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Retraction

Retracted: Short-Term Load Monitoring of a Power System Based on Neural Network

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] D. Yang, "Short-Term Load Monitoring of a Power System Based on Neural Network," *International Transactions on Electrical Energy Systems*, vol. 2023, Article ID 4581408, 10 pages, 2023.

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Research Article

Short-Term Load Monitoring of a Power System Based on Neural Network

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In order to improve the accuracy of power load forecasting, this paper proposes a neural network-based short-term monitoring method. First, the original energy load signal is decomposed by the CEEMDAN algorithm to obtain several eigenmode function components and residual components; several eigenmode function components and residual functions are fed into the NARX neural network for computational purposes. The partial hypothesis is superimposed in the following part to obtain the final short-term forecast. According to the test results, the MAPE of the CEEMDAN-NARX model is 4.753%, 3.540%, and 0.343% lower than the SVM, RNN, and NARX models, respectively, and 3.741% and 2.682% lower than CEEMDAN-SVM and CEEMDAN-RNN, respectively. The MAPE and RMSE of the CEEMDAN-NARX model are 0.765% and 101.7 MW, respectively, which are 0.468% and 45.2 MW lower than NARX models, respectively. Compared to CEEMDAN-SVM, the MAPE of CEEMDAN-NARX and CEEMDAN-RNN decreased by 0.986% and 0.692%, respectively, and the RMSE of CEEMDAN-NARX decreased by 111.5 and 65.7 MW, respectively, compared to CEEMDAN-SVM. Conclusion is that the load forecasting model based on the combination of CEEMDAN algorithm and NARX neural network can effectively connect, reduce the negative impact of noise on forecasting results, and improve forecasting accuracy.

1. Introduction

The rapid development of smart grids is important for the sustainable development of the entire business community. The successful deployment of smart grids projects has a positive impact on the energy sector. At the same time, the needs of the electricity industry for the power grid are gradually improving. The operation of the power system needs to be safe and stable in order to provide a guaranteed power environment for industrial production and residents' lives. However, there are difficulties in the phased generation, transmission, consumption, and direct storage of a large amount of electric energy in the power system, which leads to a large waste of power resources that cannot be consumed in social production and life, causing serious environmental pollution and instability of the power system. The accuracy of short-term power load forecasting can provide guarantee for the safe and stable operation of the power system and help power companies to arrange production and distribution plans according to the actual power load, thus reducing waste. In addition, the electrical equipment shall be inspected and maintained in a planned way to provide safety guarantee for the sustainable production of electric power. Therefore, it is necessary to strengthen the load monitoring and planned distribution of electric power enterprises. Among them, short-term power system load forecasting is one of the important studies of the power system [1]. In order to achieve the accuracy and efficiency of short-term power load forecasting results, it is necessary to consider many factors that affect power load forecasting. However, in the process of power load forecasting, in addition to the internal factors that can be controlled, it will also be affected by uncontrollable external factors, resulting in inaccurate forecasting. With the rapid development of artificial intelligence technology, the neural network model has been widely used in the field of power, and more and more researchers have applied it to short-term power load forecasting. Because it has adaptive and nonlinear adaptive ability, it can solve the power load forecasting problem under the influence of complex factors [2]. The main driving factors of power load include social production, residents' life, and meteorological factors. Due to the uncertainty of social production, life, and meteorological factors, it is necessary to consider the combination of external factors when carrying out effective, accurate, and reliable short-term power load forecasting. For example, the meteorological factor temperature, in summer and winter, human production, and life need high-energy consumption power equipment for refrigeration or heating, so the power load consumed is far greater than that in other seasons [3]. When energy load data is collected, problems such as electrical equipment failure, meter failure, and signal interference can cause abnormal or incomplete data, resulting in biased short-term energy load forecasting. Therefore, the data needs to be preprocessed. In summary, the results of short-term energy load forecasting are important for all areas of human society. However, in order to achieve accurate prediction results, it is necessary to create an effective short-term energy load forecasting model by combining artificial intelligence technology, energy load forecasting features, and load influencing factors [4]. Power load forecasting can be understood as statistical analysis of the change trend of historical power load, and the change law obtained in the analysis process can be used in the future power load forecasting research. Theoretically, power load forecasting is used to explore the balance between different forecasting methods, power load data, and power load influencing factors.

