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Establishment and application of a novel heating load model for building complex： a load based on hybrid mechanistic and data driven approach

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ABSTRACT

Accurate prediction of the heat-side load of a central heating system is of great importance to meet the thermal comfort of users, while saving energy and reducing emissions. Most of the current research reports on load models rarely consider the difference and time-varying of actual user demand room temperature. In this paper, user room temperature is introduced into the heat load model, and a hybrid mechanistic and data-driven approach is used to construct a heat load model for a building complex, including base load, cumulative temperature effects and determination of model parameters, which is applied to two practical engineering cases. The results show that: the relative deviations of the simulated values compared with the actual are all no more than 3% for annual cumulative loads, and no more than 25%, 20%, and 18% for daily, three-days, and weekly loads, respectively. The heat load model in this paper can reflect the demand loads of a building complex at different target room temperatures. By setting the target room temperature values with reference to the design specifications, it is found that both cases have great energy-saving potential, with the annual cumulative load being reduced by 32.2% for case 1 and 62.7% for case 2.

Keywords: building complex; load forecasting model; target room temperature; time-zoning; energy-saving potential

1. INTRODUCTION

With the emergence of network control and management platforms for centralized heating systems, it has become possible to obtain environmental parameters of end-users and equipment operation information, which also extends the horizon of heat load prediction studies for centralized heating systems [1]. Guiding the operation and regulation of the heating system based on heat load prediction can significantly improve the heating effect. For example, a heat supply enterprise in Dalian, Liaoning Province, applied a heat load prediction model to guide the operation regulation, and the complaints of heat users decreased after 20 days of the experiment [2]. The comparison between two similar heat exchange stations of a heating company in Changyuan County, Henan Province, showed that the heat exchange station with the heat load prediction control method saved 15.01% of heat than the one with the second network supply temperature control method [3]. The average energy saving rate during a 5-day test period was 8.2% at a peaking furnace heat station in Ranghu, Daqing, by applying a heat load prediction model to guide operational regulation [4]. Therefore, the study of heat load prediction of heating systems is of great significance to realize intelligent heating.

However, most of the current studies, which do not consider the variation of indoor temperature, usually use the common room temperature of the building for heat load prediction and the heat load of a building complex was predicted for the purpose of operation stability. For example, for heat exchange stations, methods such as BP neural networks [5], wavelet neural networks [6], Elman neural networks [7], and extreme learning machines [8] are commonly used for short-term heat load prediction, and regression methods [9-10] are used for long-term heat load prediction. Heat sources and district heat exchange stations are mainly focused on the centralized effect, and do not take advantage of the technical advantages brought by the newly emerged network control platform for centralized heating systems, thus are not applicable for heat load prediction based on end-user demand.

Assessing the actual energy consumption of buildings is a key issue to guide future energy efficiency efforts or operational regulation of a building complex. Several universities and research institutes have developed a large number of commercial building energy simulation-specific software, such as DOE2.2, EnergyPlus, eQuest, DEST, Blast, and Transys, for commercial transient simulations for energy consumption prediction and energy-saving potential assessment [11-13]. Mao et al. used eQuest to simulate the energy consumption of an office building, and the relative deviation of the simulated annual heating energy consumption from the actual use was -21.1% [14]. Reinhart et al. analyzed the results of building energy simulations for typical buildings in several urban areas, with relative errors of 5%-20% in the annual heat load [15]. For the assessment of energy-saving potential, the following scholars analyzed the energy-saving potential at the envelope level. Lei et al. used EnergyPlus simulation software to analyze the impact of envelope on building energy consumption for a residential building [16]. Chen et al. used Design Builder to quantify the energy-saving potential of the early buildings of Hunan University, and the energy-saving potential of the envelope retrofit was as high as 50% [17]. Fang et al. considered solar radiation and wind speed factors to replace the outdoor air temperature by the integrated ambient air temperature for heating system operation regulation, which can reduce the heat supply of the system to achieve the energy-saving potential with 8.8% to 11.5% for solar resource class I and class II areas [18].

However, most of the current research reports on heat load models rarely consider the variability and timeliness of actual user room temperature demand.In this paper, user room temperature is introduced into the novel heat load model, and a hybrid mechanistic and data-driven approach is used to construct a dynamic building complex heat load model. The novel model can characterize the physical characteristics and actual energy use behavior of buildings and reflect the the demand heat load of a building complex at different target temperatures in a timely and accurate manner. It also analyzes the energy-saving potential from the demand room temperature of demand-side users and provides O&M guidance for energy-saving on the demand side.

