THERMAL ENERGY STORAGE THERMAL DATA PROCESSING FOR HEATING SYSTEMS

by

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In order to solve the problem that the traditional industrial control methods cannot control the heating flow and water temperature in a timely and effective manner due to the high delay and complex coupling characteristics of the urban central heating system, the authors propose deep learning-based data processing and management for thermal heating systems. The author analyzes the non-ideality of district heating system and its influence on the application of deep learning technology, and gives solutions, respectively, finally, a primary side regulation scheme of district heating system based on deep learning and automatic control technology is proposed as a whole. The experimental results show that, by comparing the water supply temperature predicted by the equipment model of the primary side heat station with its actual measured value, the mean square error of the prediction results using the model directly is 1.30%, and the mean square error after model correction is 0.094%. The secondary return water temperature was controlled by adjusting the opening of the primary side electric valve, the expected secondary return water temperature in the scheme was compared with the actual secondary return water temperature, and the mean square error was 0.102%. It is proved that the scheme can achieve good control effect in the actual system, and the data result proves that the scheme is feasible.

Key words: *central heating, flow regulation, deep learning, LSTM model*

Introduction

In the traditional district heating mode in the past, such a heating method will not only lead to the waste of heat, but also cause the uneven situation of different district heating [1]. The heating system in most areas uses manual experience combined with temperature meter to analyze the outdoor temperature to judge the heating temperature, this heating method is not accurate enough, and due to the huge amount of heating data, if the data is not analyzed and studied, it will not be good to monitor the heat consumption of the users and the heat supply of the boiler [2].

In terms of heat load prediction of district heating system, the domestic research on data prediction is less than that of foreign countries, and the intelligent construction and system data collection of domestic district heating system start late, so the research on heat load prediction of domestic existing district heating system should receive more extensive attention. Domestic and foreign scholars usually use different shallow neural networks (such as BP neural network, support vector machine*, etc.*) or their combined prediction models to predict the heat load, and the accuracy of the prediction results needs to be further improved. At present, the

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deep learning prediction model has achieved more accurate prediction results in data prediction. At the same time, due to the continuous application of various optimization mathematical algorithms in deep learning, the accuracy of the prediction results of the deep learning model has been further improved. Therefore, the use of the algorithm optimized deep learning model to predict the heat load of the district heating system is more accurate, The predicted value will play a guiding role in the specific operation of district heating system.

On the feature selection of heat load prediction of heating system, using too many input features means that more data will be collected and the calculation speed will decrease. If the input features are insufficient, the model cannot be guaranteed to obtain accurate prediction results. Therefore, reasonable feature selection is an important factor to ensure the accuracy of data prediction. Different prediction models have different selection of features, and it is particularly important to select reasonable features for deep learning prediction models. In terms of optimization of operation parameters of district heating system, algorithms are often used to optimize the heat distribution of various heating equipment in the system, the selection of heating pipe diameter, or the regulation and co-ordination with other auxiliary systems. It is a key problem how to translate the prediction results of system heat load into the design of specific operation parameters of the system. In addition, the GA has achieved remarkable results in the process of system optimization, which can be reasonably applied to the optimization of district heating system.

Literature review

Gao *et al.* [3] improved on the previous network, in forecasting the daytime heat loads of two different district heating systems, by comparing earlier works, it is found that after using non-linear automatic selection for input features, the simple linear model is more accurate to predict the heating load of district heating system users. Aiming at the situation that the input features are not selected by non-linear automatic selection, the author proposes a deep learning model, its prediction results are relatively accurate, the mean absolute percentage error (MAPE) in the first case is as low as 8.77%, in the second case the MAPE was as low as 4.44%. Kindaichi *et al.* [4] studied district heating systems assisted by geothermal heat pumps, by using BP neural network and three different models for comparison, the BP neural network model proposed by the author mainly consists of two-stages, the first has a single level, while the second consists of three levels. According to the prediction results, the maximum error is 3.0092%. The minimum error was 0.0018%. The multi-stage artificial seed network model is summarized and applied in the energy system, the calculation process takes less time. Ma *et al.* [5] created simple algebraic formulas. When combined with traditional weather services, they can predict the temperature on an hourly basis the day after the day before. The model is only estimated based on the historical data of daily average temperature and natural gas consumption, and divides the hourly average natural gas demand into six levels. Consumption at any level at any time is associated with consumption at this level at a particular time. In the forecast, the average temperature at night in December, January and February is more than three times the average temperature at night in the April and November, during the peak at 7:00 a. m. in December, February, and January is less than twice the corresponding maximum in April and November. Osanu *et al.* [6] uses regional heat data collected in Sweden's typical buildings, uses machine learning technology to develop heat prediction models, and uses side thermometers outdoor, heat load history, time and operation of the heat transfer station as input. The model is evaluated using a different hourly forecast from 1-48 hours. The results show that the minimum error of support vector machine is 0.07 in 24-hour prediction.