2. Literature Review

Tang et al. proposed a short-term energy load forecasting method based on support vector regression (SVR). This method uses a special selection process for automatic input model selection and an optimization mechanism for SVR superparameter optimization, which reduces operator interaction. The experimental results confirm the effectiveness of this method. In the literature, a short-term load forecasting model based on empirical mode decomposition (EEMD) and segmented particle optimization (SS-PSO) was proposed to predict ultra-short-term energy loads, with the results being effective [5]. Guo et al. proposed an improved hybrid power load forecasting method that combines the least squares algorithm, Kalman filtering algorithm, and chaotic Kalman filtering algorithm and uses different weighting methods to optimize the short-term power load forecasting model [6]. Liang uses an improved support vector machine (SVM) method, and using the nonlinear relationship between load forecasting and load impact parameters, to establish holiday and non holiday power load forecasting models, and achieves short-term power load forecasting. With the development of the Internet of things and smart meter technology, researchers have introduced deep learning based on the Internet of things to get the characteristics of the data received and accurately predict the future before load values [7]. Guo and others have proposed machine learning-based predictive modeling. This method uses a small amount of data to estimate power consumption patterns and peak operating times. Experimental results show that this algorithm can save 0.62–2.28 percent of energy costs compared to other traditional energy estimation methods [8]. Yang et al. proposed an optimal method of speed estimation based on Gaussian process quantile regression (GPQR) and applied it to smart grid [9]. Zhou et al. proposed a nonparametric kernel regression method to estimate energy [10]. Su et al. used dynamic neural networks to predict daily energy consumption to manage production and social life and to increase the efficiency of energy systems [11]. Demirdelen et al. proposed an improved postpropagation neural network based on technology decomposition and pollination-optimization for short-term forecasting [12]. Guo et al. proposed a hierarchical neural model with a time window and used it to predict long-term energy [13]. Xie et al. proposed a hybrid forecasting model combining flight path optimization (FOA) and the general regression neural network for energy load estimation [14].

Regarding the reduction of the accuracy of power load forecasting caused by the time change of energy load and noise, this paper presents a short model of forecasting based on the combination of CEEMDAN algorithm and NARX neural network. The CEEMDAN algorithm decomposes the original power load signal into different components, which effectively suppresses noise and reduces errors, and solved the time-varying problem using NARX neural network dynamics and feedback.

3. Research Methods

3.1. Power Load Forecasting Method. The initial development period of power load forecasting technology was in the 1960s. At that time, the economic development of the world was in the initial stage, and the demand for electricity also increased, which led to the development and expansion of the entire power system, and load forecasting also got preliminary development.

Traditional forecasting methods use the collected power load time series data to find out the law of power consumption and make a guiding method for power load forecasting. Traditional prediction methods include trend extrapolation, regression analysis, and time series.

Although the classical forecasting method is simple and easy, the accuracy of forecasting is difficult to meet the requirements and theoretical research such as artificial neural network (ANN), wavelet transform (wavelet transform), fuzzy logic (FL), and combined estimates.

The short-term power load is greatly affected by economy, weather, politics, and other uncertain factors, and there are periodic changes within a year. Therefore, in short-term load forecasting, it is necessary to comprehensively consider various influencing factors and understand their periodicity. Generally speaking, the basic steps of short-term load forecasting are as follows:

First, we formulate a prediction plan according to the prediction purpose. We fully understand the content and purpose of load forecasting and analyze its nature. The load characteristics of different regions, different times, and different power grids are different.

Second, data should be collected. The main research object of power load forecasting is historical data. The selection of sample data will directly affect the effect of load forecasting. In addition, the work of sorting out data is also very important. For the missing values and abnormal values in the sample data, appropriate methods should be selected to deal with them to ensure the reliability of the data.

Third, we choose prediction methods and build prediction models. Through the analysis of historical load data, according to the advantages, disadvantages, and applicability of different load forecasting methods, we select the appropriate forecasting method and establish the model on this basis. Establishing a model is a crucial step in load forecasting. After the model is established, the optimal parameters are found by adjusting parameters.

Fourth, we take the prediction and analyze the prediction error. The prediction results are generated from the defined prediction model and the measurement model, and the error of the prediction is analyzed. The difference between the estimated value and the actual value can be taken as the final result if it is within the specified range. If the difference between the estimated value and the actual value is large, various parameters of the model are adjusted and readjusted until the forecast is achieved.

Fifth, we look into the summary and reflection. After getting the prediction results, through analyzing the prediction error and comparing the performance of various methods, this paper summarizes the success and shortcomings of load forecasting and looks forward to the next research content.

3.2. CEEMDAN Algorithm Principle

3.2.1. EMD Algorithm and Its Improved Algorithm. The Empirical Mode Decomposition (EMD) algorithm can transform linear and nonstationary systems into linear and steady-state functions (IMFS). EMD has the advantages of efficient and complete conversion, but poor conversion affects the actual decomposition of EMD. By improving the EMD algorithm, we can obtain empirical mode decomposition (EEMD) and all ensemble empirical mode decomposition (CEEMD) algorithms. The EEMD algorithm optimizes the existing problems of EMD, reduces the conversion error of the upper and lower envelopes, makes the local effect of abnormal signals, and thus changes the mode EMD, but the residual noise remains to be the signal. The CEEMD algorithm adds positive and negative white noise to the original signal and each EMD signal and finally gives the calculated result. The CEEMD algorithm can save the calculation time and remove the noise from the IMF components. It not only solves the problem of modal aliasing but also accurately reconstructs the original signal. However, if the parameters are improperly selected, wrong components will be generated, resulting in the components that do not meet the definition of IMF components [15].

In essence, the solution process of empirical mode decomposition algorithm is a "screening" process, from which the eigenmode function with high frequency to low frequency is obtained, and finally, there is a monotonic residual sequence that can no longer be decomposed, which is also known as trend term.

