in the percentage of hours when natural ventilation is used in the mixed mode cases. This type of building can be utilized in the future, even though its reliance on natural ventilation is reduced. During the heat wave, the average outdoor temperature during the occupied hours was of 34.6˚ C, with all indicators being considerably higher, confirming the findings of Ahmed; et al., (2021), which state that only using natural ventilation during heat waves and future climates will not be enough to maintain internal thermal comfort standards. The reference case presents the worst results, reaching 80% of the occupied period above the upper comfort limit in the future and 100% during the heat wave for all cases. This confirms the need for retrofit, as buildings are not adequate for the historic or future climates, and that passive strategies are not enough during periods of intense heat.

3.1 Historic and future yearly simulations

Implementing an opening factor of 1 (effective opening area of 100%), significantly improves the classroom’s performance in general, with the IOD value going from 3.5 to 1.9, and a decrease in the percentage of hours of discomfort from 80.4% to 54.4% for 2080 when looking at the naturally ventilated cases (Figure 1), as well as a significant impact on cooling demands for the mixed mode case (Figure 2a). The performance of the naturally ventilated case with an opening factor of 1 in 2080 is similar to that of the reference case in 2020, with both showing IOD values around 1.6 and 55% percent of the hours with discomfort. In the mixed mode cases, using

[1] Average of the difference between the indoor operative temperature and the upper comfort limit (25.9˚ C) during occupied hours.

an opening factor of 1 significantly increases the use of natural ventilation (Figure 2b). Because the impact of increasing the opening factor to 1 was so significant, all the following strategies were implemented in combination with this one.

Active strategies, such as air-conditioning, need to be considered for future and extreme scenarios (Borghero et al., 2023), since cases show up to 50% of the occupied hours with discomfort for 2080.

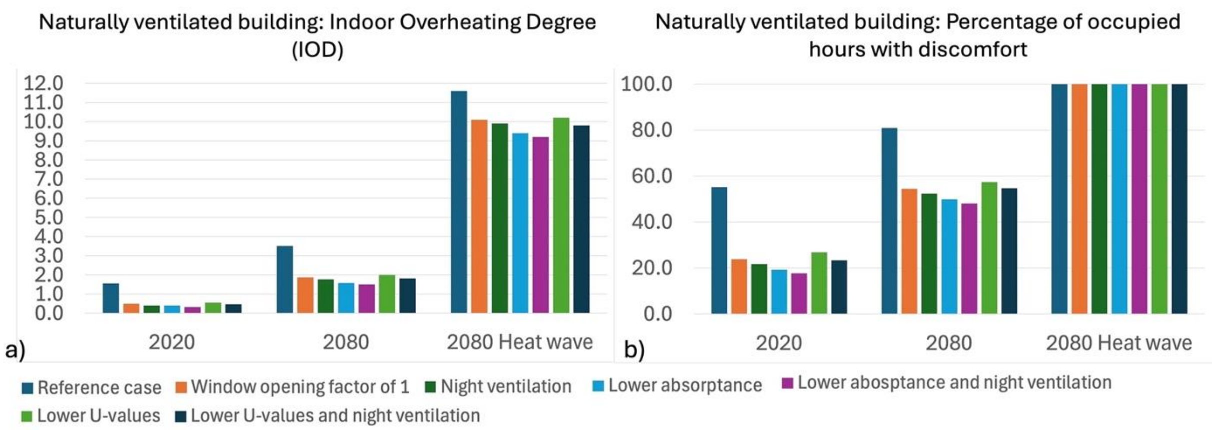

Figure 1. Naturally ventilated cases indicators a) IOD and b) percentage of occupied hours with discomfort.