The author concentrates on the analysis of the difference between the actual situation and the ideal situation of the district heating system, and gives the targeted solutions, it provides a complete technical solution for the application of deep learning technology in the primary side control system of district heating, and gives the effect of the scheme applied in the actual heating system after long-term stable operation.

Methods

Application of deep learning in heating system

The high delay and large inertia of district heating system, combined with its time-varying characteristics, make the PID control method commonly used in industrial control difficult to operate effectively. In the previous case, the control method based on model prediction is usually adopted, that is, the value of the high delay variable (usually the indoor temperature) in the future time is predicted by the low delay variable in the system, as the input of PID control, the difference between the value of high time delay variable and the optimization target is taken, in order to control the variables to be adjusted at the primary side (usually the opening of the electric valve at the primary side), and solve the problems caused by the high time delay of the system, the specific process is shown in fig. 1 [7].

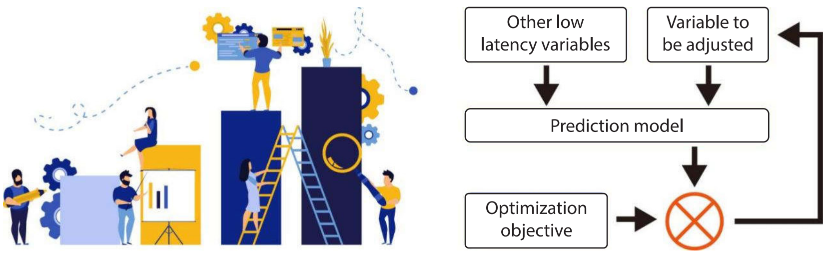

Figure 1. Application of deep learning in primary side regulation of district heating system

Because of the complexity of the heating zone, it is difficult to pred ict the slow change with the slow change from the measurement process. As a prediction technique, deep learning can predict slow changes with enough data and computational resources. Considering the large inertia of the heating district, the output of the system does not depend on the current input, but also depends on the input during the first N times. Therefore, the author adopts the deep learning model LSTM [8], which is good at dealing with time. Ideally, in order to improve the accuracy of the LSTM model, as much data as possible should be used. Therefore, the LSTM model uses all the measured parameters as input parameters, including the opening of the first side, flow of the first side, water temperature of the first side*, etc.* bottom water temperature on the first side, return high water on the first side, the water return on the first side, the flow on the secondary side, the water return temperature, and the outdoor temperature. They are denoted:

$$v,\ f_1,\ t_{1,\text{input}},\ t_{1,\text{output}},\ p_{1,\text{input}},\ p_{1,\text{output}},\ f_2,\ t_{2,\text{input}},\ t_{2,\text{output}},\ t_{\text{outside}}$$

The model uses the variable expected to be optimized – indoor temperature as the model output, denoted by t_{inside} [9].

Primary side adjustment based on deep learning

In this case, the expected secondary measurement return water temperature $t_{2,\text{output,expect}[n]}$ is calculated from the current outdoor temperature $t_{\text{inside}[n]}$, through the secondary test heating network model, the expected secondary test water supply temperature

$t_{2,\text{input,expected}[n]}$ is calculated from the expected secondary test return water temperature, through the equipment model of the primary heating station, the opening degree $v_{\text{expect}[n]}$ of the primary side electric regulating valve is calculated from the expected secondary water supply temperature, so as to realize the primary side adjustment of the district heating system [10].