IMF must meet the following two qualifications:

(1) The number of maximum and minimum points of the whole data must be equal to or no more than the number of points passing through the origin.

(2) The mean value of the upper and lower envelopes generated by the maximum and minimum values of the whole data is zero.

The specific stages of the EMD algorithm decomposition are as follows:

(1) The upper and lower envelopes and the middle envelope $m_1(t)$ use the cubic spline interpolation method based on the maximum and minimum values of the original signal.

(2) The intermediate signal is the difference between the original signal and the mean envelope to judge whether the intermediate signal meets the conditions of IMF. If the intermediate signal conforms to the assumption of eigenmode function, the first IMF component is obtained. If the limiting conditions are not met, the intermediate signal needs to continue the previous step 1 to obtain the mean envelope $m_2(t)$ and then obtain a new intermediate signal and so on; until the intermediate signal meets the conditions, it is recorded as imf_1.

(3) After obtaining imf_1, we use the original signal to subtract imf_1 to obtain a new original signal and then perform the previous steps 1 and 2 on the new original signal to obtain imf_2. We repeat steps 1–3 mentioned above until no new IMF component can be generated and the decomposition process is over.

3.2.2. CEEMDAN Algorithm. Aiming at the problems of EEMD algorithm and CEEMD algorithm, this paper uses the CEEMDAN algorithm to process power load signal. CEEMDAN is an improvement based on EMD and EEMD algorithms.

The CEEMDAN algorithm adds adaptive white noise in each decomposition stage, so that the reconstruction error tends to zero. The CEEMDAN algorithm can not only eliminate the mode aliasing in EMD by adding adaptive noise but also solve the nonstationary problem of the signal by decomposing the load signal into components of different frequencies. The steps of the CEEMDAN algorithm are as follows:

(1) The power load signal set containing white noise is generated as follows (1):

$$x^i(t) = x(t) + w^i(t), \tag{1}$$

where $w^i(t)\,(i = 1, 2, \ldots, I)$ is the noise satisfying the Gaussian distribution, and I is the total number of samples in the power load signal set [16].

(2) We perform EMD on $x^i(t)$ to obtain the first-order component IMF_1^i of each sample and take its mean value as the first-order IMF component of $x(t)$, that is, the following formula:

$$\widetilde{\mathrm{IMF}}_1(t) = \frac{1}{I}\sum_{i=1}^{I}\mathrm{IMF}_1^i. \tag{2}$$

(3) We calculate the first-order residual quantity and the second-order component. The expressions of the first-order residual quantity and the second-order component are, respectively, as follows :

$$r_1(t) = x(t) - \widetilde{\mathrm{IMF}}_1(t), \tag{3}$$

$$\widetilde{\mathrm{IMF}}_2(t) = \frac{1}{I}\sum_{i=1}^{I}E_1\left\{r_1(t) + \varepsilon_1 E_1\left[w^i(t)\right]\right\}, \tag{4}$$

where $E_i(\cdot)$ represents the i-order IMF component of the signal, and ε_i is the parameter controlling the white noise energy.

(4) The expressions for calculating the $k\ (k = 2, 3, \ldots, K)$ (K is the highest order of the IMF component) order residual, the $k + 1$ order IMF component, and the $k + 1$ order IMF component are as follows:

$$r_k(t) = r_{k-1}(t) - \widetilde{\mathrm{IMF}}_k(t), \tag{5}$$

$$\widetilde{\mathrm{IMF}}_{k+1}(t) = \frac{1}{I}\sum_{i=1}^{I}E_1\left\{r_k(t) + \varepsilon_k E_k\left[w^i(t)\right]\right\}. \tag{6}$$

(5) We repeat step 4 until the residual cannot be decomposed again, and the judgment standard is that the number of extreme points of the residual is at most 2. If the residual satisfies the following equation:

$$R(t) = x(t) - \sum_{k=2}^{K}\widetilde{\mathrm{IMF}}_k(t), \tag{7}$$

then the original signal of power load is finally decomposed into the following formula:

$$x(t) = \sum_{k=2}^{K}\widetilde{\mathrm{IMF}}_k(t) + R(t). \tag{8}$$

3.3. Training of NARX Neural Network. The NARX neural network is a dynamic neural network with memory and feedback functions, which can store historical load data and calculate it together with future load data. Therefore, the network has dynamic performance and is not easy to lose information [17]. The tasks of prediction and classification, the one-dimensional and two-dimensional prediction of highly nonlinear relations, and nonlinear classification boundaries that can be achieved by the multilayer network are completed by the nonlinear excitation function in the hidden neuron. The weight of the network controls the characteristics of the nonlinear excitation function. The training starts to adjust continuously when it contacts the weight characteristics, so that the excitation function can gradually approach the expected response, and the process of the network prediction error gradually falling below the specified error threshold is called network learning. The typical NARX neural network structure is shown in Figure 1.

