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Application of LSTM to Determine the Water Supply Temperature in Central Heating Systems

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ABSTRACT

Based on the heat demand of users, adjusting the water supply temperature and regulating the heating system can achieve matching the heat dissipation of heat dissipation equipment of heat users with the demand heat load of users and prevent energy wastage caused by high room temperature. This paper proposes a model and method for determining the water supply temperature of heat sources based on load and flow constraints for specific engineering cases, and uses LSTM deep neural network and multiple regression to simulate and analyze the water supply temperature. The results show that the deviation of LSTM is 7.22% compared to the actual value, which is much lower than the 18.20% of multiple regression.

Keywords: LSTM, multiple regression, water supply temperature model, regulation, central heating system

1. INTRODUCTION

Heat loss arising from uneven heating and cooling is one of the common problems in the operation and regulation of central heating systems in China. It is basically caused by the inability of flow and water supply temperature to change accurately in response to changes in customers' demand for load [1]. In order to ensure the quality of the heat supply and to meet the demand of the heat users, the heat supply system needs to be regulated for heat supply. The operational regulation of central heating involves quantitative regulation, which changes only the flow of the heating system, and qualitative regulation, which changes only the temperature of the water supply [2] . This paper focuses on the qualitative regulation of the heating system. The current common practice of calculating the water supply temperature is to draw a heating curve based on data or by building a mathematical model based on the heat transfer equation. For example, Wang et al [3] and Jin et al [4] set a heating curve in a heating boiler control system so as to regulate the boiler discharge temperature according to the outdoor temperature. Jie et al [5] built a mathematical model of the water supply temperature based on the heat transfer equation. Bolonina A et al [6] built a mathematical model of a district heating system for cogeneration to regulate the water supply temperature.

However, with the development of smart heating technology, more and more scholars have applied artificial intelligence methods to water supply temperature simulation and prediction. Currently, neural networks such as BP [7, 8], Elman [7] and RBF [9] have been used for water supply temperature modelling. Hu et al [7] established a BP water supply temperature model with a MAPE of 5.66% and an Elman water supply temperature model with a MAPE of 4.32%. Bu et al [9] established a water supply temperature model based on RBF and improved it. In addition, Li et al [10] proposed a water supply temperature prediction model based on tensor distance. Li et al [11] obtained the optimized setting value of water supply temperature on the primary side based on DHP algorithm. Laakkonen L et al [12] used an adaptive algorithm modeling to cut the peak heat load and optimize the water supply temperature. Fan et al [13] used Tensok for coupled hydraulic-thermal simulation and calculated the water supply temperature on the primary side. The existing water supply temperature models based on neural networks and

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other artificial intelligence techniques are trained and predicted using samples from the same heating season.

Long Short-term Memory (LSTM) neural networks have been used to predict the heat load of heating systems. The water supply temperature is related to the heat load [2]. Xue et al [14, 15] point out that the heating load has time characteristics on three time scales, namely hourly, daily and weekly, and constructed a heat load prediction model based on LSTM neural network. Xu et al [16] learned the intrinsic connection of the heat load in the time dimension based on LSTM models and made short-term prediction of the heat load. By comparing 12 models, Wang et al [17] found that LSTM model was the most accurate model for predicting heat load in deep networks. Considering the advantages of LSTM in time prediction and the characteristics of time series prediction[18], this paper proposes that the LSTM model can be trained with samples from historical heating seasons to predict the water supply temperature for the next heating season.

The aim of this study is to establish a water supply temperature model based on LSTM deep neural network. Under the flow constraint, the demand water supply temperature is calculated based on the demand load, so as to regulate the heating system and save energy while meeting the heating demand.

2. MODEL AND METHOD

2.1 Research methodology

In this paper, in order to realize on-demand heating and avoid energy waste caused by the mismatch between supply and demand in heating systems, a rolling model based on LSTM deep neural network was established for the water supply temperature of heat stations [14, 19, 20] and applied to the centralized heating system of a university to verify its validity by comparing the model value with the actual value. The framework of the method is shown in Figure 1.

2.2 Regulation of the heating system

Qualitive regulation of the heating system is to keep the same amount of circulating water in the system while changing the water supply temperature, so that the heat dissipation of heating customers' cooling equipment adapts to the changing law of customer demand for heat load, in order to prevent heating customers from experiencing too high or too low room temperature, resulting in a waste of energy. As can be seen from Figure 2, there is a relationship between the water supply temperature and the heat load. Gustafsson et al [21] indicate that the water supply temperature and the flow of circulating water are the easiest to control, so a heating system operation regulation strategy can be developed based on these two heating parameters [5].

