An Energy Planning Oriented Method for Analyzing Spatial-temporal Characteristics of Electric Loads for Heating/cooling in District Buildings with a Case Study of one University Campus

Abstract

Accurate grasp of district power demand is of great significance to both sizing of district power supply and its operation optimization. In this study, an index system has been established and visualized through a Geographic Information System, for revealing both temporal and spatial characteristics of district power loads caused by heating/cooling systems, including load level and fluctuation characteristics, spatial distribution of electric loads, and load coupling relationships between individual buildings and the district. Principal component analysis was applied to identify the buildings with significant impact on district load management. Using this method, the spatial-temporal characteristics of electric loads caused by heating in one university campus in China were analyzed. The results showed that building type and the operation modes had great effects on the level and volatility of the district electric load caused by heating. Buildings with high load levels and strong coupling with the peak district electric load, such as academic buildings, often had a major impact on the power demand of the district. Therefore, they were considered as key targets for energy-saving renovation and operation optimization. Buildings with large load fluctuation, such as teaching buildings, could contribute to the peak load shaving by adjusting the heating systems' operation.

Keywords: district electric load for heating and cooling; spatial-temporal

characteristics; load coupling; campus buildings; GIS

1. Introduction

With the large-scale construction of sustainable communities, district energy planning has become increasingly important. Rational design and optimal operation of district power systems generally need an accurate grasp of characteristics of district power load [1]. In a certain district, there may exist many types of buildings, with significantly different characteristics of energy load. In particular, the power loads for heating and cooling have dynamic characteristics dependent on season and time of day [2]. The dynamic characteristics of power loads for a district is not a simple addition of load characteristics of individual buildings, but an orderly coupling considering both time and space [3]. To better support district power supply capacity allocation and power dispatch, it becomes fundamental of identifying key indicators and developing appropriate analysis methods to capture both spatial and temporal characteristics of district power load, as well as the coupling relationships between the load of single buildings and the total district load [4].

Existing studies on district heating and cooling loads and energy consumption have investigated several analytical indicators using either field measured data or simulation results, but more efforts on improving the indices system are still highly needed. For example, using three indicators, namely, water consumption, electricity consumption and natural gas consumption, Zhou et al. [5] scrutinized data collected between 2006 and 2010 from 98 universities in Guangzhou, and allocated investigated universities with various types regarding to their energy consumption characteristics.

Noussan et al. [4] analyzed annual and monthly average heating loads, and hourly heating intensity of one district heating system, to reveal its main characteristics for heating load variation. Based on the simulation results, Xu et al. [6] have used two indices, namely, load rate and peak-valley difference ratio, to evaluate the performance of load leveling by different floor area ratios for office buildings, shopping malls and hotels. Cai et al. [7] monitored the cooling energy consumption of a certain district in Shanghai, and suggested a coincidence factor of about 0.5 for that district. Zhang et al. [8] used the DeST simulation package to model the hourly cooling load of 9 types of buildings located in the Guangzhou University Community, and adopted the coincidence factor to analyze the time difference in the peak loads among various types of buildings. Zhou et al. [3] utilized peak load, mean standard deviation and load ratio when analyzing the measured cooling capacity of a residential community in Shanghai, from perspectives like peak shaving, wave reduction and load sizing. From the study, they found that with more buildings involved, the district load exhibited less volatility, and the peak district load became smaller. Guan et al. [9] have analyzed the characteristic of daily, monthly and yearly energy use of university campus buildings, and calculated the coincidence factor of electric load, water load and heating load for a university campus in Norway using hourly measured field data. To measure diversity, Weissmanna et al. [10] have developed the peak load ratio (PLR) index to represent the reduction in peak load of a district system from a simple sum up of peak loads from individual buildings. For a theoretical analysis, a total of 144 load profiles of residential buildings were created in the dynamic building simulation package IDA ICE, and the PLR reached 15%. Lu et al. [11] established a model to verify that the power supply can be adjusted according to HVAC's hourly load for a better grid load balancing. Using a robust database of monthly consumption, Derenski et al. [12] examined electricity and natural gas consumption intensity for hundreds of schools in Los Angeles County, and its relationships to key structural and categorical characteristics, including size, geography and school type. Corgnati et al. [13] have used a statistical model to predict energy consumption of 120 schools in Turin, Italy, in order to establish performance indicators on heating energy consumption as baseline values for heating supply contracts.

A building energy management system contains large amount of operational information for buildings, and GIS (Geographic Information System) is an effective tool for analyzing building loads and energy consumption characteristics in district and urban scales. Luca et al. [14] investigated the electricity consumption of big consumers in southern Canton Ticino, Switzerland, to verify if there was a significant district cooling demand, and the possible district cooling connections between the consumers and the utilities were selected and mapped by GIS, as well as density of electricity consumption and peak power. Giuliano Dall'O et al. [15] have developed a database for building energy consumption and mapped the energy consumption of an Italian city on a GIS platform. Howard et al. [16] selected New York as a case study and established a statistical model based on a government database. The model was capable of estimating air-conditioning and domestic hot water loads for different building types in the city. The GIS platform can show the spatial differences of building loads in the urban scale, and can also be used to guide formulation of energy policies with contributions from model predictions. Utilizing the multi-linear regression function of ARC GIS, Ma et al. [17] inserted missing values in the building information database and managed building information, such as shape coefficient and energy consumption per unit area, on the GIS platform. Quan et al. [18] used the GIS platform for data processing and building energy system modeling. In their study, Manhattan was used as a case study to analyze the regional spatial and temporal differences in building energy usage.

According to the above literatures, existing studies indicated that: 1) from the perspective of data sources, building information data used in existing studies were either simulation data or monthly measured data, and there was a lack of high-resolution data such as daily and hourly data. Therefore, it is impossible to perform in-depth analysis on dynamic characteristics of buildings; 2) in terms of index systems and analysis methods, existing indices were very simple and unitary, and could not address the regional load characteristics amongst district buildings at the full scale. Most existing studies focused on the magnitude of the building load only, such as monthly load characteristics, i.e. maximum value, minimum value, average value and standard deviation, and very few studies have analyzed coincidence factors. Additionally, no index system and methods are currently available to reveal the coupling relationship between the loads of single buildings and the total district load, as well as the contribution of single buildings to the district scale. Moreover, existing studies using GIS systems were mainly for establishing district building performance database and for analyzing and displaying building attribute data. They did not effectively combine comprehensive analysis of district building load characteristics and space-time visualization; 3) building types investigated in existing studies were mainly from residential communities, so the analyses could not well reflect the diversity in building types, as well as its impact on the district load.

To address the above mentioned issues, this study established a GIS-based index system, aiming to comprehensively reveal the temporal dynamic characteristics, load fluctuation characteristics and spatial distribution characteristics of district load, as well as coupling relationships of power loads for heating and cooling between individual buildings and the entire district. Using the principal component analysis method, the multi-criteria index system can well identify buildings that have significant impact on the district power operation. The work mentioned here can be used to serve energy-saving renovations, optimal operation and management of space heating and cooling systems, as well as district power dispatches. Finally, considering the high variation of university buildings, a university campus has been selected as a case study, and the developed index system was used to analyze spatial-temporal characteristics of the power load of space heating for all buildings in the campus, based on field monitored data from the campus energy monitoring platform.

2. Development of the Spatial-temporal Characteristics Analysis Method for Managing Power Loads of space heating/cooling in District Buildings

Fig. 1 shows the proposed analysis method regarding to spatial-temporal characteristics of power loads for heating/cooling district buildings. Firstly, from the perspective of time dynamic characteristics, load fluctuation characteristics and coupling relationships between the loads of single buildings and the total district load, an index system for analyzing the power load characteristics of heating and cooling systems for buildings within the district was established. Using this index system, both power load characteristics of space heating/cooling in individual buildings and the coupled power load characteristics of individual buildings within the entire district can be analyzed. Using the GIS platform, the spatial distribution characteristics of district loads could be clearly visualized. The differences in both time and space among various types of buildings can be very useful for power deployment within the district. Finally, using the principal component analysis method, buildings with significant contributions to the overall district load would be identified, according to their load characteristics.

