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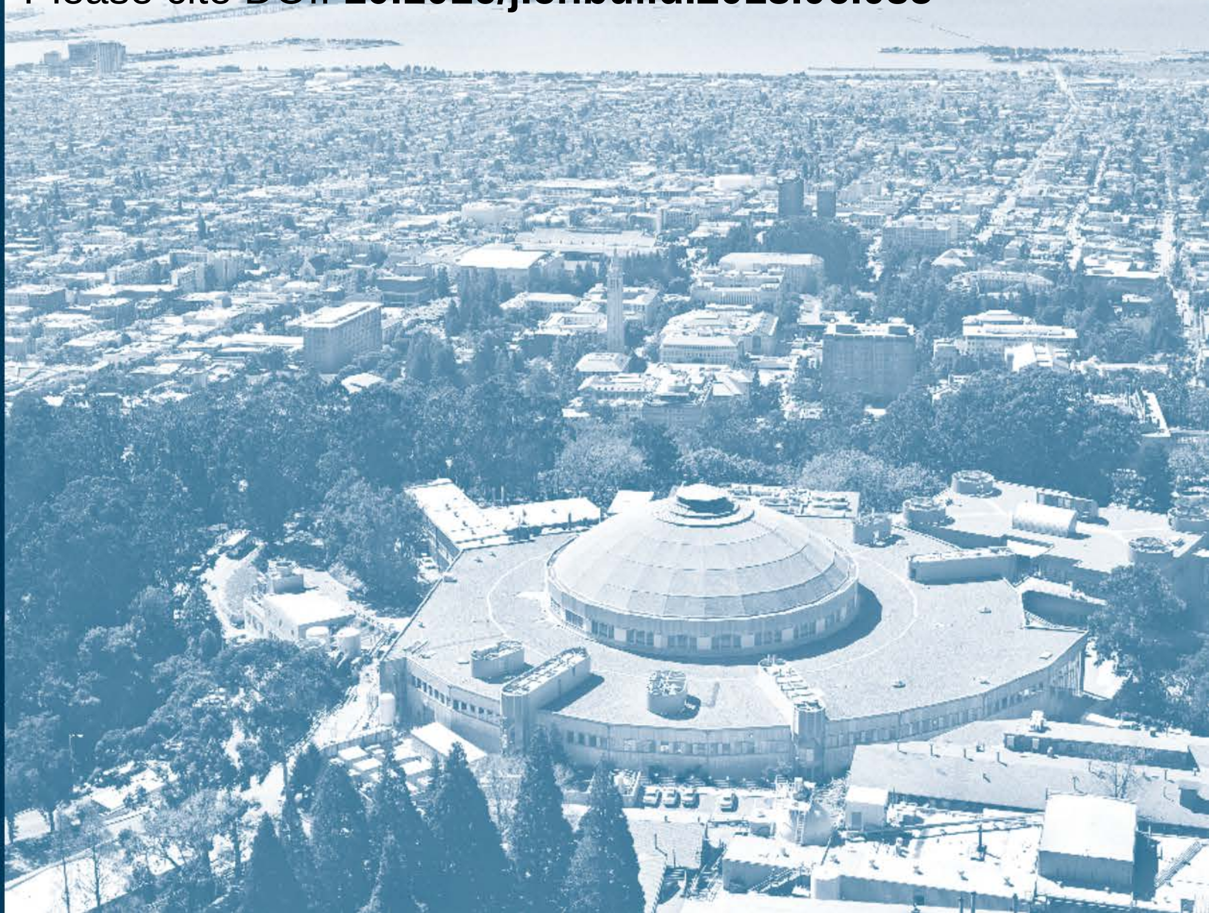

Clustering and statistical analyses of air-conditioning intensity and use patterns in residential buildings

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Abstract

Energy conservation in residential buildings has gained increased attention due to its large portion of global energy use and potential of energy savings. Occupant behavior has been recognized as a key factor influencing the energy use and load diversity in buildings, therefore more realistic and accurate air-conditioning (AC) operating schedules are imperative for load estimation in equipment design and operation optimization. With the development of sensor technology, it became easier to access an increasing amount of heating/cooling data from thermal energy metering systems in residential buildings, which provides another possible way to understand building energy usage and occupant behaviors. However, except for cooling energy consumption benchmarking, there currently lacks effective and easy approaches to analyze AC usage and provide actionable insights for occupants. To fill this gap, this study proposes clustering analysis to identify AC use patterns of residential buildings, and develops new key performance indicators (KPIs) and data analytics to explore the AC operation characteristics using the long-term metered cooling energy use data, which is of great importance for inhabitants to understand their thermal energy use and save energy cost through adjustment of their AC use behavior. We demonstrate the proposed approaches in a residential district comprising 300 apartments, located in Zhengzhou, China. Main outcomes include: Representative AC use patterns are developed for three room types of residential buildings in the cold climate zone of China, which can be used as more realistic AC schedules to improve accuracy of energy simulation; Distributions of KPIs on household cooling energy usage are established, which can be used for household AC use intensity benchmarking and performance diagnoses.

Keywords: air-conditioning; clustering analysis; KPIs; use pattern; AC usage benchmarking; residential building

1. Introduction

Energy consumption in residential buildings accounts for a large portion of global energy use, which drives many researchers and policy makers towards energy conservation of residential buildings. In 2012, the U.S. residential sector accounted for 22.2% of the total primary energy consumption [1]. In the northern part of the European Union, residential buildings account for 30% of the total energy consumption [2]. In 2015, the total building energy consumption in China was 864 million tce (Mtce), accounting for approximately 20% of the total energy use, while the urban residential buildings (excluding northern urban heating) consumed 199 Mtce (including 430 TWh of electricity), accounting for 23% of the total building energy use. The total energy use of the subsector of urban residential buildings has tripled from 2001 to 2015. Domestic water heating, space cooling, and space heating, are smaller end-uses, but they have increased considerably and at a high rate from 14% to 31% in the last 15 years [3,4].

There is a wide variation in household cooling energy use. Li et al. [5] carried out a survey of the air-conditioning (AC) energy consumption in 25 residential apartments in Beijing in 2006, and found that the electricity consumption for cooling systems varied from 0 to 15 kWh/m^2 among households in the same building. An et al. [6] studied the household cooling usage distribution in a community with approximately 400 households, and found that the highest consumed 8,000 kWh of cooling energy in two months, which is three times higher than the average cooling energy use. Brounen et al. [7] investigated 305,001 Dutch homes in 2008–2009 and also found a wide variation in household consumption. Parker et al. [8] verified the home energy saver suite for online simulation, by conducting a detailed year-long study. The homes studied exhibited a three-fold variation in measured energy use.

Yoshino et al. [9] summarized the outcomes from IEA EBC Annex 53. They reported six key factors influencing real energy use in buildings: building envelope, building equipment (energy systems), building operation and maintenance, weather, indoor comfort criteria, and occupant behavior, and the latter three factors related to occupants have greater influence than the former three. The behavior of occupants is a key factor influencing the building life cycle and determining energy use in buildings [10,11]. Yun and Steemers [12] analyzed the relationship between the cooling energy and influencing factors, such as the climate, occupant behavior, and house type, in residential buildings in the USA, thus revealing that the occupant's behavior was the most significant issue in determining how often, and where AC was used. Ren et al. [13] concluded that the AC usage in the summer is not only related to the weather and the characteristics of AC systems, but is also strongly influenced by the residents' behavioral patterns. Zhou et al. [14] discussed the influence of AC use modes on the energy consumption in residential communities using simulations, and revealed that AC use modes can lead to more than ten times of variation in electricity use among households. Eguaras–Martinez et al. [15] showed that the inclusion or exclusion of occupant behavior in building simulations, could result in up to a 30% difference in predicted energy use. IEA EBC Annex 66 introduced new methods and tools to standardize the representation and simulation of occupant behavior [16]. Better consideration of occupant's interaction with building equipment and system, including the adjustment of thermostats for comfort, switching lights, opening/closing windows, pulling up/down window blinds, and moving between spaces, can improve the prediction of thermal loads and energy use in buildings [17,18].

Duo to the privacy concerns of residents, many researchers have analyzed occupants' behavioral patterns in residential buildings based on questionnaire surveys and case studies [13,14,19,20]. However, these methods have some limitations: Questionnaire survey is more suitable for large-scale data collection, but the reliability of results highly depends on the questionnaire design, sampling method and qualify of response; Case study is a more specific but time-consuming method, which is often applied to detailed investigation and modeling of typical households instead of to obtain the behavior distribution of a large group of occupants. With the development of sensor technology, it became easier to access an increasing amount of data. Accompanied by various data analysis methods, large-scale metered data contributes to have a comprehensive understanding of building energy usage and occupant behaviors [21–26]. Pan et al. [24] extracted occupant-behavior related electricity load patterns using the K-means clustering approach from smart-metering data in two communities in China. Zhao et al. [27] proposed a data mining approach to understand the occupant behaviors and power consumption in an office building in the USA. Luo et al. [22] developed load shape parameters, and representative load shapes, based on electric load meter data for small- and medium-sized commercial buildings in California, USA, and applied these data to energy benchmarking and retrofit analyses.

