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Analysis of Cooling Load Characteristics in Chinese Residential Districts for HVAC System Design

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Abstract: Energy consumption in residential buildings accounts for a large portion of global energy use. Understanding residential building load characteristics is important in both the design and technical suitability analysis of residential air conditioning systems in terms of energy efficiency and carbon reduction. However, most current research mainly focuses on the load characteristics of individual buildings and not on the variation in load characteristics of building aggregation. In addition, the load characteristics of building aggregations vary with the building scale; however, most studies have compared those of buildings under a certain scale, and the change with the increase in building scale is still unclear. The main purpose of this study is to explore load characteristic differences among residential buildings of different scales and the impacts of those differences on HVAC system design. Based on the monitoring data collected in a residential district in Zhengzhou, China, we analyzed the load characteristics among different households and combinations of different numbers of households from the variation in peak load, total consumption and load distribution, as well as the daily load volatility. We indicate that the load characteristics of heating, ventilation and air conditioning systems of different scales should be considered in the design and operation stage.

Keywords: load characteristics; Chinese residential districts; load diversity; HVAC system design

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Citation: An, J.; Zhou, X.; Yan, D. Analysis of Cooling Load Characteristics in Chinese Residential Districts for HVAC System Design. *Buildings* **2023**, *13*, 2450. https://doi.org/10.3390/buildings13102450

Academic Editor: Francesco Nocera

Received: 20 August 2023
Revised: 11 September 2023
Accepted: 25 September 2023
Published: 26 September 2023

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1. Introduction

Energy consumption in residential buildings accounts for a large portion of global energy use. In 2021, China's urban residential buildings (excluding northern urban heating) consumed 278 Mtce of energy, accounting for a quarter of the total building energy used in China [1]. With the development of economics and improvement in the living standards of residents, the average annual growth rate of energy consumption in the subsector of urban residential buildings reached 7% from 2001 to 2021 and the total energy consumption in 2021 increased five times of that in 2001 [1]. According to the results of a questionnaire survey conducted in 22 cities by the Building Energy Research Center of Tsinghua University in 2015, electric fans, split air conditioners and variable-refrigerant-flow air conditioning (VRF) are commonly used as space-cooling devices in residential buildings in China. Although only 1% of households are served by central cooling systems in China's cold climate zone and hot summer and cold winter climate zone, their use has increased rapidly in recent years [2,3]. Therefore, understanding the load characteristics of residential buildings is important in both the design and technical suitability analysis of residential air conditioning systems in terms of energy efficiency and carbon reduction.

Influenced by household composition and occupant behavior, energy use varies considerably by household. Li et al. [4] conducted a survey of air-conditioning energy consumption in 25 residential apartments in Beijing 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. [5] studied the household cooling usage distribution in a community of approximately 400 households and found that the house with the highest energy consumption consumed 8000 kWh of cooling energy in two months, which was equal to three times the average cooling energy use. Brounen et al. [6] investigated 305,001 Dutch homes and found a wide variation in household consumption. Parker et al. [7] verified a home energy-saving suite for an online simulation by conducting a detailed year-long study. The homes studied exhibited a three-fold variation in the measured energy use, with variations at the end-use level being even larger. Gouveia and Seixas [8] revealed the differences in the daily electricity consumption of different households and obtained ten typical residential electricity consumption patterns using clustering to represent the significant differences in daily and total electricity consumption.

Owing to the load diversity in different households, when a system supplies cooling for multiple households, the load volatility of the different households will cancel each other out, further affecting the load characteristics of the system. Thus, the aggregated loads differ significantly from those of a single house in terms of peak value, load volatility and uncertainty. Weissmann et al. [9] used the load profiles of 144 households to highlight load diversity and its impact on the overall peak load. They observed that, owing to the temporal diversity of various households, the sum of the individual peak loads of households was larger than the overall peak load and that the excessiveness of chiller capacity increased with an increase in the numbers of households in the system. Xu et al. [10] analyzed building electricity consumption data and found that the uncertainty of aggregated load profiles decreased as the number of households in a district continued to increase. Kristensen et al. [11] concluded from data experiments that the uncertainty of energy consumption prediction results decreased gradually with an increase in the building scale. Richardson et al. [12] revealed the characteristics of the decreasing value and uncertainty of the peak load with an increasing number of households in residential buildings.

In this study, we explored the differences in load characteristics among residential buildings of different scales and the impact of differences in load characteristics on HVAC system design. It should be noted that the characteristics of residential heating and cooling loads vary greatly due to the type of system, usage method and outdoor conditions in China. Specifically, northern residential buildings employ central heating systems with a 24 h continuous supply, whereas southern residential areas rely mainly on household electric heaters and split air conditioners for intermittent heating. Most Chinese residential buildings have a part-time and part-space mode to use the air conditioning for cooling. Therefore, this study mainly focuses on the cooling load characteristics. We collected hourly household cooling loads from smart meters in a residential district in Zhengzhou, China, for quantitative analyses. We then analyzed the load characteristics among different households and combinations of different numbers of households based on actual data from the variation in peak load, total consumption and load distribution in a cooling season, as well as the load volatility on a typical day. Finally, we analyzed the impact of load characteristics on HVAC system sizing.

The remainder of the paper is organized as follows: Section 2 summarizes the recent developments and research gaps. Section 3 describes the technical approach of this study and the metrics and analysis process for load characteristics. Section 4 presents the load characteristics analysis results for residential buildings containing different numbers of households. Section 5 discusses the potential applications of the load characteristics analyzed in this study and the limitations of this study. Section 6 concludes the paper with some final considerations and future outlooks.

2. Literature Review and Research Gaps

2.1. Literature Review

To describe the load characteristics of buildings quantitatively, researchers have proposed several metrics for individual buildings and building aggregations. As shown in

Figure 1, various statistical metrics representing load levels and volatility are commonly used for the load characterization of single buildings. For central HVAC systems that supply cooling/heating for a group of buildings, the variation in characteristic parameters such as peak load with the increase in the number of buildings is very important for HVAC system design; therefore, some metrics used to represent the differences between individual buildings and building aggregations have been proposed.

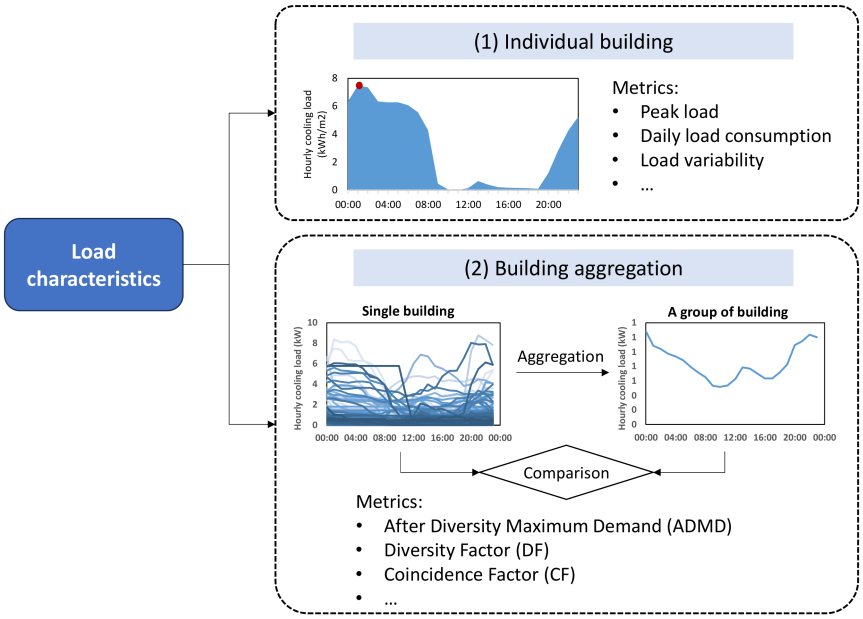


Figure 1. Classification of load characterization.

(1) **Metrics for individual buildings**.

Because the cooling load varies over time, common statistical metrics, such as maximum, minimum, mean and standard deviation, are mostly used for the load characterization of individual buildings, as shown in Table 1. The peak value of the cooling/heating load has a great influence on the size of an HVAC system. Therefore, peak load is one of the important metrics [13,14]. Because of this, the daily average load or total load consumption can reflect the average load consumption level of the building and is therefore often used in studies of different type of buildings. Chen et al. [13] compared the daily average load and total load consumption of different buildings on a campus. Roberts et al. [15] compared the average daily total load between apartments and houses. Vámos et al. [16] compared the total heating consumption of 11 building types in Budapest. Lin et al. [14] analyzed the distribution of the average cooling load in a hub airport terminal.