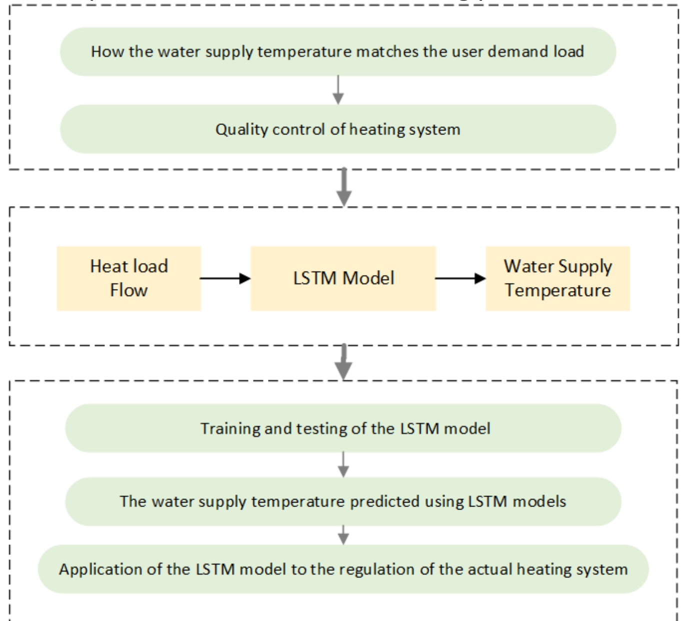


Fig.1 Methodological framework of this study

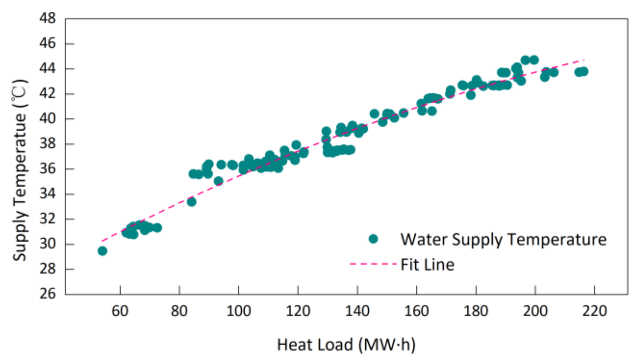


Fig.2 Correlation between water supply temperature and heat load

2.3 LSTM neural networks

Traditional RNN recurrent neural networks have been used to reduce the learning difficulty and prevent gradient explosion due to gradient concatenation during gradient backpropagation [18, 22, 23]. The LSTM is still computed according to the input layer X and the output h of the previous hidden layer, and its internal structure is shown in Figure 3.

Gates in the LSTM model can selectively control the flow of information, and there are three kinds of gates: forgetting gate ft, input gate it, and output gate O_t. It usually consists of a sigmoid neural network and a point-wise multiplication operation. σ function has an output of 0 to 1, which is consistent with off and on in the physical sense when the output is 0 or 1; tanh has an output of -1 to 1, which is consistent with the 0-centred feature distribution in most scenarios, and the gradient converges faster than the σ function as it approaches 0 [22]. The optimal (U, W, b) parameters of the three gates (forgetting gate, input gate, output gate) in the LSTM deep neural network model are obtained by continuous self-learning and correction through sample training, testing and sample rolling prediction for calibrating the model[23].

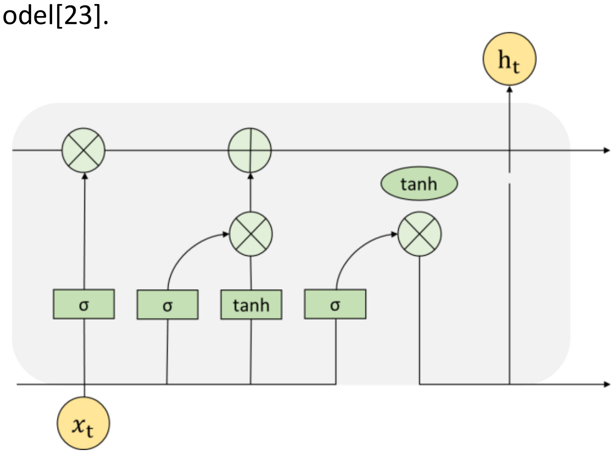


Fig.3 Internal structure of LSTM deep learning neural network

2.4 Establishment of the LSTM water supply temperature model and evaluation criteria

2.4.1 Data pre-processing

Taking the energy station of a university in Tianjin as the research object, various monitoring data such as water supply temperature, instantaneous flow and actual heating load were obtained from the intelligent heat network control platform with an interval of 6 min for data collection. The median average filtering algorithm was used to smooth the water supply temperature within 1 d by noise reduction. The average of the maximum and minimum values was taken as the water supply temperature for the day after removing the series data within 1d [16].

