Research on Short-term Load Forecasting Model of Integral Energy System Considering Demand Side Response

Xuan Xuan, Yan Zhao, Yucai Li, Ruyu Zhang, and Ping Zhang.

***Abstract*—With the rapid development and effective promotion of renewable energy, the application of renewable energy in distributed energy systems has also increased, and the diversification of demand side has brought great influence to distributed energy systems. To achieve economic dispatch and optimal operation of integrated energy systems, accurate calculations of the load of integrated energy systems are needed. Firstly, the topology and mathematical expression of the distributed energy system are summarized. Then, considering the comprehensive influencing factors of demand response, radial neural network (RBF-NN) short-term load forecasting model is constructed. The semi-trapezoidal membership function is employed to eliminate the user response fuzzy attribute, and the result of the demand response precision quantization is introduced into the RBF-NN model. Through the comparison of the results of the three cases in the actual example analysis, the method proposed in this paper can be validated to effectively consider the coupling relationship between various conformities, with high prediction accuracy. A certain theoretical basis can be provided by short-term load forecasting studies that take into account demand side responses.**

***Index Terms*—Distributed Energy System; Demand Side Response; RBF-NN Neural Network; Short-term Load Forecasting**

I. INTRODUCTION

WITH the rapid development of smart grid technologies such as distributed generation, energy storage, smart meters, and electric vehicles, demand side response is an important means of grid security for energy regulation and support for new energy access. The demand side response[1-2] aims to change the power usage of traditional users by using incentives, penalty mechanisms or real-time electricity price mechanisms to balance power demand and ensure system security[3-4]. The integrated energy system is an important part of the new generation energy system. The different links of the Netherlands and the Netherlands have realized the coupling of different types of energy, effectively optimized the energy structure, and improved the comprehensive utilization of energy. Accurate prediction of electrical thermal cooling load is the premise of integrated energy system optimization design, operation scheduling and energy management, and has important practical value.

At present, China's demand response pilot project mainly adopts the electricity price policy. Through the implementation of peak-to-valley time-of-use electricity price, the user is guided to transfer the controllable load during the peak period, so as to achieve the peak-filling effect of the load curve. At present, most of the demand response theory research is devoted to the demand response mechanism analysis or model construction, and there are few studies on the load forecasting problem that takes into account the demand response. The literature [5] uses the alternative and price-based demand response methods to establish an optimal scheduling model for the electric-gas integrated energy system considering the demand side load response and dynamic natural gas flow. The literature[6] analyzes the electricity consumption data of grid users, uses consumer psychology and least squares method, established a demand response model based on time-of-use electricity price and corrects the model parameters, and successfully applies economic principles to load forecasting. But it ignores the psychological response factors of users who are too big or too small in electricity price difference. The literature [7] is aimed at maximizing social welfare, and establishes a real-time electricity price response model suitable for home users under the constraints of satisfying users' needs. However, real-time electricity prices require high technology and equipment support, so it is not suitable for China's electricity market.

The implementation of the demand response strategy has alleviated the tension of power supply and demand to a certain extent, optimized the resource allocation of the power market, and increased the revenue of power users participating in the demand response, but at the same time, this is also brought some challenges to the short-term load forecast of the power system. Based on the above problems, this paper summarizes the topology structure and

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mathematical expression of distributed energy systems, and then constructs a short-term load forecasting model of radial nerve network that considers the comprehensive influencing factors of demand response. The semi-trapezoidal membership function is used to eliminate the user response fuzzy attribute, and the result of quantifying the demand response precision is introduced into the RBF-NN model. Through the comparison of the results of the three cases in the actual example analysis, it is verified that the proposed method can effectively consider the coupling relationship between various loads and has higher prediction accuracy. The method used in this paper provides a theoretical basis for the short-term load forecasting study that takes into account the demand side response.

