REGULATION CAPABILITY EVALUATION OF INDIVIDUAL ELECTRIC HEATING LOAD BASED ON RBF NEURAL NETWORK

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As a time-shifting load that is gradually popularized in the northern region, electric heating load has great adjustment potential. Because the electric heating operation characteristics are affected by many nonlinear factors, the traditional equivalent thermal parameters (ETP) model cannot accurately evaluate the regulation capability of individual electric heating load. Aiming at this problem, this paper proposes an evaluation method for the regulation capability of individual electric heating load based on radial basis function (RBF) neural network. Firstly, electric heating load control experiments were carried out in a typical room of a residential quarter in winter and relevant experimental data were collected. Then, based on the operation data, the RBF neural network is used to evaluate the regulation capability of the individual electric heating load. Finally, the evaluation results based on RBF neural network are compared with those based on back propagation (BP) neural network and ETP model. The results show that the proposed method has the least evaluation error and can more accurately evaluate the regulation capability of individual electric heating load.

Key words*: load modeling, load control, electric heating load, regulation capability evaluation, RBF neural network*

1. Introduction

In recent years, due to the increasing proportion of renewable energy such as wind power in the Northeast Power Grid, the "source side" active regulation resources are gradually lacking, and the "load side" adjustable resources are increasingly receiving attention [1]. Considering the long duration of severe cold in winter in Northeast China and the characteristics of fixed power by heat, the difficulty of peak shaving can be solved by vigorously promoting electric heating to increase the regulation potential of power grid in Northeast China.

Since the electric heating load can quickly respond to the control command, it is an extremely valuable schedulable resource on a short time scale, called fast flexible load [2, 3].According to statistics, in 2017, the cumulative installed capacity of electric heating equipment in Changchun City reached 290 MW, and the heating area reached 3.17 million square meters, accounting for 3.08% of the total heating capacity of the city. If the ability to adjust the electric heating load can be fully tapped, the effect of peak-cutting and valley filling can be achieved at a small cost, and the contradiction between supply and demand can be alleviated.

In [4], the equivalent thermal parameter (ETP) model is used to establish an air-conditioning polymerization model and evaluate the response potential; The literature [5] based on the first-order physical thermal model to establish a aggregated air conditioning load model, and studied the practicality of the aggregation model to provide frequency modulation standby for the grid; The literature [6, 7] constructed a aggregated temperature control load model composed of electric water heater load, and proposed a new serialization control strategy. At present, research on temperature control load such as electric heating mainly focuses on temperature-controlled load polymerization model based on ETP model, while research on evaluating the regulation capability of individual electric heating equipment is relatively rare, and the actual operating data of electric heating is lacking.When using the equivalent thermal parameter model analysis, the model is insufficient in evaluating the regulating capacity of a specific single electric heating load.

In view of the above problems, this paper proposes an evaluation method for the regulation capability of individual electric heating load based on RBF neural network. This method establishes a model by using RBF neural network algorithm based on actual electric heating operation data, evaluates the regulation capability of individual electric heating, and compares the evaluation results with BP neural network and ETP model to verify the effectiveness of the method.

2. Regulation capability experiment of the electric heating load

Load regulation capability: The load can change its original demand mode according to a certain mechanism, that is, the load can realize the flexible change of demand increase and decrease within a certain interval [8]. Electric heating load will cause energy loss in indoor temperature regulation. The regulation capability of electric heating load studied in this paper refers to the adjustable interval of electric heating load in time dimension under the given temperature constraint.

2.1. Physical model of individual electric heating load

Modeling individual electric heating load, firstly study the coupling relationship between its load power state and indoor temperature. Set $[T_-, T_+]$ to represent the range of indoor temperature change under the normal working state of electric heating. T_+, T_- and the temperature setting value of electric heating T_{set} satisfy formula (1):

$$\begin{cases} T_- = T_{set} - \delta \\ T_+ = T_{set} + \delta \end{cases} \tag{1}$$

In the formula, the meaning of δ is the temperature adjustment range of electric heating load [9].

