

A Novel Hybrid Model Using EEMD and Neural Network for Forecasting Carbon Price

Hongkai Zhao, Nan Ye, Bowen Xia

Department of Economic Management, North China Electric Power University,
Baoding, China

ABSTRACT: Carbon price prediction is of cardinal significance for promoting the development of carbon trading market. However, the strong non-stationary and nonlinearity characteristics of the carbon price pose a challenge to the carbon price prediction model. To improve the accuracy of carbon price prediction, a combined model based on ensemble empirical mode decomposition (EEMD) is proposed in this paper. In the proposed model, EEMD is used to decompose the original data into a series of relatively stable component sequences. Then, the extreme learning machine (ELM) and BP neural network (BP) optimized by particle swarm optimization algorithm (PSO) are used to respectively predict the component sequences and integrate the predicted results. Finally, the weights of the two prediction methods are determined by the variance-covariance method, and the final combined prediction result is obtained. To verify the performance of proposed model, the carbon price sequences of Shenzhen and Hubei of China were selected. The results showed that the combined model had good performance.

KEYWORDS: *carbon price forecasting, ensemble empirical mode decomposition, the extreme learning machine, BP neural network, the combination forecasting method*

1. Introduction

In recent years, global climate change caused by greenhouse gases (GHG) has attracted extensive attention at home and abroad [1]. As a major greenhouse gas, carbon dioxide (CO₂) contributes 63% to the greenhouse effect [2]. Therefore, controlling carbon emission has become a top priority for every country. On January 1, 2005, the European Union established the European emissions trading system (EU ETS) to reduce greenhouse gas emissions. The system has been proved to be

effective in reducing greenhouse gas emissions [3]. As the world's largest carbon emitter, China officially launched a pilot carbon trading program in 2011. Then, a national carbon trading market was launched in 2017 to reduce China's carbon emissions and mitigate climate change [4]. Accurate prediction of carbon price will help to understand the characteristics of carbon price and effectively reduce the risk of carbon market [5]. However, the highly non-stationary and non-linear nature of carbon prices poses challenges to policymakers' forecasts. Therefore, an accurate carbon price prediction method is needed. As the earliest carbon emission trading market, the carbon price analysis and prediction of the EU ETS has been studied by many scholars. Sung et al. proposed a finite distributed lag model (FDL) to predict carbon prices and applied genetic algorithm (GA) to optimize the coefficients. The results showed that the model was more accurate than the traditional neural network model [6]. Quan adopted the variational mode decomposition (VMD) method to decompose the data into modal components with their own characteristics. Then he employed ELM to predict each component and integrated the final prediction results [7]. Zhang et al. used signal processing technology to decompose carbon price sequence and reconstructed them. Then, the trend component was predicted by co-integration model (CIM), the random component was predicted by GARCH model, the periodic component was predicted by grey neural network optimized by ant colony algorithm (ACA-GNN). Finally, the forecasting results are integrated. The results showed that the hybrid model had good performance and could be used to predict the carbon spot price of the EU ETS in the future [8]. In addition to optimizing the prediction model, researchers also explored the effectiveness of the introduction of economic and energy index data in improving the prediction accuracy of carbon price [9].

With the maturity of China's carbon trading pilot cities, such as Shenzhen and Hubei carbon trading market, China's carbon price has gradually attracted the attention of scholars. However, previous research focused on the EU ETS, and the research on China's carbon price prediction is relatively limited. Whether the model based on the EU ETS is also applicable to China's carbon trading market, it remains to be tested. Therefore, this paper took the carbon trading markets in Shenzhen and Hubei as examples to conduct carbon price prediction model, so as to enrich the

research in this field. Guan employed GM(1,1) optimized by results to predict the carbon trading prices in Hubei and Guangdong. The results showed that the proposed model performed better than the traditional GM(1,1) model [10]. Li et al. proposed a hybrid model combining empirical model decomposition (EMD) and GARCH, and took five pilot cities of carbon trading as examples to verify its performance [11]. Yao et al. combined EMD with intelligent algorithm to predict the carbon price of Hubei [12].

