Research on short-term power load forecasting and analysis based on EEMD-LSSVM- integrated BPNN

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ABSTRACT

In view of the stability and reliability of power system operation, it is necessary to adopt accurate short-time load forecasting. In order to improve the forecasting accuracy, a very short time power load forecasting method based on EEMD-LSSVM- integrated BPNN is proposed. Firstly, EEMD (Ensemble Empirical Mode Decomposition) is used to decompose the initial power sequence into a plurality of components with different frequencies, calculate the SE(Sample Entropy) of each component, and recombine the similar components with entropy values. LSSVM (Least Squares Support Vector Machine) is used to predict the low-frequency trend components, and integrated BPNN (Back Propagation Neural Network) based on Bagging integrated learning algorithm is used to predict the remaining components. Finally, the distributed power series are comprehensively predicted. The example shows that this method is a feasible short-term power load forecasting method and can effectively improve the forecasting accuracy and stability.

Keywords: Short term load forecasting, Recombination entropy value, Bagging ensemble learning algorithm, back propagation

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1. INTRODUCTION

According to the expected location of various state events in the life cycle profile and the characteristics of the state itself, combined with the mechanism of environmental stress, the environmental events that may be experienced by the in-vehicle environmental control device during the whole life cycle are analyzed. A day or a week in advance based on the historical load change law, combined with meteorological information, human activities and other external factors, and is an important part of smart grid development planning [1]. Power system planning and operation[2]. Due to the increasing complexity and uncertainty of modern power grid, the fluctuation behavior of load has become more and more complicated. As the device is required to meet the use environment of the whole land, in addition to the above storage environment factors, it is also necessary to consider the influence of salt fog, mold and other environments on the device [3] and machine learning method represented by SVM (Support Vector Machine] [4]. There are many factors that affect the power load. The power load itself is a random non-stationary sequence, and the statistical modeling method generally does not consider meteorological information, holiday information and other influencing factors, which leads to the failure to reflect the nonlinear characteristics that affect the load fluctuation. SVR(Support Vector Regression) method combines meteorological factors to realize dynamic modeling on SVM[5]. Literature [6-7] has constructed several different forecasting models, mainly including BPNN, GRNN (General Regression Neural Network) and so on, which can consider various external factors at the same time. And the fluctuation behavior of power load becomes more and more complicated. It is gradually difficult for a single forecasting model to obtain good forecasting accuracy. In order to make the model obtain better prediction performance, the combined prediction model constructed by introducing data decomposition algorithm came into being. References [8] and [9] discussed two data decomposition methods, EMD (Empirical Mode Decomposition) and EEMD. The defect of EMD is that modal aliasing is easy to occur when decomposing the original load series, and EEMD can improve this phenomenon by adding Gaussian white noise. It should be pointed out that the existing combined forecasting model usually uses a single model to predict multiple components after obtaining multiple components by using data decomposition algorithm, which cannot guarantee that the model has adaptability to multiple frequency components. Therefore, this paper proposes a short-term power load forecasting method based on EEMD-LSSVM- integrated BPNN. Firstly, the original load is decomposed by EEMD, and multiple components with different frequencies and characteristics are obtained. At the same time, in order to reduce the modeling task, the components with similar entropy values are calculated, the low-frequency trend components are predicted by LSSVM, and the remaining components are predicted by integrated BPNN based on Bagging integrated learning algorithm. The new model is verified in an actual example, and the prediction accuracy and stability are greatly improved.

2. EEMD ALGORITHM AND SAMPLE ENTROPY

2.1 EEMD algorithm principle

The characteristic of EMD algorithm is that it decomposes the original signal adaptively with time scale characteristics without setting the basis function, which is very suitable for dealing with non-stationary and strongly random time series, and its main drawback is the phenomenon of modal aliasing [10-11].

By adding Gaussian white noise, a continuous signal to be decomposed is obtained, and then EMD[11] is performed. The EEMD with uniformly distributed characteristic noise can promote the separation of input data at different scales, without actually affecting the IMF, which can effectively extract signals from the data and suppress modal aliasing.

The steps of EEMD algorithm are as follows [12]:

(1) White noise is added to the original power load data, and 20% of the standard deviation of the signal is set as the standard deviation of the white noise, which can be adjusted.