2. MODEL AND METHODOLOGY

Sample data are cleaned and processed and the novel heat load model is constructed based on a hybrid mechanistic and data-driven approach considering factors of room temperature variation and the cumulative effect of air temperature.

2.1 Research methodology of this paper

To solve the problem of mismatch between the heat supplied by a building complex and the demand heat load of users, we consider the target demand room temperature of building complex users to match the demand side load, and further introduce the user room temperature into the novel heat load model, based on a hybrid modeling of mechanism and data hybrid-driven approach. The model is also applied to two different building complexes used as case studies to simulate the daily load and deviation analysis of the cases during the heating season. The energy-saving potential analysis of these cases based on the heat load model is carried out to guide the operation regulation of the heating system. Figure 1 shows the framework of this method.

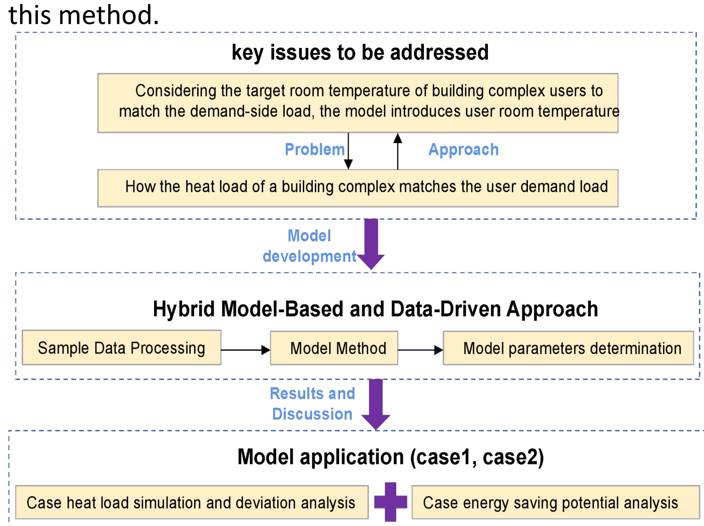


Fig.1 Methodological framework of this study

2.2 Data cleaning and processing

Before modeling, the sample data need to be cleaned and processed to determine the sample of model input parameters. Case 1 and case 2 are used to introduce the method of sample screening. Both are college buildings with almost the same user types, but their heating areas are different. The sample numbers are shown in Tables 1 and 2. Specific steps include: 1) obtain data parameters, including heat load, representative monitoring point room temperature, and meteorological temperature; 2) obtain daily load, indoor daily average temperature, and outdoor daily average temperature (high and low average temperature) by data preprocessing; and 3) obtain parameters at the same time points by data cleaning, where incomplete data are ignored [20].

Table 1. Sample size (2019-2020 heating season, 200,000m^2 heating area) in case 1 study

	Daily load	Average daily indoor temperature	Average daily outdoor temperature
Sample collection	97	89	114
Same time samples	72		
Results of sample screening	50		

Table 2. Sample size (2020-2021 heating season, 240,000m^2 heating area) in case 2 study

	Daily load	Average daily indoor temperature	Average daily outdoor temperature
Sample collection	134	138	138
Same time samples	134		
Results of sample screening	121		

2.3 A mechanism and data-driven hybrid-drive model

A hybrid mechanistic and data-driven approach is used to establish the novel heat load model. The base load model is established according to the equation for calculating the steady-state load of a building, provided by the Heating Engineering [20], as shown below,

$$Q = KF(t_n - t_w) \qquad (1)$$

where Q is the heat load of the building, K is the heat transfer coefficient of the building, F is the heat transfer area of the building, t_n and t_w are the indoor and outdoor air temperatures, respectively.

According to the equation for the temperature distribution inside the wall during cooling of an infinitely large flat wall under the third type of boundary conditions[21], there is a certain decay delay during the conduction of the temperature wave considering the unsteady thermal conductivity of the wall. Fang et al [19] showed that the current heat load of a building is not only related to the current outdoor temperature but also related to the previous outdoor temperature. Zhao et al [22] analyzed the mechanism analysis of meteorological factors affecting the heat load and obtained that the cumulative effect of temperature has a significant effect on the heat load variation.