Generally, carbon price prediction models can be divided into two types: statistical model and neural network model. Statistical model includes Vector autoregressive model (VAR) [13] GARCH [14] autoregressive integrated moving average model (ARIMA) [15] and so on. Neural network model includes BP [16], ELM (17), and other neural network models [18]. Due to its high accuracy, high speed and large processing capacity, neural network prediction models are favored by researchers. Therefore, ELM and PSO-BP were selected to predict carbon price in this paper.

The non-stationary and nonlinear characteristics of carbon price add difficulty to the performance of prediction model. Therefore, the characteristics of carbon price need be considered when forecasting carbon price [19]. Decomposition method is usually used to reduce the non-stationarity of the original data and obtain characteristics of carbon price. Zhu adopted EMD to analyze the carbon price of EU ETS to grasp the basic characteristics of carbon price change [18]. However, EMD cannot solve the problem of modal mixing, which leads to the decrease of prediction accuracy. To solve this problem, Wu and Huang proposed the EEMD model [20]. The EEMD model effectively overcomes this problem and it is widely used in various fields [21]. Therefore, EEMD method was adopted in this paper to decompose the original carbon price. The subsequences obtained by the decomposition method have different characteristics and a single prediction model cannot accurately predict all subsequences. Therefore, hybrid models are often used to predict these subsequences [22]. Previous studies usually adopt an appropriate model for each component and then integrate the final prediction results. However, the process of choosing the appropriate prediction model is often uncertain and subjective. Therefore, this paper proposed the variance-covariance method to

determine the weight of each prediction model, so as to obtain the final prediction results, effectively avoiding the above problems.

The rest of the paper is structured as follows: in the second part, the related methods and the hybrid prediction framework are introduced in detail; in the third part, the prediction model is applied to the prediction of carbon price in Shenzhen and Hubei to verify the performance of the model and the results of empirical analysis are given in this part; summarize the work and look forward to the future work.

2. Methodology

2.1 EEMD

EEMD is an improved model of EMD, which can effectively solve the modal mixing problem that EMD cannot solve. The process of EEMD is as follows:

(a) A set of white noise sequences $\omega(t)$ is added on the initial time series $x(t)$ to obtain a new sequence x'_t .

(b) Using EMD decomposes the sequence x'_t : a) find the x'_t 's extreme value, fit the upper and lower envelope by cubic spline interpolation function, calculate the mean value $m(t)$; b) let $h(t) = x'_t - m(t)$, if $h(t)$ is not stationary, substitute $h(t)$ for x'_t , repeat the above process until the mean value approaches 0, then, get the first IMF component $c_1(t)$; c) let $r_1(t) = x'_t - c_1(t)$, repeat the above two processes, get the IMF components and difference sequence until it cannot be decomposed, obtain a residual component $r_n(t)$.

(c) Repeat step (a) and (b) N times, obtain N groups of different IMF components and residual components, calculate the mean of N groups of components and take the mean value as the final result.

2.2 ELM

In 2004, Huang et al. proposed ELM based on single hidden layer feedforward

neural network (SLFN) [23]. The network structure of ELM is shown in figure 1.

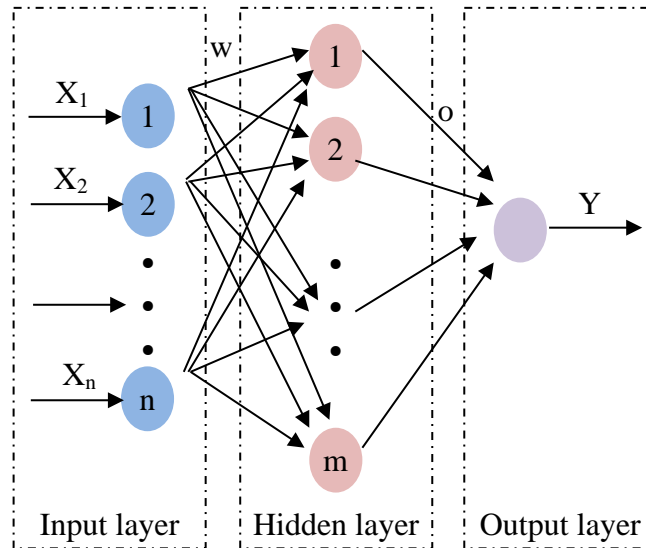


Figure. 1 Network structure of ELM

Suppose N training samples are $\{(x_i, y_i)\}_{i=1}^N$, among them, $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T$, $y_i = [y_{i1}, y_{i2}, \dots, y_{im}]^T$, and SLFN approximates the training sample with zero error, so:

$$\sum_{j=1}^K o_j g(w_j * x_i + b_j) = y'_i, i = 1, 2, \dots, N \quad (1)$$

Among them, K denotes the number of nodes of SLFN hidden layer; o denotes the connection weight vector of the hidden layer node and the output node; $g(x)$ denotes the activation function; w denotes the connection weight vector of the input node and the hidden layer node.

Formula (1) can be written as a matrix, as shown in formula (2):

$$H * O = Y \quad (2)$$

Among them, H denotes for hidden layer output matrix. In order to ensure SLFN

has good performance, the following equation should be satisfied in the training process:

$$\| H * \hat{O} - Y \| = \min_0 \| H * O - Y \| \quad (3)$$

In the process of solving \hat{O} , need to consider to whether H is square matrix, thus introducing the Moore–Penrose (MP) generalized inverse of H, as shown in formula (4):

$$\hat{O} = H^+ * Y \quad (4)$$

Among them, H^+ is the Moore–Penrose (MP) generalized inverse of H.

Compared with other neural networks, process of ELM is simple and easy to implement.

2.3 Improvement of BP neural network

2.3.1 BP neural network

The most widely used neural network is BP neural network. BP neural network has two steps: 1) forward propagation of signals; 2) error back propagation. First, the signal enters the input layer and is sent to the output layer after passing through the hidden layer. Then, the output layer transmits the error forward to adjust the connection weight of the neural network. The BP neural network is not trained until the error reaches the allowable range.

2.3.2 PSO-BP neural network

Although BP network has been widely used, it also has some defects, including: a) fall into local minimum value easily; b) it is sensitive to the initial setting of parameters. PSO algorithm is an optimization algorithm based on population information, which can quickly find the optimal extremum. Therefore, this paper employed PSO algorithm to optimize the weights and parameters of BP neural network model. The specific steps of PSO-BP neural network model are as follows:

- (a) Set the relevant parameters in the structure to construct the BP neural network.
- (b) Establish the correspondence between particle swarm and weights and thresholds.
- (c) Initialize the parameters of particle swarm, including the number of particle swarm, particle swarm velocity, position initialization and so on.
- (d) Update particle swarm position and velocity.
- (e) Determine whether the termination condition is satisfied, if not, return to the previous step; If so, the optimization result is output and the algorithm ends. Restore the final results to the corresponding weights and threshold.

2.4 Variance-covariance method

Variance-covariance method is an effective method to determine the weight of combined prediction model. The basic steps for specific application are as follows:

- (a) Calculate the variance of error of each prediction model, as shown in formula (5):

$$v_i = [(\sigma_1 - \bar{\sigma})^2 + (\sigma_2 - \bar{\sigma})^2 + \dots + (\sigma_n - \bar{\sigma})^2]/n \quad (5)$$

Among them, i denotes the model i , n denotes the predicted length; $\sigma_1, \sigma_2, \dots, \sigma_n$ denotes the square of the error between the predicted value and the actual value, $\bar{\sigma}$ denotes the mean value of $\sigma_1, \sigma_2, \dots, \sigma_n$.

- (b) Calculate the weight of each prediction model, as shown in formula (6):

$$w_i = \frac{1}{v_i(\frac{1}{v_1} + \frac{1}{v_2} + \dots + \frac{1}{v_m})} \quad (6)$$

Among them, w_i denotes the weight of the model i , m denotes the number of models.

- (c) Calculate the final predicted value, as shown in formula (7):

$$y' = \sum_{i=1}^m w_i y'_i \quad (7)$$

Among them, y'_i denotes the predicted value of the model i , y' denotes the predicted value of combined model.

2.5 Framework of the proposed model

This paper proposed a prediction model combining signal processing technology with neural network. The flow chart of the proposed prediction model is shown in figure 2.

