Available at www.sciencedirect.com

INFORMATION PROCESSING IN AGRICULTURE 5 (2018) 11–20

journal homepage: www.elsevier.com/locate/inpa

A hybrid model for dissolved oxygen prediction in aquaculture based on multi-scale features

Chen Li [a], *Zhenbo Li* [a,*], *Jing Wu* [a], *Ling Zhu* [a], *Jun Yue* [b]

[a] *College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China*
[b] *College of Information and Electrical Engineering, Ludong University, Yantai, Shandong 264025, China*

ARTICLE INFO

Article history:
Received 14 July 2017
Received in revised form
16 October 2017
Accepted 8 November 2017
Available online 13 November 2017

Keywords:
DO prediction
Aquaculture
Hybrid model

ABSTRACT

To increase prediction accuracy of dissolved oxygen (DO) in aquaculture, a hybrid model based on multi-scale features using ensemble empirical mode decomposition (EEMD) is proposed. Firstly, original DO datasets are decomposed by EEMD and we get several components. Secondly, these components are used to reconstruct four terms including high frequency term, intermediate frequency term, low frequency term and trend term. Thirdly, according to the characteristics of high and intermediate frequency terms, which fluctuate violently, the least squares support vector machine (LSSVR) is used to predict the two terms. The fluctuation of low frequency term is gentle and periodic, so it can be modeled by BP neural network with an optimal mind evolutionary computation (MEC-BP). Then, the trend term is predicted using grey model (GM) because it is nearly linear. Finally, the prediction values of DO datasets are calculated by the sum of the forecasting values of all terms. The experimental results demonstrate that our hybrid model outperforms EEMD-ELM (extreme learning machine based on EEMD), EEMD-BP and MEC-BP models based on the mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE) and root mean square error (RMSE). Our hybrid model is proven to be an effective approach to predict aquaculture DO.

1. Introduction

In recent years, the total aquaculture production of China accounts for about 70% of the world and has got the first place in the world. Nowadays, aquaculture mode in China is gradually changed from the traditional mode to modern intensive mode. Aquaculture water is an open, nonlinear, dynamic, complex system and water quality is easily affected by many factors such as physics, chemistry, biology, and human activities. DO is one of the essential factors for aquatic creatures to keep survival. Diseases are very easy to outbreak and will lead to a large number of dead aquatic creatures if DO content is less than 3 mg/L. It is important to control the DO for aquaculture. Normally, it is depended on the experience of farmers. It is not only time-consuming but inaccuracy. Therefore, establishing an accurate, practical DO prediction model is urgent and important for the aquaculture.

There are many modeling methods used for time-series data forecasting [1,2], regression analysis method, Markov models, artificial neural network, grey model and support vector machine [3–5], etc. In recent years, many researches have focused on water quality prediction and obtained

* Corresponding author.
E-mail address: zhenboli@126.com (Z. Li).
Peer review under responsibility of China Agricultural University.
https://doi.org/10.1016/j.inpa.2017.11.002
2214-3173

some achievements. Yan et al. [6] established a dissolved oxygen prediction model of water quality monitoring system based on BP neural network. Khotimah [5] proposed a prediction model based on Smooth Support Vector Machine (SSVM) to predict the aquaculture water quality. Liu [7–9] proposed several LSSVR models to predict water quality optimized by ant colony algorithm, improved particle swarm algorithm, Cauchy particle swarm algorithm, respectively. Xue [10] implemented a DO real-time prediction and early warning system in carp aquaculture using neural network and decision tree. A hybrid approach of support vector regression with genetic algorithm optimization is proposed by Liu [11] to predict aquaculture water quality. Ahmed [12,13] proposed the prediction of DO using artificial neural networks and an application of adaptive neurofuzzy inference system to estimate the DO of Surma River. Liu [14] proposes a hybrid dissolved oxygen content forecasting model based on wavelet analysis (WA) and LSSVR with an optimal improved Cauchy particle swarm optimization (CPSO) algorithm.