II. ENERGY HUB CONVERSION MODEL

A. Topology

The topology of the distributed energy system changes as shown in Figure 1. The traditional distributed energy system that uses cogeneration and output of cold, heat and electricity has begun to transform into a new distributed energy system. Table 1 summarizes the research status of distributed energy system topologies in recent years. It can be seen that most of the research involves renewable energy. This characteristic can be clearly seen in the typical structure of the literature [9].This study considers both energy storage and even electric heating. This characteristic can be clearly seen in the typical structure of the literature [10]; Therefore, the enrichment and diversification of distributed energy system elements can be directly grasped by the study of its topology [11-12]. Basic configuration and elemental representation through topology have also become the auxiliary expression tools commonly used in the research of new distributed energy systems.

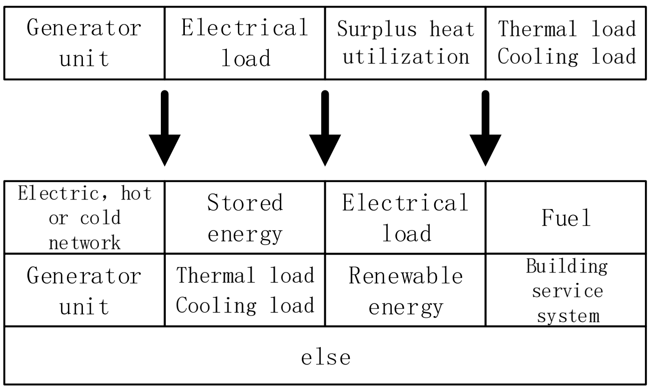

Fig. 1. Change of topological structure of distributed energy system

TABLE I
RESEARCH STATUS OF STRUCTURE OF DISTRIBUTED ENERGY SYSTEM

Year		2018	2018	2017	2017
Author		Li H.Z. etc.	Zhang Y.N. etc.	Liu Y. etc.	Zhang T.F. etc.
Power side elements	Gas			△	
	PV	△			△
	Power grid	△	△	△	△
	Heat supply network		△		
Supply side elements	CHP	△			△
	Electricity storage	△	△	△	△
	Heat accumulation	△			
Demand side elements	Heat			△	△
	Electricity	△	△	△	△

B. Input Output Model

Traditional distributed energy system energy balance [13] can be expressed as

$$\begin{pmatrix} L_1 \\ L_2 \\ \vdots \\ L_m \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{pmatrix} \begin{pmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{pmatrix} \tag{1}$$

Where: L is the load matrix; P is the energy supply matrix, which contains conventional energy and renewable energy; C is the performance parameter matrix of the energy supply system, which is a matrix of performance curve coefficients for each subsystem. The left side of the formula (1) is the load side, and the right side is the energy supply side. With the development of distributed energy systems, energy storage devices have emerged, and the energy balance of energy storage devices in the system can be expressed as

$$\begin{pmatrix} M_1 \\ M_2 \\ \vdots \\ M_m \end{pmatrix} = \begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mn} \end{pmatrix} \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{pmatrix} \tag{2}$$

Where: M is the energy output matrix of the energy storage device; A is the energy storage supply matrix; S is the performance parameter matrix of the energy storage device, which is a matrix composed of the performance curve coefficients of each energy storage.

The supply, transportation, and utilization of energy in a distributed energy system can be expressed as

$$L = (\mathbf{C}S)\begin{pmatrix} \mathbf{P} \\ \mathbf{A} \end{pmatrix} \tag{3}$$

The above progress indicates that matrix mathematical expression is a commonly used mathematical tool in the field of distributed energy research. The change of expression is actually a numerical representation of the new features of distributed energy systems.

III. USER ACTUAL DEMAND RESPONSE MODEL

A. Demand Response Mechanism

Considering the user's psychological response to too small or too large electricity price difference, and the smoothness of the change of the response curve between different electricity price segments, according to the principle of consumer psychology, a user demand response mechanism model based on Logistic function is established. In view of this, the fuzzy attribute of the demand response mechanism is given, that is, the true demand responsiveness is between the positive estimate of the demand responsiveness and the negative estimate.