2.4.2 Establishment of the LSTM water supply temperature model

The LSTM water supply temperature model was built with inputs of heat load, flow, actual water supply temperature and time, and outputs of predicted water supply temperature. The model was trained and tested on a rolling basis every 7 days, and the corresponding (U, W, b) parameters in the three gates of the LSTM model were continuously corrected to obtain the optimal (U, W, b) parameters for calibrating the model. The logic training diagram of LSTM deep neural network is shown in Figure 4[24].

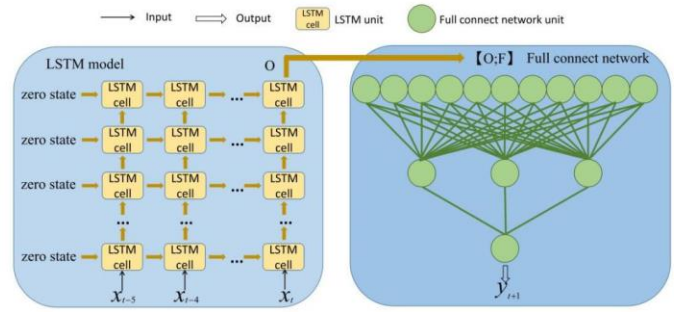


Fig. 4 Logic training diagram of LSTM deep neural network

2.4.3 Evaluation criteria for the LSTM water supply temperature model

The commonly used evaluation criteria for the water supply temperature model are mean absolute percentage error (MAPE) and mean absolute error (MAE)[14], which are calculated by the following equations.

$$MAPE = \frac{1}{N}\sum\left|\frac{Y_{pi}-Y_{ri}}{Y_{ri}}\right| \times 100\% \qquad (1)$$

$$MAE = \frac{1}{N}\sum\left|Y_{pi} - Y_{ri}\right| \qquad (2)$$

3. RESULTS AND DISCUSSION

3.1 Training and testing of the LSTM model

The proposed LSTM water supply temperature model was applied to a university energy station, as shown in Figure 5, for the heating season 2020-2021, supplying 112 d of valid data, with the first 84 d of samples by time series as the training set and the last 28 d of data as the test set.

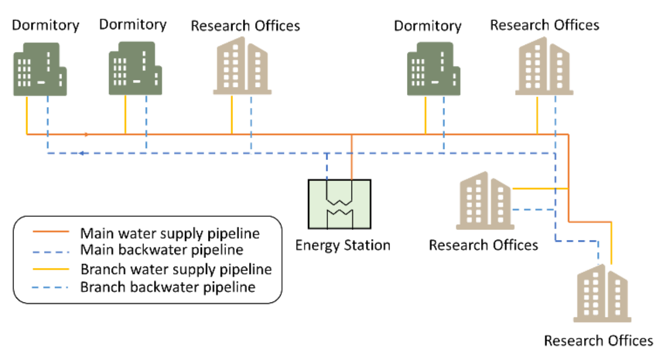


Fig.5 Simplified physical model of the central heating system

The actual operating load and flow of this energy station for the heating season 2020-2021 are shown in Figure 6, and the parameter ranges of the training and test sets are listed in Table 1.

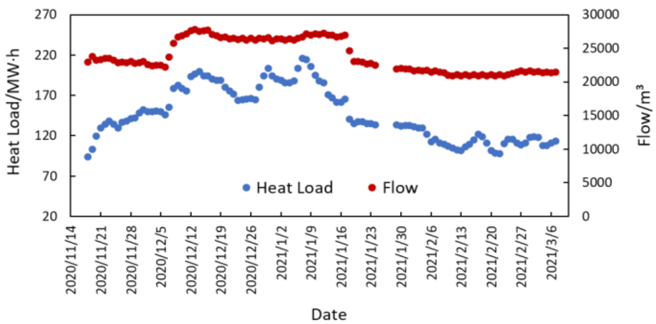


Fig.6 Actual heat load and flow (2020-2021 heating season)