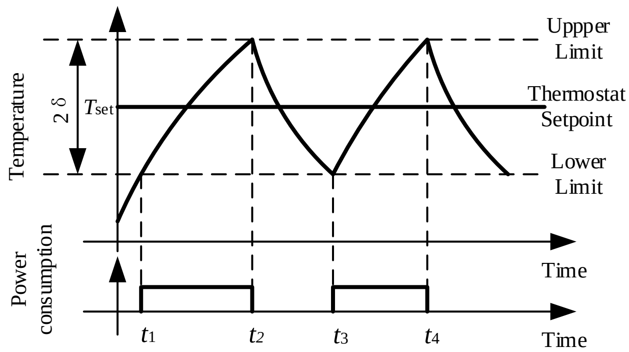

Fig. 1 Thermal behavior of a heat pump unit

As shown in figure 1, assuming that the outdoor ambient temperature does not change during the control period, when the indoor temperature is set to a fixed value, the switching state of the electric heating load will change periodically, and the corresponding indoor temperature will also change periodically within the upper and lower limits of the indoor temperature.

According to this relationship, a physical model of electric heating load is established, the most typical one is the equivalent thermal parameter model. This model is based on the equivalent heat capacity and equivalent thermal resistance with ambient temperature, energy efficiency ratio, time, and is suitable for cold/heat load modeling of residential. The building thermal model of a typically individual electric heating load room in a northern residential area is shown in Fig. 2.

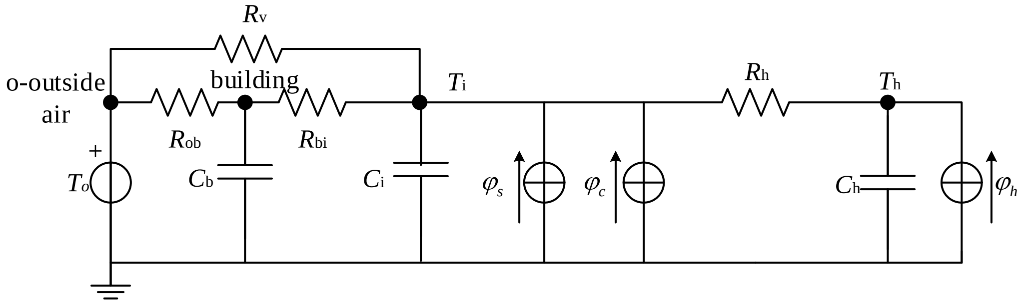

Fig. 2 Building thermal model of individual room

In figure 2, T_i is the indoor temperature; T_o is the outdoor ambient temperature; T_h is the electric heating load temperature; R_ob, R_bi and R_v represent the thermal resistance between wall and outdoor air, interior wall and indoor air, and indoor and outdoor air, respectively; R_h is the thermal resistance of electric heating load; C_b, C_i and C_h represent building wall heat capacity, indoor air heat capacity and electric heating load heat capacity respectively; φ_s is the solar radiation gains; φ_c is the human activity gains; φ_h is the electric heating heating gains.

From the point of view of simplification, the above model can be described by the first-order ETP model [10]. When the solar radiation gain has a small influence on the indoor temperature, the first-order ETP model can be used to describe the change of indoor temperature by Eq. (2).

$$\begin{cases} T_i^{t+1} = T_o^{t+1} + K^t QR - (T_o^{t+1} + K^t QR - T_i^t) e^{-\frac{\Delta t}{RC}} \\ K^t = \begin{cases} 0, & \text{off} \\ 1, & \text{on} \end{cases} \end{cases} \tag{2}$$

In the equation (2): T_i^t is the indoor temperature at time t, °C; T_o^{t+1} is the outdoor ambient temperature at time t+1, °C; C is the equivalent heat capacity of the system, J/°C; R is the equivalent heat resistance of the system, °C/W; Q is the heating power of the electric heating equipment; K is the start and stop state of electric heating, the value of 0 means that the electric heating is off, the value of 1 means the electric heating is turned on; t is the simulation time; Δt is the simulation time step.