The fuzzy demand response mechanism based on Logistic function fully considers the psychological response state of power users to different power prices. When the peak-to-valley electricity price difference is too small, it is not enough to attract users to adjust the electricity consumption mode. The peak-filling effect is very small, called “dead zone”; when the peak-valley electricity price difference is too large, the user load elasticity potential is completely excavated, and the load is cut. The rate reaches the limit, which is called “saturation zone”; when the electricity price difference is within a reasonable range, the user responds obviously with the electricity price difference, which is called “response zone”. In addition, the Logistic function is continuously steerable at different power price differential segment points a_{pv} and b_{pv} which is more in line with objective facts than the segmentation function describing the demand response mechanism. When the electricity price difference is zero, that is, when the peak-to-valley time-sharing electricity price is not used, the user is only random under the influence of external factors, and may even have a negative load-carrying rate.

In order to improve the fitting accuracy of the demand response mechanism to the peak load and the post-load load, the variable parameter of the Logistic function is extended to increase the degree of freedom of change. The function form is shown in equation (4).

$$\lambda(\Delta p)=\frac{c}{1+\mathrm{e}^{-(\Delta p-d)/\mu}}+b \qquad (4)$$

Where: Δp represents the electricity price difference; λ represents the load-shedding rate; c represents the function threshold span; d is the abscissa corresponding to the function value $c/2+b$, which can approximate the midpoint of the “response zone” electricity price difference; b is the increased variable parameter, used to translate the logistic curve up and down.

By extending the Logistic function by equation (4), the positive response estimation curve and the negative response estimation curve can be fitted with higher precision, and the user actual response curve is located between the two with fuzzy attributes.

B. Demand Response Model

The demand response mechanism has fuzzy attributes, which can easily affect the short-term load forecasting accuracy that takes into account the demand response. In this paper, the user response randomness and the positive response membership degree are combined with the "dead zone", "response zone" and "saturation zone" in the fuzzy demand response mechanism of the logistic function to probabilistically constrain the precise demand response mechanism.

The linear part of the large semi-trapezoidal membership function is selected to obtain the user's positive response membership degree under different power price differences in the "response area"[14], which is the probability constraint of the accurate demand response mechanism. Among them, the large semi-trapezoidal membership function is shown in Figure 2; the probability constraint of the precise demand response mechanism is shown in Figure 3.

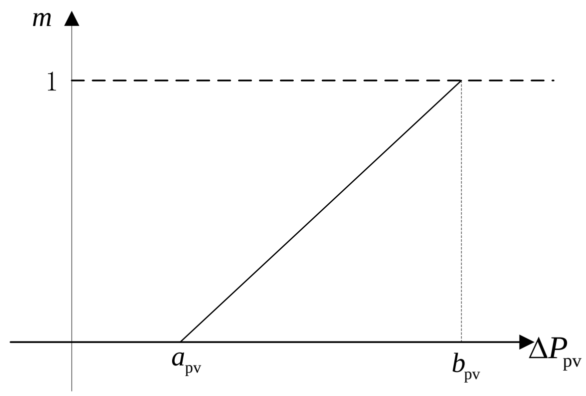

Fig. 2. Partial large semi-trapezoidal membership function

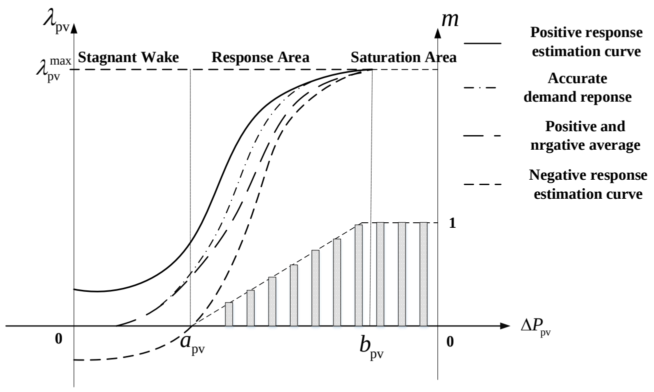

Fig. 3. Probabilistic constraints on the accurate demand response mechanism

In Figure 2: Δp_{pv} represents the difference between the peak and valley time price; a_{pv} and b_{pv} represent the demand response mechanism; m represents the positive response membership degree, which is used to characterize the probability that the user's actual response meets the positive response estimate under a certain peak-valley electricity price difference. In the fuzzy demand response mechanism, the "response area" positive response membership degree can be obtained by equation (5).