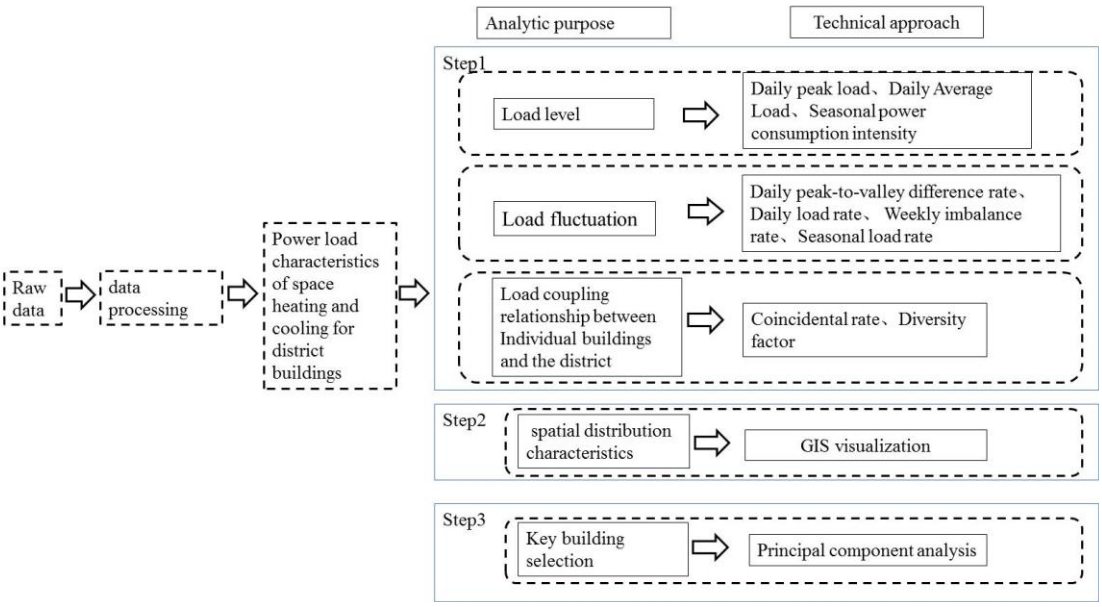

Fig. 1. Spatial-temporal characteristics analysis method of power loads for heating/cooling in district buildings

2.1. An index system for analyzing power load characteristics of space heating/cooling in district buildings

An index system representing characteristics of district power loads for space heating/cooling is shown in Table 1, based on a comprehensive literature review [3-12, 19]. When analyzing power load characteristics, load level needs to be firstly identified. Mean hourly power load is a basic index to assess the power load magnitude, while peak load is important for determining district power supply capacity. Seasonal power consumption intensity is an important index for evaluating energy consumption of space heating. Therefore, in this system, load level was determined by three indices, namely, daily peak load, daily average load and seasonal power consumption intensity. Besides load level, another main feature of power loads is load fluctuation, as it can provide useful information for equipment operation optimization, power grid dispatching and peak load shaving. Four indices, i.e. daily peak-to-valley difference ratio, daily load rate, weekly imbalance rate and seasonal load rate, therefore, would be identified to analyze load fluctuations at different time periods. Daily peak-to-valley difference rate could be used to represent load fluctuation within a day, with a larger value for a greater load fluctuation. Daily load rate reflects the balance of load distributions during the day, with a larger value for more evenly distributed load during the day. Weekly imbalance rate depicts changes in daily peak load during the week, with a greater value for a smaller load fluctuation during the week. Seasonal load rate could be used to analyze volatility of hourly load throughout the heating/cooling season, with a larger value for a smaller seasonal load fluctuation. The above two types of indices can reflect load size and its variation features for both individual buildings and the whole district from the perspective of time dimensions. Besides this, it is also important to decouple the relationships between the loads of individual buildings and the total district load. Coincidental rate and diversity factor are two important indices to reflect the degree of load coupling of individual buildings and the district. The coincidental rate is the ratio of individual building load at the moment of district peak load to its own peak load. It is used to characterize the consistency between the peak load moment of each building and the district peak load moment. The larger the value is, the more consistent the two peak load moments are, giving a higher degree of the coupling between the two. The diversity factor is the ratio of the total peak load of each building to the district peak load. The smaller the value is, the more concentrated the peak load time of each building is, and the greater the fluctuation of district load is. Regarding to this index, a higher value indicates the energy consuming behavior in each building varies larger in time, with smaller district load fluctuations accordingly.

Table 1: An index system to analyze power load characteristics of space heating/cooling in district buildings

Categories	No.	Indices	Index definitions
Load level	I	Daily peak load	Maximum hourly power load in the typical day of the heating/cooling seasons
	II	Daily Average Load	Mean hourly power load in the typical day of the heating/cooling seasons
	III	Seasonal power consumption intensity	Total power consumption per unit area during the heating/cooling seasons
Load fluctuations	IV	Daily peak-to-valley difference rate	The ratio of the difference between the maximum and the minimum hourly power loads to the maximum hourly value in the typical day
	V	Daily load rate	The ratio of mean hourly load to the maximum hourly load in the typical day

	VI	Weekly imbalance rate	Ratio of the average of the daily maximum hourly power load to the maximum hourly power load in the typical week
	VII	Seasonal load rate	Ratio of average hourly power load to the maximum value of the heating/cooling seasons
Load coupling relationship	VIII	Coincidental rate	The ratio of individual building load at the moment of district peak load to its own peak load.
	IX	Diversity factor	Ratio of the sum of the maximum hourly power load of each building to the maximum hourly power load of the district

2.2. Analysis on spatial characteristics of power loads of space heating/cooling in district buildings using the GIS system

GIS systems are a kind of data management system with professional spatial forms. The GIS technology integrates map visualization effects and geographic analysis functions with general database operations, to provide functions like data storage and query, statistics, analysis, display and forecasting. Spatial location data, attribute feature data and time domain feature data constitute the three basic elements of geospatial analysis. Making the best use of a large number of buildings within a district and the huge amount of field monitored power load data for space heating/cooling, it is a robust way to establish a district building model within the GIS system, which can instantaneously display time-domain characteristics of power loads and provide basic information for district power dispatch and operations.

2.3. Selection of key buildings using principal component analysis

The indices proposed in this study for identifying power load characteristics of space heating/cooling included load level, load fluctuation and coupling relationships between the loads of single buildings and the total district load. The three types of indices have their own emphases and the information reflected by the indices must be analyzed together so as to fully reveal actual characteristics of district loads. Using the principal component analysis method [20], a set of complex correlation variables (i.e. the above load characteristic indices) were converted into a few independent variables through linear combinations. In this way, information provided by these indices could be maximized by eliminating overlapped information and leaving major indices for a detailed analysis.

3. Data Acquisition and Process

3.1. Case study

The selected university campus was located in a climate with hot summer and cold winter in China. The annual precipitation level was high with limited solar radiation. Average annual temperature was varying between 15.9°C and 17.0°C. For summer, the outdoor design temperature was 31.6°C, with relative humidity of 64%, and for winter, the outdoor design temperature was -2.4°C, with relative humidity of 76% [21]. It was a comprehensive university with a total of seven campuses located in different cities, and this study has selected one campus for the case study. The campus mainly contained four types of buildings, i.e. teaching buildings, research buildings, offices buildings and dormitories, with a total building area of 255,724m2. Detailed information about the investigated buildings is provided in Table 2. Electricity is the sole energy resource for all the space heating and cooling systems in these buildings.