Although hourly load profiles can visualize load volatility, several metrics have been proposed to quantitatively describe it, such as the standard deviation (SD) [10] and coefficient of variation (CV) [15], where CV is the ratio of the SD of the daily load to its mean. The peak–valley difference ratio, which is the ratio of the difference between the peak and valley loads to the peak load, is also often used to present the peak–valley characteristics and stability of the load profile [10,13]. The load factor (LF) or load rate (LR) is the average load divided by the peak load and can be calculated on a daily, seasonal, or annual basis for load volatility analysis [10,13,15]. Chen [13] used the weekly imbalance rate to reflect weekly volatility, which is calculated by dividing the average daily maximum hourly load by the maximum hourly load in a typical week. Gadd and Werner [17] proposed quantitative metrics to analyze the daily and seasonal volatilities of heating loads in 20 building districts in Sweden; the results showed relatively significant seasonal volatility of the heating loads in building districts. The average seasonal volatility index was as high as 24%, but the daily volatility was relatively small.

Table 1. Metrics used in analyzing load characteristics of individual buildings in previous studies.

Parameter		Metric	Reference
Peak load		Maximum value of hourly loads	[13,14]
Total consumption level		Daily average load and seasonal power consumption intensity	[13–15]
Load volatility	Daily	Hourly load profile	[18]
		$\overline{CV} = \frac{1}{365}\sum_{j=1}^{365}\frac{\sqrt{\left(\sum_{i=1}^{24}\left(P_{h,ij}-P_{d,j}\right)^2/24\right)}}{P_{d,j}}$ where P_h is the hourly load and P_d is the daily average load	[15]
		$\overline{LF}_{daily} = \frac{1}{365}\sum_{j=1}^{365}\frac{P_{d,j}}{\max\limits_{1\le i\le 24}\{P_{h,ij}\}}$ where P_h is the hourly load and P_d is the daily average load	[15]
		$LR = \frac{average\ load}{peak\ load}$	[10,13]
		$Daily\ Peak-valley\ difference\ ratio = \frac{peak\ load-valley\ load}{peak\ load}$	[10,13]
		Annual relative daily variation, $G_a = \frac{\frac{1}{2}\sum_{i=1,j=1}^{8760,365}\left\lvert P_{h,i}-P_{d,j}\right\rvert}{P_a\cdot 8760}\cdot 100\%$ where P_h is the hourly average load, P_d is the daily average load and P_a is the annual average load.	[17]
	Weekly	$Weekly\ imbalance\ rate = \frac{daily\ maximum\ hourly\ load}{maximum\ hourly\ load\ in\ typical\ week}$	[13]
	Seasonal/ annual	Load duration curve	[18]
		$SD = \sqrt{\left(\sum_{i=1}^{n}\left(P_{h,ij}-P_{d,j}\right)^2/n\right)}$ where n is the total hours of load, P_h is the hourly load and P_d is the daily average load	[10]
		Seasonal load rate $= \frac{daily\ maximum\ hourly\ load}{maximum\ hourly\ load\ in\ heating/cooling\ seasons}$	[13]
		$LF_{annual} = \frac{P_a}{\max\limits_{1\le i\le 24,1\le j\le 365}\{P_{h,ij}\}}$ where P_h is the hourly load, P_d is the daily average load and P_a is the annual average load	[15]
		Annual relative seasonal variation, $W = \frac{24\cdot\frac{1}{2}\sum_{j=1}^{365}\left\lvert P_{d,j}-P_a\right\rvert}{P_a\cdot 8760}\cdot 100\%$ where P_d is the daily average load and P_a is the annual average load.	[17]

(2) **Metrics for building aggregations**.

To quantitatively describe the load characteristics of buildings at different scales, researchers have proposed several metrics from the perspectives of peak load, load consumption level and volatility, as shown in Table 2.

- **Peak load**

Peak loads are important in HVAC system sizing; therefore, most research related to building aggregation has focused on the variation in the peak load. Zhu et al. [19] analyzed the change in peak load and annual demand at different building scales based on simulation results using EnergyPlus (https://energyplus.net/). Obrien et al. [20] compared the peak cooling loads and peak internal heat gains of buildings with different floors.

The after diversity maximum demand (ADMD), diversity factor (DF) and coincident factor (CF), which were first used in the power industry, are now widely used to describe the difference in peak load as the number of buildings increases. Specifically, the ADMD is the maximum demand of the aggregated hourly load profiles of every building, the DF is the ratio of the sum of the individual peak loads to the overall peak load (i.e., ADMD) and the CF is the reciprocal of the DF. Mckenna et al. [21] quantitatively analyzed the building electricity loads of several typical residential districts in the UK under different combinations of energy conservation measures based on ADMD and DF metrics and provided technical recommendations in terms of the electricity loads. Wang et al. [22] also

studied the peak clipping characteristics of the electricity loads of residential districts in the UK using ADMD and DF metrics, and the results showed that the load diversity of households led to a decrease in the overall peak load to 47% of that of a single household when the number of households exceeded 30; the decrease in the overall peak load gradually tended to level off. Love et al. [23] statistically analyzed the heating loads of 696 heat pumps in the UK based on the ADMD, and the results showed that when the number of users increased to 40, 100 and 275, the overall peak load was 50%, 45% and 43% of that of a single user, respectively, proving that with an increase in the number of users, the overall peak load of the building aggregation exhibited a rapid decline followed by a leveling off. Clemente et al. [24] adopted the DF to analyze plug load profiles in office buildings in France. Roberts et al. [15] reached a similar conclusion for Australian apartments and houses using the CF; the CF approached 0.23 for aggregations over 200 customers. In contrast to other studies, Weissmann et al. [9] proposed the peak load rate (PLR) to analyze the characteristics of the peak load in a 144-household residential district in Germany. The PLR was calculated by dividing the difference between the sum of the individual peak loads and the overall peak load of a building group by the sum of the individual peak loads, which had a value between 0 and 1. Owing to the differences in the building age, building orientation and occupant behavior of these households, the heat load curves of the 144 dwellings were different and the peak loads of individual households occurred at different times, resulting in a decrease in the overall peak load of the entire district.

- **Load volatility**

Guttromson et al. [18] compared the hourly load profiles of household groups consisting of 1, 5, 20, and 100 households based on simulation data and showed that the volatility of daily load profiles of residential groups changed with the number of households owing to load diversity; however, quantitative metrics for daily volatility were lacking. Roberts et al. [15] calculated the CV and LF of load profiles for aggregations between 2 and 250 households and repeated this process 200 times to obtain the average CV and LF for each aggregate size. Based on these two metrics, they concluded that the load variability was reduced by aggregating up to 50 household loads. The Gini index, which can represent the load temporal distribution during a certain period, has been gradually applied to analyze load features in the building sector [25,26]. Yan et al. [25] compared the Gini index of the cooling loads of 3000 combinations of buildings, and the Gini index varied between 0.25 and 0.6, which reflected differences in the volatility of loads for different combinations of buildings.

Table 2. Metrics used in analyzing load characteristics of building aggregations in previous studies.

Parameter	Metric	Analysis Method	Reference
Peak load	$ADMD = max\left(\sum_{i=1}^{n} Q_{i.t}\right)$ where $Q_{i,t}$ is the hourly load of building i at time t.	Deterministic Stochastic	[22] [21,23]
	$DF = \frac{\sum_{i=1}^{n} max(Q_{i.t})}{max(\sum_{i=1}^{n} Q_{i.t})}$ where $Q_{i,t}$ is the hourly load of building i at time t.	Deterministic Stochastic	[12,21,22] [24]
	$CF = \frac{max(\sum_{i=1}^{n} Q_{i.t})}{\sum_{i=1}^{n} max(Q_{i.t})} = \frac{1}{DF}$ where $Q_{i,t}$ is the hourly load of building i at time t.	Deterministic	[15]
	$PLR = \frac{Q_{AISpeakload} - Q_{CSpeakload}}{Q_{AISpeakload}}$ $Q_{AISpeakload} = \sum_{i=1}^{n} \max(Q_{i.t})$, $Q_{CSpeakload} = \max(\sum_{i=1}^{n} Q_{i,t})$ where $Q_{i,t}$ is the hourly load of building i at time t.	Deterministic	[9]

Table 2. *Cont.*

Parameter	Metric		Analysis Method	Reference
Load volatility	Hourly load profile and load duration curve		Deterministic	[18]
	Daily	$\overline{CV}$, $\overline{LF}_{daily}$ (mentioned in Table 1.)	Stochastic	[15]
	Annual	LF_{annual} (mentioned in Table 1.)	Stochastic	[15]
		$Gini = 1 - \frac{1}{n^2\overline{\lambda}} \sum_{i=1}^{n} (2n - 2i + 1)\lambda_i$ where $n.$ is the total hours of loads, λ_i is the normalized load and $\overline{\lambda}$ is the average value of the weighted normalized load.	Stochastic	[25]

2.2. Summary and Research Gap

Even though some metrics have been proposed to analyze the characteristics of cooling/heating load from the abovementioned studies, critical knowledge gaps remain to be filled in this study, as discussed below:

(1) Lack of comprehensive metrics for load characteristics in building aggregations. Many researchers have investigated the load characteristics of buildings; however, most have focused on the load characteristics of individual buildings instead of the load characteristic variations owing to building aggregation. Research on building aggregation has focused on the peak load, but other parameters such as load volatility have not been sufficiently investigated; therefore, more comprehensive metrics for load characteristics analysis should be proposed.