The prediction model mainly includes the following steps:

(a) The original carbon price sequence is decomposed by EEMD to obtain multiple sub-sequences.

(b) Partial autocorrelation function is used to determine the input variables of each subsequence.

(c) ELM and PSO-BP are adopted to respectively predict each subsequence and integrate them to obtain their respective prediction results.

(d) The weight of each prediction model is determined by the variance-covariance method, and the final prediction result is calculated according to formula (7).

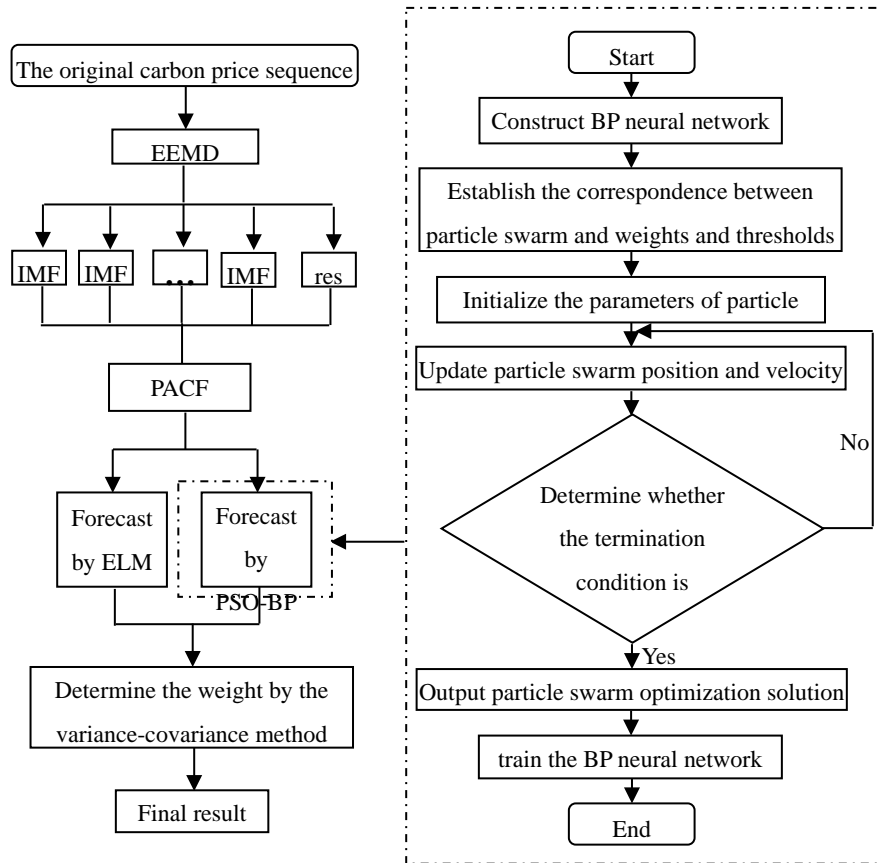


Figure. 2 The proposed model of flow chart

3. The empirical analysis

3.1 Collection of data

Since 2011, China has carried out carbon trading trials in eight regions, including Beijing, Shanghai, Tianjin, Shenzhen, Chongqing, Guangdong, Hubei and Fujian. Among them, Shenzhen carbon emission exchange is the first regional carbon trading market in China. Hubei is the region with the highest trading volume and value of carbon emissions. Therefore, this paper chose Shenzhen and Hubei carbon emission exchange as the representatives of China's carbon trading market. Table 1

shows the carbon trading volume share and carbon trading value share of each region of China. The carbon prices of Shenzhen and Hubei from June 1, 2014 to December 14, 2018 (excluding statutory holidays) were selected as empirical data. The data from June 1, 2014 to June 1, 2018 were selected as the training sets, and the remaining data were the test sets. Table 2 shows the overview of the sample data, and figure 3 shows the original carbon price data group.