(2) The signal is residual component decomposed by EMD, as shown in the following equation, and the signal to be decomposed is located on the left:

$$s(t) = \sum_{i=1}^{K} c_i(t) + r(t) \tag{1}$$

Where: is the decomposed IMF; Is the residual component after decomposition.

(3) Repeat the above steps (1) and (2) and add mutually different white noise sequences at the same time. The number of repetitions is determined according to the effect to be achieved by decomposition.

(4) After reaching the maximum number, get the average value of the corresponding IMF as the final result.

2.2 Sample entropy (SE)

The greater the complexity of time series in SE method, the greater the SE value, and the calculation has good consistency, independent of data length. Measuring the complexity of a sequence is mainly based on the probability of generating a new pattern in the measured signal [13]. At present, SE is widely used in biomedicine, brain wave recognition and other fields. In this paper, SE is used to recombine the components obtained after EEMD decomposition, which can not only improve the calculation efficiency, but also reduce the modeling task.

$\{x(i)\} = \{x(1), x(2), \cdots, x(N)\}$ is time series data and consists of N samples. The steps of SE algorithm are as follows:

(1) Set the embedding dimension m in advance, and form a group of m-dimensional vectors in sequence:

$$\{\boldsymbol{X}_m(i)\} = \{x(i), x(i+1), \cdots x(i+m-1)\}, i \in [1, N-m+1] \tag{2}$$

(2) The absolute value of the maximum difference between the orientations $\boldsymbol{X}_m(i)$ and $\boldsymbol{X}_m(j)$ of the distance $d[\boldsymbol{X}_m(i), \boldsymbol{X}_m(j)]$, namely:

$$d[\boldsymbol{X}_m(i), \boldsymbol{X}_m(j)] = \max[|x(i+k) - x(j+k)|], \ k \in [0, m-1] \tag{3}$$

(3) r ($r > 0$) is the set similarity tolerance, given that $\boldsymbol{X}_m(i)$, $B_i^m(r)$ and $B^m(r)$ are the given number ratio $d[\boldsymbol{X}_m(i), \boldsymbol{X}_m(j)] \leq r$ of $\boldsymbol{X}_m(i)$, the formula is as follows:

$$B_i^m(r) = \frac{1}{N-m} num\{d[\boldsymbol{X}_m(i), \boldsymbol{X}_m(j)] < r, i \neq j\} \tag{4}$$

$$B^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r) \tag{5}$$

(4) Add 1 to the vector dimension, and repeat the above three steps to get the $B^{m+1}(r)$ mean of $B_i^{m+1}(r)$:

$$B^{m+1}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^{m+1}(r) \tag{6}$$

(5) Calculate the SE of time series. When N is a finite value, the calculation formula is as follows:

$$SE(m, r, N) = -\ln[\frac{B^{m+1}(r)}{B^m(r)}] \tag{7}$$

3. SHORT-TERM LOAD FORECASTING BASED ON EEMD-LSSVM-BAGGING-BPNN

3.1 EEMD algorithm principle

The standard BPNN feed forward neural network is shown in Figure 1 below:

Taking the prediction accuracy and time as the comprehensive measure, through many experiments, it is determined that 20 rounds of self-help random sampling with playback are carried out in proportion, and BPNN is used as a weak learner, and 20 prediction models are trained and predicted on the test set, and a strong learner is obtained after simple equal weight average. The implementation mechanism of the algorithm is shown in Figure 2:

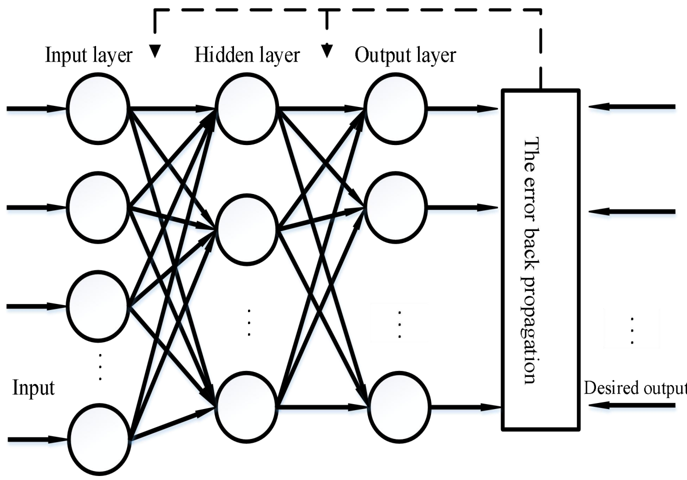


Figure 1. BPNN structure diagram

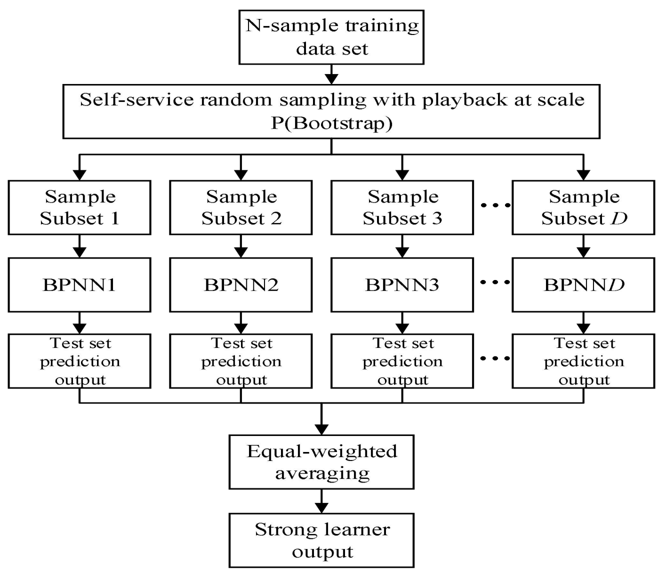


Figure 2. Realization mechanism of Bagging-BPNN algorithm

Many external factors, such as meteorological conditions, will affect the power load to varying degrees, which leads to the randomness of the power load, while the time factor makes the fluctuation of the power load show periodic changes [14]. EEMD-LSSVM-Bagging-BPNN model, and the steps are as follows:

(1) Input historical load data and preprocess abnormal or incomplete data.

(2) The prototype should be in the form of a highly compact all-in-one machine, with light weight, integration, high reliability and environmental adaptability as the main technical characteristics, and pay attention to component scheme optimization and performance matching, so as to effectively improve the actual cooling and heating adjustment effect.

(3) Analyze the characteristics of the recombined components, and select the characteristic input variables with high correlation. The characteristic pool includes meteorological, time information and historical load.

(4) Normalizing the data, using LSSVM model to predict the low-frequency trend components, using Bagging-BPNN to predict the remaining components, as shown in Figure 3 below.

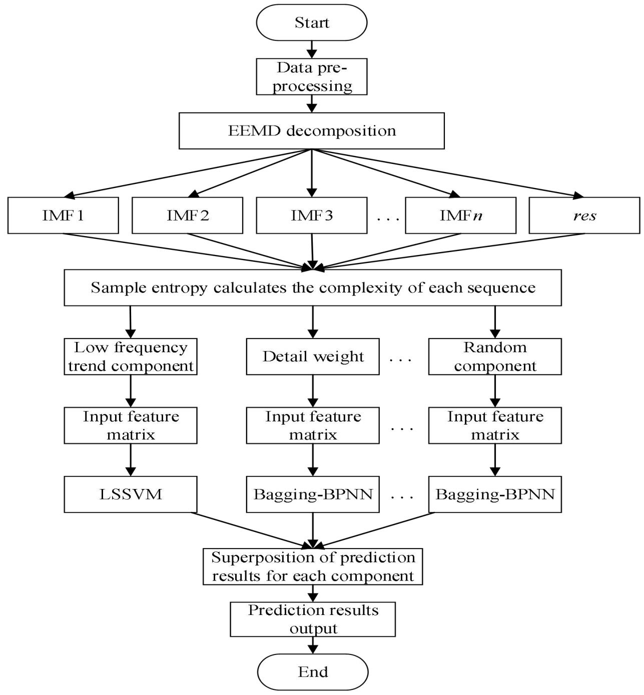
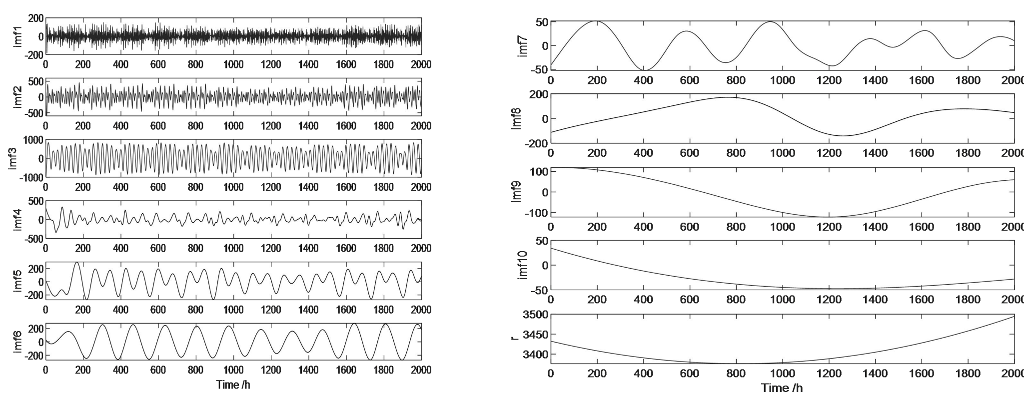