There are growing applications of district heating/cooling systems, and corresponding thermal energy metering systems in many countries. The thermal energy consumption systems can be used to record the cooling/heating consumption of each household, based on their real thermal energy usage, thereby providing incentives to inhabitants to save energy. In China, there is an increasing trend whereby thermal energy metering systems are installed in newly built residential districts with centralized heating, ventilation, and air-conditioning (HVAC) systems [28,29]. Therefore, many researchers utilized the metered data for better understanding of building energy use. For instance, Kiluk [30] took advantage of the large datasets obtained from district heating billing systems to detect system faults by applying the data mining method. Gadd and Werner [31] identified four typical load patterns based on yearly heating loads of the smart heat grids in two districts, which could be applied to define the customer categories. Shahrokni et al. [32] analyzed the energy consumption of different building vintages in Stockholm and estimated one-third of energy could be saved if the building stock is retrofitted to meet the current building energy codes. However, except for the thermal energy consumption benchmarking, current studies lack effective and easy approaches to analyze AC usage and provide actionable insights for inhabitants, which is of great importance for inhabitants to understand their thermal energy use and save energy cost through adjustment of their AC use behavior, as well as for engineers to obtain realistic AC use patterns for HVAC system design and performance simulation. Therefore, this information from thermal metering systems is of great importance, especially to developing countries, such as China, where residential occupant behavior is diverse and has significant influence on residential energy use.

This study proposes a data-driven approach to analyze the AC use patterns of residential buildings, and develops new key performance indicators (KPIs) beyond the traditional total thermal energy to gain a deep understanding of the AC usage, based on the long-term metered data of cooling loads. These KPIs could be used to benchmark inhabitants' AC cooling usage and to guide energy conservation effort. We use several KPIs to analyze the household cooling energy consumption in a residential district comprising approximately 300 households in Zhengzhou, China. The district installed a central cooling plant as well as a smart metering system to collect the long-term cooling loads of each air-conditioning equipment. The K-means clustering approach is applied to characterize the typical air-conditioning use patterns of various room types (i.e., bedroom, living room, dining room), which can be used in building performance simulation to improve the accuracy of simulated cooling energy use.

The remaining parts of this article is organized as follows: Section 2 introduces the technical approach as well as the data, methods, and indicators; Section 3 shows the analysis results for a residential district including the cooling usage analyses and representative AC use patterns; Section 4 discusses the potential applications of the research outcomes; Section 5 presents the policy implications and limitations of this study; And finally, conclusions are summarized in Section 6.

2. Data and methods

2.1. Data source

The residential district in this study was built in 2011 by one developer, and is located in the city of Zhengzhou in China. The district is in China's cold climate zone with the average temperature of the coldest month from -10 to 0^{o}C, and the warmest month from 18 to 28^{o}C. The district has eight buildings, including three high-rise buildings (two are 16 floors and one is 18 floors) with pre-installed fan-coil units (FCUs) for cooling and heating in each room except from bathrooms and corridors. The FCUs are served by a centralized ground-source heat pump system. Therefore, these three buildings constitute the research objects of this study. The sketch map of the case district is shown in Figure 1. In Figure 1, the numbering refers to the building number, and the arrow lines refer to the flow direction of chilled water. Each room, except the bathrooms and corridors, has one FCU with individual control panel, which can be operated individually by the users (e.g., turn on/off, increase/decrease the speed of supply fan). The three buildings have 324 households with 1402 FCUs, and seven apartment types with different floor area (90–160 m^2), and number of air-conditioned rooms with FCUs (3, 4, or 5 rooms). Figure 2 shows the sketch floor plan of one typical apartment unit.

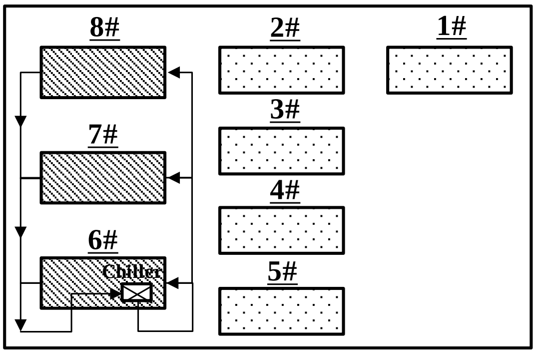


Figure 1 Sketch map of the case residential district

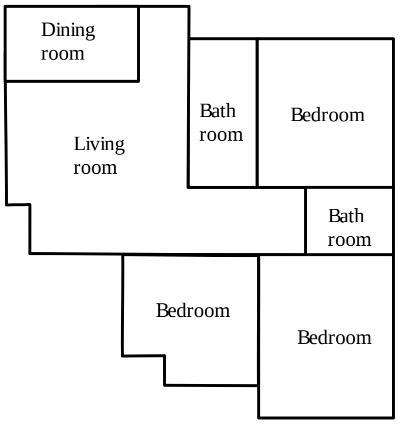


Figure 2 Sketch floor plan of one typical apartment unit

A thermal energy metering system is used to collect the cooling/heating data of each FCU for utility bills. The collected energy data is the accumulated cooling energy consumption from the time the meter was installed, which can be recorded at irregular intervals spanning from several minutes to multiple days, according to the needs of the operating staff. The difference between two adjacent data points represents the cooling energy consumed during that period. We obtained the metered data of each FCU for the three-month cooling season, spanning from June 21, 2016 to September 21, 2016, from the

Chuntsuan Energy-saving Technology Company of Zhengzhou, which is the installer and operator of the thermal energy metering system. We also obtained information on the type of rooms (e.g., bedroom, living room) served by each FCU, number of rooms and floor area of each apartment.

2.2. Methodology

Our study consists of four steps: data collection and preprocessing, analyses of the AC use intensity and patterns, discussion of potential applications, and conclusion (Figure 3). Firstly, we cleaned up the collected data for the residential district, such as removing erroneous or missing data from the original data, and converted them to appropriate format for analysis. Then, we developed several KPIs to represent the comprehensive characteristics of cooling energy consumption in all households. Cluster analysis was applied to generate the representative AC use patterns. Thirdly, we discussed the potential applications based on the research findings. Finally, we discussed the implication and limitations of this study, and draw the conclusion. The R language package was used for the statistical analyses [33].

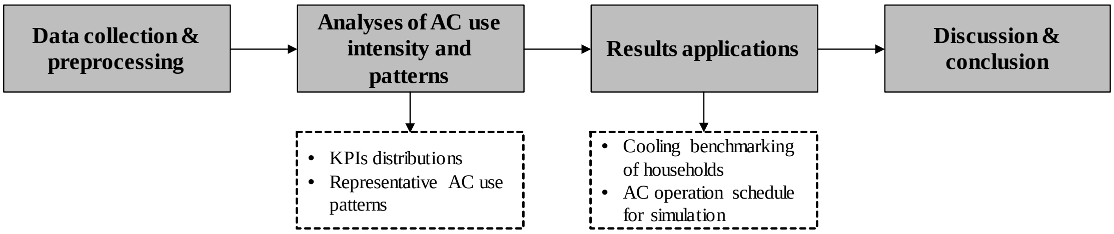


Figure 3 Schematic of the overall technical approach

2.2.1. Preprocessing of the collected data

Since the collected metered data of thermal energy use are accumulated, we assumed that the thermal loads between two adjacent data points remained constant and thus generate the data of hourly cooling energy usage. The intervals of data collecting for each FCU were irregular, ranging from several minutes to several days, according to the needs of the operating staff. The cooling energy data of some FCUs were not collected for several days during the cooling season in 2016. Therefore, we eliminated those households (approximately 60 households) with the missing metered FCU energy data.

2.2.2. Analysis of the household cooling energy usage

To analyze the household cooling energy usage, we proposed a series of KPIs including four first-tier indicators and three second-tier indicators, as shown in Table 1. The four first-tier indicators are the total cooling consumption, aggregated operating hours of FCUs, daily cooling usage and the average cooling load per FCU. The common indicators, such as the total cooling consumption, and the daily cooling usage, are influenced by too many factors to identify the dominant one. We also used the aggregated operating hours of FCUs to evaluate the AC use intensity, which can be further explained by three second-tier KPIs: the ratio of AC-on days, the daily AC-on duration, and the coincident use factor of FCUs. Dividing the total cooling consumption by the aggregated operating hours of FCUs, we obtained the average cooling load per FCU, which is the average of hourly cooling loads for each FCU in a household. This indicator can reflect the influencing factors of energy usage except for those related to the aggregated operating hours, such as the indoor air temperature, and windows operation (opening /closing).