Table 1. The carbon trading volume share and carbon trading value share

Region	Shenzhen	Hubei	Beijing	Tianjin	Shanghai	Guangdong	Chongqing	Fujian
Volume	14.1%	32.2%	7%	1.6%	7.5%	29%	4.2%	4.3%
Value	17%	27.9%	18.4%	1%	8.8%	22.3%	0.7%	3.8%

Table 2. the overview of the sample data

Region	Sample	training sets	test sets	data
Shenzhen	1117	984	133	2014/6/1-2018/12/14
Hubei	1117	984	133	2014/6/1-2018/12/14

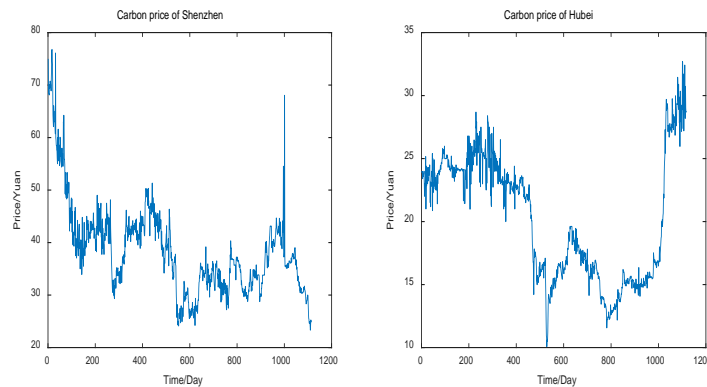


Figure. 3 The original carbon price data group

3.2 Model performance evaluation criteria

In order to compare the prediction accuracy of the model, it is necessary to evaluate the performance of the model. In this paper, mean absolute error, mean square error and mean absolute error percentage were selected to evaluate the accuracy of the prediction model. The calculation formula is as follows:

$$\frac{\sum_{i=1}^n |y_i - y'_i|}{n}$$

$$\frac{1}{n} \sum (y_i - y'_i)^2 \tag{8}$$

$$\frac{|y_i - y'_i|}{y_i} * 100\%$$

Among them, y_i denotes actual carbon price, y'_i denotes prediction carbon price, n denotes the predicted length.

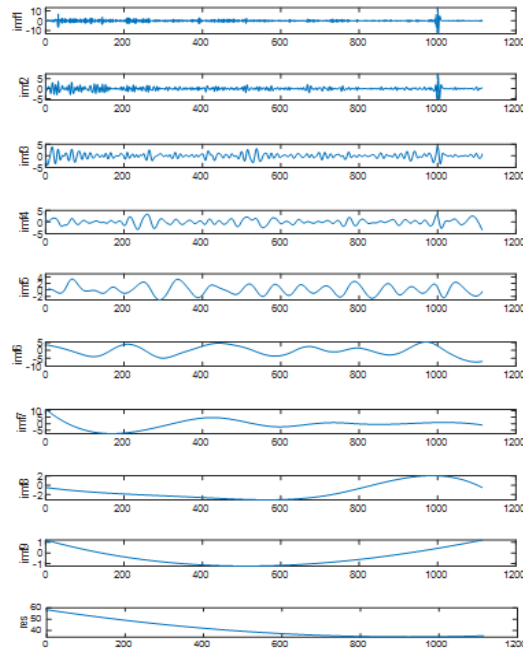
3.3 Carbon price forecasting

Step 1: Decompose the carbon price. EEMD method employed to reduce the non-stationarity of carbon price. The result of decomposition is shown in figure 4.

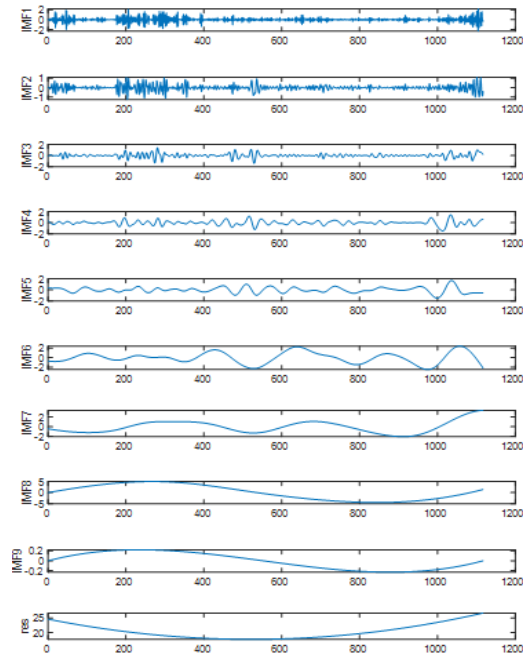
Step 2: Select the input variable. Predict the number of targets based on historical data. Therefore, this paper introduced partial autocorrelation function (PACF) to select the input variable of neural network prediction model. The analysis results of partial autocorrelation function are shown in figure 5, and the predicted input variables are shown in table 3.