(2) Lack of quantitative analysis on variations in the load characteristics of buildings at different scales. The load characteristics of building aggregations vary with the building scale. Most studies have compared the load characteristics of buildings under a certain scale; therefore, the change in load characteristics due to an increase in building scale is still unclear.

(3) Lack of consideration for load stochasticity in load characteristics analysis. Most studies have adopted a deterministic analysis method that is used for a quantitative analysis based on the results of metrics in a single statistical analysis. Considering the uncertainty of building heating/cooling loads, the single statistical results may lead to bias in the conclusions; therefore, analysis of the load characteristics should involve stochastic analysis.

3. Data and Method

Our study consisted of four steps: data collection and preprocessing, load diversity analysis, smoothing effect analysis and discussion, as shown in Figure 2. First, we collected cooling load data from a residential district and cleaned the collected data for analysis. Subsequently, we developed several metrics to represent the load characteristics of residential buildings and analyzed the cooling load diversity among different households based on the proposed metrics. Third, we selected different numbers of households and calculated the corresponding aggregated cooling load profile. Subsequently, we performed statistical analysis to explore the smoothing effect of the cooling load owing to the increase in the number of households. Finally, we analyzed the implications and limitations of this study.

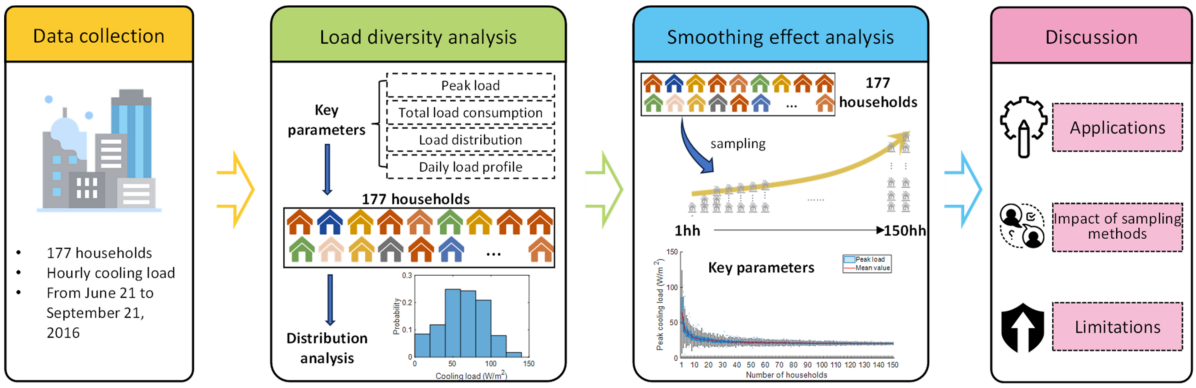


Figure 2. Research content.

3.1. Data Collection

The residential district in this study was built in 2011 and is located in Zhengzhou, China, which is in the cold climate zone. The cold climate zone has four seasons: spring, summer, autumn and winter. The summer months from June to September require cooling due to high outdoor temperatures, whereas winter requires heating. In spring and autumn, the outdoor temperature is suitable and there is no need for cooling or heating. The district has three high-rise buildings (two have 16 floors and one has 18 floors) including 324 households that have fan coil units (FCUs) installed for cooling and heating in each room, except for bathrooms and corridors. A thermal energy metering system was used to collect the cooling/heating data for each FCU for the utility bills. The data collected from the metering system pertained to the accumulated cooling energy consumption from the time at which the meter was installed; these data could be collected at irregular intervals spanning several minutes to multiple days, according to the requirements of the operating staff. The difference between the two continuous data points represented the cooling energy consumed during that period. Detailed information on the district can be acquired from a published journal article [27].

We obtained metered data for each FCU during a three-month cooling season spanning from 21 June 2016 to 21 September 2016, which is the main cooling period in the city. Because the collected metered data of thermal energy use were accumulated, to generate the data on the hourly cooling energy usage of each household we assumed that the cooling loads between two adjacent data points remained constant. Because this assumption can introduce significant errors when collecting data at large time intervals, we excluded households with large time intervals from the original data collection to improve the accuracy and reliability of the generated hourly cooling load data. The cooling energy data from some FCUs were not collected for several days during the cooling season of 2016. Therefore, we excluded households with long-term missing metered data and the days with missing metered data. In addition, since the cooling bill in this community is based on a combination of a basic charge and additional charges for exceeding the baseline amount of cooling used, a basic charge was required regardless of whether air conditioning was used for cooling. We considered that households with low cooling usage were likely unoccupied for a long time and so studying their cooling load characteristics was meaningless; therefore, we excluded those households that used less air conditioning (i.e., less than 10 kWh/a). Finally, we obtained the hourly cooling loads of 177 households over 47 days.

3.2. Parameters for Load Characteristics

Four parameters and their respective metrics were used to describe the load characteristics, as listed in Table 3.

Table 3. Parameters and comparison metrics.

Number	Parameters	Metrics	Applications
1	Peak cooling load	Maximum value of hourly cooling load during the cooling season	Total capacity selection of cooling devices
2	Total cooling consumption	Sum of hourly cooling load during the cooling season	Evaluation of total cooling consumption
3	Temporal load distribution	Gini index to evaluate the distributed load feature in a quantitative way	Selecting different combinations of cooling devices
4	Hourly load profile	Coefficient of variation to evaluate the load volatility in one day	Evaluation of control strategy of cooling devices

The peak cooling load and total cooling consumption are the two most commonly used parameters in engineering applications for load characteristics analysis. Therefore, we selected these two parameters for this study. This study also considered the temporal load distribution because it influences the selection of multiple cooling devices with varying capacities to maximize the operational efficiency under various load conditions. We used the Gini index to evaluate the distributed load features quantitatively. The Gini and Lorenz curves were first applied to the HVAC field to describe the load distribution in Zhou's study [26]. Figure 3 shows the process of using the Lorenz curve and Gini index to reflect load changes over time. The x-axis represents the cumulative share of the number of time-steps (i.e., one hour in this study) in the order of the lowest to highest load requirements, whereas the y-axis represents the cumulative share of load requirements. When the Lorenz curve deviates from the 45-degree line, it implies that the load requirements are the same at all times. The Gini index can be considered as the ratio of the area that lies between the line of equality and the Lorenz curve to the total area under the line of equality. Therefore, larger Gini indexes correspond to more uneven load distributions. In addition, hourly loads on a typical day were required to analyze the equipment control strategy; thus, this study used the daily load profile as a single parameter.

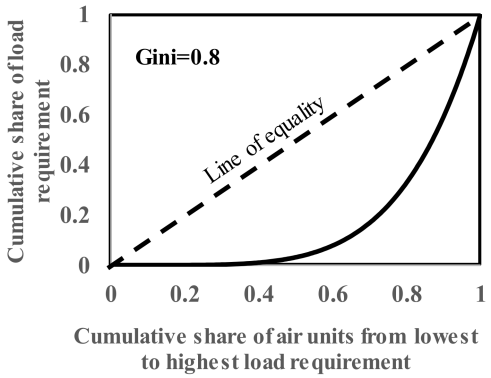


Figure 3. Example of Lorenz curve and Gini index used to evaluate the feature of load distribution.

The CV was used to quantify load volatility. The CV was determined by dividing the standard deviation by the mean value, as shown in Equation (1).

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}}}{\overline{x}} \times 100\% \quad (1)$$

where x_i represents the instantaneous load at moment i, $\overline{x}$ is the mean value of the hourly load data and n is the amount of hourly load data.

3.3. Analysis Process

This study conducted an analysis of load characteristics from two perspectives: load diversity among different households and the smoothing effect owing to the increase in the number of households.

To analyze the load diversity among different households, we first calculated four metrics used to represent the load characteristics for each household and then compared the differences in load characteristics among different households.

With an increase in the number of households in a system, the load volatilities of the different households cancel each other out, further affecting the load characteristics of the system. The number of households is a key factor that influences the smoothing effect. Therefore, we analyzed the load characteristics of groups with different numbers of households, varying from 1 to 150. For each number of households, we used a random sampling method to select the corresponding number of households and then aggregated their hourly cooling load data. Because the results for each sampling were different, we replicated the sampling process 100 times for each number of households. Finally, we obtained 15,000 hourly load profiles. Based on the sampling results, we summarized the key metrics used to represent the load characteristics. Specifically, for each number of households, we calculated the maximum cooling load and the sum of hourly cooling loads, Gini index from hourly cooling loads in the cooling season and the CV index from hourly cooling loads in a typical day for each sampling. In the end, the metrics for different numbers of households and sampling frequencies were calculated. It should be noted that the number of households represents the number of individuals served by an HVAC system and that the sampling frequency represents the number of times a specific number of households is repeatedly selected from 177 households. In addition, we investigated the changes in load characteristics due to an increase in the number of households. The analysis process is shown in Figure 4.