Table 1 Parameter ranges for the train and test sets

Sample	Heat Load/MW·h	Flow/m³	Actual Water Supply Temperature/℃
Train	85.6~216.2	21484~27826	35.0~44.7
Test	69.8~121.1	20644~21628	31.3~37.5

Figure 7 shows the simulated water supply temperature applied to the LSTM water supply temperature model for this case with a MAPE = 1.94% and MAE = 0.67. For 90% of the samples, MAPE = 1.56% and MAE = 0.59, within an absolute deviation of ±1°C, as displayed in Table 2. Figure 8 (a) shows the absolute deviation of the simulated value from the actual value and (b) shows the ratio of the simulated value to actual value. Table 3 shows the deviation analysis of the simulation results. The deviation between simulated water supply temperature and actual value was within 1°C for 90% of samples using this model, and the deviation of all samples was within 1.5°C. Li Ying Li et al [10] predicted a deviation of 2.08°C between the water supply temperature and the actual one based on the tensor distance model, and found that the proposed LSTM water supply temperature model demonstrated good simulation effect.

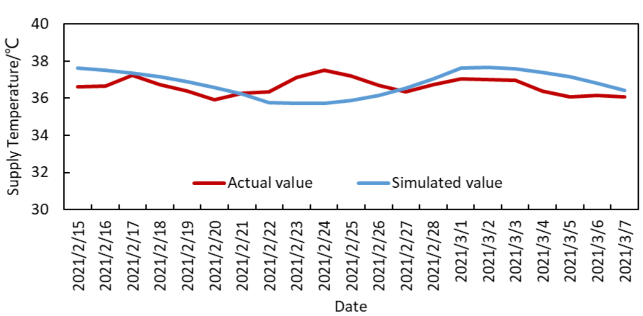
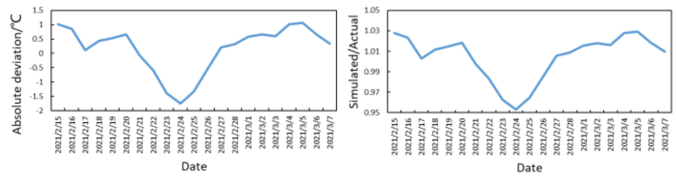


Fig.7 Actual and simulated value



(a) Absolute deviation (b) Ratio of simulated value to actual value

Fig.8 Absolute deviation and ratio of simulated value to actual value

Table 2 Errors in simulation results (2020-2021 heating season)

Sample	All samples	Screened samples (90%)
MAPE	1.94%	1.56%
MAE	0.67	0.59

3.2 The water supply temperature predicted using LSTM models

The proposed LSTM water supply temperature model was applied to a university energy station, with a total of 56 d valid samples for the 2019-2020 heating season as the training set and 113 d valid samples for the 2020-2021 heating season as the test set. The actual operating load and flow of this energy station for the 2019-2020 heating season is shown in Figure 9, and the parameter ranges for the training and test sets are listed in Table 4. The model simulation results were compared to those of a multiple regression water supply temperature model with the same inputs and outputs, as shown in Figure 10.

Table 3 Parameter ranges for the train and test sets

Sample	Heat Load/MW·h	Flow/m³	Actual Water Supply Temperature/℃
Train	54.4~138.4	19297~27038	25.9~40.4
Test	69.8~216.2	19297~27038	31.3~44.7

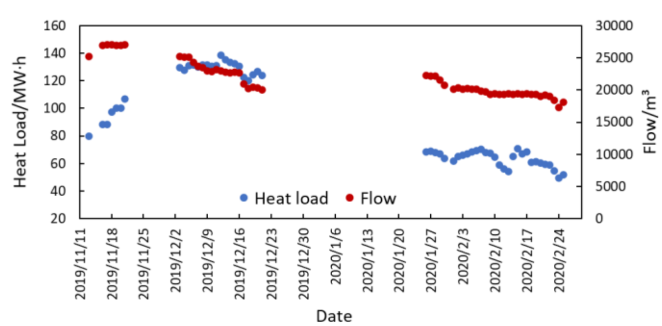


Fig.9 Actual heat load and flow (2019-2020 heating season)

Figure 10 shows the simulated water supply temperatures for the two water supply temperature models being applied to this case versus the actual operating water supply temperatures. For the LSTM model, MAPE = 7.22% and MAE = 2.81; for the multiple regression model, MAPE = 18.20% and MAE = 7.61, as shown in Table 4. As shown in Figure 8, the model error is larger than that of the 2019-2020 heating season due to the serious sample loss, but it is still within the acceptable range, much smaller than the multiple regression model error. Looking at the sample from 2020/12/16 - 2021/1/13, the multiple regression model error was very large when the water supply temperature increased abruptly from 36°C~40°C to 40°C~44°C, and this part of the fluctuation was well predicted when the LSTM model was applied to the case. The results show that the proposed LSTM water supply temperature model exhibits good simulation effect when applying the samples from the historical heating season as the training set to predict the water supply temperature for the next heating season.