Step 3: Forecast the carbon price respectively. ELM and PSO-BP were adopted to predict each subsequence, and then accumulate the predicted results respectively. Table 4 lists part of the parameters for ELM and PSO-BP.

Step 4: Combine the predicted results. The combined weights of the two forecasting methods are determined by the variance-covariance method. The weights are shown in table 5.

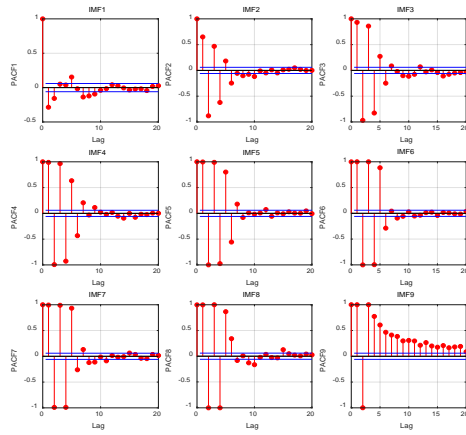


(a)

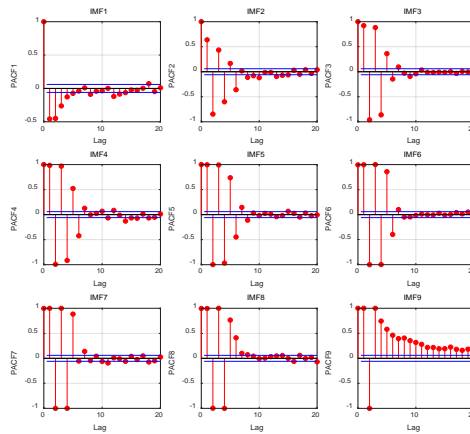


(b)

Figure. 4 The result of EEMD: (a) Shenzhen; (b) Hubei



(a)



(b)

Figure. 5 The analysis results of partial autocorrelation function: (a) Shenzhen; (b) Hub

Table 3. The predicted input variables

series	Shenzhen	Hubei
IMF 1	$X_{t-1}, X_{t-2}, X_{t-5}, X_{t-7}, X_{t-8}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-8}, X_{t-12}$
IMF 2	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-8}, X_{t-9}$
IMF 3	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$
IMF 4	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}, X_{t-8}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}$
IMF 5	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}, X_{t-8}$
IMF 6	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$
IMF 7	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-7}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-7}$
IMF 8	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-10}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}$
IMF 9	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}$
Res	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}$	$X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}$

Note: x_{t-1} denotes the day before the forecast

Table 4. Part of the parameters for ELM and PSO-BP

Model	parameter	value
ELM	hidden layer nodes	12
	activation function	“sig”
BP	hidden layer nodes	11
	learning rate	0.1
	error rate	0.00001

	iteration times	500
	activation function	“sig”
PSO	c1,c2	1.49445
	inertia weight	0.5

Table 5. The weight of models

Model	weight	
	Shenzhen	Hubei
ELM	0.686	0.628
PSO-BP	0.314	0.372

3.4 The comparisons and analysis

3.4.1 Case of Shenzhen

The predicted results of Shenzhen carbon price are shown in figure 6. Table 6 shows the values of MAPE, RMSE and MAE of the predicted results in Shenzhen.

According to figure 6 and table 6, the following results can be obtained:

(1) BP neural network optimized by particle swarm performs better than traditional BP neural network and ELM. The result shows that PSO-BP is effective and accurate.