Establish a deep learning model

– Data collection and cleaning

Set the sampling period to 5 minutes, collect the measurement values of each measuring instrument in the thermal station, including primary side electric valve opening, primary side flow rate, primary side water supply temperature, primary side water supply pressure, primary side return water pressure, secondary side flow, secondary side water supply temperature, secondary side return water temperature, outdoor temperature. They are denoted:

$$v,\ f_1,\ t_{1,\text{input}},\ p_{1,\text{input}},\ p_{1,\text{output}},\ f_2,\ f_{2,\text{input}},\ t_{2,\text{output}},\ t_{\text{outside}}$$

In order to ensure the real-time performance of the mode, this scheme only takes the data of the latest week [11].

The measured values beyond the upper and lower limits of the thermal station are considered as outliers and set as null. The resampling method is used to unify the corresponding time of each measurement value as a multiple of the sampling period, that is, the corresponding time of each measurement value is [2020-11-05.00:00:00, 2020-11-05.00:10:00, 2020-11-05.00:15:00, 2020-11-05.00:20: 00,...], the resample function of the Pandas library in python language is used to implement this function. Interpolation method is used to complete the null values in the measurement sequence, the interpolate function of the python library is used to implement this function. The first 70% data of the incoming and output time series are used as the model training data, and the last 30% data are used as the model testing data, LSTM model is used to train the data, and this function is implemented using keras library in python language [12].

– Equipment model of primary heat station

The equipment model of the primary heat station is mainly used to model heat exchangers, valves and pipe-lines in the heat station, the model is used to calculate the current situation, in order to achieve the desired secondary water supply temperature required for the primary side electrical valve opening. The [v, f_1, $t_{1,\text{input}}$, $p_{1,\text{input}}$, $p_{1,\text{output}}$, f_2] was combined as the model input time series, and [$t_{2,\text{input}}$] was used as the model output time series. The LSTM model is adopted to train the data, and the secondary heating network model F_1 can be obtained:

$$\left[t_{2,\text{input}}\right] = F_1\left(\left[v, f_1, t_{1,\text{input}}, p_{1,\text{input}}, p_{1,\text{output}}, t_2\right]\right) \tag{1}$$

The delay parameter t_{step} in the LSTM model is set to 24 (20 minutes).

– Secondary heating network model

The secondary test heating network model is mainly used to model the heating network and valves between the thermal station and the end users, the model is used to calculate the secondary test water supply temperature required to achieve the desired secondary test return water temperature under the current situation. The [$t_{2,\text{input}}$, f_2, t_{outside}] was combined as the model input time series, and [$t_{2,\text{output}}$] was used as the model output time series [13]. Using LSTM model to train the data, the secondary heating network model F_2 can be obtained:

$$\left[t_{2,\text{output}}\right] = F_2\left(\left[t_{2,\text{input}}, f_2, t_{\text{outside}}\right]\right) \tag{2}$$

The time-delay parameter t_{step} in the LSTM mode is set to 24 (120 minutes).

Calculate the expected secondary return water temperature

Referring to the operation and maintenance experience of the district heating network, the author's scheme makes the following assumptions:

The median of all f_2 values whose outdoor temperature is between –1° and 1° in historical data is used as the baseline secondary side flow and denoted as $f_{2,\text{base}}$. Assume that the base room temperature in the heating area is 26°, denoted as $t_{\text{inside,base}}$. The base outdoor temperature is 0°, which is called $t_{\text{outside,base}}$ [14]. Assuming that the outdoor temperature is $t_{\text{outside,base}}$, the secondary side return water temperature required to keep the indoor temperature of the heating area at $t_{\text{inside,base}}$ is 35°, denoted as $t_{2,\text{output,base}}$.

According to the secondary test heating network model:

$$\left[t_{2,\text{output}}\right] = F_2\left(\left[t_{2,\text{input}}, f_2, t_{\text{outside}}\right]\right) \tag{3}$$

where f_2 and t_{outside} are fixed values, F_2 is a monotonically increasing function with $t_{2,\text{input}}$ as the independent variable and $t_{2,\text{output}}$ as the dependent variable. Therefore, a simple search method can be used to calculate the secondary water supply temperature required by the model output to reach $t_{2,\text{output,base}}$ under fixed $f_{2,\text{base}}$ and $t_{\text{outside,base}}$, denoted as $t_{2,\text{input,base}}$.