In this paper, the cumulative effect of temperature and indoor temperature change are considered together to avoid the shortage of single meteorological factor analysis. Then the particle swarm algorithm is used to solve the correction coefficient of the cumulative effect of temperature.

The idea of correction for the cumulative temperature effect is to correct the temperature of the day to be predicted using the weighted temperature of the previous days, calculated as [23],

$$t_x = (1-m)t_w + mt_w - \sum_{i=0}^{p} m^{i+1}(t_i - t_{i+1}) \qquad (2)$$

where i is the *ith* day before the day to be predicted, t_x is the temperature correction value, t_w is the average temperature on the prediction day, t_i is the real temperature i days ago, p = min (n, 3), where n is the number of days that the average temperature is continuously below a certain temperature, and m is the cumulative effect coefficient.

The cumulative temperature cumulative effect coefficient m_i is solved by using the particle swarm algorithm. The optimization process for the particle swarm algorithm is as follows: the initial population is generated randomly; the particle velocity and position are updated by tracking the individual optimal value p_{best} and the global optimal value g_{best}; and the global optimal value is obtained iteratively until convergence. The particle velocity and position are calculated as [16],

$$\begin{cases} v^{k+1} = wv^k + c_1 r_1 (p_{best}^k - x^k) + c_2 r_2 (g_{best}^k - x^k) \\ x^{k+1} = x^k + v^k \end{cases} \qquad (3)$$

where v^{k+1} and v^k are the particle velocities at the (*k+1)th* and *kth* iterations, respectively; x^{k+1} and x^k are the particle positions at the (*k+1)th* and *kth* iterations; w is the inertia weight; c_1 and c_2 are the learning factors; and r_1 and r_2 are random numbers between 0 and 1.

For the parameters of the heat load model, we first determine the model input parameters following the sample data cleaning and processing step. then the function f_1 (t_n, t_w) with respect to the load and temperature difference is fitted by a least squares curve, and the deformed formula (2) are substituted into the f_1 function denoted as f_1 (t_n, m_i). Finally the particle swarm algorithm is used to identify the correction factor for the cumulative effect of temperature to solve for the temperature cumulative effect correction coefficient and to further obtain the heat load model with the highest degree of fit between the sample daily load and the corrected indoor and outdoor temperature difference. Figure 2 shows the block diagram of the heat load model.

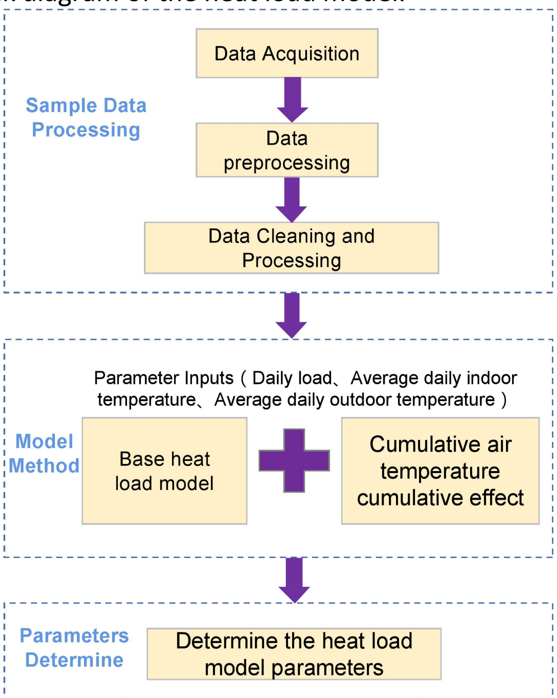


Fig.2 Block diagram of heat load modeling

3. CASE APPLICATIONS

3.1 Simulation results based on the novel heat load model for building complexes

According to the novel heat load model, two different cases for the building complexes are considered. Case 1 (the heating area is 200,000m^2 for the 2019-2020 heating season) and case 2 (the heating area is 240,000m^2 for the 2020-2021 heating season) are university building complexes with the same user type and different heating areas. User types of two cases are shown in Figure 3, including experimental workshops, internship bases, dormitories, research offices, and canteens.