The steps of network training are as follows:

(1) We set neural network parameters. The parameters to be set include the number of training steps of neural network, transfer function f of hidden layer, transfer function g of output layer, and learning rate η.

(2) We calculate the output of the hidden layer. The expression of the output is as follows:

$$H_j = f\left(\sum_{i=1}^{n}\omega_{hj}x_h(t) + \sum_{s=1}^{m}\omega_{\mathrm{sj}}x_s(t) - a_j\right), j = 1, 2, \ldots, l. \tag{9}$$

(3) We calculate the output of the output layer. The expression of the output is as follows:

$$y_v = g\left(\sum_{j=1}^{i}H_j\omega_{jv} - B_v\right), v = 1, 2, \ldots, m. \tag{10}$$

(4) We calculate the error value. The expression of the error is as follows:

$$e = \frac{1}{2}\sum_{v=1}^{m}e_v^2, e_v = o_v - y_v(t). \tag{11}$$

(5) We calculate the weight. The relevant expression is as follows:

$$\omega'_{\mathrm{hj}} = \omega_{hj} + \eta H_j x_h(t)\sum_{v=1}^{n}\omega_{jv}e_v, h = 1, 2, \ldots, n, \tag{12}$$

$$\omega'_{\mathrm{sj}} = \omega_{\mathrm{sj}} + \eta H_j y_s(t)\sum_{v=1}^{n}\omega_{jv}e_v, s = 1, 2, \ldots, m, \tag{13}$$

$$\omega'_{\mathrm{jv}} = \omega_{\mathrm{jv}} + \eta H_j e_v. \tag{14}$$

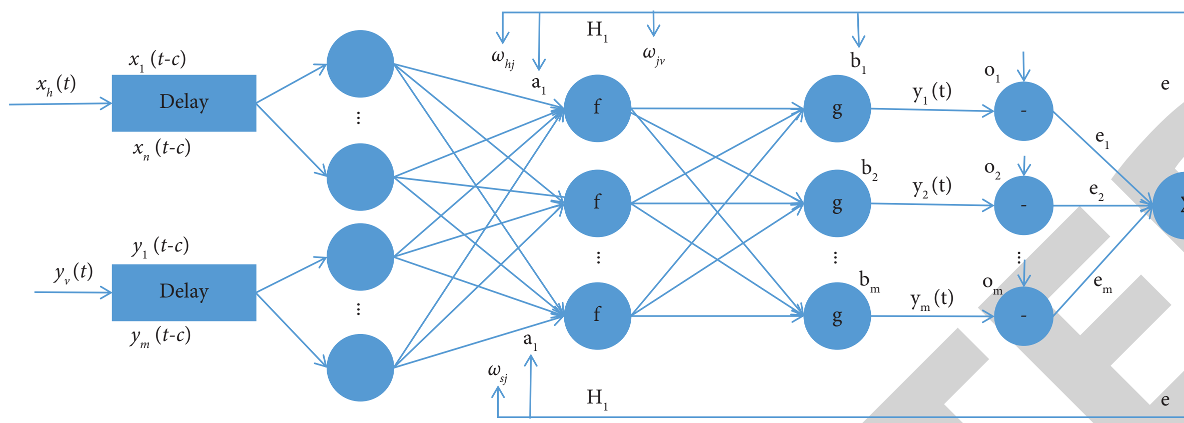

FIGURE 1: Typical NARX neural network structure.

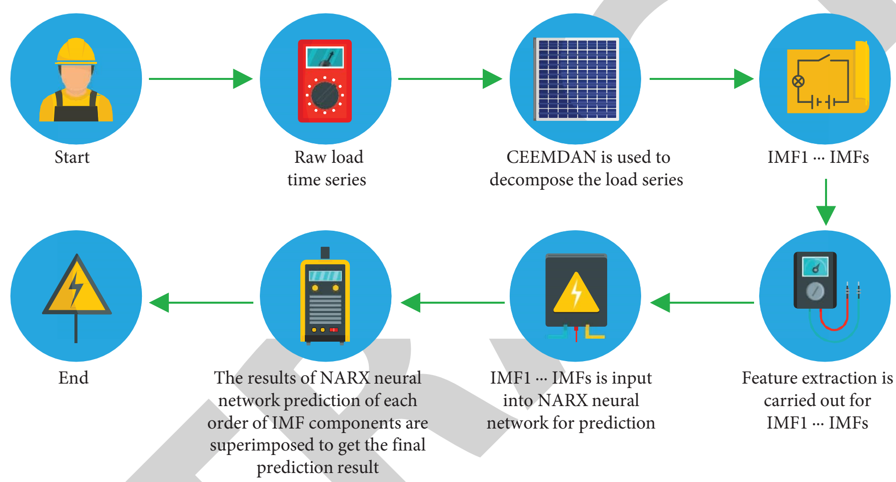

FIGURE 2: Short-term load forecasting process based on the CEEMDAN algorithm and NARX neural network.