Table 1 Key performance indicators of the household cooling energy usage

Number	Key performance indicators	Definition	Influencing factor
1	Total cooling consumption	Total cooling consumption of each household in a cooling season	Operating hours of each FCU, number of operating FCUs, number of AC-on days, temperature setpoint, indoor heat gains, window operation, etc.
2	Aggregated operating hours of FCUs	Sum of total operating hours of all FCUs in a household (an apartment unit)	Operating hours of each FCU, number of operating FCUs, number of AC-on days
2.1	Ratio of AC-on days	Ratio of number of AC-on days to the total number of days in a cooling season	Number of AC-on days
2.2	Daily AC-on duration	Average daily number of AC-on hours in each household	Operating hours of each FCU
2.3	Coincident use factor of FCUs	Nondimensional average number of operating FCUs at the same time	Number of operating FCUs
3	Daily cooling usage	Average daily household cooling consumption during AC-on days	Operating hours of each FCU, number of operating FCUs, indoor temperature setpoint, indoor heat gains, window operation, etc.
4	Average cooling load per FCU	Total cooling consumption divided by the aggregated operating hours of FCUs	Indoor temperature setpoint, indoor heat gains, window operation, etc.

2.2.3. Clustering analysis of representative AC use patterns

Cluster analysis is a process of partitioning a set of observations into subsets in a way that objects belonging to the same cluster have high similarity, while objects belonging to different clusters have low similarity. This is achieved with the use of various cluster algorithms, such as K-means and fuzzy clustering [34,35]. In this study, K-means was chosen to categorize the typical daily AC use patterns during the AC-on days, since it is recognized as one of the most extensively used cluster analysis methods that is highly popular in load curve clustering [36].

The K-means clustering method groups a dataset of N input vectors to C clusters using an iterative procedure. Initially the weights of the C clusters are determined, and a random selection among the N input vectors is made for the cluster centroids. The estimated centroids are then used to classify objects into clusters through Euclidean distances, expressed by

$$\mathrm{d}(\mathrm{x},\mathrm{y}) = \sqrt{(x_1-y_1)^2+(x_2-y_2)^2+\cdots+(x_n-y_n)^2} \quad (1)$$

where $x=(x_1,x_2,\ldots,x_n)$, $y=(y_1,y_2,\ldots,y_n)$ are two objects in a Euclidean n-space.

Next, the Euclidean distances of each object of the centroid are recalculated in such a way that each object of the centroid is the average of the object of the load patterns within the cluster. The procedure is repeated until the stabilization of the cluster centroids is achieved.

3. Analyses of AC use intensity and patterns

3.1. Distribution of total cooling consumption

The distribution of total cooling consumption during the cooling season (July 21–September 21) in the case district is shown in Figure 4. The red dashed line indicates the median level of all households, and the orange shadow shows the range from the first to the third quartiles, marked as the interquartile range (IQR). This indicates that the inhabitants living in this district tend to use less cooling. In the entire cooling period, 49% of them used less than 10 kWh/m^2 for cooling. Except for the "always-off users" (approximately 19%), there are still 30% of users who used less than 10 kWh/m^2. Moreover, 75% of them used less than 22.4 kWh/m^2 for cooling, and the median cooling consumption was 10.4 kWh/m^2, which accords with the AC use habit of the majority of Chinese citizens (i.e., intermittent and short-term operation of AC) for saving money [37]. It can be seen that there is a large variation in total cooling consumption among the households, with the highest one reaching up to 140 kWh/m^2, which is equal to 13.5 times of the median level. Owing to this diversity, the group formed by the households at the bottom half of the total cooling consumption only occupied 5% of the aggregated cooling consumption of the district, while the most energy-intensive quarter of households consumed 66%. This finding is in agreement with the measurement results carried out by Li et al. [5] in Beijing in 2007.

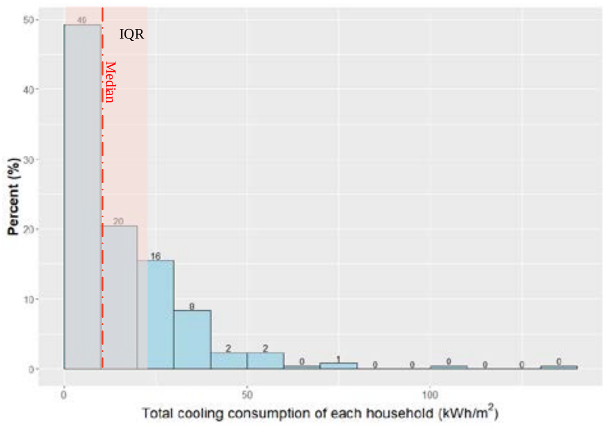


Figure 4 Distribution of total cooling consumption of each household in the case district

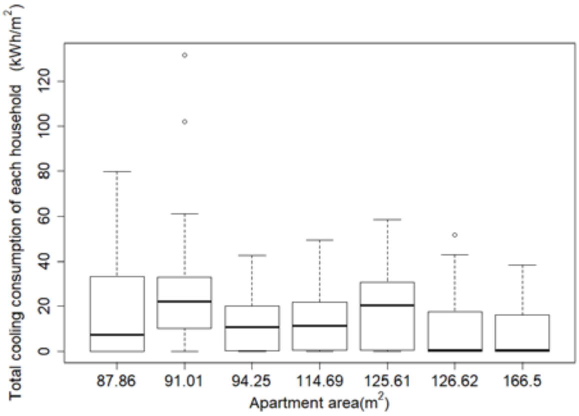


Figure 5 The variation range of total cooling consumption of seven apartment types

Since all households located in the same district, the effects of climate, building characteristics (e.g., envelope performance, HVAC system piping network) on the cooling loads were similar. In addition, we analyzed the variation range of total cooling consumption of seven apartment types as shown in Figure 5, which shows significant load diversity even in the same apartment types. Thus, it can be inferred that occupant behavior constitutes the main reason for the diverse household cooling consumption. Therefore, it is important to understand and identify AC use patterns in the case of residential buildings.

3.2. AC use patterns

Clustering analysis is used to identify typical AC use patterns during AC-on days, which can represent the diverse occupant behavior on AC operations. The attributions used are the AC on-off states from 0:00 am to 11:00 pm, which can be generated by the hourly cooling loads of each FCU during AC-on days, as introduced in Section 2. Different room types (e.g., bedroom, living room) have varying AC operation schedules owing to their different occupancies. Therefore, taking the room types into consideration, we built three groups of attributions to describe how occupants operated ACs in bedrooms, living rooms, and dining rooms. The hourly cooling loads of every FCU installed in specific room types for all AC-on days, and all residential apartment units, were grouped together to build a matrix for the room type with the size of $(\sum_{i=room}(AC - on\ days)_i) \times 24$ for clustering analyses.

The number of clusters was predefined before the clustering analyses. The Davies Bouldin Index (DBI) [38], which represents the performance of the clustering, was evaluated, with lower DBI values demonstrating better clustering performance. Figure 6 shows the results of the clustering performance using the DBI when the experiment was conducted using 3–10 clusters. Comparing the performance of the clustering solutions, we chose to group the AC use patterns of bedrooms and dining rooms into four clusters, and the living rooms into three, as suggested by the optimal number of clusters for different room types.

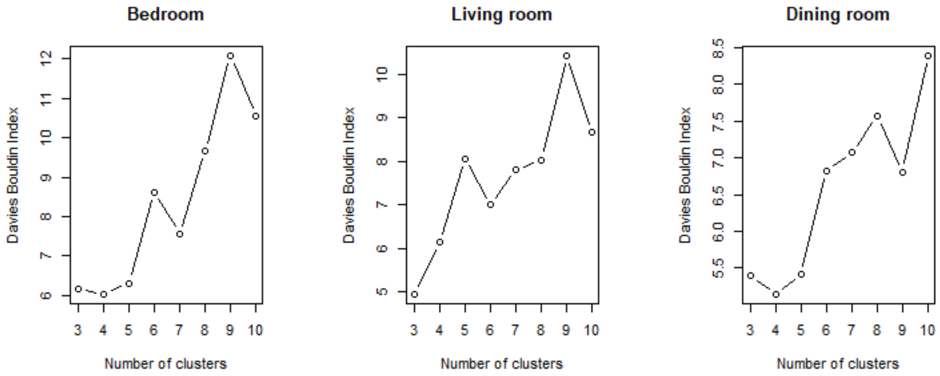


Figure 6 Clustering performance of different number of clusters

The line charts in Figures 7–9 summarize the AC-on probability curve of each cluster for the three room types during AC-on days. In addition, the pie chart refers to the number of each cluster, and the boxplot refers to the daily AC-on duration of each cluster. For bedrooms, Cluster 1, the most common pattern of AC use (accounting for up 36%), represents an infrequently use pattern with a few possibilities of turning on the AC at noon, or before sleep. A total of 28% prefer AC to be on during the entire night, which lasted 10 h approximately. Clusters 3 and 4 accounted for similar proportions. The pattern of AC use in Cluster 3 is turning on AC from noon until the sleep time, which indicates that occupants stay home in the afternoon. Furthermore, Cluster 4 corresponds to the energy-intensive families owing to the continuous AC use. Living rooms were associated with three clusters: seldom use of ACs (42%), AC intermittently on in the afternoons (32%), and AC always on (26%). Occupants usually did not use the ACs during the sleep time except for Cluster 3, which agrees with our understanding of living room use. In the case of dining rooms, Clusters 1 and 2 turned on the ACs at lunch time or dinner time separately. This accounted for a total usage of 55%. Cluster 3 represents the "afternoon-on user", and Cluster 4 the "always-on user". Overall, more than half of the households used AC intermittently, based on their different requirements of room usage, such as sleeping and eating meals. There were some families, who spent more time at home, preferring ACs to be on in all rooms during the afternoons. Some energy-intensive households always turned on ACs in all rooms.