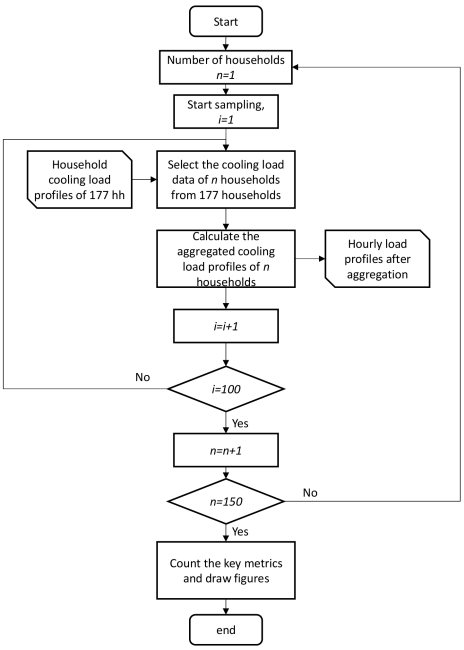


Figure 4. Flow chart of smoothing effect analysis.

Figure 5 shows a schematic to demonstrate the sampling process. We started from a group containing only one household. We randomly selected one household from 177 households 100 times and added the results of each sampling to obtain an aggregated cooling load profile. We then moved on to a group of two households. We randomly selected two households from 177 households 100 times and added the results of each sampling to obtain an aggregated cooling load profile. This process was repeated until

the number of households reached 150. Finally, we analyzed the smoothing effect with an increase in the number of households.

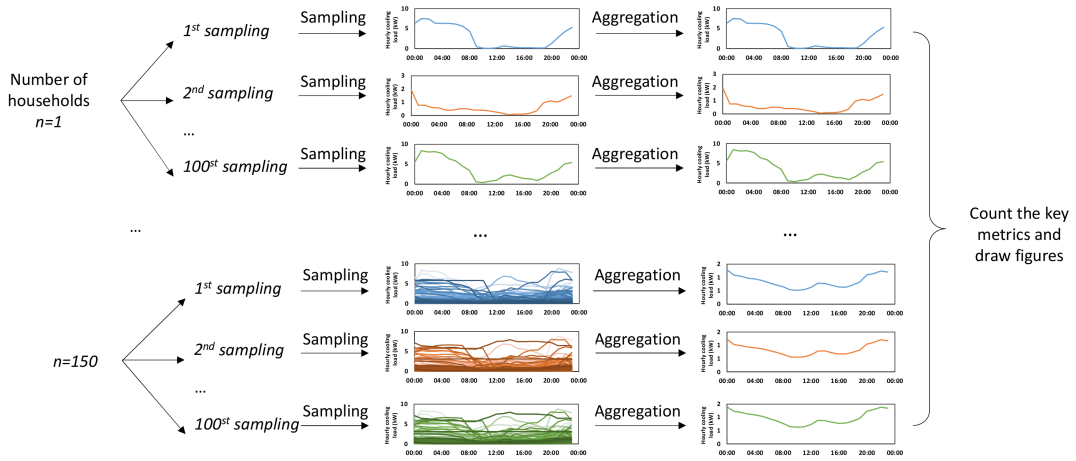


Figure 5. Schematic of the sampling process.

4. Analysis of Load Characteristics in a Residential District

4.1. Load Diversity among Different Households

Large differences were observed in the cooling load demands of different households. The peak cooling load and total consumption during the cooling season among different households are depicted in Figures 6 and 7, respectively. The peak cooling load was 3.7–123.7 W/m^2, for which most cases were concentrated in the range 40–90 W/m^2. The peak load distribution was approximately normal. The total load consumption was 0.2–122.4 kWh/m^2/a, and most cases had less than 40 kWh/m^2/a.

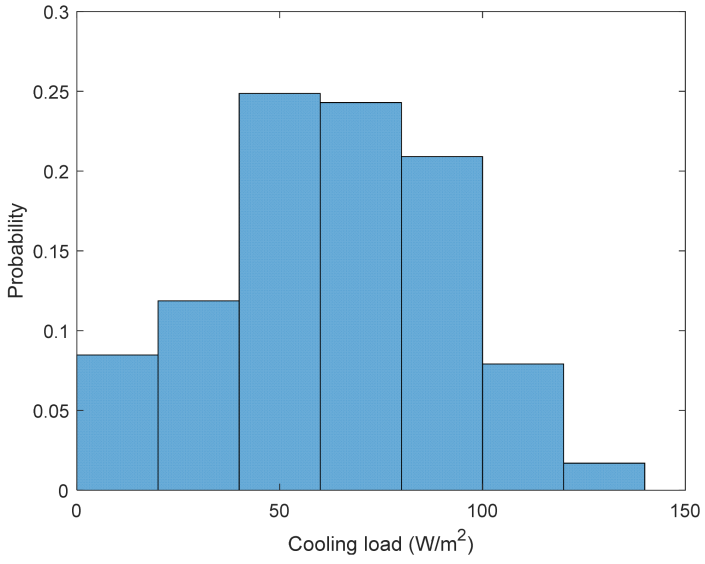


Figure 6. Peak load distribution of 177 households.

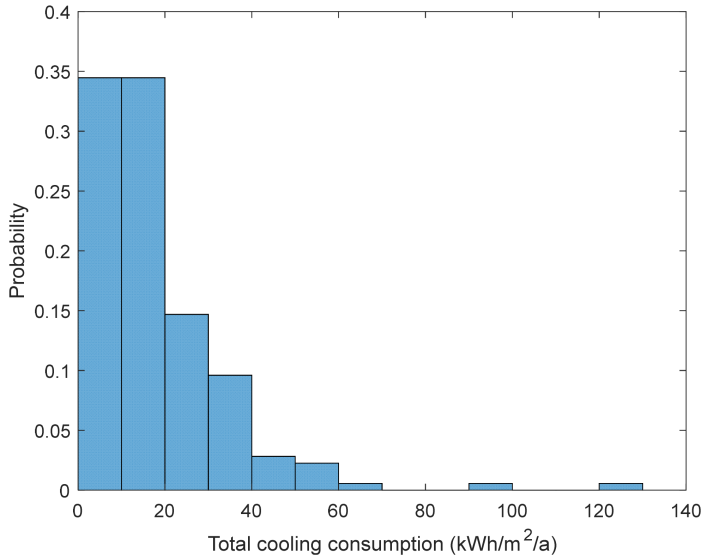
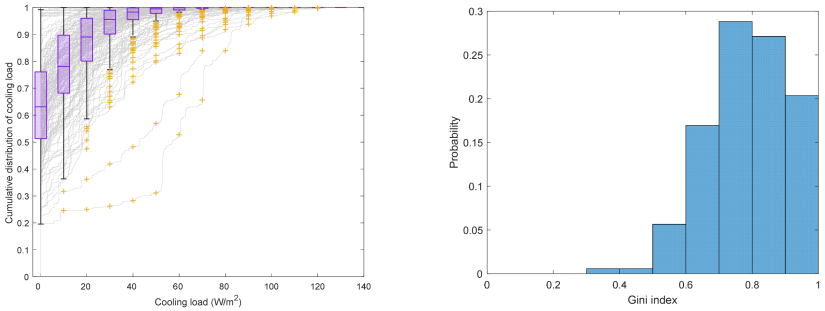


Figure 7. Total cooling consumption distribution of 177 households.

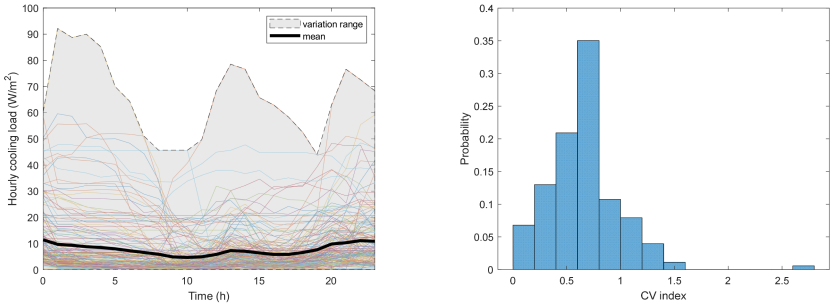
In addition, we obtained the cumulative distribution curves of hourly cooling loads in the cooling season of each household, which are displayed as light grey lines in Figure 8a. In addition, a boxplot was used to show the distribution among households under different cooling loads. Large differences were observed in the load distribution of different households. To describe the diversity among households quantitatively, we calculated the Gini index of the load distribution for each household. The Gini index is between 0 and 1, with a smaller value representing a more even load distribution. Figure 8b shows that the cooling load of most households was distributed unevenly and that the Gini index was larger than 0.4.