At any time n, the current outdoor temperature measurement value is denoted as $t_{\text{out,side}[n]}$. In order to maintain the indoor temperature equal to $t_{\text{inside,base}}$, the average temperature of water supply and return at the secondary side is $t_{2,\text{mean}[n]}$, as shown:

$$t_{2,\text{mean}[n]} = \left(t_{\text{inside,base}} - t_{\text{outside}[n]}\right)\frac{\left(\dfrac{t_{2,\text{input,base}}}{2} - \dfrac{t_{2,\text{output,base}}}{2} - t_{\text{inside,base}}\right)}{t_{\text{inside,base}} - t_{\text{outside,base}}} + t_{\text{inside,base}} \tag{4}$$

The temperature difference between the supply and return water of the secondary side $t_{2,\text{mean}[n]}$ is shown:

$$t_{2\text{mean}[n]} = \left(t_{\text{inside,base}} - t_{\text{outside}[n]}\right)\frac{\left(\dfrac{t_{2,\text{input, base}}}{2} - \dfrac{t_{2,\text{output,base}}}{2} - t_{\text{inside,base}}\right)}{t_{\text{inside,base}} - t_{\text{outside,base}}} + t_{\text{inside,base}} \tag{5}$$

The expected secondary return water temperature AA is shown:

$$\left(t_{\text{inside ,base}} - t_{\text{outside}[n]}\right)t_{2\ \text{delta}[n]} = \frac{\left(t_{2,\text{input,base}} - t_{2,\text{output,base}}\right)}{t_{\text{inside,base}-}t_{\text{outside,base}}} \tag{6}$$

Calculate the expected secondary water supply temperature

According to the secondary test heating network model:

$$\left[t_{2,\text{output}}\right] = F_2\left(\left[t_{2,\text{input}}, f_2, t_{\text{outside}}\right]\right) \tag{7}$$

where f_2 and t_{outside} are fixed values, F_2 is a monotonically increasing function with $t_{2,\text{input}}$ as the independent variable and $t_{2,\text{output}}$ as the dependent variable. Therefore, a simple search method can be used to calculate the secondary measurement water supply temperature $t_{2,\text{input,expect}[n]}$ required for the model output to reach $t_{2,\text{output,expect}[n]}$ when $f_2[n]$ and $t_{\text{outside}[n]}$ are known [15].

Calculate the opening of the primary side electric adjusting valve

According to the equipment model of the primary heat station:

$$t_{2,\text{input}} = F_1\left(\left[v, f_1, t_{1,\text{input}}, p_{1,\text{input}}, p_{1,\text{output}}, f_2\right]\right) \tag{8}$$

where f_2 and t_{outside} are fixed values, F_2 is a monotonically increasing function with $t_{2,\text{input}}$ as the independent variable and $t_{2,\text{output}}$ as the dependent variable. Therefore, a simple search method can be used to calculate the secondary water supply temperature $t_{2,\text{input,expect}[n]}$ needed for the model output to reach $t_{2,\text{output,expect}[n]}$ when $f_{2[n]}$ and $t_{\text{outside}[n]}$ is known.

Model output correction

– Calibrate the secondary heating network model

According to the actual secondary test of the maximum return water delay of the heating network, the calibration period is set as 120 minutes, the deviation $t_{2,\text{output,delta}[n]}$ between the actual measured secondary side return water temperature $t_{2,\text{output}[n]}$ and the expected secondary side return water temperature $t_{2,\text{output,expect}[n]}$ calculated by the model is calculated every 120 minutes:

$$t_{2,\text{input}} = F_1\left(\left[v, f_1, t_{1,\text{input}}, p_{1,\text{input}}, p_{1,\text{output}}, f_2\right]\right) \tag{9}$$

In the calculation at the next moment, the modified expected secondary return water temperature $t_{2,\text{output,revised}[n+1]}$ is used instead of $t_{2,\text{output,expect}[n+1]}$.