(6) We calculate the threshold. The relevant expression is the following formula:

$$a_j' = a_j + \eta H_j \sum_{v=1}^{m} \omega_{jv} e_v, \tag{15}$$

$$b_v' = b_v + e_v. \tag{16}$$

(7) We set the number of iterations as the number of hidden layer neurons to judge whether the iteration is over, if not, we return to step 2 to continue the iteration. If the iteration ends, we complete the training.

3.4. Short Term Load Forecasting Model Based on CEEMDAN Algorithm and NARX Neural Network. NARX neural network-based CEEMDAN algorithm and short-term load prediction model CEEMDAN algorithm is used to process the initial energy load signal, obtain several species and residues, extract the sequence and characteristics of each residue, and then subtract them. The features of each order and more are fed into the NARX neural network for prediction. The NARX neural network handles feedback efficiently, and the output is a function of the historical data and the current input. The NARX neural network is capable of feedback, delay, memory storage, and integration with historical data, so the predictive model can adapt to changes over time signal load [18]. Figure 2 shows the short bootstrap process based on CEEMDAN algorithm and NARX neural network.

Figure 2 shows that the NARX neural network parameters, the number of layers, and the latency affect the accuracy of the prediction model. The input and output process vector dimensions are set to 4 and 1, respectively, depending on the nature of the external input and prediction. The structure of the NARX network is shown in Figure 3.

4. Result Analysis

4.1. CEEMDAN Algorithm Is Used to Process the Original Signal of Power Load. The original power load signal in this paper is selected from the 88 day power load data of a city in Hebei Province, China, as shown in Figure 4. The sampling period in Figure 4 is 30 min, and the total number of samples is 4416.

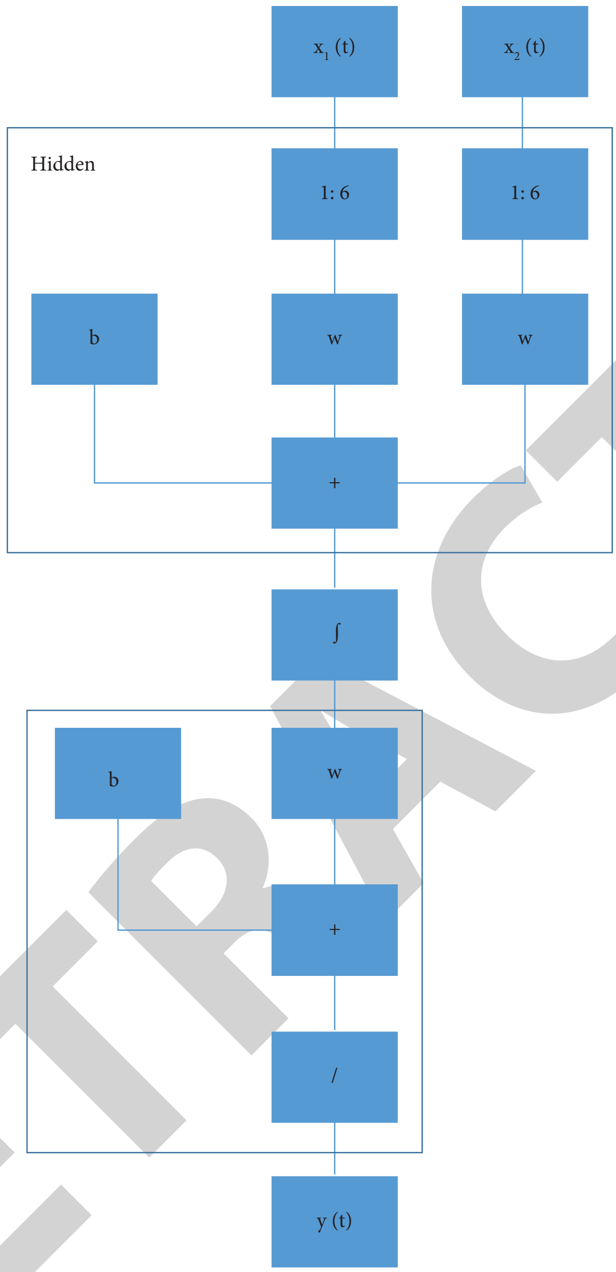

Figure 3: NARX network structure constructed.

Power load signals not only have linear and nonstationary problems but in an increasingly complex power environment, many factors can make power load signals unstable. Therefore, linear and nonstationary electrical load signals need to be linearized and stabilized using the CEEMDAN algorithm [19]. The energy load signal can be decomposed into IMF components and residual components in order of frequency, and the complex signal can be decomposed into a problem, and more physically meaningful frequencies that can be obtained are distinguished by different types of linear and nonstationary between signals. The energy load signal was decomposed by the CEEMDAN algorithm, and the results are shown in Figure 5(a) and 5(b).