Figure 3. EEMD-LSSVM- integrated BPNN model prediction flow chart

3.2 Load decomposition and reorganization results

In this paper, the load of Denmark, a central and northern European country, from April 1, 2015 to September 19, 2015 is selected as the research object, and the data sampling frequency is 1h. After EEMD, 11 components are obtained, and the selected parts are shown in Figure 4.



(a) 6 modal components (b) Four modal components and residual components

Figure 4. EEMD decomposes load sequence

If these 11 components are modeled separately, it will increase the computational complexity of overall model training and prediction. In order to reduce the modeling task and improve the calculation efficiency, a new sequence is obtained after using SE, in which the embedding dimension $m = 2$ and similarity tolerance $r = 0.2 \times \mathrm{std}(IMFi)$ are included. As can be seen from fig. 5, the SE value decreases with the decrease of the frequency of each component, and some adjacent components have similar SE values. Among them, the SE value of IMF1 is the highest, representing the highest sequence complexity, and IMF1 is taken as a random component alone; Reorganize IMF2, 3 and 4 into detail components; The rest are reorganized into trend components.

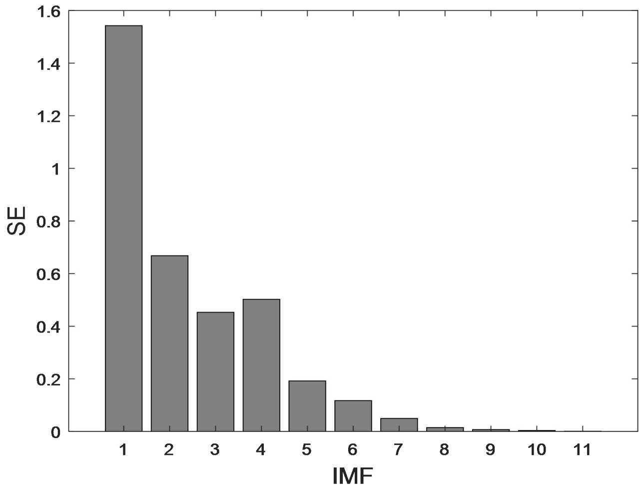


Figure 5. Entropy value of each component sample

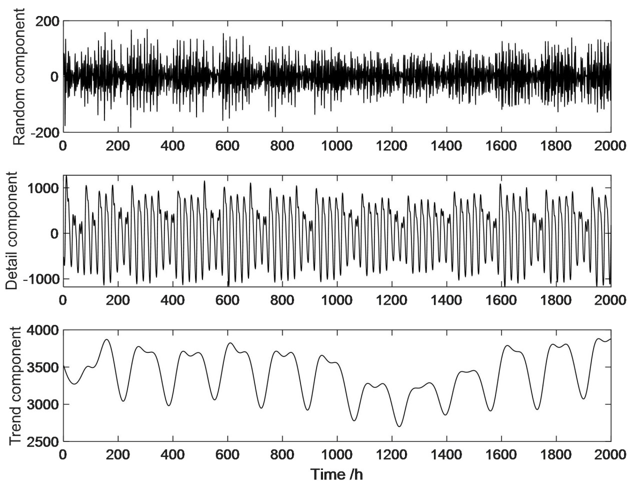


Figure 6. Sequence merging result

As can be seen from Figure 6, the random component has strong randomness and high frequency, which is mainly influenced by external factors. The detail component changes periodically on a daily basis, which has certain regularity. The trend component is the most gentle, changes periodically in weeks, and its load value is the largest. It can be known that the trend component is the base load part of the original sequence load and has the strongest correlation with the historical load. Under this condition, the device and the parts with ventilation or leakage will be affected by dust, especially the condenser and condensing fan. The heat exchange fins of the condenser are easily blocked by dust, and the fan blades are easily damaged by dust.