Table 2: Buildings under investigation

Buildings	Total area (m^2)	Year of construction	Heating and cooling systems	Heating and cooling area (m^2)	Building types
A	15269	2007	Split heat pump	10180	Academic bldg.
B	20511	2005	VRV	12780	Academic bldg.
C	37500	2001	Split heat pump/VRV	11880	Academic bldg.
D	21157	2006	Split heat pump	14750	Teaching bldg.
E	40795	2001	Centralized all air System	18799	Teaching bldg.
F	37500	2001	Split heat pump/Centralized heat pump system	11435	Academic bldg.
G	14000	2004	VRV	8250	Office bldg.
H	46592	2006	VRV	24300	Academic bldg.
I	5600	2002	Split heat pump	2088	Dormitory
J	5600	2002	Split heat pump	2088	Dormitory
K	5600	2002	Split heat pump	2088	Dormitory
L	5600	2002	Split heat pump	2088	Dormitory

3.2. Data acquisition and processing methods

The university has installed a building energy monitoring platform on the campus. From 2008, the electricity used for space heating and cooling has been monitored and recorded hourly for each building within the campus. This study used hourly electric load data of space heating collected within a whole winter period between October 2016 and March 2017.

The processing of raw data exported from the energy monitoring platform revealed the following types of outliers [22]:

(1) Short-term continuous zero values: this was often due to power-off caused by

maintenance, monitoring equipment failures etc. ;

(2) Individual zero value: a single zero value occurred in consecutive non-zero values, which may be due to data transmission failures;

(3) Load glitches: a sudden increase or decrease of adjacent values, may be caused by a failure of monitoring equipment or data processing error;

(4) Consecutive mutations: the value increases or decreases over a continuous period of time.

The existence of abnormal values will cause deviations in the analysis results. Because of the large sample size of this study, it was impossible to filter outliers manually. To tackle this, the Local Outlier Factor (LOF) [23] method was adopted to identify and process existing outliers in the raw data for this study. The LOF method is an outlier monitoring algorithm proposed by Breunig, on the basis of data density differences. When using this method, the reachability distance of two data points *q, p*, defined as $reach\_dist_k(q,p)$, is calculated by Equation (1),

$$reach\_dist_k(q,p)=max\{dist_k(p),dist(q,p)\} \quad (1)$$

Where, $dist_k(p)$ is the K distance between data point p and its kth nearest data; $dist(q,p)$ is the Euclidean distrance; and $dist(q,p)\leq dist_k(p)$.

The reciprocal of the average reachable distance of the defined data q to data k is the local reachable density. Then the local reachable density of point q, namely *lrdk (q)*, is,

$$lrd_k(q)=\frac{k}{\sum_{p\in KNN(q)} reach_{\_dist(q,p)}} \quad (2)$$

Where *KNN(q)* is the k-adjacent set of point q.

Finally, the outlier degree of point q, namely $LOF(q)$, is the average of the ratio of the k-adjacent reach density of q to the reachable density of point $q,$ and the equation is as follows,

$$LOF(q) = \frac{\sum_{p \in KNN(q)} \frac{lrd_k(q)}{lrd_k(p)}}{k} \tag{3}$$

If the LOF value is much bigger than 1, it means that the density of point q is very different from the overall data density, and data point q is considered as an outlier. The closer to 1 the LOF value is, the more normal the point q is.

Based on the calcuation results of outlier degree of the data in this case study, existing outliers in the raw data were identified by the rule that LOF is larger than 3. For those continuous zero values appearing in the data, they were replaced by the energy use data under similar meteorological conditions. For other abnormal values, they were corrected by linear regressions.

4. Data Storage and Calculation of District Power Loads of Campus Buildings in the GIS System

As one type of GIS systems, ArcGIS has the capability of storing data, analyzing data and then visualizing the results. All kinds of data could be imported into the ArcGIS, and be categorized and stored with concept of layers. For example, the building with its geographic coordinates and geospatial information can be imported into the ArcGIS as one layer, and data regarding to the building's performance and electricity use can be imported into the ArcGIS as another layer. These data can be considered as attributes for different buildings, expressed as attribute tables, where datasets could be integrated, transformed and aggregated. By joining or uniting datasets with common characteristics, data for the same kinds of buildings could be integrated into one single table. Data transformation and aggregation including calculation or statistics are necessary steps to analyze the collected preliminary data, and the processed results could be created as new attributes to be visualized through the ArcGIS.

All geospatial information for the buildings within the selected university campus has been imported into the ArcGIS. After filtering collected data for heating consumption, hourly electricity consumption for space heating all campus buildings were imported and stored into the ArcGIS as well. In Fig. 2, the original hourly data measured from October 2016 to March 2017 for the electric load of space heating were stored in the table and were then analyzed by ‘summary statistics’. Therefore, the electric load of space heating in any hour during the measurement period could be spatially displayed for all buildings in the ArcGIS. What is more, the indices discussed in Part 2.1 were also calculated by either built-in functions or simple programming in the ArcGIS based on the corrected data measured from the buildings. In this situation, both spatial distribution and dynamic variation of the electric loads of space heating for all campus buildings under investigation could be visualized, combined with the developed index system and GIS technic.

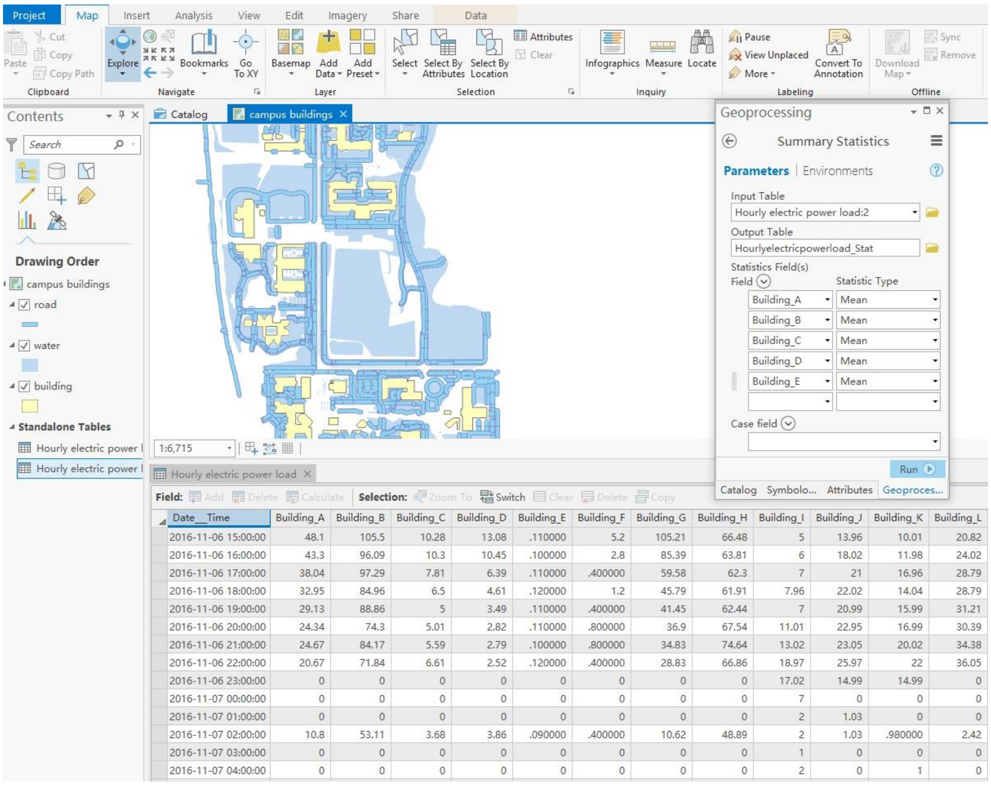

Fig. 2. The storage and analysis interface of original data in the ArcGIS.

5. Analysis of Spatial-temporal Characteristics of Space Heating Electric Load for all Campus Buildings

The GIS system stored all corrected raw hourly data of electricity consumption by individual buildings, for the whole winter period under investigation. As a case study to demonstrate the spatial-temporal characteristics of electric load of space heating in campus buildings, typical-day data were selected for the index analysis in this part. The date with maximum hourly electric load in the heating season was selected as a typical day, and the week with the typical day was defined as a typical week to represent the building's maximum load level in the entire heating season. To exclude extreme values caused by extreme weather conditions and accidental factors, The slip averaging method is used to calculate the maximum load in the heating season, which was defined as the maximum of the rolling average of three-hourly loads [24].