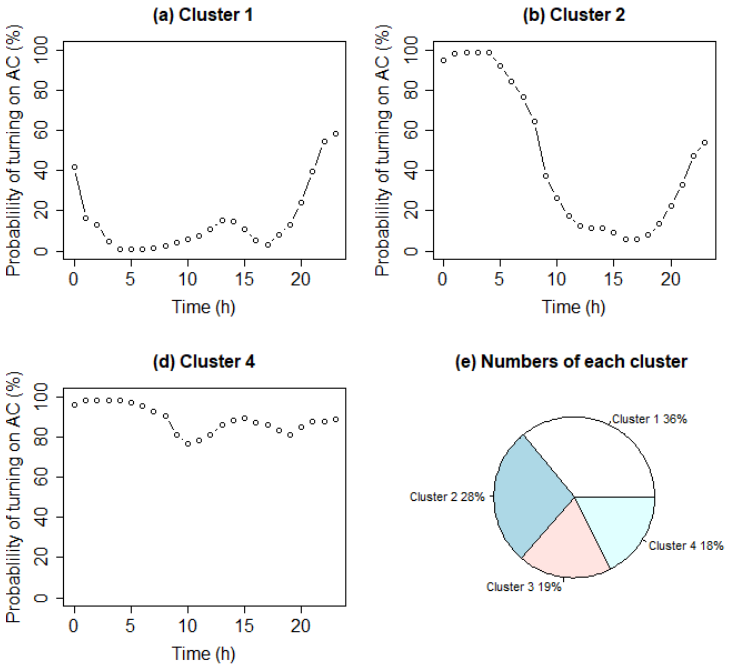


Figure 7 Clustering results for the bedrooms

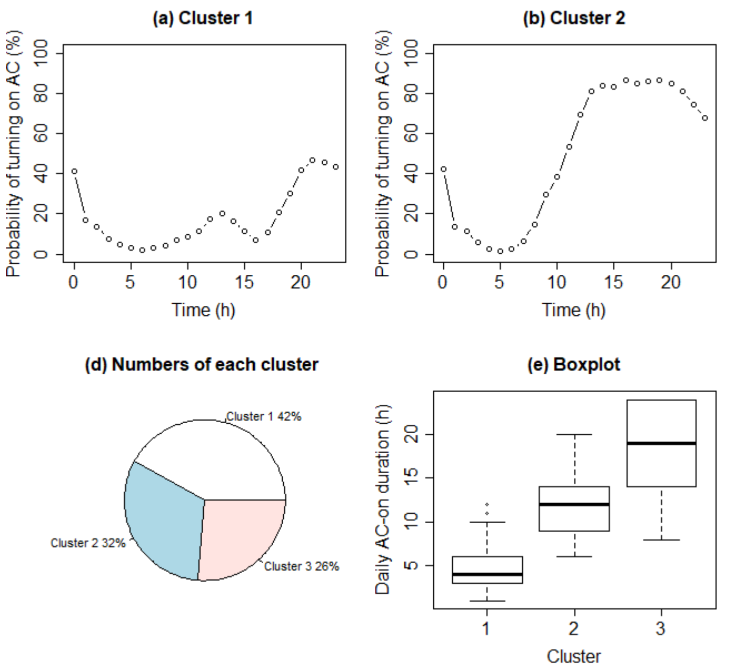


Figure 8 Clustering results for the living rooms

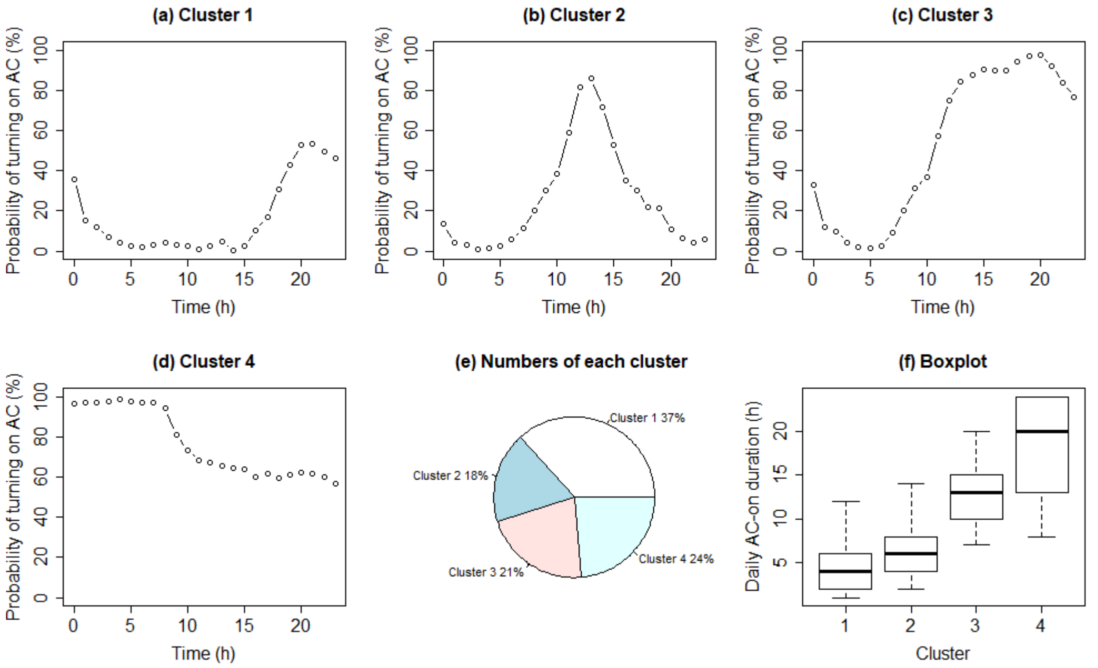


Figure 9 Clustering results for the dining rooms

The clusters of each room type are categorized by the daily 24-hour cooling loads during all AC-on days, and account for all apartments. Previous studies and observational data have revealed the significant relationships between the frequency or probability of AC operation and indoor climate or outdoor condition [17]. Different daily climates may impact the clustering results, so we also carried out correlation analyses between the proportion of each of the clusters at different time periods, as shown in Tables 2 and 3. It is noted that the number of AC operating hours increased as the cluster number increased from one to four, indicating that Cluster 1 represents the infrequent AC users, Cluster 3 of the living room and Cluster 4 of the bedroom and dining room always-on users.

Table 2 shows the distribution of clusters in weekdays and weekends. Since there was no prolonged Chinese holiday during the cooling season, we only distinguished the days of the week in accordance to the weekday and weekend classifications. The results indicate that there are small discrepancies of the distribution of clusters between weekdays and weekends, which can be due to the Chinese culture of retired parents who live with their children to help take care of grandchildren. This leads to lack of differences in the living conditions between weekdays and weekends. However, there is still a trend, whereby occupants tend to use the AC less frequently, especially in dining rooms during weekends. One possible reason is that occupants will likely go out for fun during the weekends, leading to less frequent AC use.

Table 2 Distributions of clusters during weekdays and weekends

Room type	Bedroom				Living room			Dining room			
Cluster	1	2	3	4	1	2	3	1	2	3	4
Weekday (%)	35	27	20	18	41	32	27	34	18	23	25
Weekend (%)	40	28	16	16	45	30	24	44	20	16	19

We also analyzed the distribution of clusters in different months. Zhengzhou city is located in China's cold climate zone with July and August being the two hottest months. We can infer that more occupants tend to use ACs more in July and August than June and September. Table 3 lists results with trends that are opposite to the expected results in accordance to our common sense. This is because these clusters are generated by hourly cooling load profiles during AC-on days. There are fewer households using ACs in June and September, so the remaining AC users are energy-intensive users with increased use of AC.

Table 3 Distributions of clusters in the four summer months

Room type	Bedroom				Living room			Dining room			
Cluster	1	2	3	4	1	2	3	1	2	3	4
June (%)	27	34	19	21	40	30	29	36	15	31	18
July (%)	39	27	19	15	44	37	19	40	25	22	13
August (%)	37	27	20	17	41	30	29	38	13	19	29
September (%)	31	27	16	27	38	19	44	23	14	16	46

3.3. KPIs of household cooling energy usage

Based on the long-term metered data of cooling loads of each FCU, we can use more indicators beyond the total cooling loads, enabling a deeper understanding of the cooling energy usage of the district. Therefore, we carried out further analyses on cooling usage, based on three additional perspectives as explained below.