The feature pool considered in this paper includes meteorology, time information and historical load. Historical data is select as that data of the first 24 time points of the forecast time point, so as to forecast the load value of the next time point; Meteorological information includes wind speed and temperature, and considering the lag effect of temperature on load, the temperature of the first five time points of the forecast time point is also taken as the characteristic input variable; Time information includes week type, time point type and holiday type, and the time information is coded by unique heat coding [15]. In order to model the recombined components, the three components are sorted by mutual information correlation analysis [16], and the low-frequency trend component, as the base load part, has the least correlation with meteorological information, so meteorological information is not considered when modeling the trend component, and there are 56-dimensional characteristic input variables, and the rest components have 63-dimensional characteristic input variables.

3.3 Predictive evaluation index

In this paper, MAPE and RMSE are used to quantify the error and evaluate the effectiveness of the prediction model. The calculation formula is as follows:

$$MAPE=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i-Y_i^{'}}{Y_i}\right|\times 100\% \tag{8}$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i-Y_i^{'})^2} \tag{9}$$

The smaller the calculation results of these two indicators, the better the prediction performance; Y_i is the actual value of the i sample, and $Y_i^{'}$ is the predicted value; N is the total number of predicted outputs.

4. EXAMPLE ANALYSIS

4.1 Overview of calculation examples

In order to verify established separately the validity of the forecasting method proposed in this paper, the load and meteorological data of Denmark, a central and northern European country, from April 1, 2015 to September 18, 2015 are selected as established separately the research object. In order to facilitate the comparative analysis, the EEMD-LSSVM-Bagging-BPNN model proposed in this paper and six forecasting models, namely LSSVM, BPNN, Bagging-BPNN, EEMD-LSSVM and EEMD-Bagging-BPNN, are established to compare the forecasting performance. Among them, the penalty coefficient of LSSVM and the parameters of radial basis function are selected by grid search optimization method, and the parameter range is set to [0,10] and the iteration step is 1. When forecasting the original load series, the BPNN model selects a single hidden layer structure, the number of hidden layer neurons is set to 15, the transfer function is tansig, the learning rate is 0.01, the learning target is 0.001, and the number of iterations is 100. Levenberg-Marquardt optimization is adopted, and the prediction results are averaged several times. When EEMD and SE methods are used to get the trend, details and random components after recombination, and the model is established separately, the structural parameters of BPNN in EEMD-Bagging-BPNN model are 56-12-1, 63-15-1 and 63-11-1 respectively, and the other settings are consistent with the above.

4.2 Prediction result analysis

Firstly, BPNN, Bagging-BPNN and EEMD-Bagging-BPNN models are established to verify the effectiveness of Bagging ensemble learning algorithm in the destination city, and the prediction results are compared and analyzed. The load and meteorological data of Denmark from April 1, 2015 to September 11, 2015 are trained to predict the big load data of 24 hours on September 12, 2015, and the two results are very shown in Figure 7. It can be seen from Figure 7 that structural parameters compared with BPNN, the predicted results of EEMD-Bagging-BPNN and Bagging-BPNN can better fit the real value. Table 1 shows the MAPE values and RMSE values of the three models. It can be seen that the MAPE values and RMSE values of Bagging-BPNN model are small reduced by 27.33% and 19.54% respectively compared with the BPNN model, which proves that the introduction of Bagging ensemble learning algorithm can effectively optimize the prediction performance of BPNN. At the same time, after EEMD decomposition, each component is modeled separately to predict, and the MAPE values and RMSE values are also reduced by 9.17 compared with the Bagging-BPNN model.