The slip averaging method considers n data and uses the mean value of adjacent m data (m=2n+1), namely f_n, to replace the original data of y_n, and compose a new dataset noted as N_f, so as to effectively eliminate errors in the data, as shown in Equations (4) - (6) [24].

$$N = \{y_n\} \tag{4}$$

$$f_n = \frac{1}{2n+1}\sum_{i-n}^{i+n} y_i \tag{5}$$

$$N_f = \{f_n\} \tag{6}$$

5.1. Characteristics of electric load levels for space heating

The index system detailed in Section 2 was used to analyze the electric load characteristics of space heating for campus buildings, and results were visualized using the GIS technology, as shown in Fig. 3 to Fig. 5.

Fig. 3 depicts the campus buildings' daily peak electric load for heating in the winter typical day. The daily peak electric loads of academic buildings were much higher than other building types, and for Buildings H, C, F, and B the values were 418.7kW, 265.38kW, 259.85kW, and 254.44kW respectively; the Office Building G reached 209.41kW; The Teaching Buildings E and D had values lower than those of the first two types of buildings, with 154.79kW and 79.27kW respectively; the daily peak loads of dormitories were the lowest, with values between 98.19kW and 53.19kW.

Fig. 4 analyzes the campus buildings' daily average electric load for heating in the winter typical day. It seems like that the average daily loads of different types of buildings differed significantly. Academic Buildings had a mean value of 164 kW; Office Building went up to 114.96kW; Teaching Buildings and Dormitories had lower mean values, which were 65 kW and 36 kW respectively. Both daily average electric load and peak load for heating are mainly related to the installed capacity, the hourly usage rate and the types of space heating systems, with the installed capacity also related to the floor area of the buildings. Larger floor area normally needs larger installed capacity. The centralized heat pump system includes both water and air systems, besides heating sources, and hence the electric load was higher than that of split heat pumps. The investigated academic buildings usually have larger floor area and centralized heat pump system, and these resulted in their higher daily average electric load and higher peak load. On site investigations also found that the internal heat gain in winter in teaching buildings was high, due to their high occupancy density; and the students were also used to wear much clothes in winter; the two reasons led to the lower hourly usage rate in teaching buildings, and hence the two indices were found to be relatively lower for teaching buildings. Dormitories also had low values due to their smaller floor area and installed split heat pump systems.

Fig. 5 depicts the seasonal electricity consumption intensity of campus buildings in winter. Academic buildings had the highest electricity use intensity in winter, with the mean value ranging between 28.91 and 16.96 (kW·h)/m^2, followed by office buildings. The electricity consumption intensity of dormitories had values between 19.17 and 13.88 (kW·h)/m^2, lower than the first two types. The lowest value was found for teaching buildings, with electricity use intensity of 6.87 (kW·h)/m^2 and 3.55

(kW·h)/m^2 for Buildings E and D, respectively. The difference in the electricity use intensity was obvious among different building types, but was relatively smaller among the same type of buildings. Reasons behind may be academic buildings had the longest operational time and high comfort level, controlled by occupants themselves, leading to their highest energy consumption. Electricity consumption from dormitories was low because students paid their electricity bills by themselves, which may lead to a more economical use of energy. Teaching buildings had the lowest energy consumption, which may because of their limited use of heat pumps and shorter usage in winter due to the winter holiday. Additionally, some departments, such as the logistics department, have installed central management systems for heating their teaching buildings, and this measure effectively helped to avoid energy waste.

In summary, according to the above three indices, the level of electric load of space heating was the highest for academic buildings, followed by office buildings. The electricity consumption intensity of teaching buildings was lower than that of dormitories, but its daily peak load and daily average load were higher than those of dormitories. This reflects that although the peak load of teaching building was high when being used, the electric consumption intensity for the entire space heating season was the lowest among all building types, due to the limited use in the winter vacation. Therefore, analysis based on electric consumption intensity only cannot effectively determine the building's load level. The identification work should consider other indices as well.

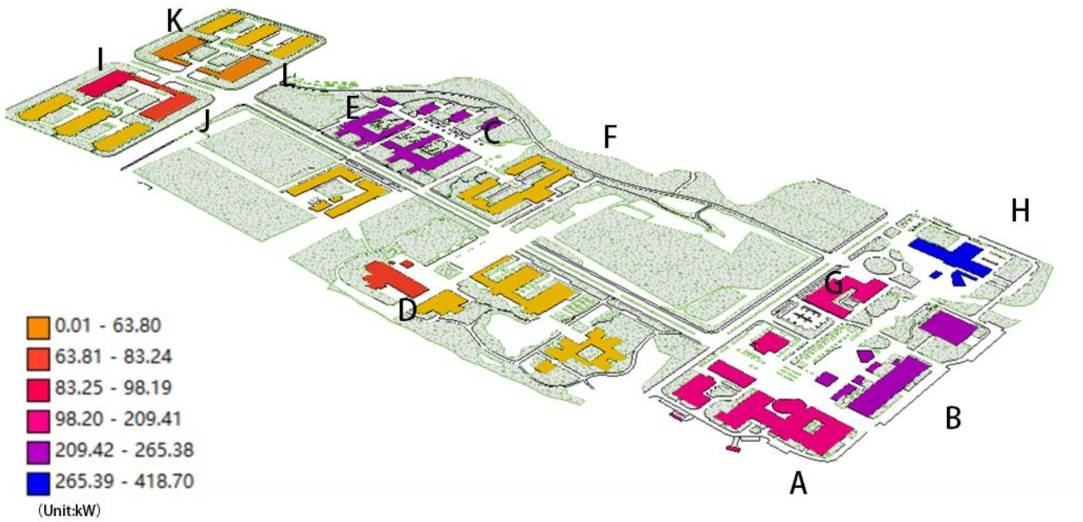

Fig. 3. Daily peak load of space heating in campus buildings in winter.

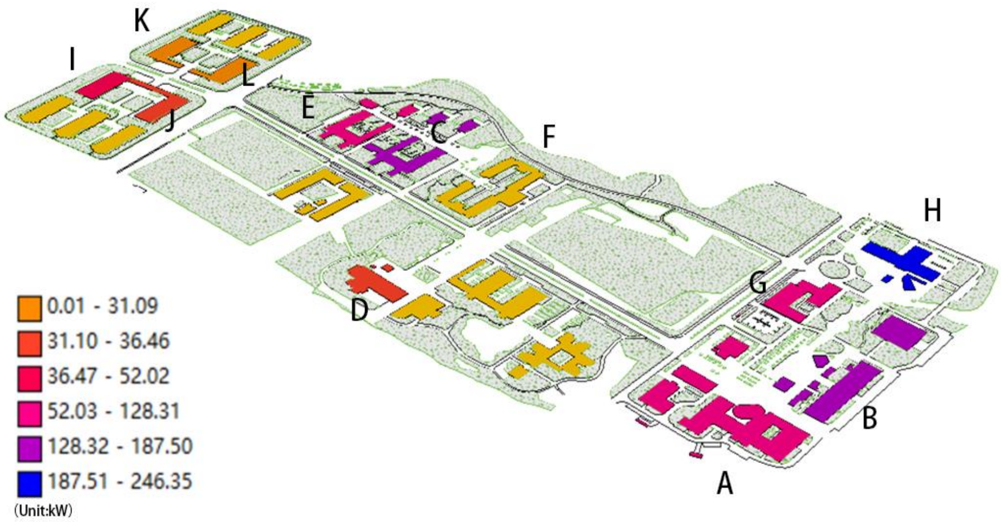

Fig. 4. Daily average load of space heating in campus buildings in winter.