3.3.1. Household AC use intensity

Various AC operating hours and number of FCUs of each household can reflect their AC use intensity directly, such as long-time user and short-time user. Therefore, we introduced another indicator known as “aggregated operating hours of FCUs” to represent the cooling use intensity of each household, whose definition has been introduced in Section 2.2. Figure 10 shows the distribution of this indicator for all households in this district. The blue dashed lines indicate the first and third quarter levels. It can be seen that 40% of households used ACs for less than 500 FCU·h, while approximately 46% of the households used AC between 1000–3000 FCU·h.

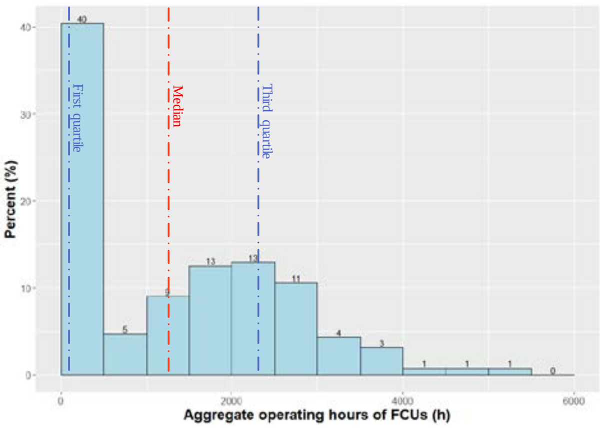


Figure 10 Distribution of the aggregated operating hours of FCUs in the cooling season

The aggregated operating hours of FCUs are influenced by three factors: the ratio of AC-on days during the cooling season, the daily AC-on duration during AC-on days, and the coincident use factor of FCUs (calculated as the ratio of number of operating FCUs to the number of installed FCUs), which are explained individually as follows.

Some household occupants did not stay at home every day for a number of reasons (e.g., job-related reasons), so they used the ACs less frequently than other households. Furthermore, some households used ACs less frequently owing to their habits. Therefore, each household has different number of AC-on days, which can influence its total cooling energy consumption. Figure 11 shows such a variation. The ratios of AC-on days to the total number of days during the cooling season for different households exhibit polarization. Approximately 40% of households seldom used AC during the entire cooling season, while approximately 40% of them used AC frequently.

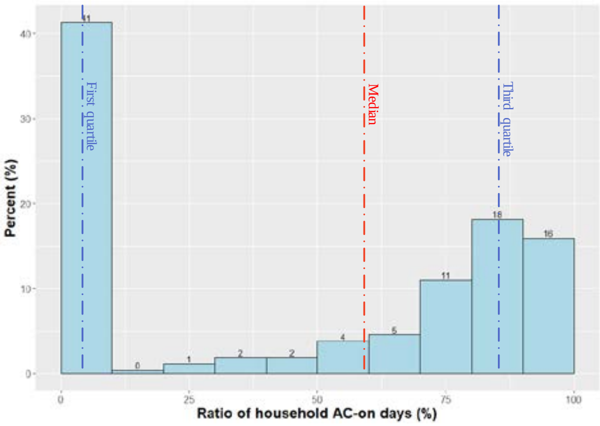


Figure 11 Ratio of household AC-on days during the cooling season

Figure 12 shows the distribution of daily AC-on duration of each household during the AC-on days (excluding the “always-off users”). The daily AC-on duration is the average AC-use duration of the entire apartment instead of a single room, meaning that the AC of an apartment is on if any room in the apartment has an AC that is turned on. The duration of operation hours varied from household to household with a median “on” duration of approximately 12.5 h, and with half the households operating the ACs between 10 and 15 h during the AC-on days.

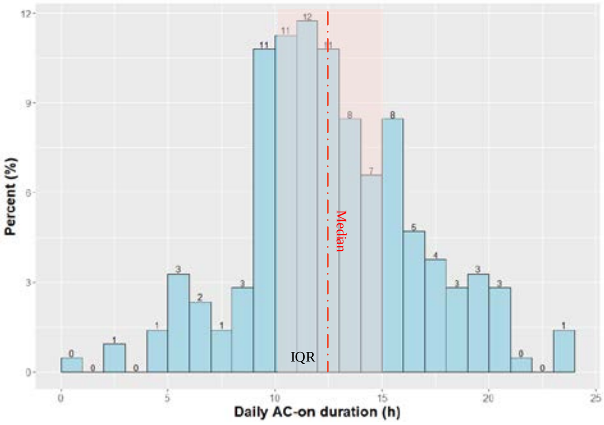


Figure 12 Distribution of the daily AC-on duration of all households

Figure 13 plots the probability distribution of the coincident use factor of FCUs of each household except for the “always-off users”. There are three to five FCUs in each apartment. Some households operated all FCUs at the same time, while others preferred turning only one or two units on when cooling was needed. The coincident use factor of FCUs is an indicator that is used to present this habit for each household. Similarly, this indicator has different values among all households with a median value of 0.33. It also indicates that the households in this district usually operated one or two FCUs simultaneously.

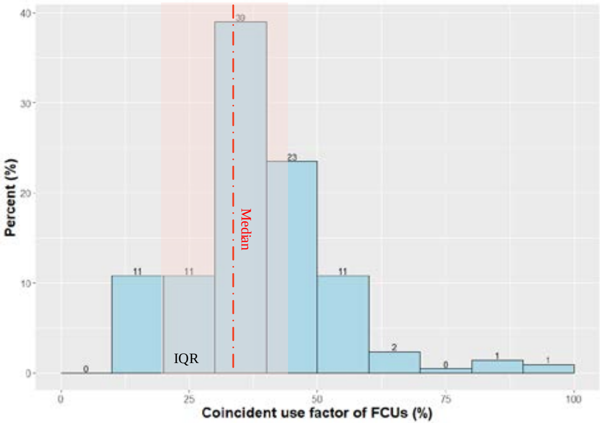


Figure 13 Distribution of the coincident use factor of FCUs in all households

3.3.2. Daily cooling energy usage

Daily cooling energy usage during AC-on days is another important indicator to analyze household cooling usage (Figure 14), which is influenced by the same factors as the total cooling energy consumption of each household except for the ratio of AC-on days. This distribution does not include the “always-off users,” which take up approximately 19% of all households. The daily cooling usage during AC-on days for the majority of households (i.e., 75%) is less than 0.3 kWh/m^2. The daily cooling usage varies considerably and can be as high as 1.4 kWh/m^2.

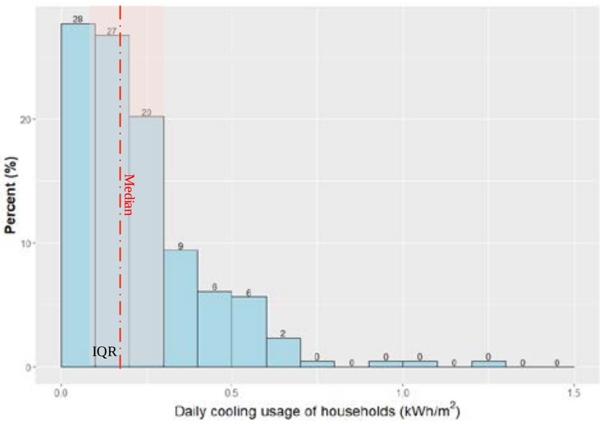


Figure 14 Distribution of daily cooling energy usage of all households during AC-on days

3.3.3. Average cooling load per FCU

Dividing the household cooling consumption by the aggregated operating hours of FCUs, we can obtain the average cooling load per FCU for each household. To make sure this indicator is not influenced by the number of operating hours, we conducted a correlation analysis between this indicator and the aggregated operating hours of FCUs. The results are plotted in Figure 15 showing no obvious relationship between them. Therefore, we can consider that the average cooling load per FCU is an independent indicator.

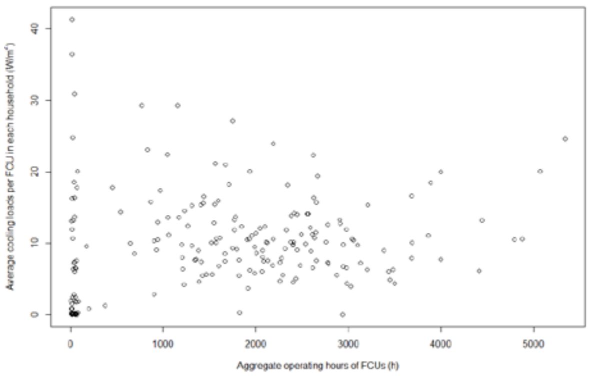


Figure 15 Correlation of the aggregated operating hours of FCUs with the average cooling loads per FCU for all studied households

The average cooling loads per FCU was influenced by many other factors, such as the indoor comfort temperature setpoint, the fan speed of FCU (i.e., high, middle, and low speeds), and indoor heat gains. Owing to the lack of other data (e.g., indoor temperature), we could not explain the variation of the average cooling loads, which should be enhanced in future work. In this study, we only used the average cooling load per FCU of each household to represent this feature, as shown in Figure 16. The median cooling load per FCU was 9.3 W/m^2.