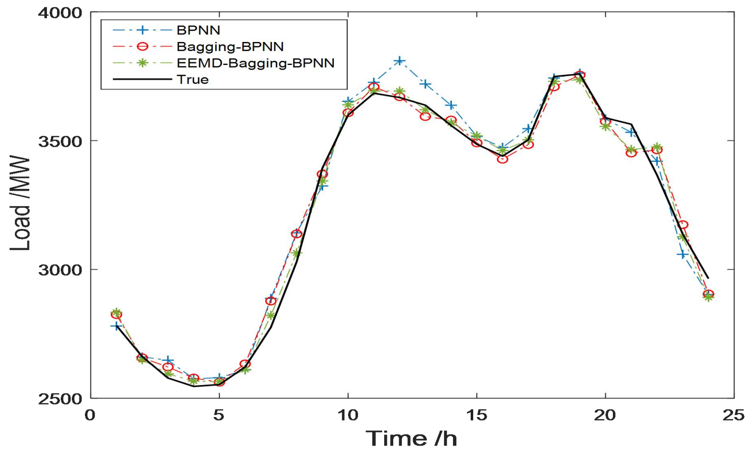


Figure 7. Comparison of Bagging-BPNN and BPNN Prediction Results Curve on September 12th

Table 1. Comparison of evaluation indexes of September 12 forecast results

model	**MAPE/%**	**RMSE/MW**
BPNN	1.50	62.02
Bagging-BPNN	1.09	49.93
EEMD-Bagging-BPNN	0.99	42.12

However, Bagging-BPNN still has an over-fitting phenomenon on the decomposed low-frequency trend components. The prediction result of low-frequency trend components on September 12, 2015 is shown in Figure 8, from which it can be seen that the prediction result of LSSVM model is closer to the real value. Thus, the EEMD-LSSVM-Bagging-BPNN prediction model is established, the LSSVM model is used to model the low-frequency trend component, and the Bagging-BPNN model is used to model the detailed and random components.

Fig. 9 shows the forecast results of six forecasting models, namely LSSVM, BPNN, Bagging-BPNN, EEMD-LSSVM, EEMD-Bagging-BPNN and EEMD-LSSVM-Bagging-BPNN, on September 12th. It can be seen from the local enlargement that the EEMD-LSSVM-Bagging-BPNN forecasting.

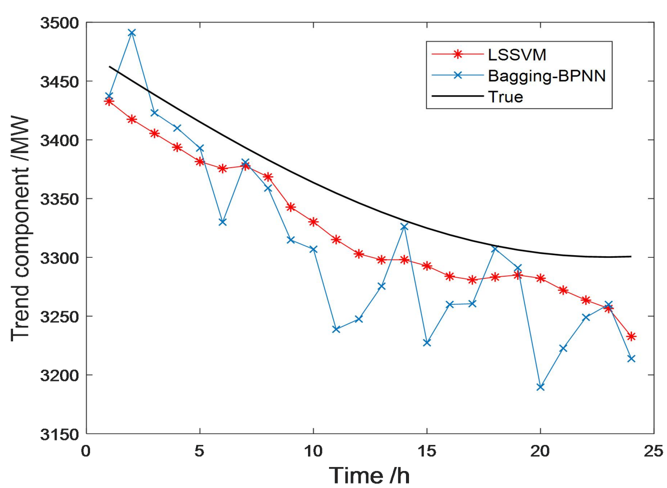


Figure 8. Comparison of prediction results of trend components

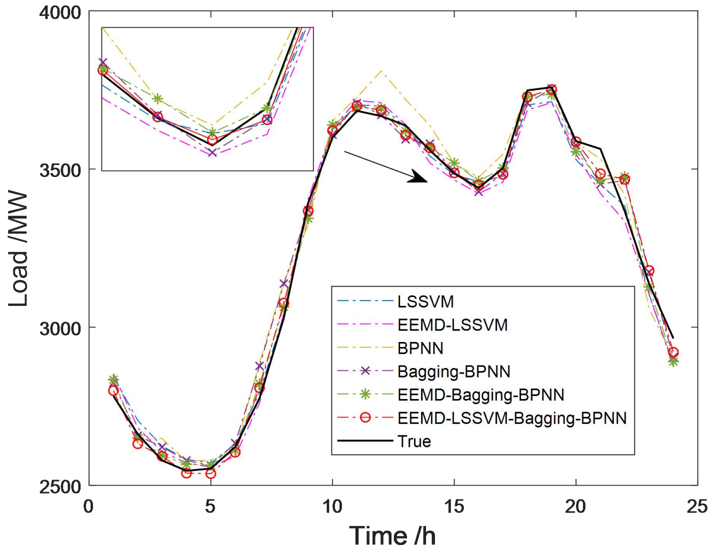


Figure 9. Comparison of prediction results curves of all models on September 12th.