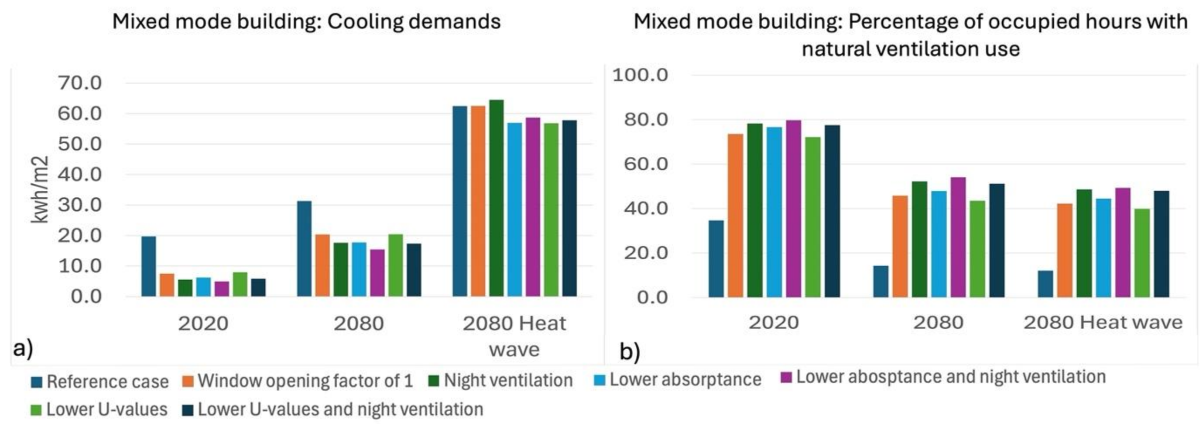

Figure 2. Mixed mode cases indicators a) cooling demands and b) percentage of use of natural ventilation.

Night ventilation and lower absorptance values have a minimal impact on naturally ventilated and mixed mode scenarios for both 2020 and 2080. However, when both are combined, a slight difference is observed, resulting in the lowest values of IOD: 0.3 for 2020 and 1.5 for 2080.

When using lower U-values, the indicators show values that are very close to or slightly worse than those of the other analyzed cases. The combination of this strategy with night ventilation only evidenced that at night the excess heat is removed, not presenting any significant improvements. Therefore, this strategy is inefficient, even when combined with night ventilation.

3.2 Future heat wave simulation

Passive strategies are insufficient to maintain acceptable indoor environmental conditions during periods of extreme heat. They are not effective in reducing the hours with discomfort or the IOD in naturally ventilated buildings, as seen in Figure 1b, with 100% of the occupied hours with discomfort. In mixed-mode scenarios, the use of passive strategies shows very little impact on energy consumption (Figure 2a) in comparison to the reference case, and the use of night ventilation has a slightly negative impact and, thus, should be avoided during such periods.

4 CONCLUSIONS

This study analysed the impact of passive strategies in university classrooms in naturally ventilated and mixed-mode scenarios for historic and future climates, as well as a period of a future heat wave for the city of São Paulo, Brazil. The strategy with the greatest impact was the increase of windows' opening area from 30% to 100%. The use of lower absorptance values and night ventilation, in addition to a greater opening area, showed a small impact, with only a slight improvement. Using only natural ventilation in the future resulted in a very high percentage of time with discomfort, showing the need to use air conditioning. During the heat wave, there were 100% hours of discomfort for the naturally ventilated cases, highlighting the need for air conditioning. In the mixed-mode scenarios, passive strategies had very little impact on energy consumption. In fact, using night ventilation slightly increased energy consumption. Some limitations of this work should be considered, such as the use of the 5th IPCC report and the consideration of only one climatic scenario. Future studies should consider assessing other scenarios based on more recent reports, as to validate the findings of this work.

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Classification of Consumption Patterns for HVAC Systems in Terminal Buildings Based on Feature Extraction and Cluster Analysis

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SUMMARY

The energy consumption of building heating and cooling systems poses a major challenge for climate change mitigation. As large public buildings, airport terminals exhibit complex, nonlinear, and dynamically fluctuating HVAC power consumption influenced by various factors. Although some Chinese airports have adopted energy management systems, existing methods often fail to effectively quantify the impact of these factors. This study proposes a power consumption pattern classification method combining mutual information and random forest for feature extraction with K-means clustering. The method accurately identifies key factors and underlying patterns affecting HVAC power consumption. Results show that, during the cooling season, energy use is mainly driven by outdoor temperature and passenger flow. Power consumption patterns are further classified into six categories based on trends in average daily outdoor temperature. These findings provide a quantitative basis for system optimization and anomaly detection in airport terminal HVAC operations.