Table 4 Errors in simulation results (2020-2021 heating season)

Model	LSTM	Multiple Regression
MAPE	7.22%	18.20%
MAE	2.81	7.61

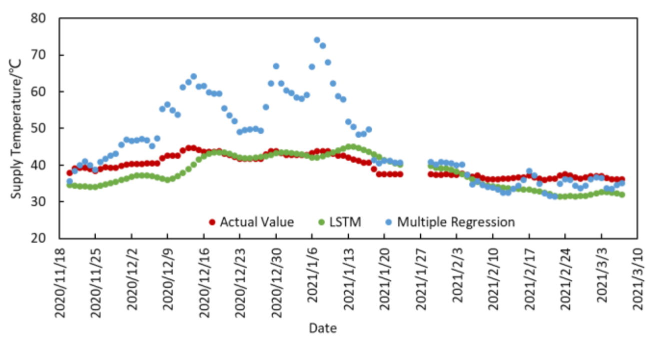


Fig.10 Actual and simulated values (2020-2021 heating season)

3.3 Application of the LSTM model to the regulation of the actual heating system

The proposed LSTM water supply temperature model was applied to this energy station for the heating season 2020-2021 to derive the demand water supply temperature under the actual flow constraints to meet the demand heat load of users, thus providing regulation of the heating system. Figure 11 shows the actual heat load and water supply temperature and demand heat load and demand water supply temperature.

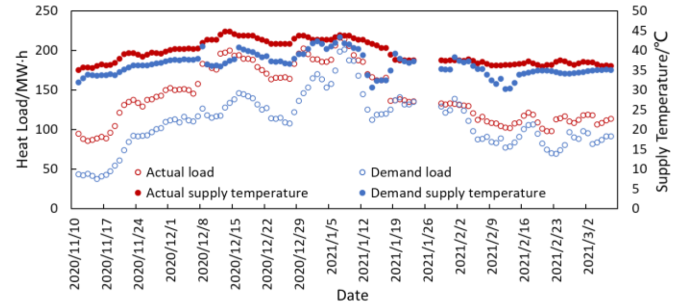


Fig.11 Actual and demand values of heat load and supply temperature

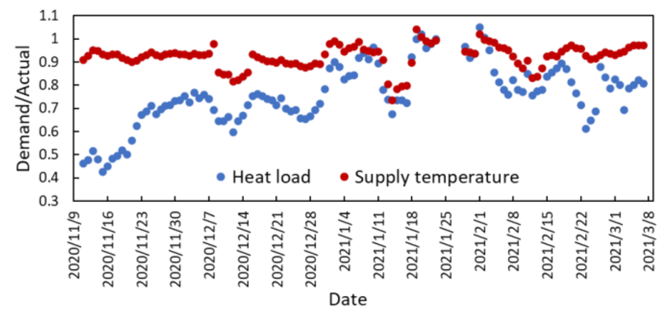


Fig. 12 Ratio of demand load to actual load and demand supply temperature to actual supply temperature (2020-2021 heating season)

Figure 12 shows the ratio of demand load to actual load and the ratio of demand water supply temperature to actual water supply temperature. According to the proposed LSTM water supply temperature model for adjustment of the actual heating system of a university, the water supply temperature was reduced by 7.69%, with an average decline of 3°C; the heat load was reduced by 3811.59MW·h and 23.67% in total, with significant energy saving effect.

4. CONCLUSION

In this paper, a water supply temperature model based on LSTM deep neural network was proposed, and the model was applied to a university energy station and compared with a multiple regression model. The results show that the deviation of LSTM is 7.22% compared to the actual value, which is much lower than the 18.20% of multiple regression.

Under certain flow constraints, the model and method were used to calculate the demand water supply temperature based on the demand load of heat users, so that the heating system was regulated to match the heat supply with the required load of users and save energy while meeting the heat supply demand.

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