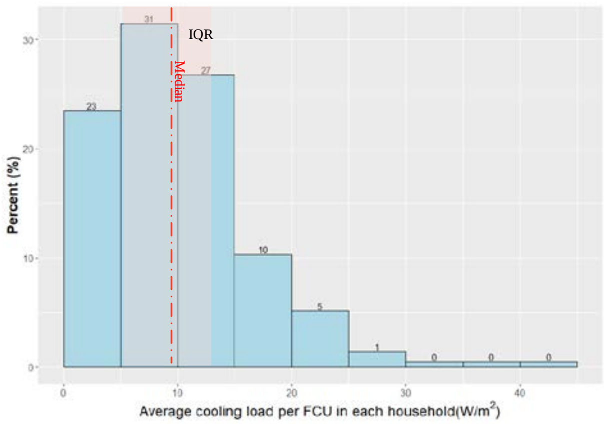
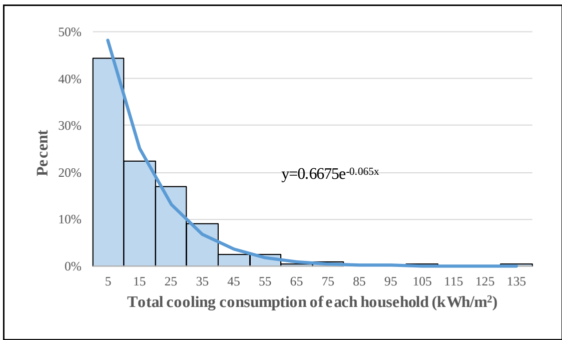


Figure 16 Distribution of the average cooling load per FCU for each household

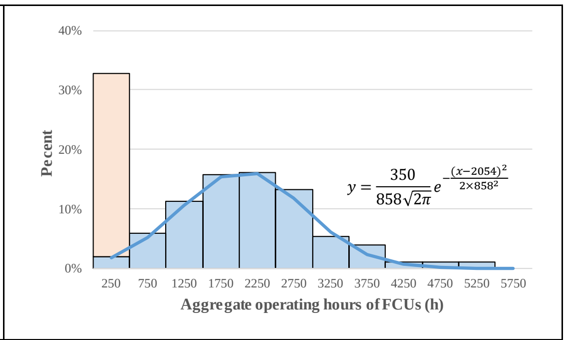
3.3.4. Summary

We used four first-tier indicators and three second-tier indicators to study the household cooling energy usage in the case district. The four first-tier indicators represent different characteristics of the household cooling usage. The total cooling consumption is a combined result of many factors, such as operating hours, number of FCUs, and internal heat gains. We used the aggregated operating hours of FCUs to represent the AC use intensity, and three second-tier indicators to explain the AC use intensity for the ratio of AC-on days, daily AC-on duration, and the coincident use factor of FCUs. The daily cooling usage during AC-on days is affected by the same influencing factors as the total cooling consumption except for the ratio of AC-on days. The average cooling load per FCU excludes factors related to operating hours and number of FCUs. Therefore, we can infer some information on the temperature setpoint, indoor heat gains, and fan speed of FCU, which has three levels (i.e., high, middle, and low speeds) through the adjustment of the fan's motor frequency.

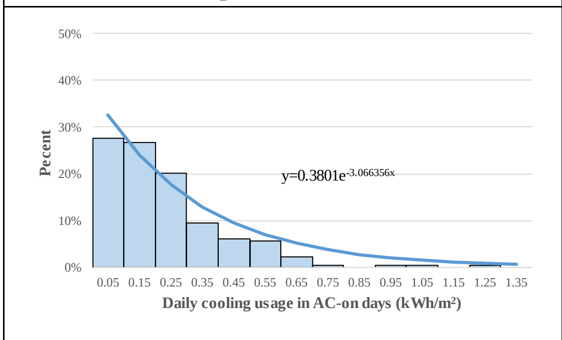
In the case district, the four first-tier indicators have different distributions (Figure 17). The distributions of the total cooling consumption and the daily cooling usage are presented as exponential distributions. However, the distribution of the total cooling consumption exhibits a more abrupt drop, because it is associated with more percentage of smaller values, while the daily cooling usage has eliminated the AC-off days. The distribution of the aggregated operating hours of FCUs yields two peaks, namely, one larger peak between 0 and 500 h, and the other at approximately 2000 h. All the total cooling consumption values are normally distributed except those around zero (0–200 h). The distribution of the average cooling load per FCU is similar to a skewed normal distribution with a different median value compared to the average value, and a longer right tail.



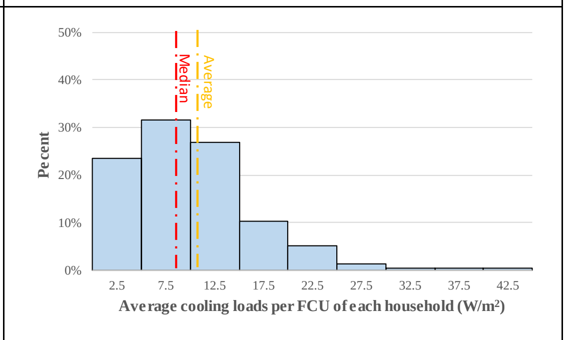
(a) Distribution of the total cooling consumption of each household



(b) Distribution of the aggregated operating hours of FCUs



(c) Distribution of daily cooling usage of each household during AC-on days



(d) Distribution of average cooling loads per FCU of each household

Figure 17 Distributions of the four first-tier indicators

4. Potential applications of outcomes

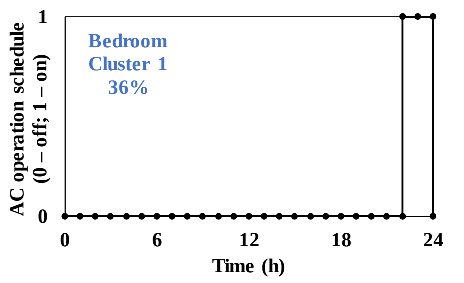
4.1. Application of AC operation schedules for simulation of cooling energy in buildings

Building energy modeling (BEM) programs are commonly used to simulate cooling energy consumption and the peak cooling loads for equipment sizing (e.g., chillers, air-handling units) [39]. Currently, the most commonly used inputs related to occupancy, equipment state, climate, and other parameters in the BEM programs, are known as the schedules [40,41]. The AC schedule is the most important and direct factor influencing the cooling loads in building simulations. There are several methods to define the AC schedules. The so-called full-time full-space method assumes that AC is always on in every room of a building, which is still used in the design standards in China, and extensively used as the input schedule in BEM for HVAC system design [42]. In addition, some default schedules are provided by various simulation tools. Compared with the full-time full-space method, or default schedules, realistic AC schedules are more accurate for simulation. Several researchers have attempted to determine AC schedules to simulate the energy consumption of buildings based on questionnaire surveys or measurements [43].

This study clustered representative AC use patterns for three main room types (i.e., bedrooms, living rooms, and dining rooms) from the metered cooling energy use data. To apply the clustering results to real projects, we need to generate representative AC operation schedules for use in building energy simulation, which usually assumes the same AC use schedules for all rooms in all apartments. As the AC use has two states: on and off, we should convert the possibility of turning on AC into on/off state to generate the AC operation schedules. We assumed that AC was on when the probability of turning on AC was greater than half, otherwise it was off. The results generated from the above clusters are listed in Table 4, which represent the same features as the aforementioned probability curves. The percentage of each cluster is marked inside the diagrams in Table 4. It is noted that the AC operation schedule of Cluster 1 for living rooms represents the always off state, supporting the scenario of no use of ACs in living rooms.

These clustered AC use patterns can be used for the residential buildings with installed HVAC systems of adjustable air supply terminals such as FCU and split AC, and in the cities in the cold climate zone. Although FCU system has different system efficiency and energy consumption from the split type system, the studied FCU system can be controlled individually by the users, and their utility bills were charged based on actual cooling energy usage. From the perspective of AC use patterns, these two systems are similar so that the clustered patterns can also be used in split type systems. Besides, the studied system is located in Zhengzhou city in China, which is a typical city in China's cold climate zone. As climate is one of the most important factors driving occupant behavior, it is feasible to apply the clustered AC use patterns and schedules in the cities in the cold climate zone. These more practical AC schedules for residential buildings in the cold climate zone of China can be used to improve the accuracy of simulated cooling energy.