KEYWORDS

Airport Terminal；HVAC Systems；Mutual Information-Random Forest Algorithm；K-means Clustering；Electricity Consumption Patterns

1 INTRODUCTION

Airport terminals, as large and complex public buildings, experience high passenger traffic and strict environmental comfort requirements, leading to significantly higher energy consumption than typical public buildings. The HVAC system alone accounts for over 40% of total terminal energy use, making it a key target for energy conservation and carbon reduction [1]. However, due to the nonlinear and dynamically fluctuating nature of electricity consumption, traditional energy management methods often fail to effectively monitor and analyze such systems. Although the adoption of IoT technologies and sensor networks has improved building energy efficiency, the lack of in-depth analysis of Airport Energy Management System (AEMS) data still hinders informed optimization decisions.

Previous studies have examined airport energy consumption under different climatic conditions. It is widely recognized that energy use strongly correlates with passenger numbers and flow dynamics[2]. For example, Gu et al.[3] used clustering and correlation analysis based on actual operational data to identify the significant impact of passenger flow and meteorological parameters. Lin et al. [4]proposed energy-saving strategies through sensitivity analysis. However, many studies struggle to analyze high-dimensional, nonlinear data effectively, limiting interpretability and prediction accuracy.

With advances in big data analytics and machine learning, data-driven methods have become powerful tools for improving energy management. This study proposes a classification approach integrating mutual information, random forest-based feature extraction, and K-means clustering. Using AEMS data from a large airport terminal in China, we analyze dynamic HVAC power consumption, identify key influencing features, and classify distinct consumption patterns. This methodology supports HVAC system optimization, consumption profiling, anomaly detection, and demand forecasting. The main contributions are as follows:

(1) Identification of key features affecting HVAC power use—specifically outdoor temperature and passenger flow at the previous time step (T–1)—through data-driven selection.

(2) Effective classification and interpretation of HVAC power consumption patterns based on daily average temperature zoning and time-dependent dynamics, providing a more rational and quantitative understanding of system operation in airport terminals.

2 METHODS

2.1 Data Collection and Preprocessing

Electricity consumption data (from the terminal's AEMS), passenger statistics, and meteorological data for the 2023–2024 cooling season were collected. To ensure data quality, all data were min-max normalized and cleaned in MATLAB R2023a. Zero values and outliers were detected using the percentile method and smoothed with a moving average, while missing values were filled via linear interpolation.

2.2 Feature Extraction

This study leverages the strengths of Random Forest and Mutual Information methods to capture both linear and nonlinear relationships in the data. The mutual information approach quantifies the information transfer between two variables by calculating the difference between the entropy of each variable and their joint entropy. A large mutual information value indicates a strong dependency between the two variables. The mutual information $I(X_i,Y)$ between feature X_i and target variable Y is calculated as:

$$I(X_i,Y)=\sum_{i=1}^{t}\sum_{j=1}^{t}p(X_i,Y)\log_2\left(\frac{p(X_i,Y)}{p(X_i)p(Y)}\right) \tag{4}$$

The entropy $H(X)$ of the feature X_{i} is calculated by:

$$H(X)=-\sum_{i=1}^{t}p(X_i)\log_2(p(X_i)) \tag{5}$$

where $p(X_i)$ and $p(Y)$ are edge probability density functions and $p(X_i,Y)$ is the joint probability density function.

Random Forest is an ensemble learning algorithm that reduces variance and accurately extracts features by aggregating predictions from multiple decision trees. It excels at modeling complex nonlinear relationships and is robust to noise and dynamic data changes. Its parallelizable training process and simple tree structure result in high computational efficiency. A key advantage of Random Forest is its ability to provide feature importance scores, aiding in feature selection. Additionally, it does not require data normalization and can handle various input features, streamlining the feature engineering process. Feature importance is typically assessed by measuring changes in prediction error when a specific feature is randomly permuted. The importance score $V(X)$ is determined as:

$$V(X)=\frac{1}{N}\sum_{i=1}^{n}(e_i^k-e_i) \tag{6}$$

where X is the input feature variable; $V(X)$ is the feature importance; and N is the number of decision trees in the random forest.