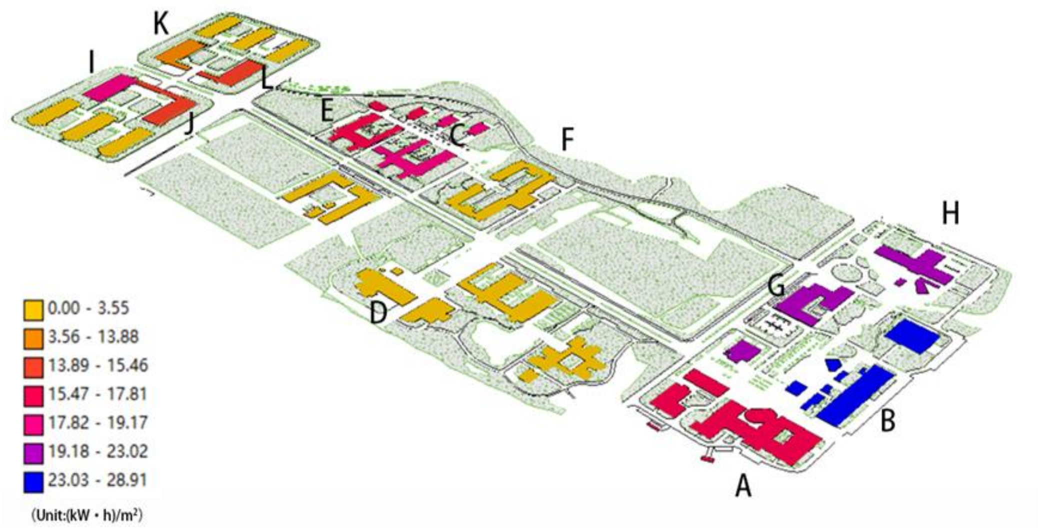

Fig. 5. Seasonal electricity consumption intensity of space heating in campus buildings in winter.

5.2. Characteristics of space heating electric load fluctuation of campus buildings

The characteristics of electric load fluctuation of space heating for campus buildings are shown in Fig. 6 to Fig. 9.

The daily peak-to-valley difference rate was used to reflect the daily load fluctuation, with a bigger value for a greater load fluctuation. Fig. 6 analyzes the daily peak-to-valley difference ratio of electric load of space heating for the investigated campus buildings. Ranked according to the index of daily peak-to-valley difference ratio, a descending order of the buildings in winter was obtained, i.e. domitories, teaching buildings, office buildings and academic buildings. The daily peak-to-valley difference rate of dormitories was close to 1.00, and Dormitories L, K, J, and I had values of 1.00, 1.00, 0.99 and 0.93, respectively. This is mainly because students would reduce the use of heat pumps by wearing more clothes in winter to reduce energy consumption and save money, leading to a winter peak-to-valley difference of nearly 1.00. The values for Teaching Buildings D and A were 0.88 and 0.85; Office Building G was 0.80; Academic Buildings F, E, H, C and B were 0.83, 0.79, 0.77, 0.71 and 0.56, respectively. The operational mode and outdoor air temperature had important influences on the peak-to-valley difference in buildings. Out-of-usage during the nighttime for teaching buildings caused sudden decrease in space heating electric load to nearly zero, hence resulting in a significant peak-to-valley difference. In dormitories the difference between the daily peaks and valleys in winter was high as well, and the electric load fluctuations of space heating in dormitories was varying with the time.

The daily load rate reflects the uniformity of the daily load, with a larger value for a more uniform hourly load distribution within a day. Fig. 7 analyzes the daily electric load rate of heating systems in the campus buildings in winter. In all types of buildings, the daily electric load rate of academic buildings in winter was highest, with values between 0.74 and 0.57, whereas the fluctuation of electric load was smallest. The value of Office Building G was 0.55; teaching buildings and dormitories were low as well, ranging between 0.53 and 0.42. Academic buildings showed high values, and teaching buildings and dormitories showed low daily load rates, and the reason is similar to that for the peak-to-valley difference rate.

The weekly imbalance rate reflects the volatility of the maximum load for each day of the week. The greater the value is, the smaller the daily peak load fluctuation in this week is. Fig. 8 analyzes the weekly imbalance rate of electric load for space heating in the investigated campus buildings. The imbalance rate for research buildings was the highest, ranging from 0.85 to 0.71; Office Building G reached 0.78; dormitories and teaching buildings were slightly lower, i.e. between 0.76-0.64 and 0.74-0.65, respectively. The variance of daily loads in one week is related to the operation schedules in different days, and the load difference between weekdays and weekends has become an important factor affecting this index. Various types of campus buildings had different operational schedules. Academic buildings were always occupied with researchers and graduate students, and many of them had additional work during the weekends, so the load difference between weekdays and weekends was smaller than other building types, hence with small load fluctuation but high weekly imbalance rate. The load of teaching buildings was high in weekdays, but reduced significantly during weekends. Therefore, teaching buildings had lower weekly imbalance rate.

The seasonal load rate reflects the electric load fluctuation for the entire space heating season. The larger the value is, the smaller the volatility is. Fig. 9 analyzes the seasonal load rate of electric load for space heating in the investigated campus buildings. Office buildings and academic buildings had high seasonal load rates and small fluctuations in electric load of space heating. Among them, Office Building G had maximum seasonal load rate, which was 0.84, and Academic Buildings A, H, B, F and C had seasonal load rates of 0.83, 0.82, 0.82, 0.78 and 0.72, respectively. The winter load rates for Teaching Buildings E and D were 0.73 and 0.67, respectively, and the values for dormitories were between 0.62 and 0.54. The difference in seasonal load rates for the same type of buildings was not significant in winter. The seasonal load rate is related to the operation of space heating systems in the heating season, affected by both duration of usage and hourly load. Comparing to the other two types of buildings, both hourly usage rate and usage period of heat pumps in research buildings and office buildings were higher in winter. Researchers and students, especially postgraduates, often had shifts at night and long-time work even in the winter holiday period, with a requirement of using heat pumps to provide comfortable indoor environment. Some scientific research studies needed to be conducted 24 hours a day, resulting in long-time usage for space heating. All of these led to the relatively smaller fluctuations in hourly load of the space heating. Teaching buildings and dormitories had either low usage rate or short usage period or both during the winter vacation, resulting in a low seasonal load rate.

Based on the above analyses, it can be found that the fluctuation of electric load for space heating is highly correlated with the operational modes of the building and its heating systems. Among the four types of campus buildings investigated, academic buildings and office buildings had smaller daily, weekly and seasonal electric load fluctuations, comparing to teaching buildings and dormitories.

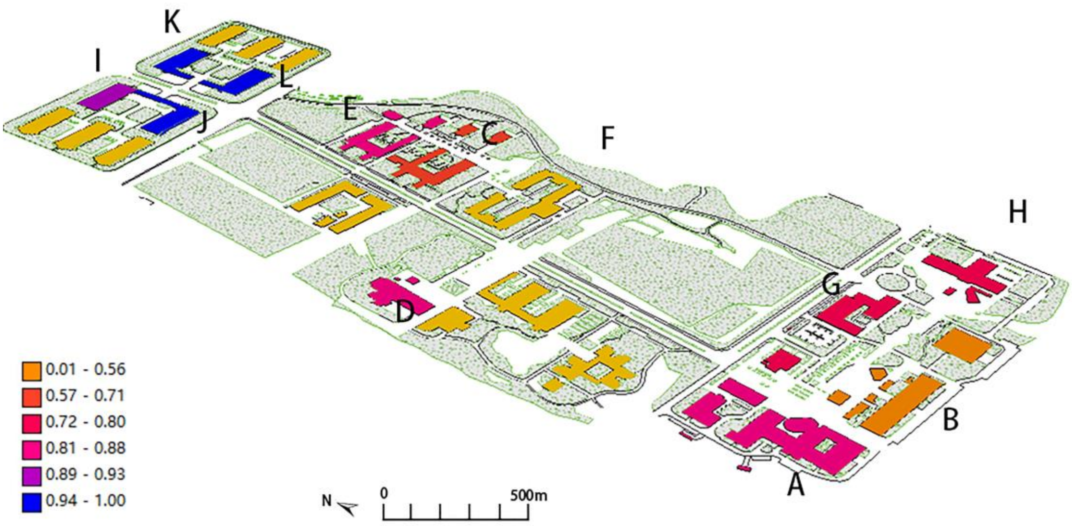

Fig. 6. Daily peak-to-valley difference ratio of space heating in campus buildings in winter.