Table 4 Representative AC operation schedules for three residential room types

<table>
<tr>
<td rowspan="2">(a)Typical AC operation schedules for bedrooms</td>
<td>
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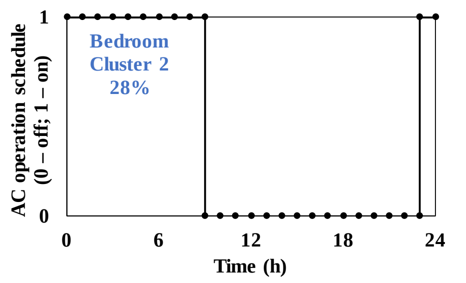
<td>
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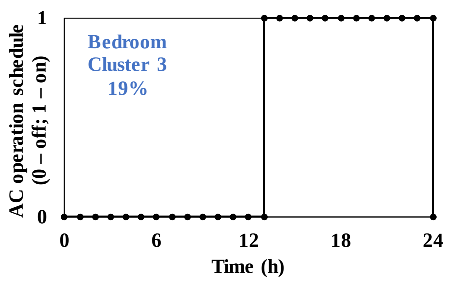
<tr>
<td>
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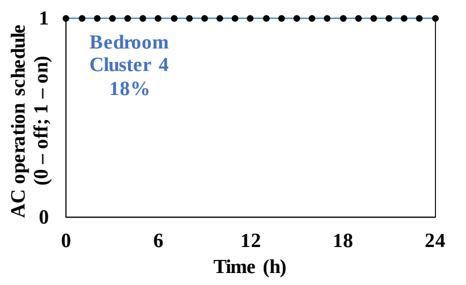
<td>
</td>
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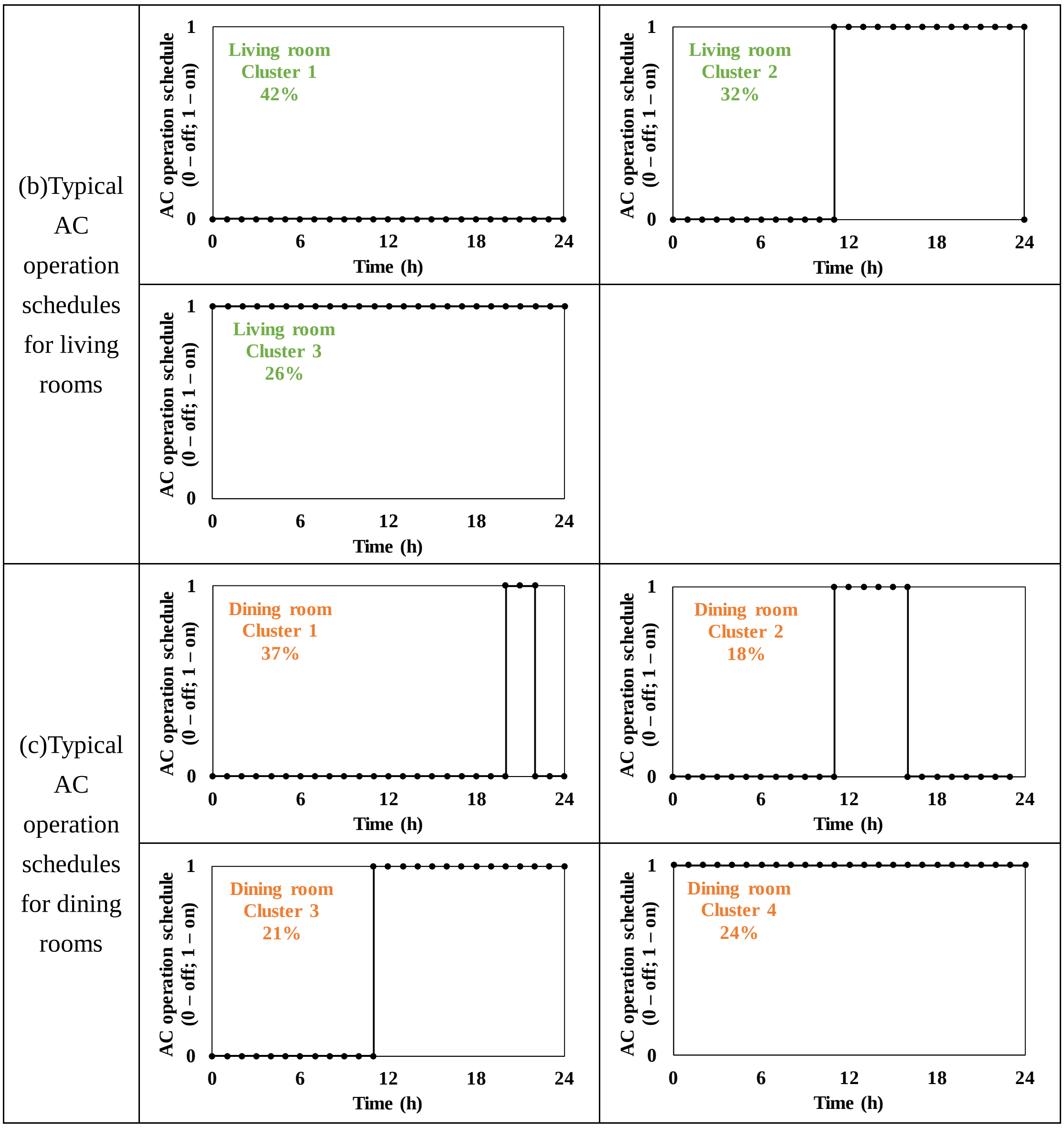
</table>

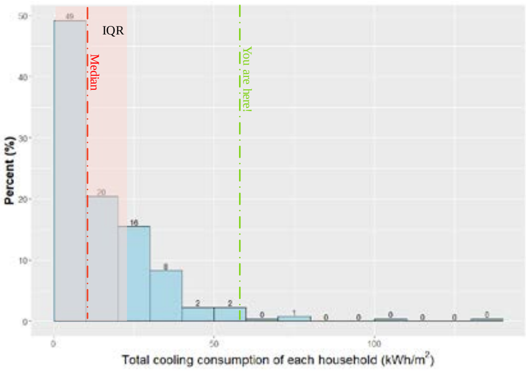
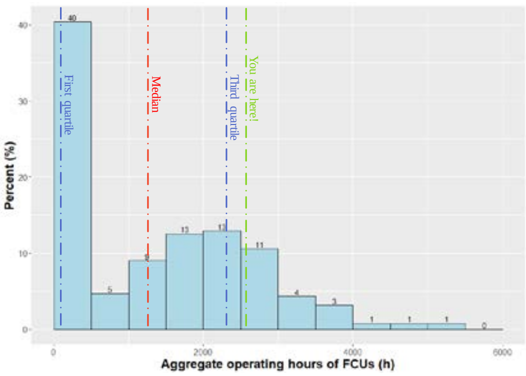
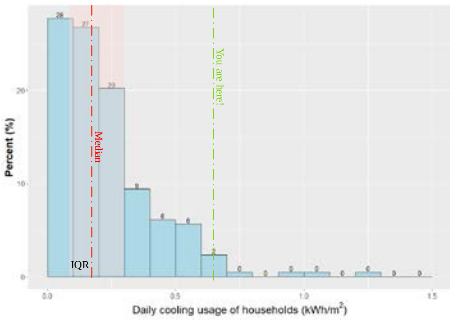
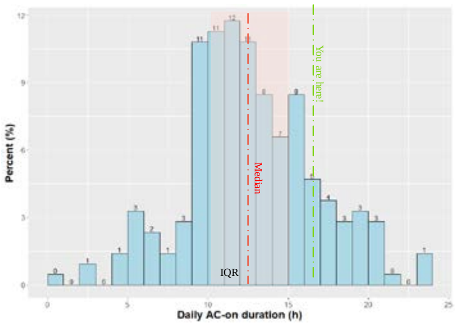


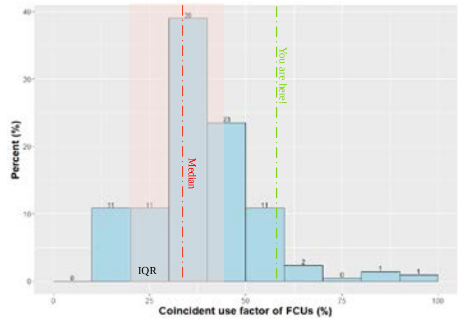
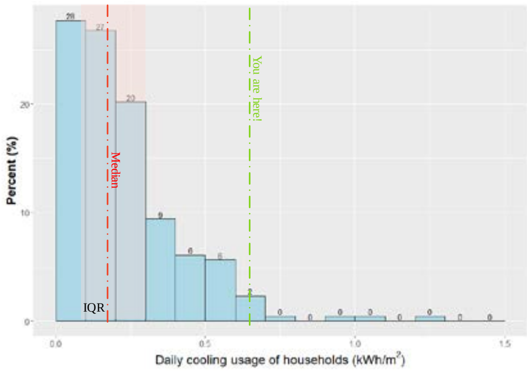
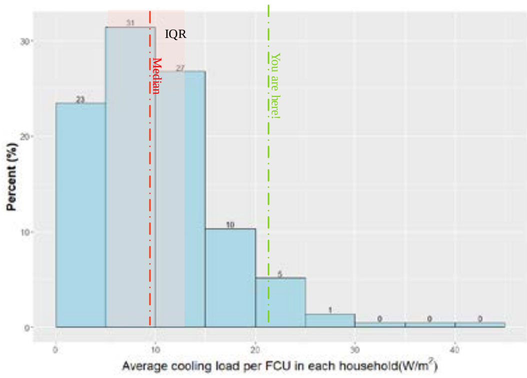
4.2. Application of KPIs for household cooling use benchmarking

We generated several distributions on household cooling energy usage in the district case, which have potential applications, such as cooling energy benchmarking, and cooling energy performance diagnosis. The group of KPIs proposed in this study present the household AC usage beyond the total cooling consumption. We presented this possible application of household cooling use benchmarking for a case household as an example in Table 5.