2.3 Cluster Analysis

K-means clustering algorithm, as a classical partitional clustering method, belongs to the unsupervised learning algorithm, which usually uses the Euclidean distance as a measure of dissimilarity (e.g., Eq. (4)). Due to its high computational efficiency and good clustering effect, K-means algorithm is widely used in clustering analysis of building electricity consumption patterns.

$$\rho=\sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2} \tag{7}$$

where (X_1,Y_1) and (X_2,Y_2) are data points in the feature space. The optimal number of clusters K is determined by the silhouette coefficient and Davies-Bouldin index.

3 RESULTS And DISCUSSION

3.1 Data Preparation

The HVAC system consumption data from AEMS was normalized and cleaned as outlined in Section 2.1 to ensure data validity.

3.2 Electricity Consumption Feature Extraction

Key parameters influencing electricity consumption were identified, including meteorological conditions (e.g., outdoor temperature, humidity, wind speed, solar radiation) and passenger flow metrics (e.g., number of arriving and departing passengers) at time steps T and T−1. Figure 1 shows the feature importance scores for the summer cooling season (May to September), derived using the Mutual Information–Random Forest method. Among all variables, the outdoor temperature at T−1 holds the highest importance score of 1.0, highlighting its dominant influence on electricity consumption and the significant thermal inertia of the building envelope. Passenger flow at T−1 also plays a notable role, with an importance score of 0.518, indicating a strong correlation between occupancy fluctuations and HVAC energy use. In contrast, other meteorological factors like humidity, wind speed, and solar radiation have lower importance scores, likely due to their weaker direct effects or collinearity with stronger predictors.

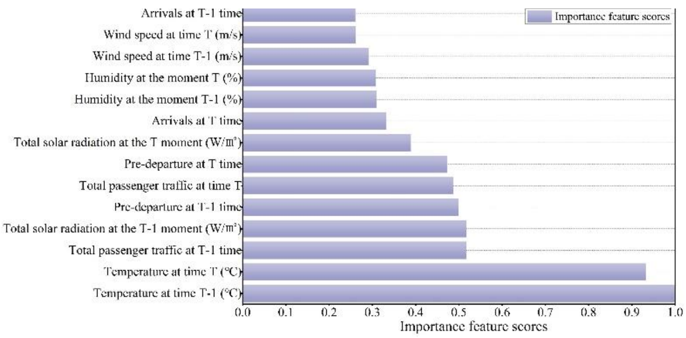


Figure 1． Relative importance scores obtained by combining the two methods

3.3 Characteristic Parameter Influence on Electricity consumption

Figure 2 shows the annual variation of outdoor air temperature and its impact on HVAC electricity consumption. Climatic conditions exhibit distinct seasonal changes, dividing the year into three main periods: the summer cooling season, the winter heating season, and the transitional seasons. The summer cooling season, from early May to mid-September, is characterized by significant temperature fluctuations. In early May, the average daily temperature ranges from 17°C to 25°C, rising to 22°C–30°C in June, and peaking in July with daily averages between 23°C and 33°C, reaching extreme highs of 38°C-40°C. Temperatures slightly decrease in August, dropping to 20°C-27°C by mid-September. The winter heating season, from mid-November to mid-March, sees a sharp temperature drop, with January being the coldest month (average daily temperatures of -6°C to 4°C, extreme lows reaching -15°C). The transitional seasons, from late March to late April and from late September to early November, are marked by lower HVAC energy consumption, primarily for ventilation and air exchange rather than active heating or cooling. Empirical data show a strong correlation between outdoor temperature and HVAC electricity consumption. Additionally, the building's thermal inertia causes a delayed response to temperature and humidity changes, further influencing power demand.