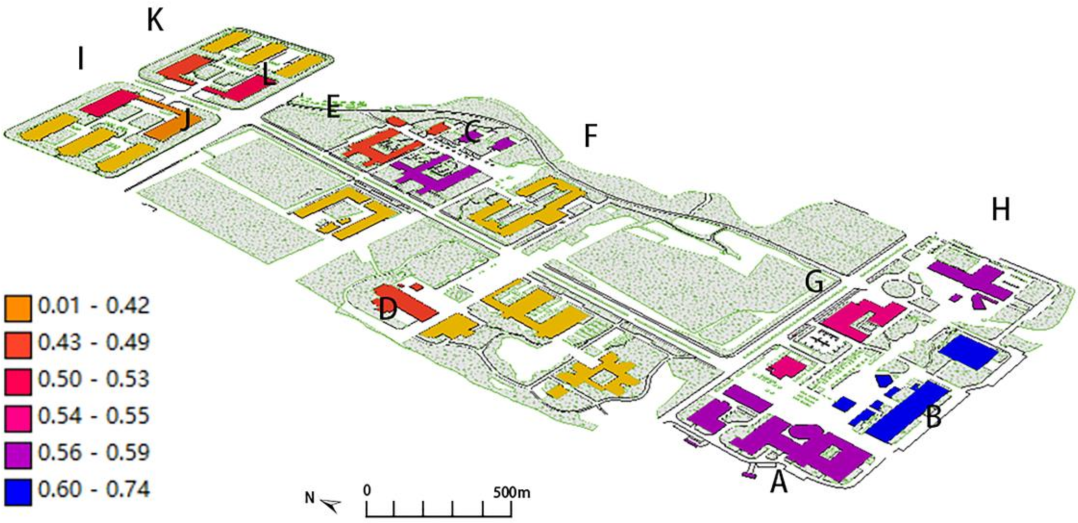

Fig. 7. Daily load rate of space heating in campus buildings in winter.

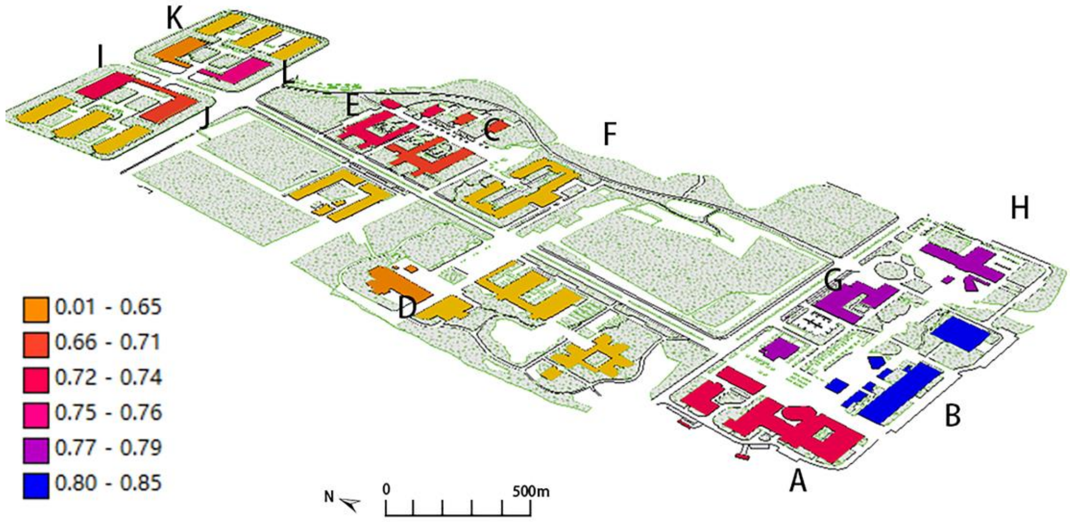

Fig. 8. Weekly imbalance rate of space heating in campus buildings in winter.

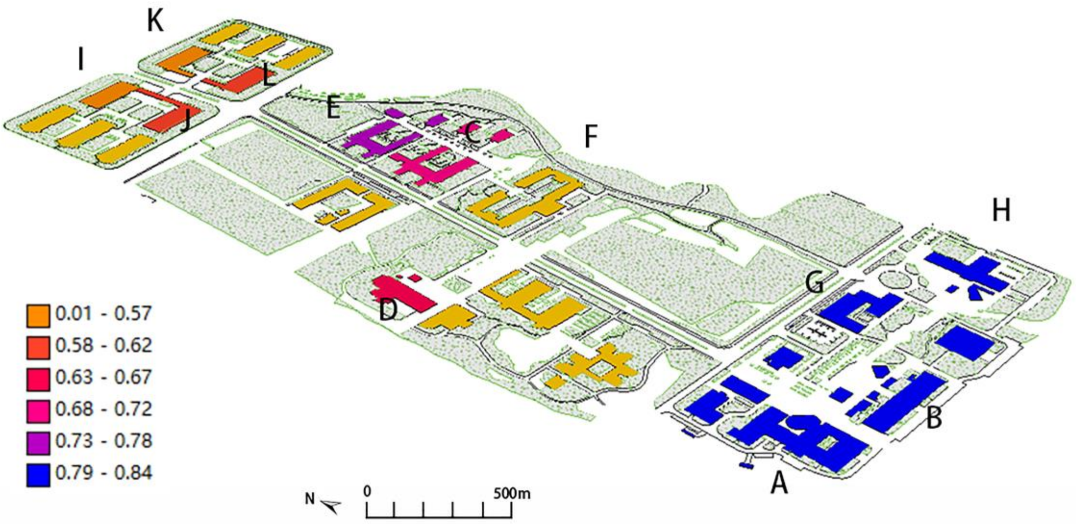

Fig. 9. Seasonal load ratio of space heating in campus buildings in winter.

5.3. Coupling characteristics of electric load of individual buildings to total district load

The coincidental rate reflects the occurrence consistency of the peak electric load of space heating for individual buildings and the peak district electric load of space heating. The larger the value is, the more consistent occurrence of the peak load of individual buildings and the peak district load. As shown in Fig. 10, the coincidental rates of Academic Buildings A, F, B, C and H were 0.94, 0.87, 0.86, 0.75 and 0.67, respectively, in winter, and Office Building G reached 0.90. For Dormitories I, L, K and J, the values were 0.76, 0.60, 0.57 and 0.54, respectively. The lowest coefficients were found in Teaching Buildings E and D, which were 0.42 and 0.30. This shows that the peak loads of academic buildings and office buildings make great contribution to the district peak load. The load reduction of these two types of buildings would have larger effect on reducing the district load and installation capacity of power grid. On the contrary, dormitories and teaching buildings helped to shave the peak district heating load.

During the winter period, the measured peak load on the campus was 1874kWh, while the sum of peak loads from each building was 2121kWh, with a diversity factor of 1.13 for winter.