$$m=\frac{\Delta p_{pv}-a_{pv}}{b_{pv}-a_{pv}}, \quad a_{pv}\le \Delta p_{pv}\le b_{pv} \qquad (5)$$

In Figure 3, when the electricity price difference is $\Delta p_{pv}=a_{pv}$, the positive response membership degree of the user's actual response is 0, that is, the responsivity is the average of the positive response estimate and the negative response estimate; when the electricity price difference is $a_{pv}<\Delta p_{pv}<b_{pv}$, the user response enthusiasm is opened with

the electricity price difference. Gradually, the accurate demand response gradually moves from the average value to the positive response estimate; when the electricity price difference is $\Delta p_{\mathrm{pv}} \geq b_{\mathrm{pv}}$, the user response is consistent with the positive response estimate, and at the same time meets the "saturation zone" characteristic. The positive response membership degree corresponding to the difference between the peak and valley electricity price is used as the probability constraint to represent the degree to which the actual response of the user tends to positively respond to the estimation, and the actual demand response mechanism of the user is determined. The exact load-shedding rate is as shown in equation (6).

$$\tilde{\lambda}_{\mathrm{pv}} = \begin{cases} \dfrac{\lambda_{\mathrm{pv}}^{\max} + \lambda_{\mathrm{pv}}^{\mathrm{nin}}}{2}, & 0 \leq \Delta p_{\mathrm{pv}} < a_{\mathrm{pv}} \\ \lambda_{\mathrm{pv}}^{\min} + \dfrac{\Delta\lambda_{\mathrm{pv}}}{2} + \dfrac{\Delta\lambda_{\mathrm{pv}}}{2} \cdot m, & a_{\mathrm{pv}} \leq \Delta p_{\mathrm{pv}} < b_{\mathrm{pv}} \\ \lambda_{\mathrm{pv}}^{\max}, & \Delta p_{\mathrm{pv}} \geq b_{\mathrm{pv}} \end{cases} \tag{6}$$

Where: $\tilde{\lambda}_{\mathrm{pv}}$ represents the exact load-carrying rate of the peak-to-valley; $\lambda_{\mathrm{pv}}^{\max}$ and $\lambda_{\mathrm{pv}}^{\min}$ represent the clipping load rate of the positive and negative response estimates, respectively; $\Delta\lambda_{\mathrm{pv}} = \lambda_{\mathrm{pv}}^{\max} - \lambda_{\mathrm{pv}}^{\min}$ represents the span of the fuzzy load-carrying rate under a certain peak-valley electricity price difference.

Using the same method, the exact load-carrying rates and of the user's peak-to-flat and flat-turn valleys can be obtained separately. Then, the amount of load transfer generated by the user's actual demand response is as shown in equation (7).

$$DR_t = \begin{cases} -\tilde{\lambda}_{\mathrm{pf}} L_{\mathrm{p}}^{\mathrm{av}} - \tilde{\lambda}_{\mathrm{pv}} L_{\mathrm{p}}^{\mathrm{av}}, & t \in T_{\mathrm{p}} \\ \tilde{\lambda}_{\mathrm{pf}} L_{\mathrm{p}}^{\mathrm{av}} - \tilde{\lambda}_{\mathrm{fv}} L_{\mathrm{f}}^{\mathrm{av}}, & t \in T_{\mathrm{f}} \\ \tilde{\lambda}_{\mathrm{pv}} L_{\mathrm{p}}^{\mathrm{av}} + \tilde{\lambda}_{\mathrm{fv}} L_{\mathrm{f}}^{\mathrm{av}}, & t \in T_{\mathrm{v}} \end{cases} \tag{7}$$

Where: t represents the point of load sampling; T_{p}、T_{f} and T_{v} respectively represent the peak period, the flat period and the valley period corresponding to the time-sharing electricity price; $L_{\mathrm{p}}^{\mathrm{av}}$、$L_{\mathrm{f}}^{\mathrm{av}}$ and $L_{\mathrm{v}}^{\mathrm{av}}$ respectively represent the peak-to-valley time-sharing electricity price before the implementation of the peak period, the flat period and the valley period The average value of the load; DRt represents the amount of load transfer due to the demand response at the point of the first load sampling. This is called the DR signal.