Setting that the opening time is τ_{on} and the closing time is τ_{off} in the control cycle of electric heating load, the Eq. (1), (2) iterative calculation can get Eq. (3), (4):

$$\tau_{on} = CR\ln(\frac{QR + T_{set} + \delta - T_o}{QR + T_{set} - \delta - T_o}) \tag{3}$$

$$\tau_{off} = CR\ln(\frac{T_o - T_{set} + \delta}{T_o - T_{set} - \delta}) \tag{4}$$

2.2. Collection of experimental data

In order to obtain real and effective experimental data, the electric heating load control experiment was carried out on the electric heating system of a residential area in Changchun city. The floor plan of the electric heating residential building is shown in Fig. 3, and experimental room is shaded position.

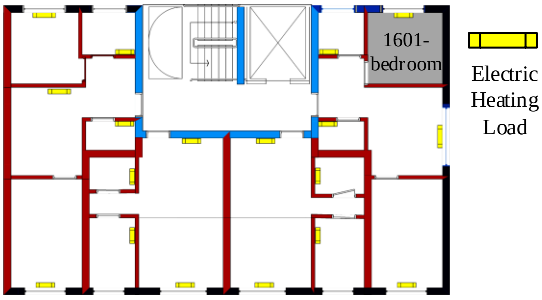

Fig. 3 Plan of standard floor of an electric heating residential building

In this experiment, 1601 typical bedroom was used for electric heating load control, and the time of data collection is 2018/2/24 18:00 - 2018/3/4 18:00. The T_+ and T_- are set to 24 ℃ and 19 ℃ respectively, and the sampling time interval is 5 minutes. The experimental room is in the shaded side, and the effect of solar radiation on the indoor temperature is negligible. As shown in Fig. 4: The main test equipment includes: Distributed electric heating load, and the function is to adjust the indoor temperature; Thermostat, the function is to accept and execute temperature control instructions; Network box, function for wireless connection network box and cloud control platform.

(a) (b) (c)

Fig. 4 Laboratory equipment: (a) Electric heating load; (b) Thermostat; (c) Network box

3. Experimental data preprocessing

3.1. Raw data interpolation

The experiment limits the sampling time resolution to 5 minutes due to the device itself. In order to more accurately reflect the actual indoor and outdoor temperature changes and the working state of the electric heating load, this experiment uses the cubic spline interpolation method to interpolate the original data, thereby improving the time resolution. The time resolution after interpolation was 1 minute, with 11520 sets of data. The changes before and after partial data interpolation are shown in Fig. 5.

From the figure 5, it can be seen that after interpolation, the indoor temperature curve tends to be smooth, and the working state of electric heating load has shifted (At 7 minutes, the on-state of the electric heating is shifted to the time of 8 minutes; the opening state at 61 minutes is shifted to the time of 58 minutes; the closing state at 75 minutes is shifted to the time of 73 minutes).

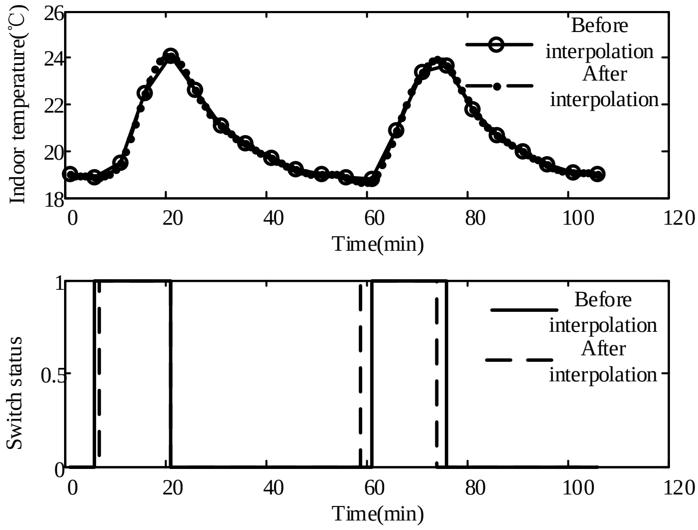

Fig. 5 Changes in room temperature and load switch status before and after interpolation