After the decomposition of the CEEMDAN algorithm, 11 IMF components and 1 residual component are obtained. The decomposed material and the rest are 88 days of data, from which Saturday and Sunday's data are extracted to make 12 groups of weekend's data. Data from the first holiday group is used for feature extraction. The average of 10 groups of data is used as training to estimate the final group of holiday's data

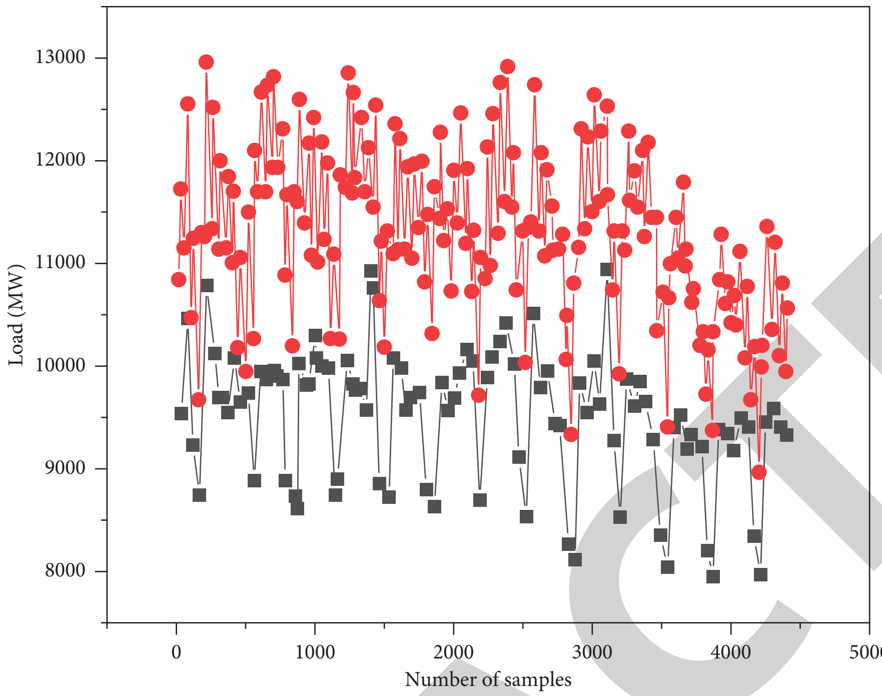

Figure 4: Power load of a city.

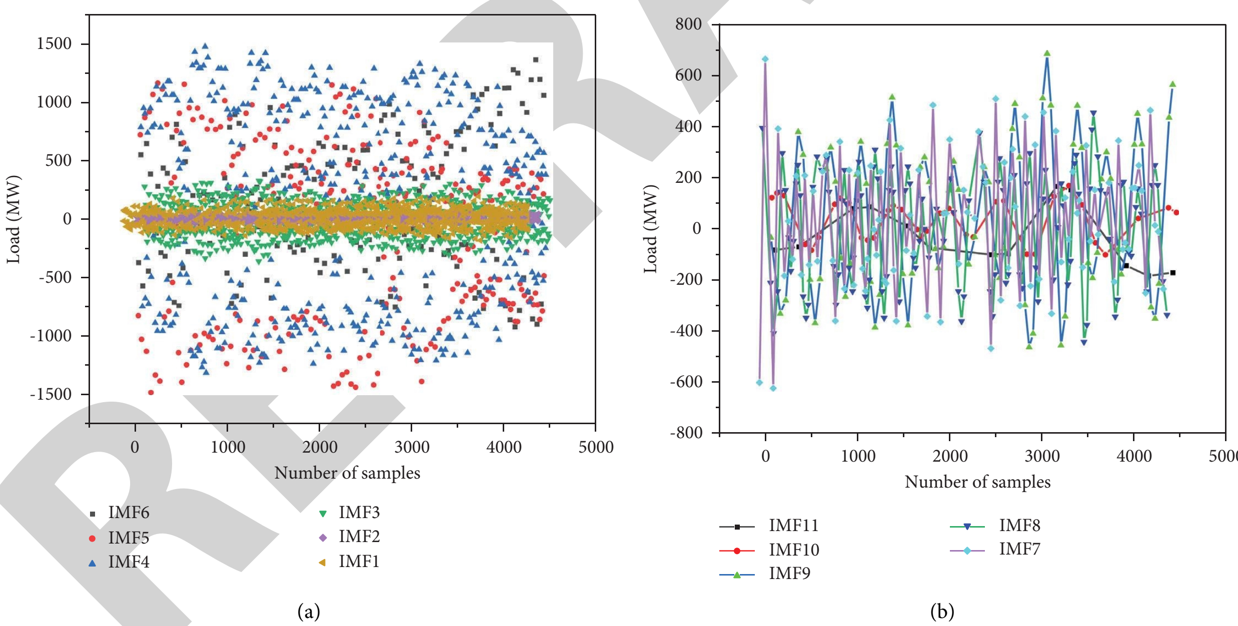

Figure 5: Decomposition results of the CEEMDAN algorithm. (a) Six IMF components. (b) Six IMF components and 1 residual component.

[20]. Preprocessed components and residual parts are fed into the NARX neural network for prediction, respectively, and 12 groups of data are obtained. The final short-term load estimate is obtained by overlaying 12 sets of forecast data.