IV. RBF-NN Prediction Model Based on Energy Hub

A. RBF-NN Model

RBF-NN is a multi-input and single-output forward neural network model [15], which includes input layer, hidden layer and output layer. The model structure is shown in Figure 5. The input layer is used to receive multiple elements with strong correlation with the output result and pass to the hidden layer; the hidden layer performs multivariate nonlinear transformation on the input vector for feature extraction; the output layer determines the hidden by model training The output weights of the layered neurons are linearly combined and output.

In Figure 5: $x = \begin{bmatrix} x_1 & x_2 & \ldots & x_m \end{bmatrix}$ represents the m-dimensional input vector; ci represents the center of the i-th hidden layer neuron transfer function, $1 \leq i \leq n$; n represents the number of hidden layer neurons; $\Phi_i\left(\|\mathbf{x} - \mathbf{c}_i\|\right)$ represents the i-th hidden layer neuron transfer function, A Gaussian function is usually selected, as shown in equation (8); ω represents the connection weight of each linear combination part at the output; y represents a single-dimensional output of the model.

$$\Phi_i\left(\|x - c_i\|\right) = \exp\left[-\frac{1}{2}\left(\frac{\|x - c_i\|}{\delta_i}\right)^2\right] \tag{8}$$

Where δ_i represents the distribution width of the Gaussian function of the i-th hidden layer neuron.

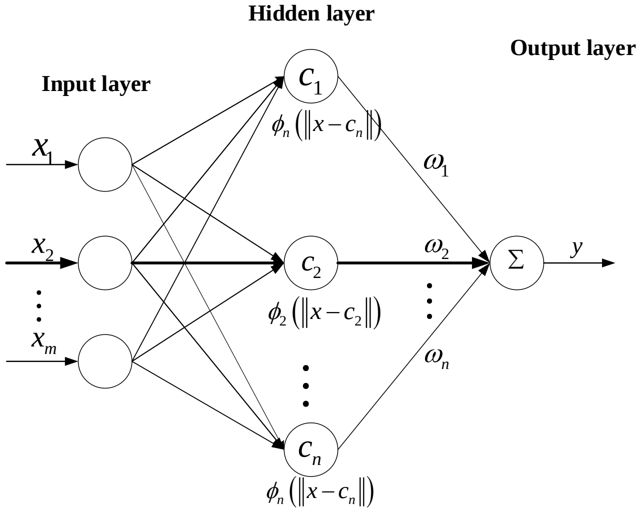

Fig.4. Architecture of RBF-NN model

Compared with the traditional BP-NN, RBF-NN has good global optimization performance, and does not appear to be non-converged or fall into local optimum. It is more suitable for power system load time series prediction.

B. RBF-NN Model Considering The Comprehensive Influencing Factors of Demand Side Response

In the short-term load forecasting problem of traditional power systems, the demand response is not involved. The load influencing factors usually only include external factors such as temperature, weather conditions and day types. The time interval of the load time series is set to 15 min. Taking the load power at d day k as an example, the traditional input composition of the neural network can be as shown in Fig.5.

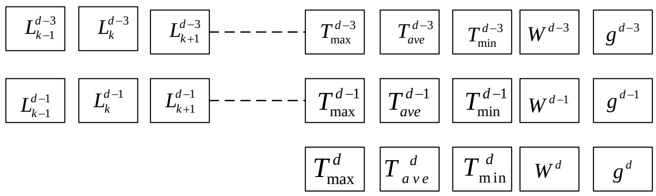

Fig. 5. Traditional input component of neural network

In Fig.5, d indicates the number of days, that is the date; k indicates the number of points at the time of load, $1 \leq k \leq 96$; L_k^d indicates the historical load value at k on day d; $T_{\max}^d$、T_{ave}^d and $T_{\min}^d$ indicate the maximum temperature, average temperature, and minimum temperature quantified value of d day respectively; W^d represents the daytime weather condition quantified value; g^d represents the day type quantized value of d day. The traditional input of neural network consists of 29 dimensions, including 9-dimensional historical load data and 20-dimensional external influence factors.