3.2. Preprocessing of outdoor temperature data

Due to the lack of real experimental data in traditional research, outdoor ambient temperature measurement usually sets a constant value, ignoring the change of outdoor ambient temperature, while the actual outdoor ambient temperature is constantly changing, and there are even great differences in different time periods. In this paper, by analyzing the response time of the heating and cooling process in each control cycle of electric heating load, as shown in Fig. 6, it can be seen that the heating time is basically stable within 15 minutes, and the cooling time is stable within 40 minutes.

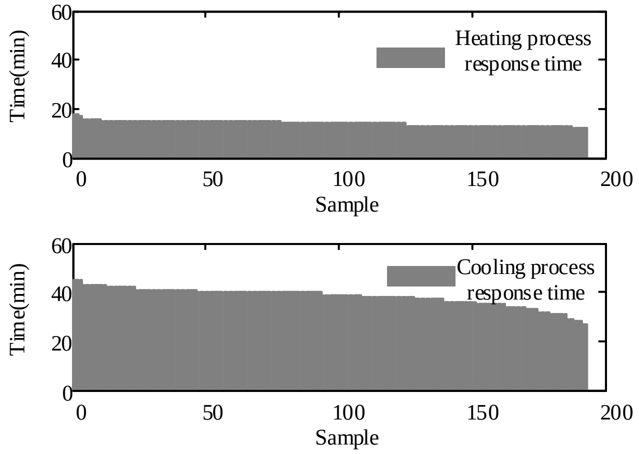

Fig. 6 Electric heating load response time range

Define the current time as M time, and after 40 minutes it is M+40 time. During the cooling process, the range of temperature difference between outdoor ambient temperature at M time and that at M + 40 time is shown in Fig. 7.

The analysis shows that 94.30% of the data changes in outdoor temperature stable between −1.5-+1 ℃, the average temperature of 0.66 ℃, the outdoor environment temperature has no obvious change. Therefore, in order to reduce the fluctuation of outdoor temperature on a short time scale and reflect the overall trend of outdoor temperature in a short time period, it is feasible for this paper to take the average value of outdoor environmental temperature at time M and time M+40 as the input data of outdoor temperature.

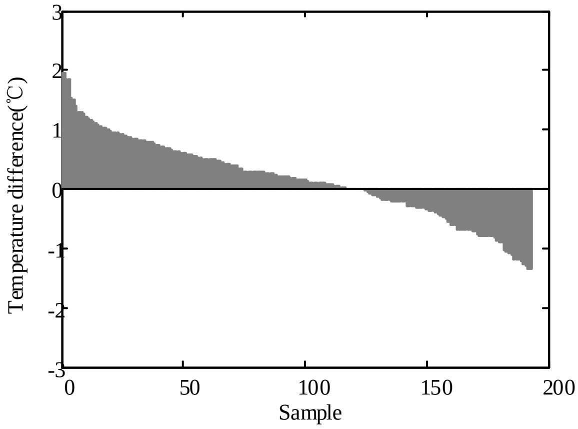

Fig. 7 *M* time and *M*+40 time outdoor temperature difference range

3.3. Experiment process

The process of evaluating the regulation capability of individual electric heating load based on the RBF neural network algorithm is shown in Fig. 8.