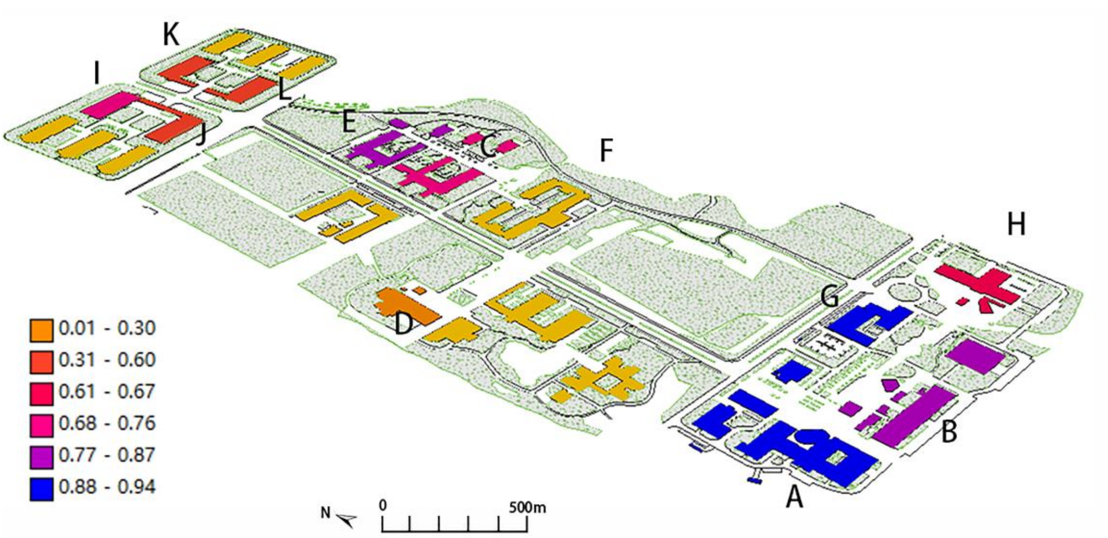

Fig. 10. Coincidental rate of campus buildings in winter.

6. Selection of Key Campus Buildings Using Principal Component Analysis

6.1. Analysis method

Based on the analyzed electric load characteristics of space heating from campus buildings, the principal component analysis method was used to identify key buildings with big influences on the district load, and these buildings would deserve more attentions for energy-saving renovation, optimization of operations and district power dispatch.

In the principal component analysis method, it is assumed that there are n samples and j variables ($j<n$), and the original data matrix, $X=[X_1, X_2, X_3, \ldots, X_j]$, consists of j vectors [19]. The covariance matrix of X is noted as Σ, and the eigenvalues of the covariance matrix are named λ_i. Arrange the eigenvalues in a descending order, i.e. $\lambda_1 \geq \lambda_2 \geq \lambda_3 \ldots\ldots \geq \lambda_j \geq 0$, and their corresponding eigenvectors are $\grave{e_i}$, $i=1,2,\ldots,j$.

Then a linear combination could be proposed, as defined in Equation (7),

$$PC_i = X\grave{e_i} \qquad i=1,2,\ldots,j \qquad (7)$$

PC_i is the i^{th} principal component, and its value is the score of the i^{th} principal component. e_{1i}, e_{2i}, e_{3i}..., e_{ji} are the loads of the i^{th} principal components respectively, and these loads form the load vector $\grave{e_i} = (e_{1i}, e_{2i}, e_{3i}..., e_{ji})^T$. The principal components are arranged in a descending order corresponding to the values of the eigenvalue of λ_i, namely the first principal component, the second principal component, and the i^{th} principal component.

Basic principles of the main component analysis method are: 1) using the z-score (zero-mean normalization) method, the values of X are normalized, so as to eliminate the influences of dimensions and magnitudes; 2) finding the dimensionless correlation coefficient matrix R; 3) obtaining the eigenvalues, eigenvectors and contribution rates of R; 4) determining the number of principal components based on the amount of information contained in each principal component. The variance of the linearized combination is considered as an index to evaluate the amount of information contained within it. The larger the variance is, the more information the principal component contains. Therefore, PC_1, PC_2, ..., PC_i are sorted in the descending order of variances, and are referred to as the first principal component, the second principal component, and the i^{th} principal component. The x% criterion judges the required number of principal components according to the threshold accumulated by the interpretation ratio of the principal components' variances [25]. According to empirical evidence, when the threshold is 80%-85%, the extracted principal component can retain enough information in the original variables. In this study, the number of principal components was determined when the threshold value reached more than 80%; 5) explaining the meaning of the principal component factors, which are usually determined by indices with large weights; 6) calculating the score of each principal component, which is the main component score for each building. In the model used in this study, the samples were the buildings under investigation, and the variables were the indices, and the index values for each building formed the matrix *X*. For the overall evaluation of the building load characteristics, this study has adopted the Prcomp function in the R software to calculate the *PC*, which is a linear combination of evaluation indices. According to the x% criterion, the number of main components extracted in winter was 2, with a cumulative value of proportion higher than 80%.

6.2. Analysis results

The load of each principal component and the score of each building were calculated from the index values, and the biplot of the principal components in winter is shown in Fig. 11. In this figure, the bottom axis and the left axis are the first and the second principal component score axes, respectively, and the top axis and the right axis represent the load values of the first and the second principal components. Letters A-L represent individual buildings under investigation. Its projections on the top axis and the right axis indicate the scores of the building as the first and the second principal components. The red Roman letters and arrows represent each index. The projections of the arrow on the bottom axis and the left axis are the load values of the indices in the first and the second principal components. A positive load indicates that the principal component is positively correlated with the index, and a negative value means the opposite. The influences of different indices on the principal components is measured by the absolute values of the load values of the indices, that is, the distance from the load value to the origin. The closer to the origin, the smaller the influence of the index value on the sample building's score.

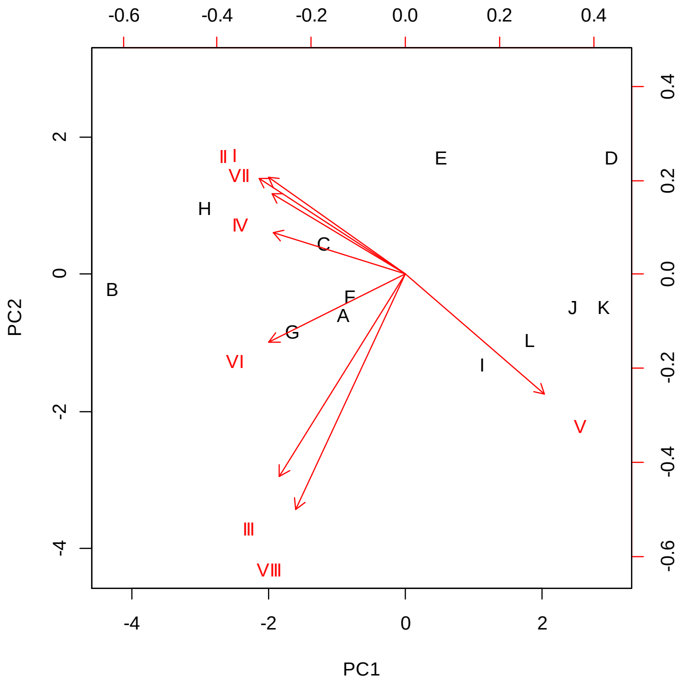

Fig. 11. Biplot of principal components in winter.

Fig. 11 shows the biplot of principal components to reveal the electric load characteristics of space heating for campus buildings in winter. It shows that the score of first principal component was positively correlated with the daily peak-to-valley difference rate, and was negatively correlated with other indices such as the seasonal load ratio and the weekly imbalance ratio. The greater the daily peak-to-valley difference rate was, the smaller the seasonal load ratio and the weekly imbalance rate were, the greater the load fluctuation was, and the greater the score of the first principal component was. Therefore, the first principal component could be used to reflect load fluctuations. Further analysis found that first principal component scores were also negatively correlated with daily peak load and daily average load. The larger the daily peak load and the daily average load were, the higher the load level was, and the smaller the score of the first principal component was. Considering the score of each building, Dormitories I, J, K, L and the Teaching Building D had large load fluctuations and low load levels in winter. Academic Buildings B and H had low winter load fluctuations and high load levels.

There was a negative correlation between the second principal component and the indices of seasonal electricity consumption intensity of heating systems in winter, as well as for the coincidental rate. The absolute load values of the two indicators were greater than the other indicators, which had greater impact on the second principal component. The higher the seasonal electricity consumption intensity was, the greater the coincidental rate was; the larger the contribution of the single building to the district load was, and the smaller the score of the second principal component was. Therefore, the second principal component could be used to reflect the contribution of each single building to the district power load. It can be seen that the Office Building G and Academic Buildings A and B contributed a lot to the district load in winter. The Dormitory I within the dormitory group contributed much to the electric load of space heating in winter, while Teaching Buildings D and E contributed less.