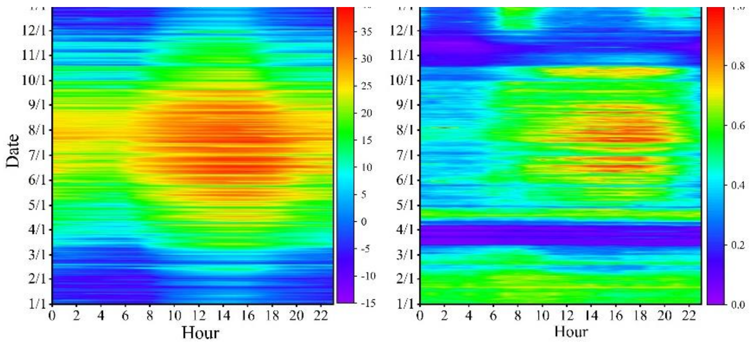


Figure 2. Correspondence between outdoor air temperature and electricity consumption at time T, with (a) annual variation of outdoor air temperature and (b) hourly electricity consumption variation.

Passenger flow shows a clear daily pattern, divided into three periods: trough (0:00-5:00), smooth (7:00-19:00), and decline (20:00-23:00). The trough period, with minimal occupancy (0.3-2%), offers the greatest energy-saving potential due to low temperatures and reduced internal heat gains. The smooth period (5.5-6.1%) corresponds to peak occupancy and higher temperatures, resulting in the highest energy demand. The decline period (2.5-4.4%) sees moderate consumption as both temperature and passenger flow decrease.

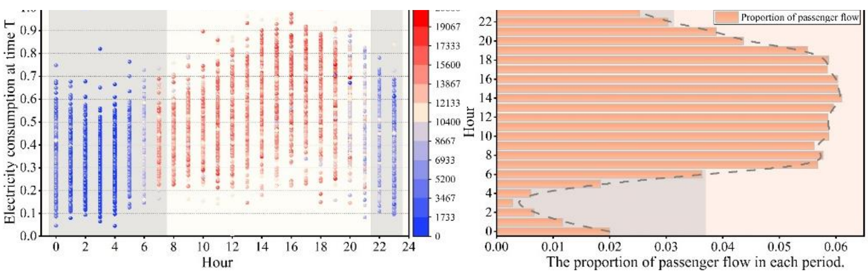
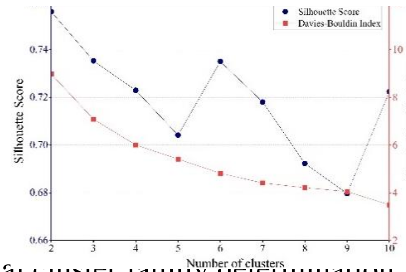


Figure 3. Correspondence between passenger flow and electricity consumption at time T, with (a) hourly passenger flow and electricity consumption and (b) percentage of hourly passenger flow.

Air-conditioning Cooling Season Electricity Consumption Patterns

To identify and classify the electricity consumption patterns of HVAC systems, the cooling season data were analyzed using the K-means clustering method, which revealed an optimal number of 6 clusters (Figure 4). However, as an unsupervised learning method, the success of K-means clustering depends on whether the results can be reasonably explained. The time of day and corresponding temperature intervals are key factors that differentiate the clusters.

As illustrated in Figures 5 and 6, electricity consumption can be classified into six distinct modes, each reflecting different combinations of time periods, temperature conditions, and passenger flow levels. Overall, electricity consumption increases progressively with rising temperatures and extended operational hours. Modes 1 and 2 represent low to medium-low consumption, typically occurring during late-night and early-morning hours when outdoor temperatures are low and passenger flow is minimal. These modes are characterized by stable and minimal energy demand. Modes 3 and 4 show moderate to moderately high consumption, with electricity use increasing alongside rising temperatures during the day and early evening. These periods coincide with a gradual increase in cooling demand and human activity. Modes 5 and 6 exhibit the highest electricity consumption, driven by high ambient temperatures and peak passenger flow. These modes, concentrated in the afternoon and early evening, highlight significant energy-saving potential. Modes 5 and 6 show significant energy-saving potential, warranting further exploration of their energy-saving potential. Special attention should also be given to abnormal fluctuations in electricity consumption under similar outdoor temperature conditions, as these instances represent key targets for low-carbon energy-saving operations.