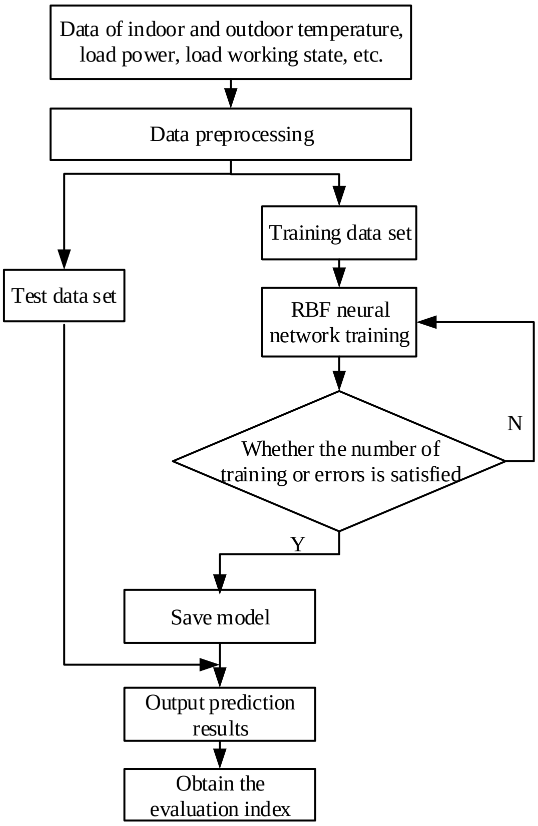

Fig. 8 Experimental procedure of RBF neural network method

The specific steps are described as follows:

(1) Based on the ETP model, the important parameters needed to establish the evaluation model are determined, and important parameter data is collected as the basic data into the database.

(2) First, the basic data is processed, including increasing the time resolution and short-time scale outdoor temperature averaging processing; then dividing the data set into a training set and a test set. In this experiment, the input vector is determined as: the switching state of the electric heating load, the

power of the load, the current indoor temperature, the indoor temperature of the next moment, the outdoor temperature; the output vector is determined as: the response time of the electric heating load;

(3) Based on the training samples, the network performs training. When the maximum number of trainings is reached or the model accuracy reaches the set requirement, the training ends, and an electric heating adjustment capability evaluation model is established;

(4) Based on the input of the test sample, the model performs prediction and outputs the predicted result;The evaluation index is calculated according to the predicted value of the load response time and the true value, and the performance of the model is evaluated by the evaluation index.

In this paper, the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percent error (MAPE) are selected as the evaluation indicators of the model prediction effect:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^{'}\right| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{'})^2} \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^{'}}{y_i}\right| \times 100\% \tag{7}$$

In the formula: y_i , $y_i^{'}$ represent the true and predicted values of the data, respectively, and n represents the total number of data. The smaller the MAE, RMSE and MAPE values are, the closer the network prediction values are to the real values and the higher the prediction accuracy is.

4. Experiment results and discussion

4.1. Simulation analysis based on first-order ETP model

When evaluating the electric heating load regulation capability based on the first-order ETP physical model, the important parameters in the model should be determined first. According to reference [8], the equivalent heat capacity *C* and the equivalent thermal resistance *R* of the first-order ETP model are determined based on a large number of measured data. The main system parameters of the electric heating room are shown in Tab. 1.

Tab. 1 Typical bedroom electric heating - building system parameters

Parameter	Value	Parameter	Value
R	0.1279℃/W	δ	2.5℃
C	1887.7403J/℃	T_{set}	21.5℃
Q	900W		

Taking the indoor temperature heating process as an example, the forecasting results of the capacity of electric heating load up-regulation in some time periods are shown in Fig. 9.

Figure 9 shows that the relative error of ETP model in predicting the response time of electric heating load during heating process is between −91.3% and +25.5%, and the relative error of 67.42% of the samples is between −20% and +20%, and the relative error of 43.82% of the samples is between −10% and +10%. Among them, the prediction of the regulation capability of the sample data in the time scale of 1 to 5 minutes is the main reason for the relative error greater than 20%. As shown in Tab. 2.