(**a**) (**b**)

Figure 8. Cooling load distribution in the cooling season for 177 households: (**a**) Cumulative distribution of cooling loads; (**b**) Distribution of Gini index.

Finally, we show the differences in the daily load profiles among the different households in Figure 9a; the daily load profiles of different households are shown in colorful lines, and the mean values and variation ranges for all households are depicted. To ensure the daily load profile for each household is representative, this study used k-means clustering to obtain the average daily load profile of the largest cluster in each household. An apparent diversity in the hourly load profiles was observed among different households. The mean hourly load of 177 households was relatively stable, whereas the load of individual households varied dramatically throughout the day. The CV index was to describe the volatility of the cooling load for one day, as shown in Figure 9b. CV is a dimensionless index where a larger value represents higher volatility. The hourly cooling load in one day strongly fluctuated in most households; therefore, energy storage devices should be employed to reduce the volatility of electrical loads.



(**a**) (**b**)

Figure 9. Hourly cooling load on a typical day for 177 households. (**a**) Daily cooling load profiles; (**b**) Distribution of CV index.

Overall, there are significant differences in cooling load demands among different households that are reflected in four aspects, including peak load, total cooling consumption, temporal load distribution, hourly load profile in a typical day and so on.

4.2. Smoothing Effect of the Cooling Loads

Figure 10 summarizes the peak cooling loads for every combination of the number of households (ranging from 1 to 150) in the 100 samplings. The x-axis represents the number of households served by one system, whereas the y-axis represents the peak cooling load. For each abscissa value, six indicators are shown in the box plot: the maximum value, upper quartile, median, lower quartile, minimum value and outliers. The mean value of the peak cooling loads for each combination of different numbers of households is marked with a red line. We can conclude that the variation ranges of the peak loads with the same abscissa values decreased with increasing abscissa value. This indicates that there is a large difference in the peak cooling load among systems with a small number of households. However, there is less difference in the peak cooling loads among systems that serve more than a dozen households. In addition, the mean peak loads with the same abscissa values decreased as the abscissa value increased from 64.8 to 20.4 W/m^2. Because of the load diversity among different households, the peak loads of different households had different values and occurred at different times; therefore, the peak load of a large system should be much smaller and more stable than an individual peak load.

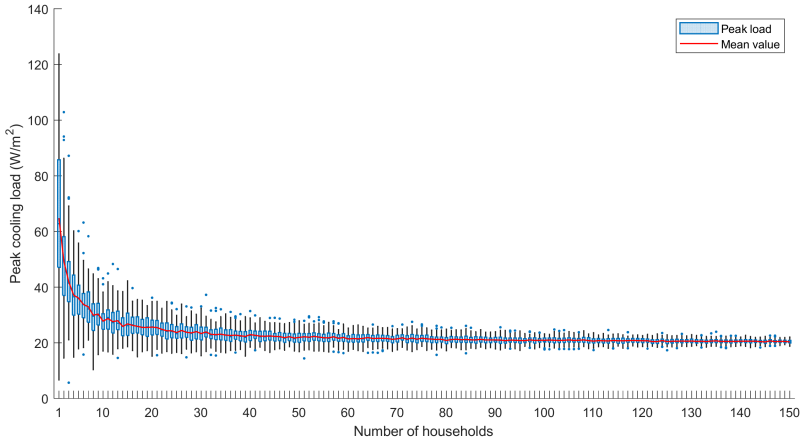


Figure 10. Variation in peak cooling loads for combinations of different numbers of households.

Figure 11 shows the peak load distributions for combinations with 1, 10, 50, 100 and 150 households. When the system scale was small, the mean values and variation ranges of the peak loads of the different systems were large. With an increase in system scale, the mean value and variation range of the peak loads of different systems decreased. Therefore,

when determining the total capacity of HVAC equipment such as chillers, the impact of building scale should be considered.

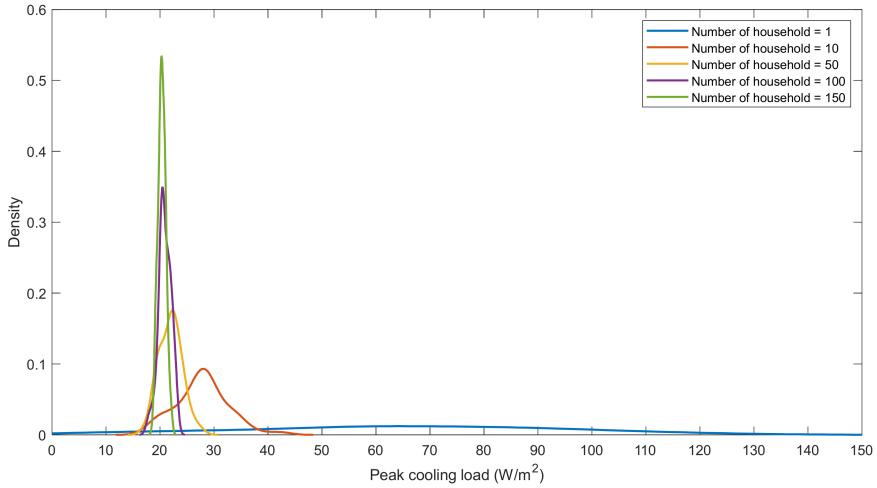


Figure 11. Peak load distribution of combinations with different numbers of households.

Figure 12 depicts the total cooling consumption for every combination of different numbers of households ranging from 1 to 150 in 100. The x-axis in Figure 12 is the same as that in Figure 10, whereas the y-axis represents the total cooling load consumption. Similar to the variation in peak loads, the variation range of total cooling consumption decreased with an increase in the number of households. In addition, the mean total consumption with the same abscissa value did not change significantly under different abscissa values, which indicated that the load diversity among different households had less influence on the total load consumption. This indicates that when evaluating the total cooling consumption of a building aggregation, the results obtained by simulating a prototype building are close to the results obtained from the building aggregation. Using a prototype building for modeling, analysis and evaluation can reduce the workload of engineers.

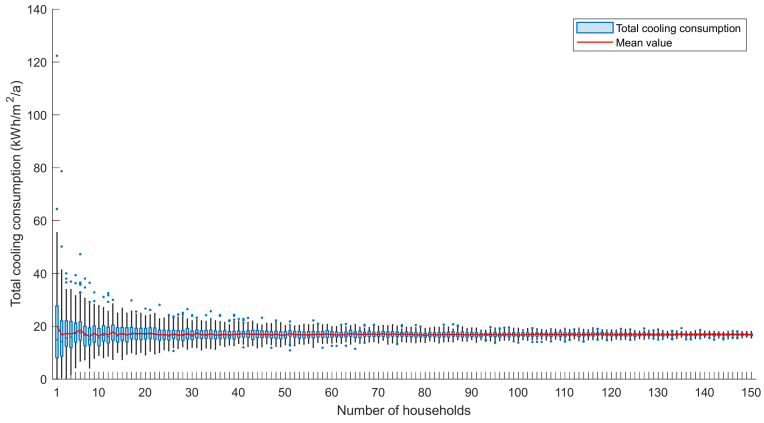


Figure 12. Variation in total cooling consumption for combinations with different numbers of households.

Figure 13 shows the total consumption distribution for combinations with 1, 10, 50, 100, and 150 households. The mean of the total consumption of the different systems remains the same; however, their variation range decreased when the building scale increased.

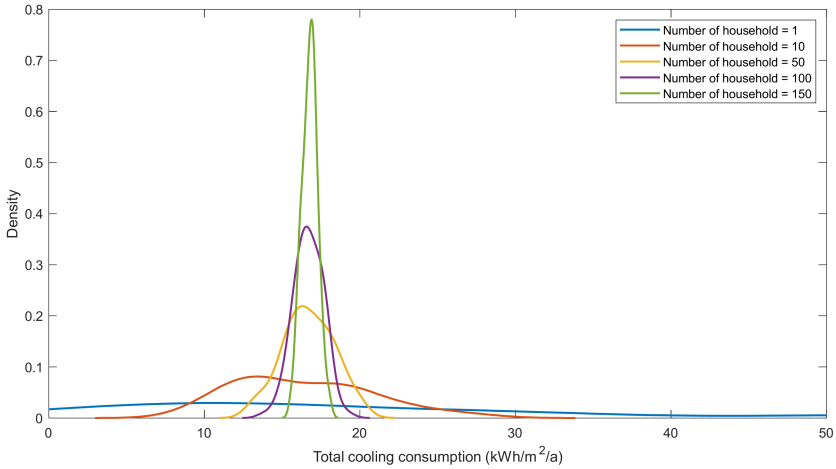


Figure 13. Total load consumption distribution for combinations of different numbers of households.