Regardless of the electricity price policy type or the incentive policy type demand response project, the user load curve will change due to the demand response and tend to cut the peak and fill the valley. The traditional input composition of the neural network is bound to continue to work accurately, and the traditional neural network model is needed. Make adjustments or improvements. The next day load transfer amount, that is, the DR signal, can be fitted by the user's actual demand response mechanism model. In the RBF-NN model, this paper treats it by external influence factors to reflect the effect of the electricity price mechanism on demand response. The input composition of the RBF-NN model considering the DR comprehensive influencing factors is shown in Fig.6.

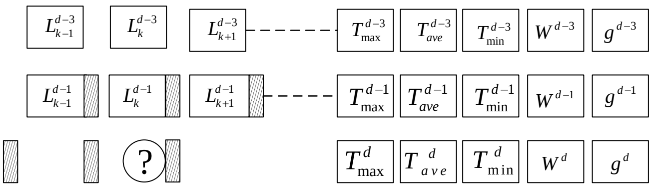

Fig. 6. Input component with DR of RBF-NN model

In Fig.6, the shaded box has a corresponding meaning according to its specific location, and DR_k^d represents the amount of load transfer at k on day d. The input component of the RBF-NN model considering the comprehensive influencing factors of DR contains 38 dimensions, including 9-dimensional historical load data, 20-dimensional external influence factors, and 9-dimensional DR signals.

In order to prove the important role of considering the comprehensive influencing factors of demand response in the RBF-NN prediction model, this paper will combine the actual grid load data to form the RBF-NN model input with the two structures of Figure 6 and Figure 7, respectively. At the same time, the prediction performance of the model in both cases is compared.

C. Forecast Evaluation

Mean absolute percentage error (MAPE) is used as an evaluation index for prediction accuracy

$$\varepsilon_{MAPE} = \frac{1}{J}\sum_{j=1}^{J}\left|\frac{\tilde{Y}_j - Y_j}{Y_j}\right| \times 100\ \% \qquad (9)$$

Where: $\tilde{Y}_j$ 、 Y_j is the predicted value and the true value respectively; J is the quantity of all predicted values.

V. Case Analysis

This paper selects the data of the regional integrated energy system of a demonstration operation in Shanghai from November 1st to December 19th, 2018 as an example. Training modeling was performed using data from November 1 to December 18 to predict various types of loads on December 19.

In order to verify the effect of the RBF-NN model based multi-energy supply system load forecasting method proposed in this paper, the following three cases are set:

Case 1: Considering the coupling of electricity, gas and heat load, using RBF-NN model for prediction;

Case 2: Regardless of the coupling between electricity, gas and heat load, the RBF-NN model is used to predict the electrical load, air load and heat load respectively;

Case 3: Considering the coupling of electricity, gas and heat load, BP-NN model is used for prediction.

The short-term prediction results of electricity, gas and heat load in the three cases are shown in Figure 7, Figure 8 and Figure 9, respectively. The prediction accuracy is shown in Table 2.

It can be seen that the MAPE of Case 1 is smaller than Case 2, whether it is electric load, gas load or heat load, that is, considering the coupling between electricity, gas and heat load can significantly improve the prediction accuracy. In addition, the electric, gas and heat load error values of Case 1 are smaller than Case 3, and the difference is large, indicating that the prediction effect of the RBF-NN model is significantly better than the BP-NN model. This means that the RBF-NN model has strong tracking ability for various loads, and the prediction error is small, which can effectively improve the prediction accuracy.