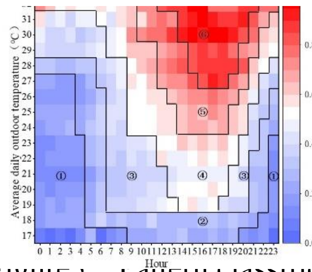


Figure 4. Optimal cluster family determination Figure5. Pattern classification results

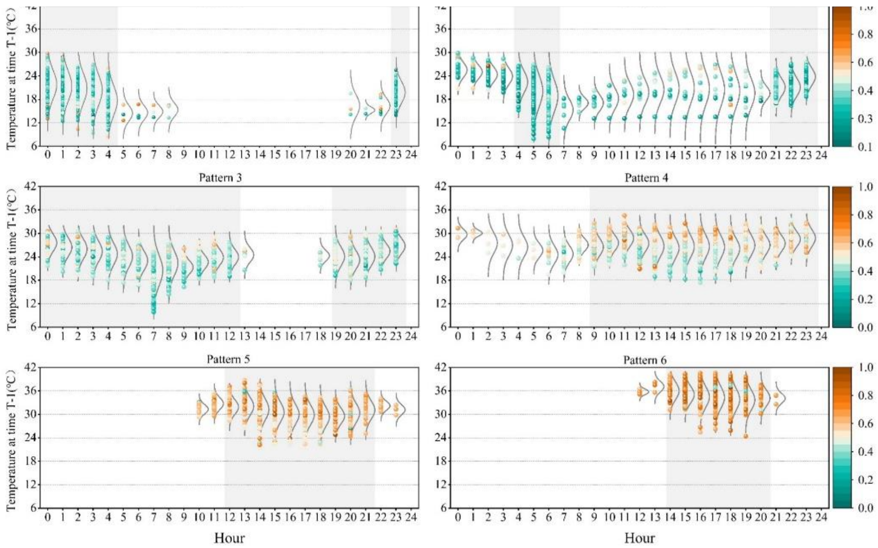


Figure 6. Correspondence of electricity consumption with time and temperature at time T−1 for different modes.

4 DISCUSSION

This study reveals the distribution characteristics of electricity consumption patterns and their variation with temperature during the cooling season, demonstrating the diversity and complexity of the energy response of the air-conditioning system. These findings provide a key basis for further optimizing the operation strategy of the air-conditioning system. Notably, the influence of seasonal variations on power consumption patterns highlights that these patterns are driven by both external climatic conditions and power demand. Despite the practical value of the current approach, there are some limitations. Firstly, the Random Forest-Mutual Information method depends on the comprehensive identification of all influencing factors, and any omission or change in sample size may affect the feature extraction results. Secondly, while K-means clustering, an unsupervised learning method, can reduce high-dimensional and complex data, it does not define the relationship between the clustering results and the characteristic parameters of HVAC system electricity consumption. Therefore, introducing more refined feature engineering or more complex algorithmic models is necessary to classify and explain electricity consumption patterns more accurately.

5 CONCLUSIONS

In this study, a feature extraction and clustering-based method is proposed to analyze the characteristics and patterns of electricity consumption of HVAC systems using outdoor meteorological and passenger flow data of a large airport terminal building. The results of the study provide a scientific basis for system optimization and energy saving. The main conclusions are as follows

(1) The Mutual Information - Random Forest method was used to identify outdoor temperature and passenger flow at T-1 time as the most critical factors with importance scores of 1 and 0.518, respectively, to support the categorization and interpretation of electricity usage.

(2) Combined with the K-means clustering method, the electricity consumption of HVAC transmission and distribution systems during the cooling season was classified into six categories with interpretable patterns based on the momentary and daily average outdoor air temperatures.

(3) The operating hours corresponding to Mode 5 and Mode 6, as well as the nighttime hours, have great potential for energy saving and deserve further study. Special attention needs to be paid to the abnormal behavior of large fluctuations in electricity consumption under the same outdoor temperature conditions, which should be regarded as the key object of low-carbon energy-saving operation.

6 ACKNOWLEDGEMENT

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