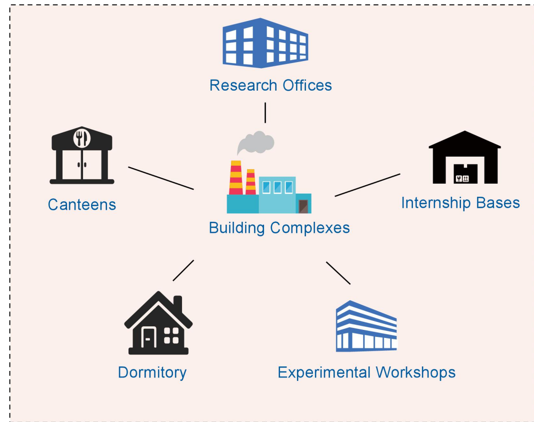
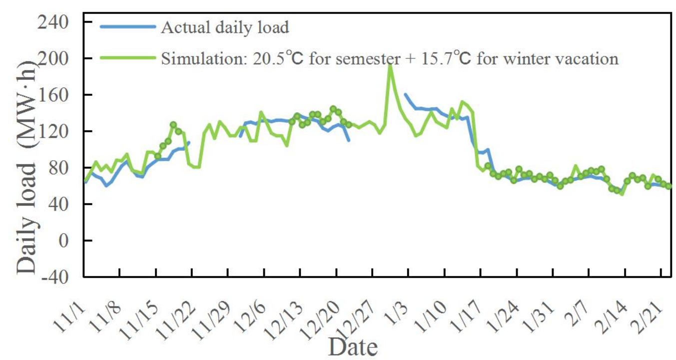
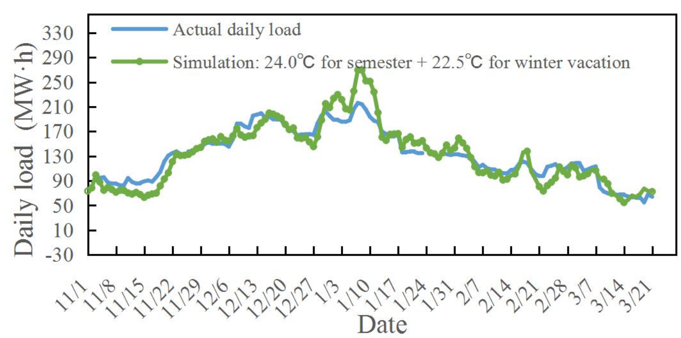


Fig.3 Schematic diagram of building complex user types

Figure 4 shows the actual daily loads and simulated loads for case 1 and case 2. The model room temperature characteristics for the actual operational simulation can be obtained from the calculated mean values of the representative room temperatures selected to characterize the building complex. Case1 model room temperature characteristic values (20.5°C for semester and 15.7°C for winter vacation) and case 2 model room temperature characteristic values (24.0°C for semester and 22.5°C for winter vacation) are substituted into the calibrated heat load models for different case samples to simulate the actual daily load.



(a) Case 1



(b) Case 2

Fig.4 Actual daily load and simulated load for the two simulated cases (case1: 2019-2020 heating season, 200,000m^2 heating area, case2: 2020-2021 heating season, 240,000m^2 heating area)

Comparing the annual cumulative load simulated by the model with the actual, there is a relative deviation of 2.3% between the simulated and actual values for case 1 and 0.01% for case 2. Reinhart et al. analyzed the results of building energy consumption simulations for a number of typical urban building areas, and the relative deviation of the annual heat load is 5%-20%[15]. Mao et al. simulated the annual heating energy consumption of an office building with a relative deviation of -21.1% from the actual[14]. The results show that this new daily load model for building complexes simulates annual cumulative loads well.

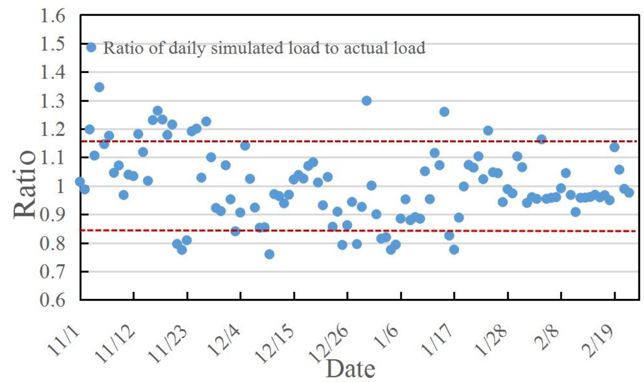
The ratio of simulated load to the actual load for different time scales (daily, three days, and one week) is shown in Fig. 5 and Fig. 6. The red dashed lines in the figures refer to the samples with relative deviations of no more than 15%. In both cases, the samples with relative deviation of no more than 15% for different time scales account for more than 75%, and the samples with relative deviation of no more than 15% for weekly cumulative load account for more than 89%. The relative deviation of the annual cumulative load in both cases is less than 3%.