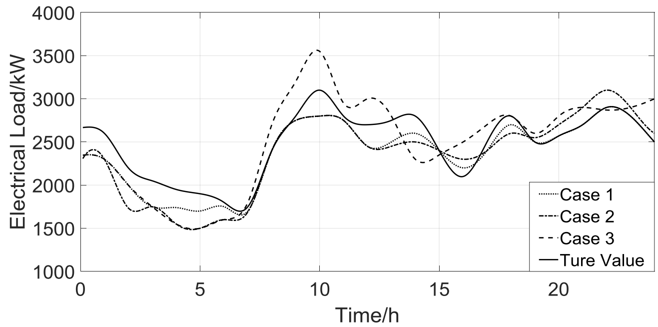

Fig. 7. Power load forecasting

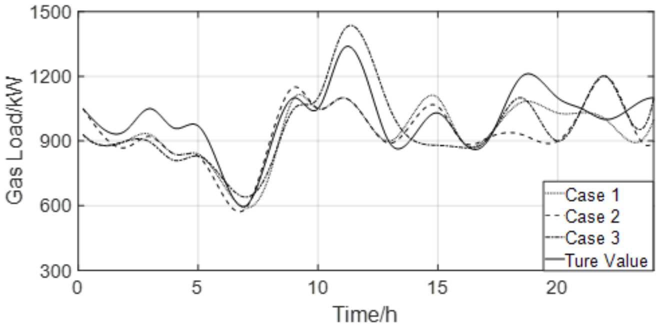

Fig.8. Gas load forecasting

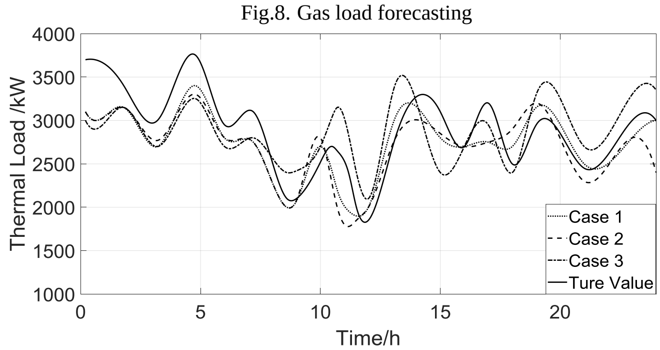

Fig.9. Heating load forecasting

TABLE 2
PREDICTION ACCURACY IN MAPE

	Electrical load	Gas load	Thermal load
Case 1	3.563	5.125	5.957

The load curve containing the DR signal is randomly selected for prediction for three days. The error of the DR signal factor load prediction model and the DR signal factor prediction model are not shown in Table 3.

TABLE 3
ERROR ANALYSIS RESULTS BEFORE AND AFTER IMPROVING THE FORECASTING MODEL

Demand response serial number	No DR factor	DR factors
	Mean relative error 1%	Mean relative error 1%
1	2.33	1.47
2	2.25	1.35
3	2.12	1.20

It can be seen from Table 3 that the prediction error of the prediction model is large when the DR signal factor is not taken into account, and the range of the average relative error and the maximum relative error respectively reach 2.32%-2.52% and 7.52%-8.68%, respectively. After considering the DR signal factor in the input of the prediction model, the prediction performance is effectively improved. The maximum fluctuation limit of the average relative error does not exceed 1.69%, and the fluctuation range of the maximum relative error does not exceed 5.81%. The above analysis fully demonstrates the importance of demand response factors for load forecasting.

VI. CONCLUSION

Radial neural network (RBF-NN) short-term load forecasting model is constructed considering the comprehensive influencing factors of demand side response Combined with practical examples, the main conclusions are as follows: The peak-filling effect of peak-to-valley electricity price is revealed in the constructed user demand response mechanism model, which can effectively identify the user's response parameters to peak-to-valley time-of-use electricity price based on peak-to-valley time-of-use electricity price and user psychology. The RBF-NN model has better predictive performance when considering the demand-side response load; Analytical modeling of the coupling relationship between multiple loads of energy systems has high prediction accuracy and provides a theoretical basis for short-term load forecasting studies that take into account the demand side response.

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