(2) Compared with ELM, EEMD-ELM has better prediction accuracy. While compared with PSO-BP, the prediction results of EEMD-PSO-BP perform poorly. The results show that when the combination of EEMD and single prediction model forecast carbon price, a suitable prediction model should be selected

(3) By comparing EEMD-ELM and EEMD-PSO-BP with the proposed model in this paper, the prediction accuracy of the proposed model performs better. The results show that the weight determination by variance-covariance method can effectively improve the prediction accuracy of the model.

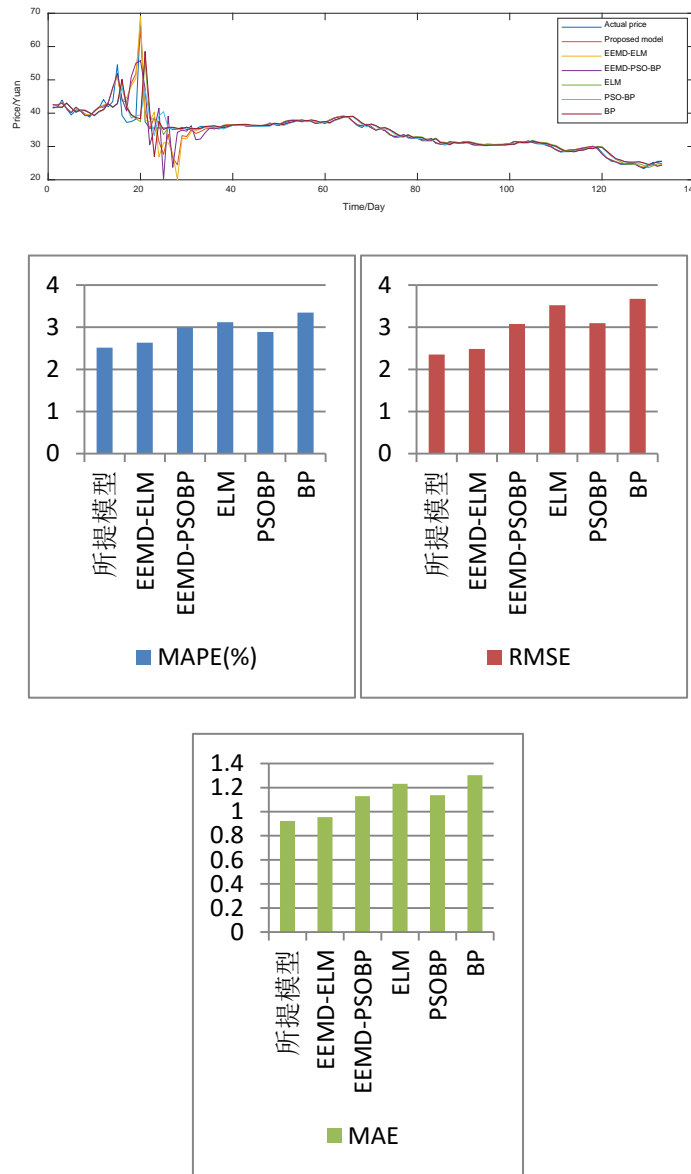


Figure. 6 Forecast results of carbon price of Shenzhen

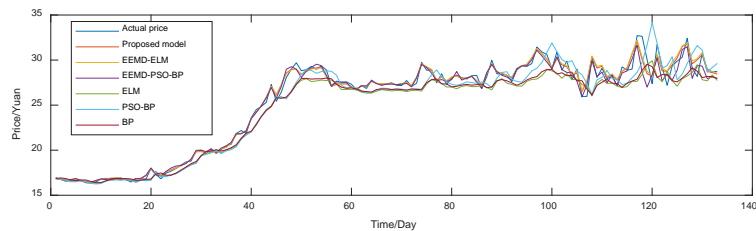
Table 6 The performance of predicted model in Shenzhen

model	MAPE(%)	RMSE	MAE
Proposed model	2.5162	2.3503	0.9227
EEMD-ELM	2.6321	2.4856	0.9542
EEMD-PSOBP	2.9887	3.0764	1.1286
ELM	3.1204	3.5211	1.2307
PSOBP	2.8876	3.0953	1.1365
BP	3.3466	3.6741	1.3028

3.4.2 Case of Hubei

The predicted results of Hubei carbon price are shown in figure 7. Table 7 shows the values of MAPE, RMSE and MAE of the predicted results in Hubei.