Among them:

$$t_{2,\text{output,revised}[n+1]} = t_{2,\text{output,expext}[n+1]} + t_{2,\text{output,delta}[n]}$$

– Calibrate the equipment model of the primary heat station

According to the actual maximum response time of heat exchanger, set the calibration period to 15 minutes, the deviation $t_{2,\text{input,delta}[n]}$ between the actual measured secondary side water supply temperature $t_{2,\text{inputt}[n]}$ and the expected secondary side water supply temperature $t_{2,\text{input,expect}[n]}$ calculated by the model is calculated every 15 minutes:

$$t_{2,\text{input,delta}[n]} = t_{2,\text{input}[n]} - t_{2,\text{input,expect}[n]} \tag{10}$$

In the calculation at the next moment, the modified expected secondary measurement water supply temperature $t_{2,\text{input,revised}[n+1]}$ is used instead of $t_{2,\text{input,expect}[n+1]}$:

$$t_{2,\text{input,revised}[n+1]} = t_{2,\text{input,expect}[n+1]} + t_{2,\text{input,delta}[n]} \tag{11}$$

Results and discussion

The data of the actual thermal station of the project company are used to compare the temperature of water returned from the secondary test predicted by the heating network model with the actual measured value, as shown in fig. 2, the mean square error of the prediction results by directly using the model is 0.83%, and the mean square error after model correction is 0.022%.

Using the actual thermal station data of the project company, compare the water supply temperature predicted by the equipment model of the primary heat station in the secondary measurement with its actual measured value, as shown in fig. 3, the mean square error of the prediction results directly using the model is 1.30%, the mean square error is 0.094% after model correction [16]. Because its error value is very low, the three lines are basically coincident in the figure.

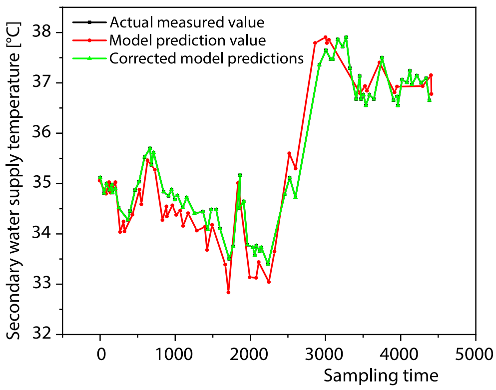

Figure 2. Performance of heating network model in secondary test

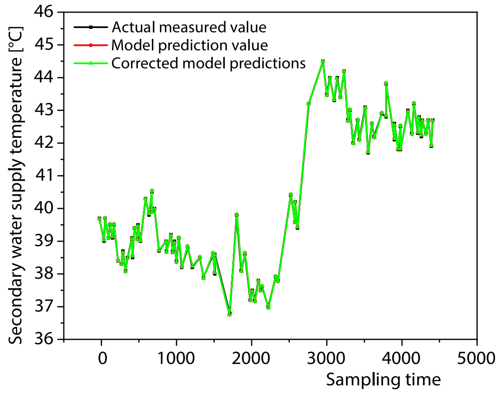

Figure 3. Performance of equipment model for primary thermal power station

Operate the complete scheme in the thermal power station of the project company, the secondary measured return water temperature is controlled by adjusting the opening of the electric control valve at the primary side, compare the expected secondary measured backwater temperature in the scheme with the actual secondary measured backwater temperature, as shown in fig. 4, with a mean square error of 0.102% [17].

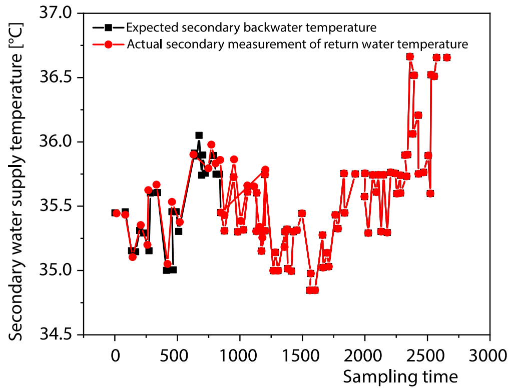

Figure 4. Primary side regulation performance of central heating system

Conclusion

The author analyzes the influence of the non-ideality of the central heating system on the application of deep learning, and proves through data that the deep learning technology is not suitable for direct application the central heating system, and puts forward corresponding solutions. By combining deep learning technology with thermal engineering principles and automatic control, the author proposes a primary side regulation scheme of central heating system based on deep learning, the operation results in the actual central heating system show that the scheme can stably and effectively optimize the central heating system, and achieve the purpose of improving the end user experience and saving energy and consumption.

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