The mean absolute percentage error (MAPE) and root mean square error (RMSE) are used to measure the model's predictive performance. The formula for calculating MAPE and RMSE is as follows:

Table 1: MPAE and RMSE under hidden layer 3.

Delay order	5	6	7
MAPE (%)	0.788	0.805	0.776
RMSE (MW)	105.1	105.4	104.5

Table 2: MPAE and RMSE under hidden layer 4.

Delay order	5	6	7
MAPE (%)	0.824	0.765	0.759
RMSE (MW)	107.4	101.7	104.3

Table 3: MPAE and RMSE under hidden layer 5.

Delay order	5	6	7
MAPE (%)	0.751	0.823	0.778
RMSE (MW)	111.5	121.1	118.2

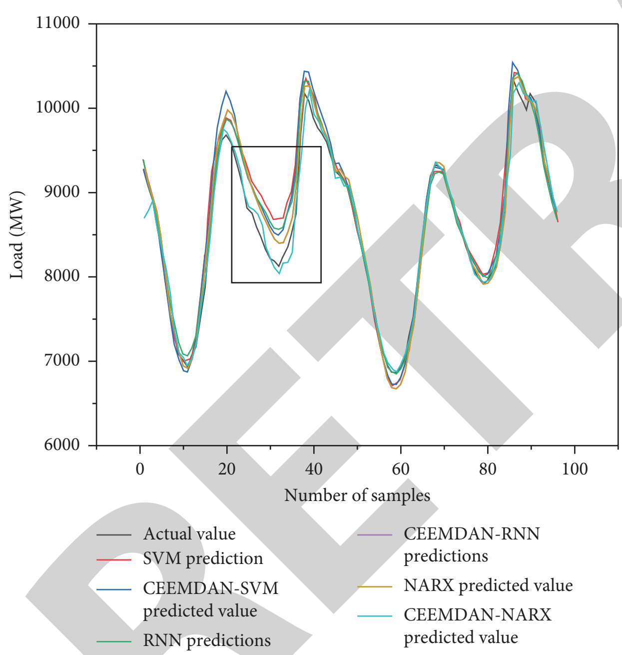

Figure 6: Comparison of prediction results of 6 models.

$$\text{MAPE} = \frac{1}{M}\sum_{t=1}^{M}\left|\frac{Y(t) - Y^{'}(t)}{Y(t)}\right| \times 100\%, \tag{17}$$

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{t=1}^{M}\left(Y(t) - Y^{'}(t)\right)^{2}}, \tag{18}$$

where $Y(t)$ is the actual load value at the time, $Y^{'}(t)$ is the predicted load value at the time, and M is the predicted number of points [21].

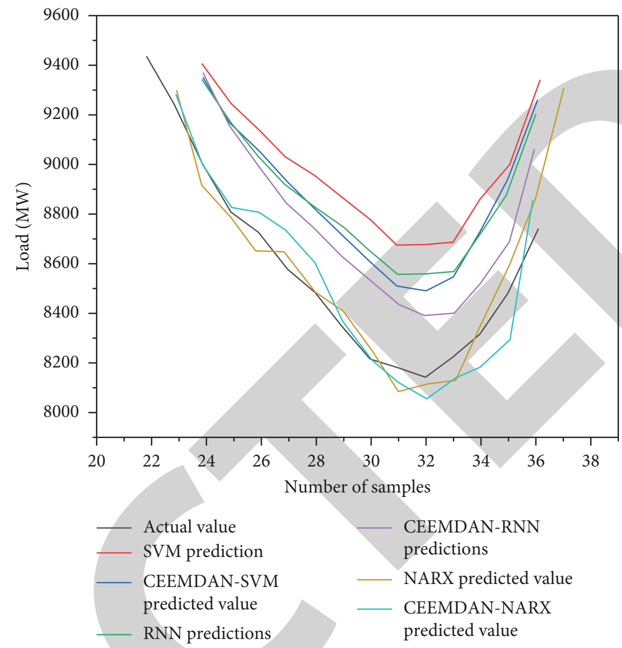

Figure 7: Enlarged view of the marked area in Figure 6.

Table 4: Evaluation indicators of each model.

Model	MAPE (%)	RMSE (MW)
SVM	2.034	231.5
CEEMDAN-SVM	1.751	213.2
RNN	1.495	179.1
CEEMDAN-RNN	1.457	167.4
NARX	1.233	146.9
CEEMDAN-NARX	0.765	101.7

Table 5: Evaluation indicators of local prediction of each model.

Model	MAPE (%)	RMSE (MW)
SVM	5.454	475.2
CEEMDAN-SVM	4.442	387.7
RNN	4.241	368.6
CEEMDAN-RNN	3.383	298.4
NARX	1.044	129.3
CEEMDAN-NARX	0.701	70.4

4.2. Determining NARX Neural Network Parameters. MPAE and RMSE in different parameter combinations are shown in Tables 1–3.

As shown in Tables 1–3, the number of hidden layers is 4 and the order delay is 6 when CEEMDAN algorithm and NARX neural network model have the best prediction performance.