As the cooling load varied over time during the cooling period, we obtained the cumulative distribution curves of the hourly cooling loads in a cooling season for combinations with 1, 5, 10, 50, 100 and 150 households, as shown in Figure 14. The colors and symbols are the same with Figure 8a. The variation range of the load distribution curves for the same system scale continued decrease with an increasing system scale. For systems serving one household, the load distribution curves showed significant differences among different systems. However, for systems serving more than 100 households, the load distribution curves of the different systems were almost equal. As mentioned previously, the Gini index can be used to evaluate the distributed load features quantitatively. The Gini index was between 0 and 1, with a smaller value representing a more even load distribution. We found that the more households served by one system, the more evenly the cooling load was distributed in the cooling season, as shown in Figure 15. Therefore, the impact of building scales should be considered for the matching of equipment such as chillers and energy storage devices.

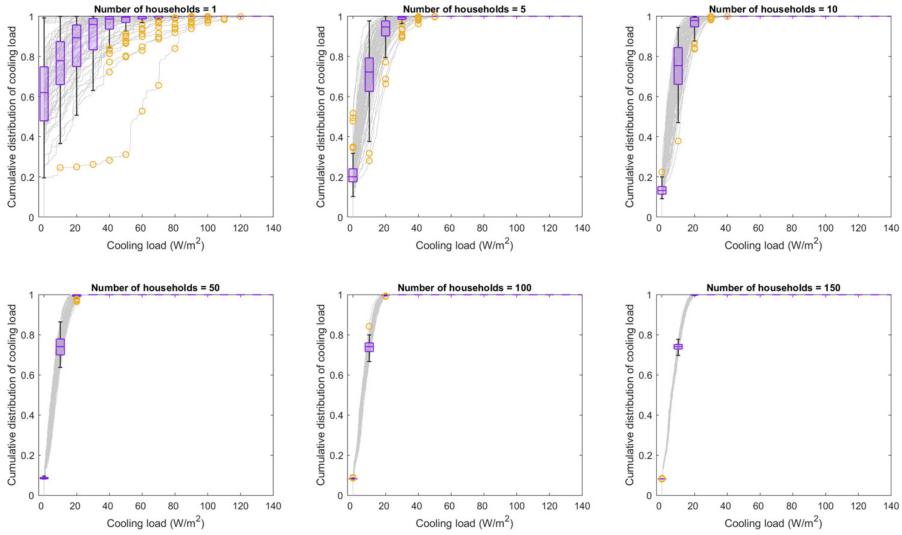


Figure 14. Cumulative distribution of cooling load in a cooling season for combinations of different numbers of households.

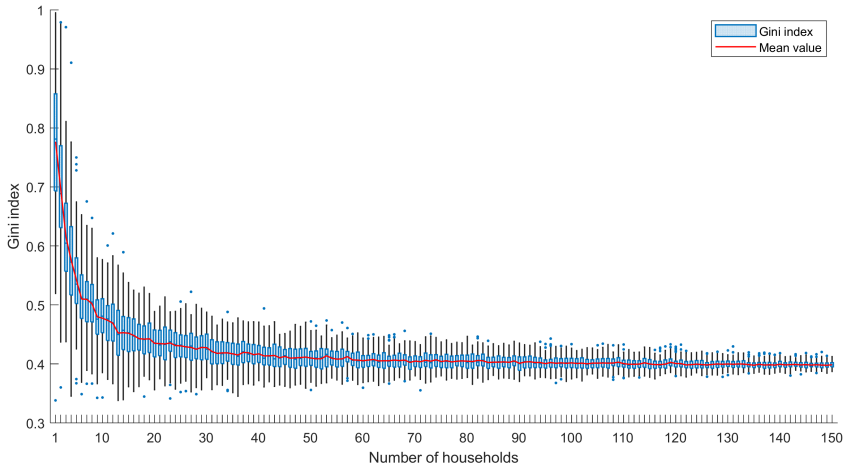


Figure 15. Variation in Gini index for combinations of different numbers of households.

We analyzed the influence of system scales varying from 1, 5, 10, 50, 100 and 150 households on the hourly cooling loads for a typical day. The colors and symbols of Figure 16 are the same with Figure 9a. As shown in Figure 16, the variation range of the household load profiles under the same system scale decreased with an increase in system scale. The CV index for systems of different scales in 100 runs of random sampling, which represents the daily volatility of the cooling load, is shown in Figure 17. We found that the more households served by one system, the smoother the daily cooling load. Unique equipment operation strategies for buildings of different scales should be proposed based on their different typical daily load profiles.

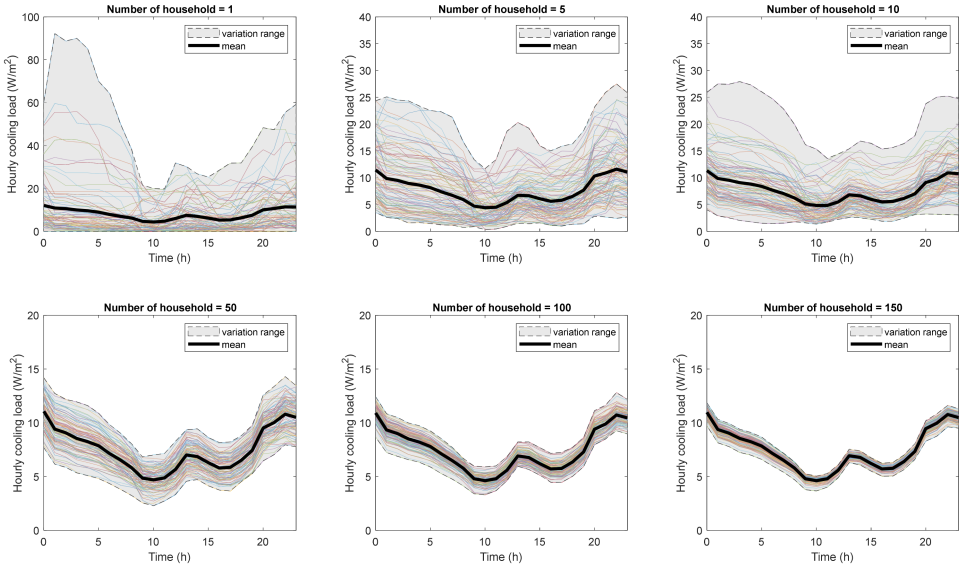


Figure 16. Daily cooling load profiles of combinations with different numbers of households.

In conclusion, owing to the load diversity among different households, when a system supplies cooling to multiple households, the load volatilities of the different households cancel each other out, further affecting the load characteristics of the system. We compared the peak load, total load consumption, temporal load distribution and daily load profile with different system scales and conclude that the variation range of the above four parameters, the mean value of peak load, Gini index for temporal load distribution and CV index for daily load profile decrease rapidly when the system scale increases until the system serves approximately 50 households, after which the variation range and mean value change less as the system scale increases further. However, the mean value of the total load consumption remains almost constant as the system scale increases.

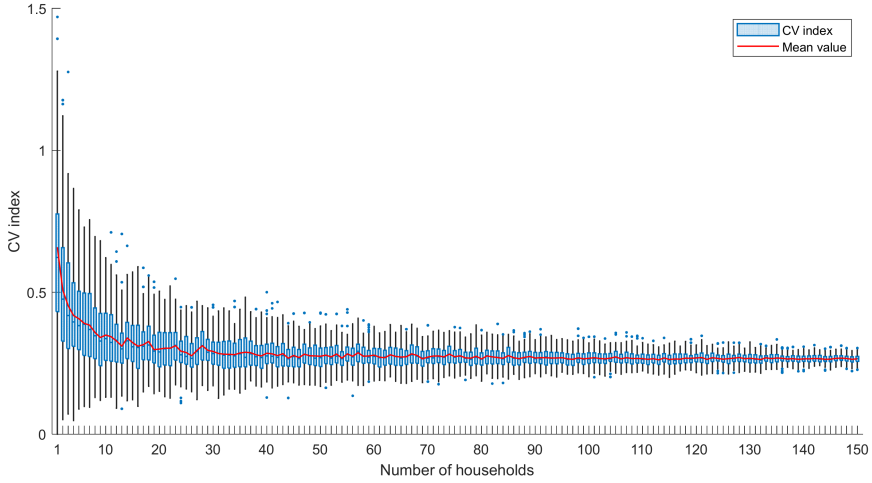


Figure 17. Variation in CV index for combinations of different numbers of households.