Table 3 shows the range of the ratio of simulated load to actual load for 90% of the samples in the two cases. It can be seen that the relative error between the simulated and actual values is less than 20% for 90% of the samples with time scales of three days and one week in case 1 and case 2, which meets the engineering requirements. The error level is within the maximum error range specified in the ASHRAE Guideline 12-2002 for the energy consumption results of a single building, therefore the energy consumption of the building complex is acceptable. In addition, the larger the time scale is, the smaller the ratio range of 90% of the samples is, and the more accurate the simulation results are.

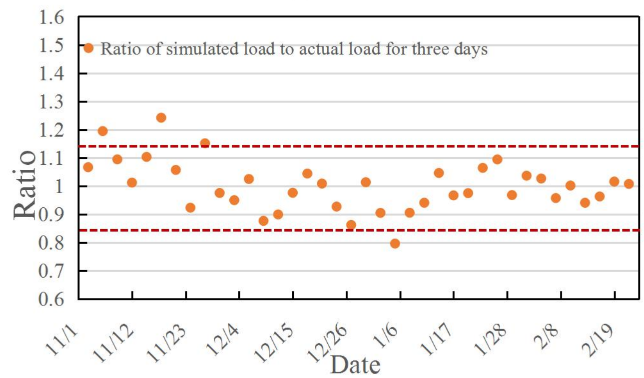
The results show that the larger the time scale, the less the load simulation results will be affected by the cumulative effects of building, system inertia and temperature, thus, the more accurate the simulation results will be. It can be used for load forecasting for the next three days, one week, one month, etc. The start and stop of heat source units and the adjustment of the operation mode of the heating system can be considered three days, one week or one month in advance, so that reasonable and effective heat network index prediction and heat network regulation can be made in advance, and the annual cumulative load prediction can assess the energy-saving space for the next year for operation and maintenance guidance.

Table 3. Ratio of simulated load to actual load (90% of samples, case1: 2019-2020 heating season, 200,000m^2 heating area, case2: 2020-2021 heating season, 240,000m^2 heating area)

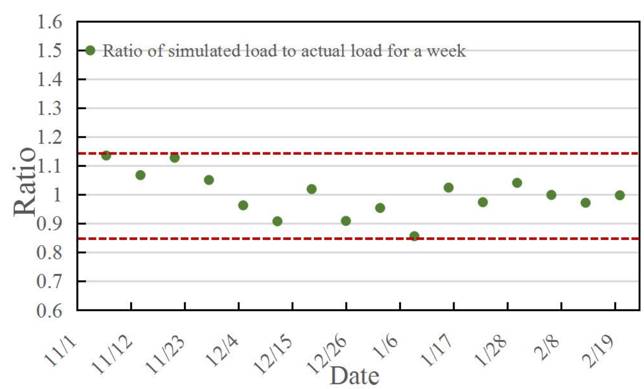
	Daily	Three days	Week
Case 1	0.79-1.21	0.87-1.15	0.908-1.12
Case 2	0.766-1.22	0.80-1.17	0.823-1.123