It is noted that the green dashed lines indicate value of the case household. Its total cooling consumption was higher than 98% of all households, which can be a good candidate to explore energy conservation measures to decrease the total cooling consumption. Compared to its total cooling loads, the aggregated operating hours of FCUs are not as considerable. However, attentions should be paid to the daily AC-on duration as well as to the number of simultaneously operating FCUs. The daily cooling usage during AC-on days was greater than 96% of all the households, which is caused by the longer daily AC-on durations, the greater coincident use factors of FCUs, as well as the larger average cooling loads per FCU (higher than 95% of all the households). Larger average cooling loads per FCU indicate that the specific household might have some unusual habits, such as the setting of a lower indoor comfort temperature, or having increased internal heat gains. This ought to be double checked by the occupants, and certain actions ought to be taken to conserve energy, e.g., reducing the daily AC use hours, or operating the FCUs only as needed in an energy efficient, part-time part-space mode, rather than using the full-time full-space mode.

Table 5 Results of the cooling energy benchmarking for a case household

<table>
<tr><th>First-tier indicators</th><th>Second-tier indicators</th></tr>
<tr><td>Total cooling energy consumption

</td><td></td></tr>
<tr><td rowspan="3">Aggregated operating hours of FCUs

</td><td>Ratio of household AC-on days

</td></tr>
<tr><td>Daily AC-on duration

</td></tr>
<tr><td>Coincident use factor of FCUs</td></tr>
</table>

<table>
<tr><td></td><td>
</td></tr>
<tr><td>Daily cooling energy usage

</td><td></td></tr>
<tr><td>Average cooling load per FCU

</td><td></td></tr>
</table>

Based on the benchmarking results, we found that the Chinese like to use AC part-time and part-space, and the AC operating hour can influence the cooling consumption significantly. The KPIs related to AC operating hour can help inhabitants understand the temporal and spatial characteristics of AC use. If there are any unreasonable behaviors, they can adjust their behaviors to decrease their AC energy consumption. Therefore, the KPIs proposed in this study are useful and applicable for general Chinese household cooling benchmarking.

5. Discussion

5.1. Policy implications

There are significant differences in occupant behaviors in residential buildings between China and the USA [44,45]. The predominant Chinese lifestyle and behavior is the part-time, part-space use of building services (and thus energy consumption), which is regarded as an effective energy-saving measure. Many researchers advocate that Chinese should maintain this green lifestyle and economical part-time, part-space use, and avoid the full-time full-space use mode in the future, thereby meeting the requirements of energy conservation in urban residential buildings in China [3,46]. While in the USA, full-time and full-space use mode is typical due to most existing houses use a single-zone central cooling and heating system without individual room-level AC control. We analyzed the correlation between the daily cooling energy usage and the AC operating hours, and showed the correlations for two typical apartment types in Figure 18. The x-axis is the daily AC-on duration, the y-axis is the average number of simultaneous operating FCUs, and the area of the circle represents the daily cooling energy usage during AC-on days. We found that an obvious positive correlation exists between the two factors in the case of the residential district in Zhengzhou, China; and the degree of correlation varies with different cases, for instance, the correlations in the right figure is not as significant as the left one. The daily cooling usage is influenced by many other factors such as outdoor temperature, indoor temperature setpoint except for operating hours of AC, which were not shown directly in this figure. Taking the blue circle shown in the bottom left of the right figure as an example, its coordinate is (8.33, 1.48); this household only used AC twice during the whole summer, and the thermal mass effect during the long AC-off hours (more heat is stored in the building thermal mass) could lead to higher cooling load when AC was switched on; thus its daily cooling consumption during AC-on days was higher than other households with similar AC operating hours. In general, the daily cooling consumption is highly related to AC operating hours. Therefore, we can infer that under the current situation, the part-time, part-space use mode is a worthwhile measure to adopt to save energy in China.

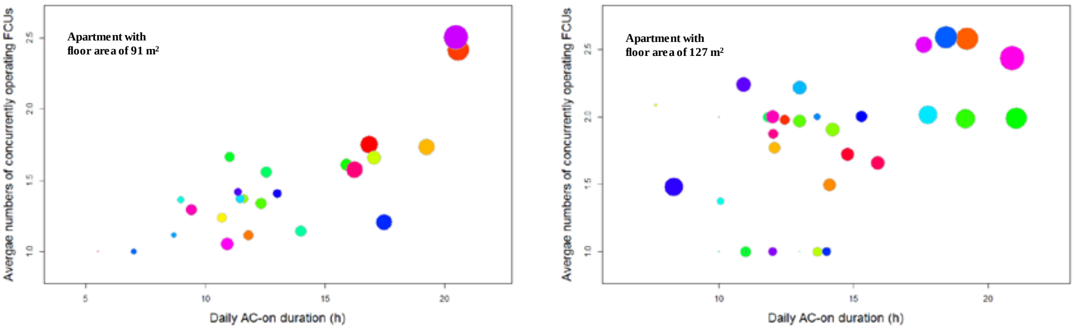


Figure 18 Correlation between the daily cooling energy usage and the number of operating hours (The areas of circles represent the daily cooling usage in AC-on days (kWh/m^2))

5.2. Limitations of the current work

In the case district, we had access to the metered cooling energy usage data of each FCU, and the number of rooms and floor area of each household. However, it would be valuable to have other data, e.g., number of occupants per household, income level, family demographics, and indoor air temperature, to improve the analyses. Specifically,

(1) For the representative AC use schedules of each room type generated by this study, we could not analyze the actual reasons behind different clusters, due to the lack of socio-economic user information mentioned above. Therefore, we considered the apartment type and location (i.e., ground floor, low level (2-7), high level (8-15/17), the top level (16/18)) as two proxies for these parameters, and carried out a simple correlation analysis to examine the relationship between AC use pattern and apartment type, and between AC use pattern and apartment location by using Spearman's rank correlation coefficient. The results show that the apartment location is related to the clustered AC use patterns, which means users lived at higher levels tend to use AC for a longer

time. Whereas the relationship between clusters and apartment type is not obvious, implying the apartment type might not represent the user's information, which needs further study in future.

(2) For the household cooling energy usage, we could not identify reasons behind different distributions of performance indicators. Particularly, the average cooling load per FCU for each household was influenced by various factors, such as the indoor comfort temperature setpoint, and the internal heat gains, which could not be explained without the support of other data, such as indoor temperatures. Therefore, the KPIs proposed in this study can only point out the direction of reasons leading to unreasonable cooling usage, while the exact causes need to be double checked by users.

(3) We had not taken advantage of the load shapes, which should be an important indicator to benchmark the cooling energy usage for households. For instance, if we could access the information on household composition (e.g., double (couple) occupancy versus a single residency occupancy) and their jobs, we could assume the time they spent at home according to their professions, and we could then determine whether their AC use patterns were reasonable or not.

In the future, we will try to collect more information in addition to the metered cooling energy data to fully understand the phenomena discovered in this study, and fully utilize the load shape for residential cooling energy benchmarking.

6. Conclusions

In this study, data-driven approaches comprising clustering, KPIs and statistical analysis were employed to analyze the AC use patterns, benchmark and interpret inhabitants' AC use in residential buildings, using the long-term metered cooling energy consumption data. This study demonstrated the use of the approaches for a residential district in Zhengzhou, China. There are four main outcomes from the study that provide insights to the research and industry for improving building energy efficiency especially reducing air-conditioning energy use.

(1) There were large variations in the total cooling energy consumption among all households in the same district with same climate conditions and envelope performance, with the highest amounting to 140 kWh/m^2, which is 13.5 times of the median level. This load diversity was mainly caused by occupant behavior based on the analyses of real data.

(2) The generated representative AC use patterns and their corresponding proportions (four schedules for bedrooms and dining rooms, three schedules for living rooms) can provide more realistic AC use schedules for building simulation to improve the accuracy of the estimated cooling energy and peak cooling loads for HVAC equipment sizing.

(3) Four first-tier and three second-tier performance indicators were introduced to analyze the cooling energy usage distributions of a residential district. More in-depth understanding of the AC use habits (such as operating ACs for longer time periods) is obtained, beyond the household cooling energy consumption levels. Based on the proposed set of performance indicators, the household cooling energy usage can be benchmarked more comprehensively as demonstrated in Section 4.2.

(4) There is a significant positive correlation between the cooling energy usage and operating hours that supports the part-time, part-space, AC use mode. Therefore, this is a highly useful measure for energy savings in Chinese residential buildings.

Future work should study the relationship between clustered AC use patterns and user's information such as profession, family demographics, and apply the representative load curves in the household cooling benchmarking. Furthermore, new research is expected to obtain not only the household information but also the indoor parameters such as temperature and CO_2 concentration to improve the analytics and provide more effective energy conservation recommendations for inhabitants in the contemporary energy-conscious environment.

Acknowledgement

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