5. Discussion

5.1. Suggestions for HVAC System Design

Through the previous analyses on load characteristics under different system scales, we found that large central air conditioning systems have noticeably different cooling load characteristics than small air conditioning systems, causing a difference between the district cooling system design and split air conditioners. Our findings are consistent with previous research but more comprehensive as we consider not only peak values but also hourly load profiles and distribution variations. Taking the peak cooling load as an example, as shown in Figure 18, large central air conditioning systems, such as systems serving 150 households, have a smaller mean peak load than split air conditioners. In addition, the peak cooling loads do not vary significantly in different large central air conditioning systems, whereas single apartments have diverse peak load requirements for split air conditioners among different households. The total chiller capacity in the case study was 2460 kW and 62 W/m^2, which was close to the average household peak cooling load (i.e., 64.8 W/m^2) but significantly larger than the average value of the peak cooling loads of systems serving 150 households (i.e., 20.4 W/m^2), which was partly because HVAC engineers use the same value to determine the capacity for spilt air conditioners and the chillers of central air conditioning systems. If we use the average value for the individual peak loads of every household to select the chiller, the chiller will most likely be significantly oversized; for example, approximately 3.25 times the actual peak load of the district in the case study, resulting in a waste of investment and the low-efficiency operation of chillers.

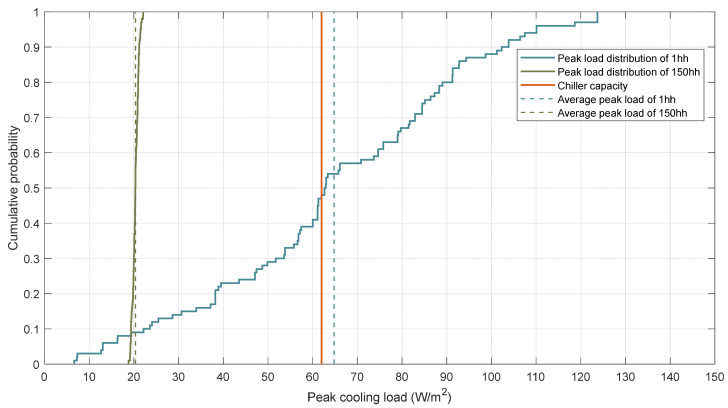


Figure 18. Comparison of the installed chiller capacities for the peak loads.

As the temporal load distribution has an impact on the design of chillers and thermal energy storage devices, we compared the temporal load distribution during the cooling season in a household and in a system serving 150 households, as shown in Figures 19 and 20. The split air conditioner had a large peak cooling demand. However, it was used only approximately 34% of the time during the cooling season and its usage under different load rates was relatively the same. Compared with split air conditioners, central air conditioning systems have a much smaller peak cooling demand and operate approximately 85% of the time during the cooling season. The cooling load shows a peak at a 25% load rate, as shown in Figure 19, and the usage decreases with an increase in the load rate. Therefore, a small chiller, according to the 25% peak cooling load, is recommended to increase the energy efficiency of an HVAC system.

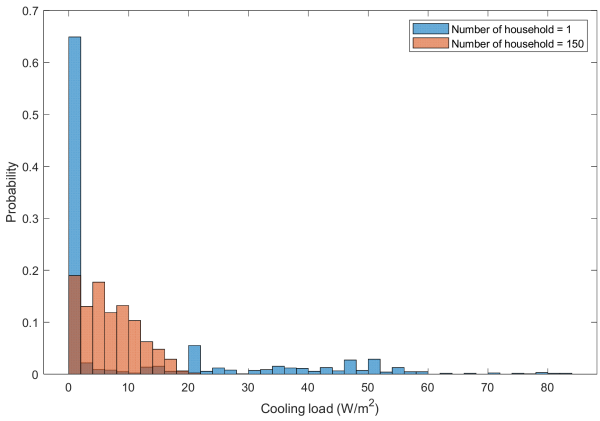
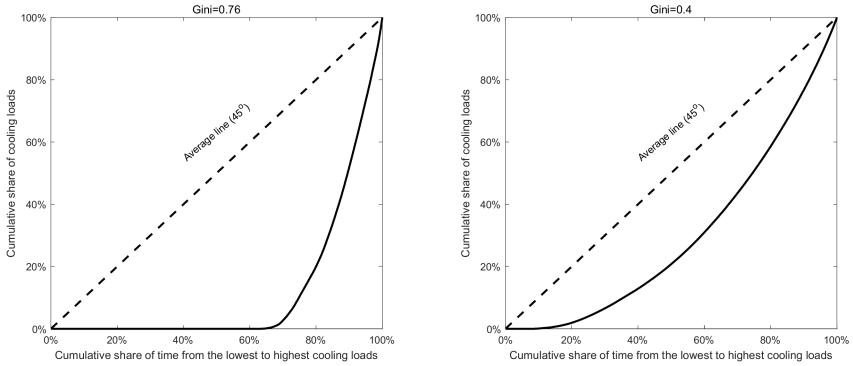


Figure 19. Comparison of cooling load distribution in a cooling season for combinations with 1 and 150 households.



(**a**) (**b**)

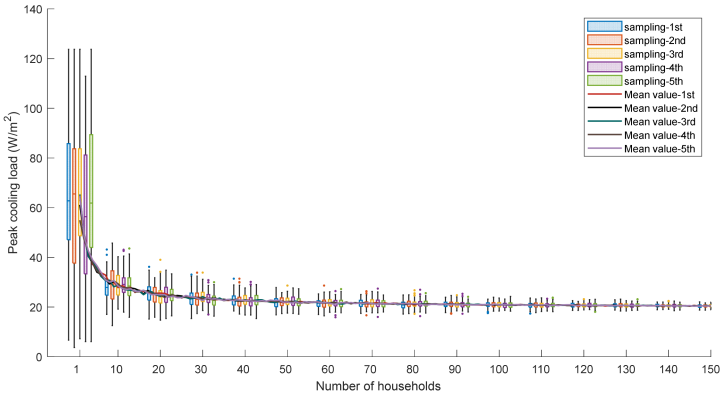
Figure 20. Comparison of Gini index for combinations with 1 and 150 households. (**a**) 1 household; (**b**) 150 households.

5.2. Impact of Sampling Methods on the Load Characteristics

For each number of households, we used a random sampling method to select the corresponding number of households and replicated the sampling process 100 times. The results for each sampling were added together to obtain the aggregated cooling load profiles for further analysis. Because the results for each sampling were different and the sampling frequency might have had an impact on the analysis results, we analyzed the impact of sampling methods on the load characteristics.

We repeated the entire analysis process (shown in Figure 4) five times. In each round of sampling, 100 runs of sampling were conducted for each number of households. We compared five rounds of sampling (Figure 21) and found that the results of each repetition

had some differences when the number of households was small (i.e., less than 20). Overall, the conclusions based on these results were very similar.



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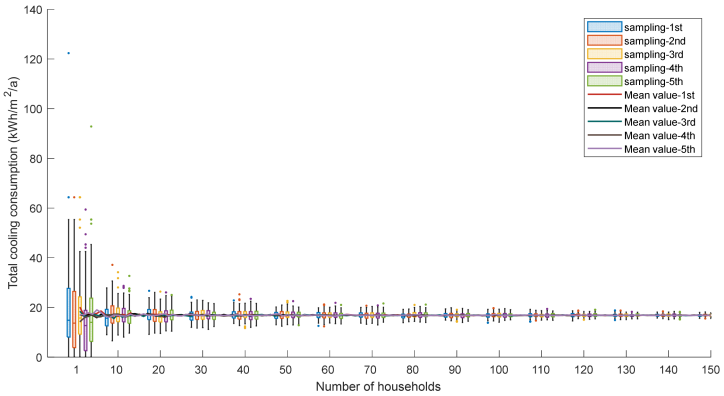

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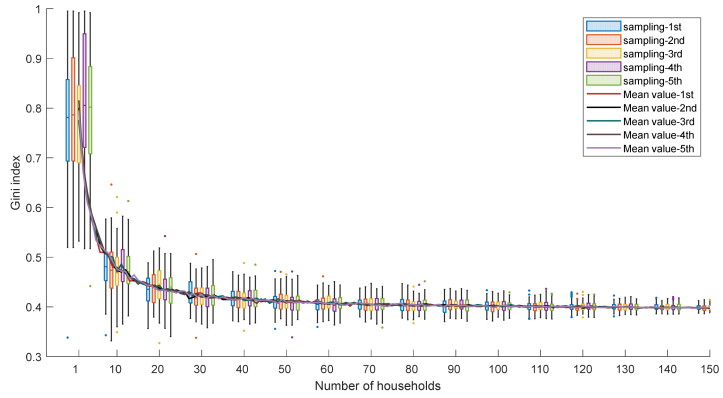
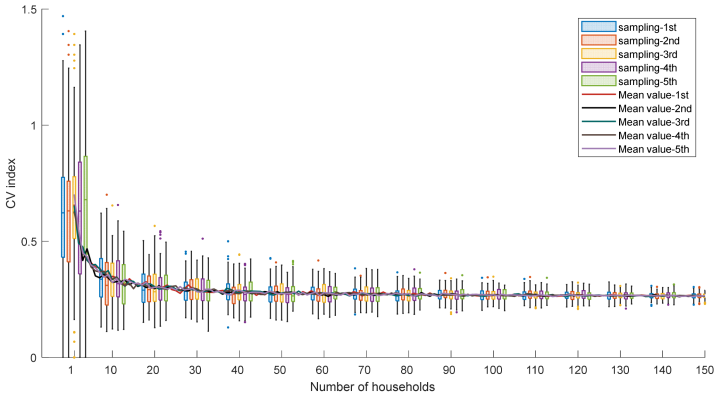