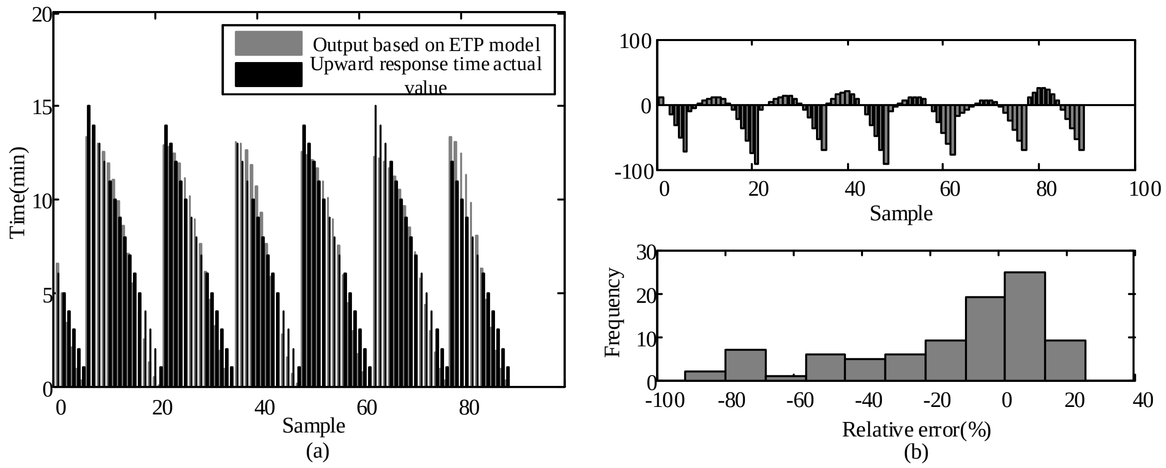

Fig. 9 (a) The capacity of electric heating load up-regulation; (b) Relative error and error distribution

Tab. 2 Partial 1-5min time scale adjustment ability prediction

Actual value	5	4	3	2	1
Predictive value	3.926	2.487	1.317	0.516	0.086
Relative error	−21.48%	−37.83%	−56.10%	−74.20%	−91.40%

4.2. Evaluation of electric heating load response potential based on neural network

When the artificial neural network method is used to model 1601 electric heating room in this example, there were 3089 sets of data in the indoor temperature heating process during the experimental period. The first 3000 sets of data were used as training samples, and the last 89 sets were used as test samples. There were 8431 sets of data in the cooling process. The first 8370 sets of data were used as training samples, and the last 61 sets were used as test samples. The number of nodes in the network input layer is 5 and the output layer is 1.

4.2.1 Simulation prediction based on RBF neural network

This example determines that the RBF neural network Mean Squared Error Goal is 0.1, and the Radial Basis Function Expansion Speed is 1.Taking the heating process as an example, Fig. 10 shows the prediction results of the response time after training by RBF neural network algorithm.

Figure 10 shows that the relative error of the response time of the electric heating load based on the RBF neural network is between −41.7% and +57.0%, and it is normally distributed. Among them, 86.52% of the samples have a relative error between −20% and +20%, and 71.91% of the samples have a relative error between −10% and +10%.

For the prediction of the response time of the cooling process, the experimental method is similar to the heating process, and the experimental results are as follows: a) Using Eq. (4), based on the ETP model, the relative error of the electric heating load in the response time of the cooling process is between −97.9% and +15.1%. The relative error of 20.69% of the samples is between −20% and +20%, and the relative error of 10.34% of the samples is between −10% and +10%. b) Based on RBF neural network, the relative error of the load is between −27.2% and +80.8%. The relative error of 77.59% of the samples is between −20% and +20%, and the relative error of 56.90% of the samples is between

−10% and +10%. Similar to the heating process, the prediction of the adjustment ability of the sample data in the time scale of 1-5 minutes is the main reason for the relative error of more than 20%.