(a) Daily

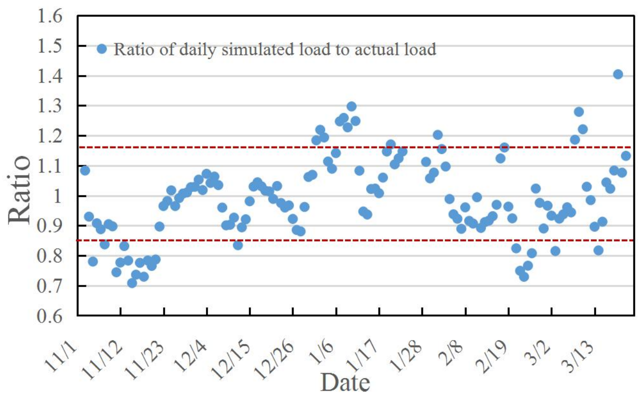


(b) Three days

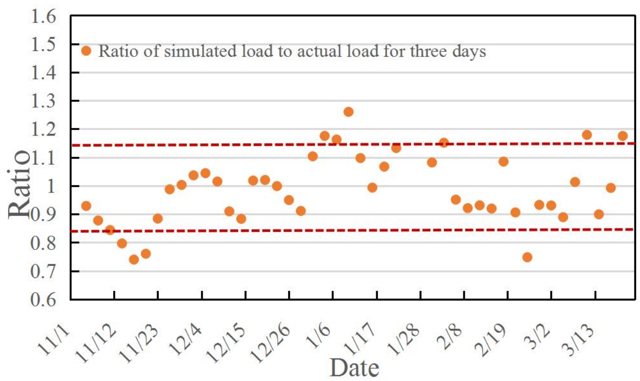


(c) Week

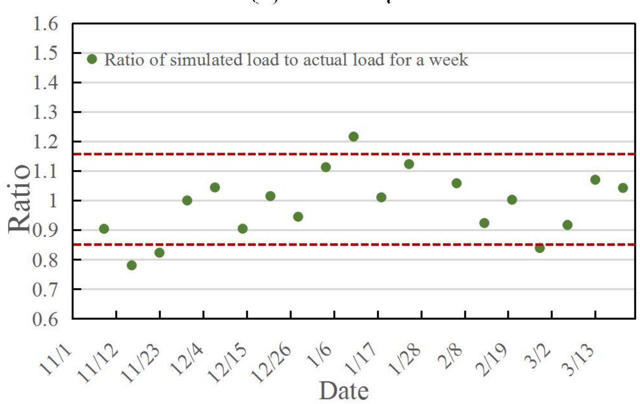
Fig.5 Ratio of simulated load to actual load under different time scales (daily, three days, one week) for case 1 (2019-2020 heating season, 200,000m^2 heating area)



(a) Daily



(b) Three days



(c) Week

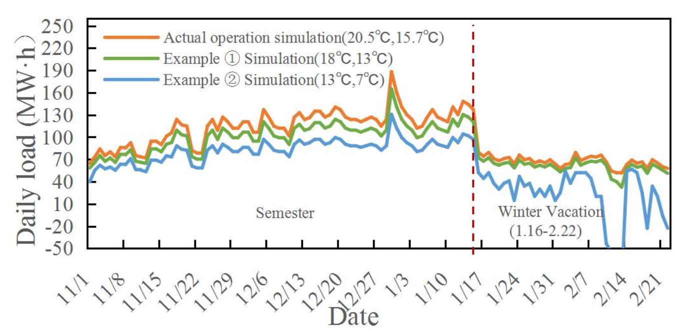
Fig.6 Ratio of simulated load to actual load under different time scales (daily, three days, one week) for case 2 (2020-2021 heating season, 240,000m^2 heating area)

3.2 Analysis of energy saving potential

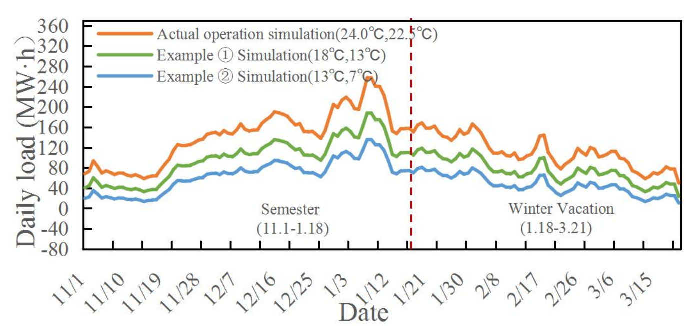
Readers are referred to the design specification on how to set the room temperature target value, use the model described above to calculate the demand daily load, carry out energy-saving potential analysis and guide the heating operation regulation related to case 1 and case 2 studies.

According to the actual operation simulation, the case 1 model room temperature characteristic value is 20.5°C in the semester and 15.7°C in the winter vacation, and the case 2 model room temperature characteristic value is 24.0°C in the semester and 22.5°C in the winter vacation. The daily load of case 1 and case 2 were calculated using the room temperature characteristic value of 18°C in the semester and 13°C in the winter vacation as example ① and 13°C in the semester and 7°C in the winter vacation as example ②. Shown in Figure 7 are the daily load curves corresponding to the actual daily load simulated values and the set values, for case 1 and case 2 building complexes, respectively.