(**c**)

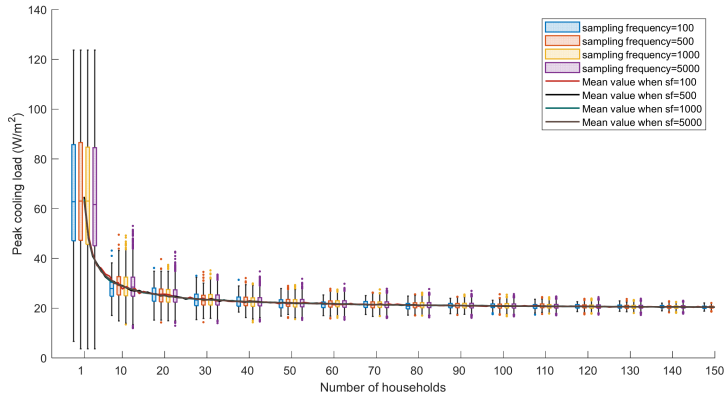
Figure 21. *Cont.*



(**d**)

Figure 21. Comparisons of key metrics under five repetitions. (**a**) Peak load; (**b**) Total consumption; (**c**) Gini index; (**d**) CV index.

In addition, we conducted an analysis of the sampling frequencies, changing from 100, 500, 1000 and 5000 for each number of households, and compared the results of key metrics varying from the number of households (Figure 22). We observed that the mean values with different sampling frequencies were very similar but the variation range increased as the sampling frequencies increased and outliers were more likely to occur. Therefore, analyses with a larger sampling frequency are required to obtain more accurate results.



(**a**)

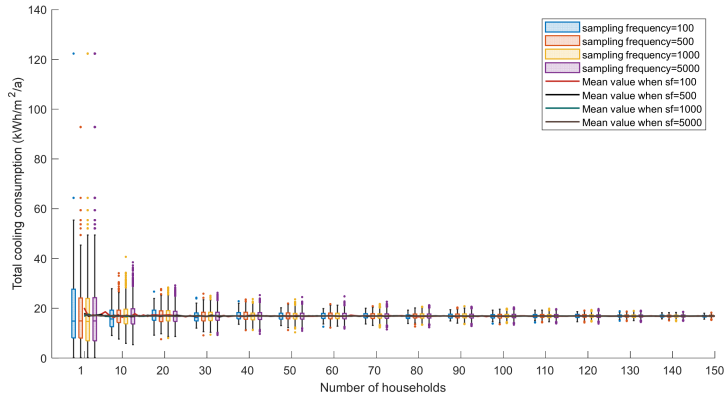


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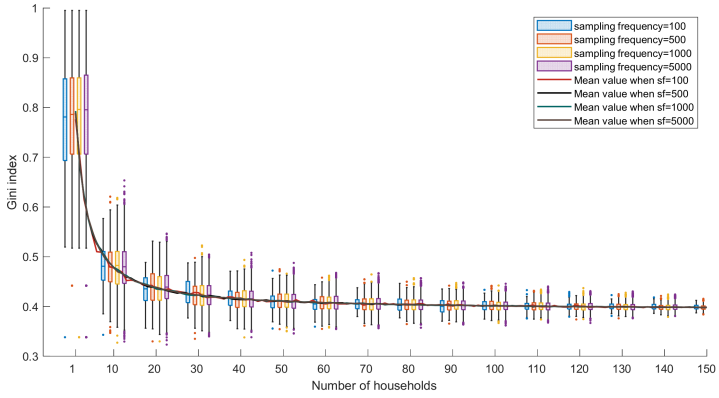
Figure 22. *Cont.*



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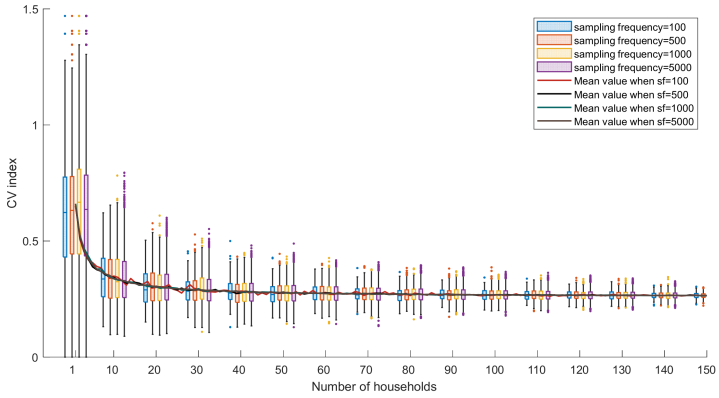

(**d**)

Figure 22. Comparisons of key metrics with different sampling frequencies. (**a**) Peak load; (**b**) Total consumption; (**c**) Gini index; (**d**) CV index.

5.3. Limitations

This study compared the cooling load characteristics of systems serving different numbers of households in a residential district and discussed the impact of system scale on HVAC system design. However, this study only analyzed the cooling load characteristics of a residential district in Zhengzhou, China. There are five climate zones in China according to the monthly average temperature of the coldest and hottest months: the severe cold zone, cold zone, hot summer cold winter zone, hot summer warm winter zone and temperate zone [28]. Residents' habits for using air conditioning systems also vary due to different outdoor meteorological conditions. Owing to the lack of sufficient practical cooling load data for residential districts in different climate zones, empirical formulas cannot be provided for engineers to use in HVAC system design. Therefore, more measurements/surveys and related research should be conducted in different cities in the five climate zones of China in the future. In addition, the proposed method should be applied to other building types, such as office buildings and hotels, to better understanding the characteristics of cooling loads in different building types. Further research is required on the heating load characteristics.

6. Conclusions

Understanding the characteristics of cooling load demand in buildings is very important for the better design and operation of air conditioning and energy storage systems. In this study, a residential district was selected as the study object. Based on the long-term monitoring data for every household in the summer of 2017, a load characteristics analysis was conducted from two perspectives using four parameters to describe the cooling loads. The following are the main conclusions:

Significant load diversity among different households. In a cooling season, the peak cooling loads of different households was 3.7–123.7 W/m^2, the total load consumption varied from 0.2 to 122.4 kWh/m^2/a and the load distributions and hourly load profiles in one day differ significantly among households. In addition, in most households, cooling is distributed unevenly and the hourly cooling load in one day fluctuates significantly.

Decreased peak values and fluctuations owing to building aggregation. Owing to the load diversity among different households, when a system supplies cooling to multiple households, the load volatilities of the different households cancel each other out, further affecting the load characteristics of the system. Therefore, the variation range of the peak load, total load consumption, temporal load distribution, hourly load profile, mean value of peak load, Gini index for temporal load distribution and CV index for hourly load profile decreases rapidly with an increase in system scale until the system serves approximately 50 households, after which the variation range and mean value change less as the system scale increased further. However, the mean value of the total load consumption remains almost constant as the system scale increases.

Specialized considerations in system design for different building scales. The different characteristics of the cooling load between large and small systems significantly influence the design of HVAC equipment, such as chillers and energy storage devices. Taking the residential district investigated in this study as an example, an oversized chiller would be selected without considering the smoothing effect of cooling loads in hundreds of households, leading to a waste of investment and low-efficiency chiller operation. In addition, the load distribution of a large system differs from that of a split air conditioner, which can affect the matching of multiple chillers. Therefore, the cooling load characteristics of HVAC systems for different scales should be considered in future designs.

In conclusion, this study focused on the quantitative methods for describing load diversity among different households and the smoothing effect of the cooling load with an increase in the number of households and indicated that the load characteristics of HVAC systems with different scales should be considered in the design and operation stage.

Author Contributions: Conceptualization, J.A., X.Z. and D.Y.; methodology, J.A. and D.Y.; investigation, J.A.; data curation, J.A.; writing—original draft, J.A.; writing—review and editing, J.A., X.Z. and D.Y.; supervision, D.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Natural Science Foundation of China (Grant Number 52108068 and Grant Number 51978137) and the Pyramid Talent Training Project of Beijing University of Civil Engineering and Architecture (Grant Number JDYC20220815).

Data Availability Statement: Not applicable.

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

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