4.3. Analysis of Prediction Results. In order to verify the validity of the proposed model, this paper presents the experimental results of three traditional power load forecasting models (SVM, RNN, and NARX) and three

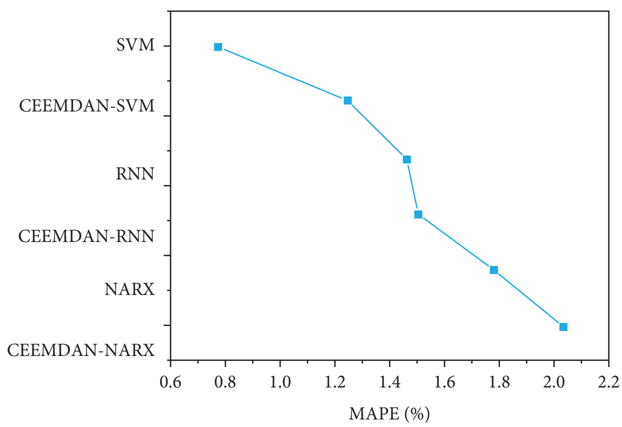

Figure 8: Histogram of MAPE of 6 models.

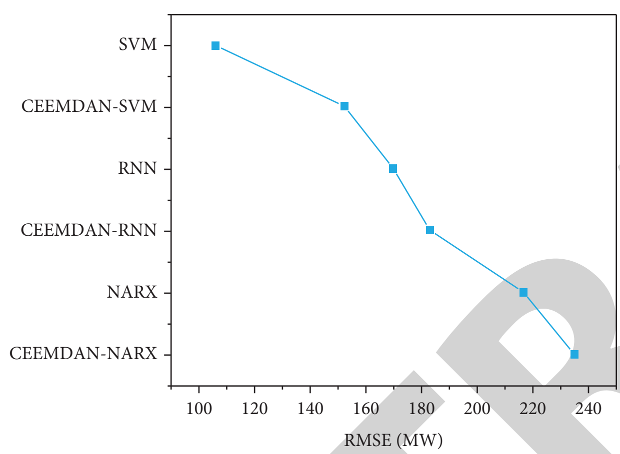

Figure 9: Histogram of RMSE of six models.

combined load forecasting models (CEEMDAN-SVM, CEEMDAN-RNN, and CEEMDAN-NARX). The results obtained by combining these three models with the CEEMDAN algorithm are compared [22]. A comparison of the prediction results of the six models is shown in Figure 6. Figure 7 is a magnified view of the area marked in Figure 6, where the selected area is near the electrical load cavity. Figure 7 shows that each model has a large prediction bias caused by the sudden drop in electricity load demand.

According to equations (17) and (18), the evaluation MAPE and RMSE indexes of each model can be obtained, and the results are shown in Table 4. Table 4 shows that the MAPE and RMSE of the CEEMDAN-NARX model proposed in this paper are 0.765% and 101.7 MW lower than other models, respectively. The lower the value of the evaluation index, the better the performance of the model and the more feasible the CEEMDAN-NARX model.

Table 5 shows the local prediction evaluation metrics for each model [23]. Table 5 shows that the MAPE of the CEEMDAN-NARX model is 4.753%, 3.540%, and 0.343% lower than that of the traditional bootstrapping single model SVM, RNN, and NARX, and 3.741% and 2.682% lower than the bootstrapping model combined prediction model CEEMDAN-SVM and CEEMDAN-RNN, respectively. These data show that the prediction accuracy of the CEEMDAN-NARX model is better than the other models, even in special cases such as near the trough.

In order to more intuitively express the differences between MAPE and RMSE among the six models, the histograms of MAPE and RMSE of the six models are shown in Figures 8 and 9 respectively.

It can be seen from Figures 8 and 9 that the MAPE and RMSE values of the combined model composed of SVM, RNN, NARX, and CEEMDAN are smaller than their corresponding single model, so the prediction accuracy of the combined model composed of CEEMDAN is relatively high [24]. The MAPE and RMSE of the CEEMDAN-NARX model proposed in this paper are 0.765% and 101.7 MW, which are reduced by 0.468% and 45.2 MW, respectively, compared to the same NARX model. Compared to CEEMDAN-SVM, the MAPE of CEEMDAN-NARX and CEEMDAN-RNN are reduced by 0.986% and 0.692%, respectively. Compared to CEEMDAN-SVM, the RMSE of CEEMDAN-NARX is reduced by 111.5 and 65.7 mW, respectively.

5. Conclusion

This paper presents a short-term load monitoring of power model based on the CEEMDAN algorithm and NARX neural network. First, the CEEMDAN algorithm decomposes the original energy load signal into components and residual components, which can suppress noise, reduce the frequency of separation, and improve the degree of integration. The decomposed objects and residual objects are fed to the NARX neural network for prediction. The NARX neural network can store load history data and calculate load history together with future load data. It has dynamic performance and is not prone to data loss. The combined model was compared with existing predictive models. According to the MAPE and RMSE test result values, the prediction accuracy of the CEEMDAN-NARX model is high, indicating that the model can monitor power load capacity.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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