Figure 8 shows the ratio of the simulated total cumulative load to the actual cumulative load in different examples for cases 1 and case 2. In case 1, the simulated cumulative load can be reduced by 11.5% compared to the actual operating simulated load in example ① (18°C in the semester, 13°C in the winter vacation), and the simulated cumulative load can be reduced by 32.2% compared to the actual operating simulated load in example ② (13°C in the semester and 7°C in the winter vacation). In case 2, the simulated cumulative load can be reduced by 40.8% compared to the actual operating simulated load in example ① (18°C in the semester, 13°C in the winter vacation), and the simulated cumulative load can be reduced by 62.7% compared to the actual operating simulated load in example ② (13°C in the semester and 7°C in the winter vacation).

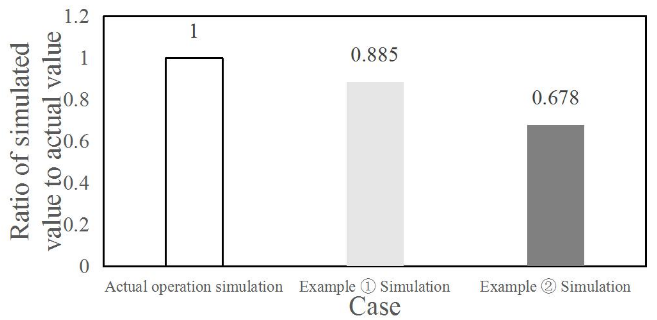


(a) Case 1

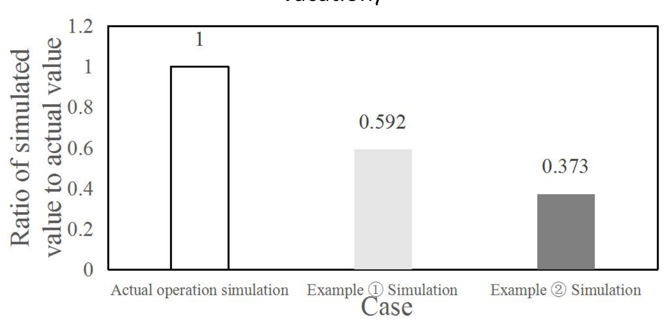


(b) Case 2

Fig.7 Actual daily load simulation and set value daily load curve for case building complex (case1: 2019-2020 heating season, 200,000m^2 heating area, case2: 2020-2021 heating season, 240,000m^2 heating area)



(a) Case 1
(Actual operation simulation: 20.5°C in the semester and 15.7°C in the winter vacation, Example ① simulation: 18°C in the semester, 13°C in the winter vacation, Example ② simulation: 13°C in the semester and 7°C in the winter vacation)



(b) Case 2
(Actual operation simulation: 24.0°C in the semester and 22.5°C in the winter vacation, Example ① simulation: 18°C in the semester, 13°C in the winter vacation, Example ② simulation: 13°C in the semester and 7°C in the winter vacation)

Fig.8 Ratio of the simulated total cumulative load to the actual cumulative load for the different examples in case 1 and case 2 (case1: 2019-2020 heating season, 200,000m^2 heating area, case2: 2020-2021 heating season, 240,000m^2 heating area)

4. CONCLUSIONS

In this paper, user room temperature is introduced into the novel heat load model, and a hybrid mechanistic and data-driven approach is used to construct a heat load model for building complexes, and two cases of university building complexes with the same user types and different heating areas are used as examples for model evaluation and analysis. The main findings are as follows:

(1) The simulated loads in the two case models are compared with the actual for deviations, the samples with relative deviations of no more than 15% for different time scales accounted for more than 75%,and the samples with relative deviation of no more than 15% for weekly cumulative load account for more than 89%. The relative deviation of the annual cumulative load in both cases is less than 3%.

(2) The larger the time scale, the less the load simulation results are affected by building, system inertia and cumulative temperature effects, thus the more accurate the load simulation results are. It can be used for load prediction for the next three days, one week, one month, etc., so that reasonable and effective heat network index prediction and heat network regulation can be made in advance.

(3) The novel heat load model in this work takes into account the differences in the actual demand of the users' room temperature and the time-varying effect to predict the demand load of a building complex at different target temperatures, and provides guidance for the supply demand in operation and maintenance, which is conducive to satisfying the users' thermal comfort and maximizing energy saving and emission reduction at the same time.

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