Combining the first and second principal component scores, it could be found that the Teaching Building D had low power load in winter, large load fluctuation and little contribution to the district power load. Dormitories J, K and L had large load fluctuations and low load levels. Hourly load variance of domotories and teaching buildings are greatly different from academic buildings and office buildings. The peak hour of domitories usually ocuurs at night, and teaching buildings still have the relatively high loads in the evening or even at night, while academic buildings and office buildings usually have large loads during the daytime. So domitories and teaching buildings play a role in load shift of the district. Comparing to other living quarters, the Dormitory I performed a large contribution to the electric load of district heating in winter, hence some regulations on electricity prices and student behavior management can be made to encourage the students in the Dormitory I to shift the energy use behaviors from daytime to the night. The Office Building G contributed greatly to the district electric load, as it had a high load level in both the whole winter period and every week, plus a significant daily load fluctuations. Energy-saving renovation in the building performance and space heating systems are the useful approaches to reduce the load level, while some energy storage technologies, such as phace change material, can be also used to to shift the large peak loads. For Academic Buildings B and H, their space heating load fluctuations were small, but the high load level had a large contribution to the district space heating electric load in winter. Hence, the improvement for both envelope performance and the efficiency of space heating system for the two buildings is meaningful for the reduction of district loads. Besides that, the operation of some experimental machines in these two buildings can be moved from the daytime to the night, to realize the effect of peak shaving and valley filling at a certain degree for the electric load of space heating, if there is no need for the staffs to work during the operation period.

7. Discussion and Conclusions

An in-depth understanding on power load characteristics of space heating and cooling for various types of buildings has an important role in robust design of district power supply capacity and optimal operation of district energy supply systems. The Chinese government has paid a great amount of funding to construct energy use monitoring platforms for large commercial buildings and campus buildings. Unfortunately, the collected power load data have not been deeply analyzed yet, and therefore, the potential contributions from the installed monitoring platforms to both energy conservation management and energy efficiency retrofit have not been fully realized. In this study, an index system representing the characteristics of power loads of space heating and cooling has been developed, covering temporal dynamic characteristics of building loads, load fluctuation characteristics and load coupling relationships between individual buildings and the district load. An ArcGIS system has been used to store and visualize the spatial distribution characteristics of power loads of space heating and cooling. Using the principal component analysis method, buildings with significant contributions to the total district load were identified. Using this energy planning-oriented method, the spatial-temporal characteristics of loads for a district were revealed to help district power supply and dispatch of power grid. Key buildings with large loads or large load fluctuations were identified to implement further energy-saving measures or optimal operation strategies. Combined with this method and the energy use monitoring platform in Chinese universities, energy efficiency management in university campuses could be implemented more effectively in China.

As a case study, the spatial-temporal characteristics of power load of space heating for campus buildings in one Chinese university were analyzed. The results demonstrated that the method developed in this study was able to clearly and accurately reveal the spatial-temporal characteristics of electric loads of space heating for the campus buildings under investigation, and identify the contribution of each individual building to the total district load. Under this condition, through a thorough use of data collected by the energy use monitoring platform within the campus, the newly proposed method was considered as a very useful tool to reveal the load characteristics, and then provide support for energy efficiency management of campus buildings. Based on the analysis results of load characteristics in the case study, academic buildings had the highest load level, plus high peak load and coupling of district peak load. In this type of buildings, some experimental machines would run continuously and staff/students might also work beyond normal working hours. Therefore, the electric load fluctuation of space heating in such type of buildings was smaller, comparing to other types of buildings. High load level was also found in office buildings. Additionally, as most office buildings investigated in this study were not running during the nighttime, large load fluctuations were observed. Their peak loads have shown high degree of coupling with the district peak load. Due to these characteristics, academic buildings and office buildings had greater impact than other building types on both the total and peak electric loads of university campuses, and should be used as key candidates for implementing energy efficiency measures. High-performance envelope is an effective measure to reduce the space heating energy consumption, and the use of efficient space heating systems are also suggested. Some other measures, such as phase change materials, are also helpful to shift the large peak loads in the two types of buildings above. Dormitories and teaching buildings were found to have smaller winter load levels but larger load fluctuations. Both types of buildings have obvious peak-regulating effect on the total district space heating electric load. Besides that, some regulations can be made from the administrative perspective to encourage the faculties and students to reduce the electric load of space heating at the peak time.

To sum up, building types will importantly determine their level of power load, and the buildings' operational mode and usage mode of heating systems have significant impact on their load fluctuations. Peak-shaving effect can be achieved by changing the energy usage modes of the buildings. Additionally, because the power load characteristics of space heating are different for various types of buildings, an appropriate building type ratio would be helpful on reducing the total load and load fluctuation of a district, hence very important for district energy planning. Fig. 12 presents a comparative analysis of the hourly load of individual buildings and the hourly load of the total district on one winter day. It reflects the timely differences between individual buildings and the total district load. Between 7:00-10:00, the Dormitory J kept a very small space heating electric load with a slightly declining trend. The Office Building G, the Teaching Building E and the Academic Building H had their loads rising, and the hourly district load maintained the same trend as those of the Academic Building H and the Teaching Building E. After 10:00, the hourly district load started to decline, but the load of the Academic Building H still kept rising. From 18:00-20:00, both Academic Building H and Dormitory J had loads with a slightly rising trend, while the load of both Teaching Building E and Office Building G decreased, hence keeping the district load steady. The daily load rate for the four Buildings H, G, E, and J were 0.51, 0.42, 0.46 and 0.30, respectively, with the daily district load rate of 0.52. It was found that the appearance moments of peak loads for various types of buildings were not the same, leading to a "filling valley" effect that can effectively reduce both district load fluctuations and peak load. The overall effect on the district load by individual buildings was related to both the load level and the load fluctuation of individual buildings. Additionally, analysis on district load characteristics should not be sorely based on simple cumulative analysis of data collected from single buildings, without considering temporal effect. If the district peak load is obtained by simple add up of peak load of individual buildings, the peak load estimation will be overestimated.

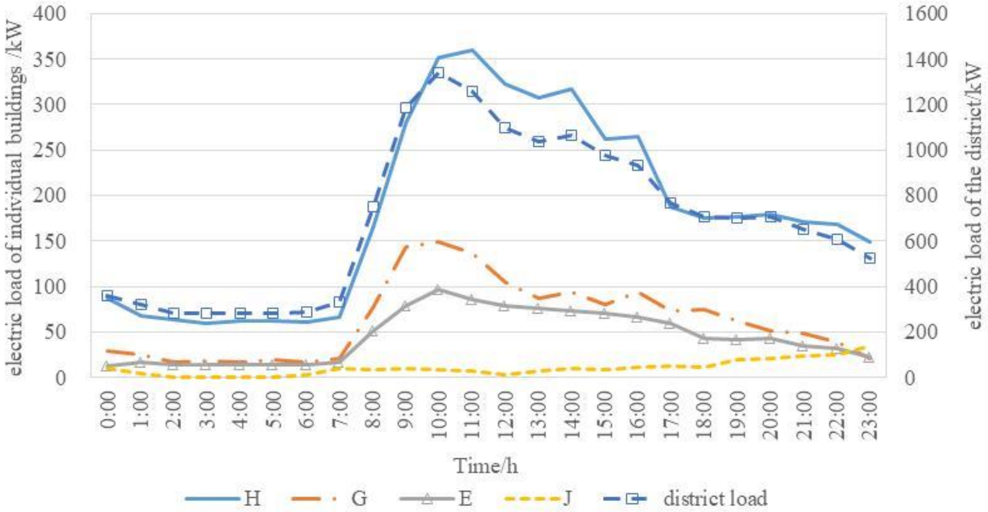

Fig. 12. Comparison of the hourly load of various types of buildings and the total hourly total load of the district in winter.

Finally, using the GIS system, the spatial characteristics of district power load can be effectively stored and visualized. For regions with large load intensity and high peak load, effective scheduling is required when the power demand is large. Because the campus scale is still relatively small, this advantage will be more pronounced for larger administrative divisions or for cities.

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