Overall, the proposed model improves predictive performance. The EEMD method can deal with the strong nonstationary and nonlinear characteristics of carbon price. In the prediction of carbon price sequence, PSO-BP has a better performance than BP, and ELM has a better adaptability to complex nonlinear problems. By combining the advantages of the two methods, the prediction results are more accurate and stable.



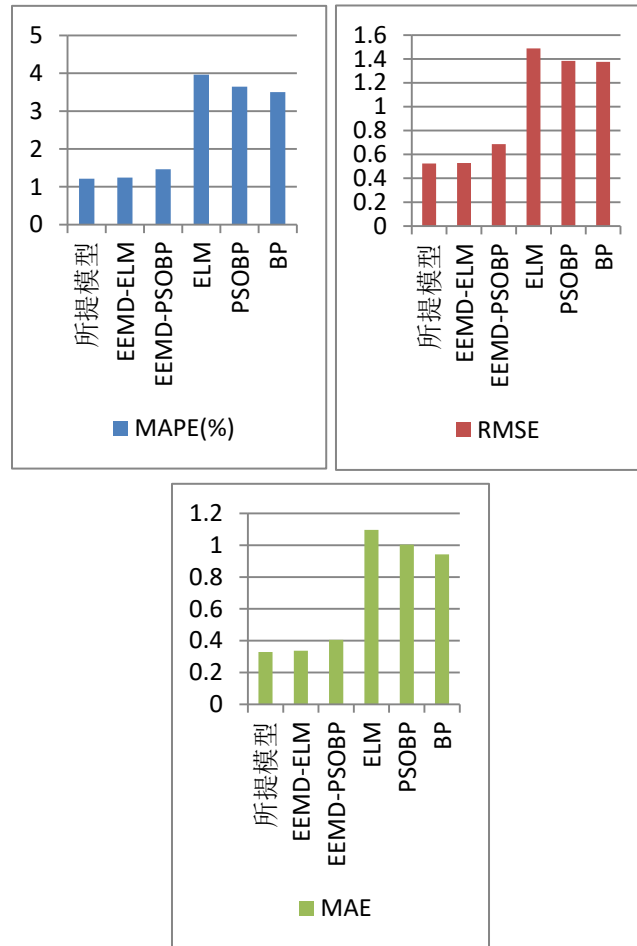


Figure. 7 Forecast results of carbon price of Hubei

Table 7 The performance of predicted model in Hubei

model	MAPE(%)	RMSE	MAE
Proposed mode	1.2124	0.5246	0.3286
EEMD-ELM	1.2442	0.5278	0.3366
EEMD-PSOBP	1.4616	0.6863	0.4052
ELM	3.9642	1.4882	1.0960

PSOBP	3.6448	1.3837	1.0043
BP	3.5033	1.3764	0.9420

4. Conclusions

In this paper, a combined prediction model based on EEMD, ELM, PSO-BP and variance-covariance method is proposed to improve the performance of carbon price prediction. The original carbon price sequence is decomposed into multiple sub-sequences by EEMD method. Then, the combined prediction results were obtained by combining ELM with the PSO-BP using variance-covariance method. The empirical results from Shenzhen and Hubei show that the performance of the proposed model is better than other comparative prediction models. The results show that: (a) BP neural network optimized by particle swarm performs better than traditional BP neural network and ELM; (b) using EEMD method to decompose the original carbon price can effectively improve the prediction accuracy; (c) a single prediction model combined with EEMD may not effectively improved prediction accuracy; (d) the combined model performs better than the single prediction model using variance-covariance method. (e) the proposed model provides a new idea for carbon price prediction. The proposed method is expected to provide useful reference for policymakers to predict carbon price. Finally, the proposed model only considers historical data, but the carbon price has strong non-stationarity and nonlinearity. Therefore, in the following research, in addition to the historical price, the influence of other influencing factors on carbon price should also be considered, such as oil price, weather factors, exchange rate and so on.

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