In order to verify the applicability of the model, the load from September 12 to September 18 is further predicted, and the prediction evaluation indicators are shown in Table 2. Based on the analysis of the average of this week's forecast results, an integrated BPNN model is constructed by introducing Bagging ensemble learning algorithm, and its forecast results MAPE 18.52% and 17.02% lower than that of a single BPNN model, which further verifies that Bagging ensemble learning algorithm can effectively improve the forecasting performance of BPNN. The original sequence is decomposed by EEMD, the low-frequency trend component is modeled separately by introducing LSSVM, and the detailed and random components are modeled by introducing Bagging-BPNN, that is, after the EEMD-LSSVM-Bagging-BPNN model is constructed, the prediction performance of the model is improved to some extent compared with EEMD-Bagging-BPNN model and EEMD-LSSVM model. MAPE value decreased by 10.92% and 27.40% respectively, and RMSE value decreased by 12.27% and 23.93% respectively. It is verified that LSSVM model is more suitable for predicting low-frequency trend components after EEMD sequence decomposition, and combining Bagging-BPNN to predict other components can effectively improve the prediction accuracy. The MAPE value of the predicted results of this model decreased by 28.86%, 34.57% and 19.70% respectively, and the RMSE value also decreased by 24.70%, 31.96% and 18.01% respectively. EEMD-LSSVM-Bagging-BPNN model is a feasible prediction model.

Table 2. Comparison of evaluation indexes of prediction results of various models from September 12th to September 18th.

date	**evaluating indicator**	**LSSVM**	**EEMD-LSSVM**	**BPNN**	**Bagging-BPNN**	**EEMD-Bagging-BPNN**	**This paper model**
September 12(th)	MAPE/%	1.10	1.16	1.50	1.09	0.99	0.79
	RMSE/MW	42.01	47.40	62.02	49.93	42.12	34.72
September 13(th)	MAPE/%	1.40	2.01	1.24	1.22	1.33	1.09
	RMSE/MW	52.84	80.65	53.91	53.52	58.33	50.20
September 14(th)	MAPE/%	1.62	1.42	1.90	1.46	1.18	1.15
	RMSE/MW	75.47	71.85	92.83	72.35	61.96	59.76
September	MAPE/%	1.58	1.46	1.93	1.72	1.66	1.64

15(th)	RMSE/MW	78.23	70.31	100.10	89.15	88.66	80.53
September 16(th)	MAPE/%	1.00	1.15	1.64	1.33	1.03	0.83
	RMSE/MW	57.69	55.12	77.47	64.82	54.64	42.35
September 17(th)	MAPE/%	2.36	1.55	1.47	1.40	1.03	0.99
	RMSE/MW	112.68	79.14	76.67	69.90	56.97	53.14
September 18(th)	MAPE/%	1.40	1.46	1.69	1.01	1.12	0.92
	RMSE/MW	68.27	77.84	76.24	47.78	55.49	46.16
average value	MAPE/%	1.49	1.46	1.62	1.32	1.19	1.06
	RMSE/MW	69.60	68.90	77.03	63.92	59.74	52.41

5. CONCLUSION

The integrated BPNN model based on Bagging integration algorithm can effectively overcome the problems of poor generalization ability and low prediction accuracy of single BPNN. The deficiency of integrated BPNN in predicting low-frequency trend components is effectively compensated by LSSVM. Finally, each component is recombined to get the final prediction. The research on related technologies and product application at home and abroad was carried out, and the equipment status, development trend and technical development and application in the field of equipment environmental control system were analyzed in detail. Based on the basic principles of advanced performance and mature technology, the technical route selection and overall scheme design optimization were carried out. At the same time, combined with the requirements of new equipment and the specific functional performance indicators of the tender, the integrated environmental detection technology of the passenger cabin, cabin ambient intelligence control technology, integrated miniaturization technology, nuclear and biochemical detection and protection technology, temperature and humidity adjustment technology, oxygen generation and cabin air purification were studied, and the overall performance of the system was matched and key technologies were verified by means of analysis, calculation, simulation and test, forming an integrated and efficient indoor environmental control scheme.

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