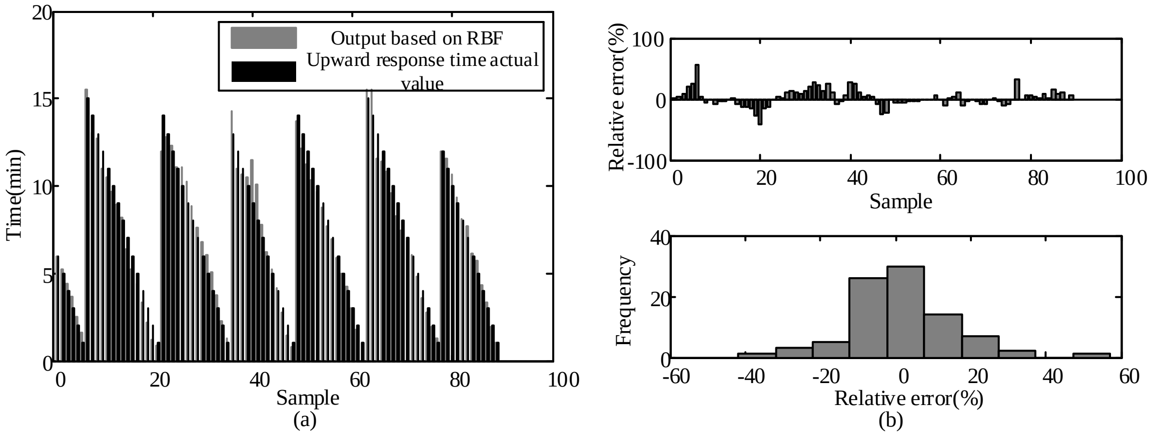

Fig. 10 (a) The capacity of electric heating load up-regulation; (b) Relative error and error distribution

4.2.2 Simulation prediction based on BP neural network

This experiment uses a three-layer BP neural network for simulation testing. The hidden layer is set to 8 nodes; the learning efficiency is set to 0.1; the error precision is 10^{-5}; the maximum number of training is 300.

The experimental operation is similar to the RBF neural network prediction, and this process will not be described again. The experimental results are as follows: The relative error of the response time of the electric heating load heating process is between −28.1% and +70.3%. Among them, 87.64% of the samples have a relative error between −20% and +20%, and 70.78% of the samples have a relative error between −10% and +10%; The relative error of the response time of the electric heating load cooling process is between −17.4% and +88.1%. Among them, the relative error of 48.28% of samples is between −20% and +20%, and the relative error of 20.69% of samples is between −10% and +10%.

The prediction error results of the three methods are shown in Table 3.

Tab. 3 Error analysis of response time prediction (UP is prediction error of up-regulation capability and DOWN is Prediction error of down-regulation capability)

	UP	UP	UP	DOWN	DOWN	DOWN
	MAE(min)	RMSE	MAPE(%)	MAE(min)	RMSE	MAPE(%)
ETP	0.9253	1.0788	22.5370	6.8255	7.8114	56.4196
BP	0.6346	0.9778	10.4521	2.9742	3.5460	29.7211
RBF	0.5235	0.7012	9.6691	1.8918	2.3445	17.5818

Table 3 shows that: a) Based on the different working states of the electric heating load, the results of the horizontal comparison of the evaluation of the regulation capability are: The time scale of the electric heating load cooling process is larger than the heating process, therefore, in the prediction of response time, the MAE, RMSE, and MAPE of the three evaluation methods have increased to some extent. b) Based on the differences in the three methods described herein, the results of the longitudinal comparison of the evaluation of electrical heating load regulation capability are: Compared with the prediction results based on the ETP model, the neural network is more accurate. The MAE, RMSE and

MAPE are smaller than the ETP model. At the same time, the evaluation accuracy of RBF neural network is higher than that of BP neural network, which can more effectively evaluate the regulation capability of individual electric heating load.

5. Conclusions

In order to accurately evaluate the regulation capability of individual electric heating load, this paper based on the experimental data, the average value of outdoor temperature in short period of time is taken as the input of outdoor temperature data, which reduces the fluctuation of outdoor temperature on short time scale and reflects the overall trend of outdoor temperature. Based on the ETP model to determine the important parameters of the model, this paper proposes a method based on RBF neural network to evaluate the regulation capability of individual electric heating load.

The simulation results show that the evaluation method based on RBF neural network proposed in this paper has the smallest error and the highest accuracy compared with the BP neural network and the first-order ETP model in the evaluation of individual electric heating regulation capacity, and can more effectively excavate the adjustable resources on the load side. It provides a reliable response potential evaluation method for dispatching center or load control agent. After that, the research on the polymerization and dispatch control methods of electric heating load will be the next work direction.

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