However, all the above studies are limited to single scale. They only get the surface features of the data itself. Multi-scale forecasting methods can get more features of predicted signals by decomposing it to several sub-sequences. Each sub-sequence reflects the different intrinsic characteristics of the signal. Empirical mode decomposition, wavelet analysis, local mean decomposition (LMD), local characteristic-scale decomposition (LCD) [15] and EEMD are usually applied to decompose signals into several scales. The forecasting methods based on multi-scale features are widely used in many fields such as short-term wind power prediction [16–18], short-term traffic flow prediction [19,20] and rainfall prediction [21], etc. Wang [16] proposed a forecasting method based on empirical mode decomposition and least square support vector machine to predict wind power. An empirical mode decomposition based recurrent Hermite neural network prediction model is proposed to predict short-term traffic flow in Chen's [20] study. Liu [21] proposed a new model based on empirical mode decomposition and the RBF neural network to apply to rainfall prediction. In the fields of aquaculture water quality prediction, Liu [22] proposes a novel water temperature forecasting model based on empirical mode decomposition and back-propagation neural network, the simulation results of the hybrid model demonstrate that the method is powerful and reliable for predicting water temperature in intensive aquaculture. According to analysis in existing literatures above, it can prove that hybrid models based on multi-scale features are suitable for data prediction in many fields. Thus, this study attempts to establish a more accurate hybrid model in aquaculture dissolved oxygen.

Motived by the above study, we propose a new hybrid dissolved oxygen forecasting model based on multi-scale features. EEMD is used to decompose the original dissolved oxygen datasets signal into several sub-sequences. And then, we can build different models for each sub-sequences, according to its intrinsic features. Experimental results shows that our hybrid model is both highly suitable and efficient for dissolved oxygen prediction in intensive aquaculture.

2. Methodology

2.1. *Ensemble empirical mode decomposition*

Empirical mode decomposition (EMD) is a nonlinear signal adaptive decomposition technique proposed by Huang et al. [23] in 1998. It is used to decompose a nonlinear and non-stationary time series into a sum of Intrinsic Mode Functions (IMFs) components with individual intrinsic time scale properties. But there is mode mixing problem in the process of EMD. Mode mixing is defined as a single IMF either consisting of signals of disparate scales, or a signal of a similar scale distributing in different IMF components. Aiming at the problem of mode mixing, a new method called EEMD is proposed by Wu et al. [24] in 2005. EEMD is a noise-assisted data analysis method. The signal is decomposed into several components by adding different white noise respectively. Then, we adopt the average of each component as the final decomposition results. EEMD can solve the mode mixing problem effectively.

2.2. *Least squares support vector regression*

LSSVR is used to transform the quadratic programming problems into linear equation groups and replace the inequality constraints by equality constraints. Compared with SVR, LSSVR has faster training speed, higher stability and better control. An optimization problem for forecasting functions in LSSVR can be followed in literature [7,8]. Aiming at the characteristics of data fluctuation, this paper builds the LSSVR forecasting model with strong adaptability, high fitting precision to predict high frequency term and intermediate frequency term, which proves that it has higher accuracy.

2.3. *BPNN optimized by mind evolutionary computation*

Back propagation neural network (BPNN) is one of the most widely used neural network models. It's a multi-layer feed-forward network trained according to error back propagation algorithm. In the network, there is usually an input layer, an output layer, and one or more hidden layers. Generally, the network weights, hidden layer threshold and output layer threshold are initialized randomly. But random initialization without optimization often makes convergence speed of BPNN slower or even makes the final results unable to be the optimal solution. Therefore, MEC proposed by Sun et al. [25] in 1998 is used to optimize the weights and thresholds to improve the prediction accuracy in our paper.

2.4. *Grey model theory*

GM(1,1) type of grey model is a first order differential equation with a single variable. This model is a time series forecasting model and it can only be used in positive data sequences [1]. In our paper, the trend term is a sequence which is positive, and it's suitable to build the grey prediction model. The experiment shows that for the trend term, grey model has a high accuracy to predict the value.

2.5. *The hybrid prediction model*

Our hybrid model is shown in Fig.1. Firstly, original dissolved oxygen datasets are decomposed into several components using EEMD. These components are reconstructed to four terms by the correlation among them. Afterwards, according to the characteristics of terms, LSSVM, MEC-BP and GM models are adopted to predict each term, respectively. Eventually, the final predicted results are obtained by adding each predicted term.

The detail implementation process of our hybrid dissolved oxygen prediction model can be described as follows.

***Step* 1.** Original DO datasets can be considered as a time series signal $x(t)$, and the white noise signal $n(t)$ is added to form the following signal noise mixed component.

$$X(t) = x(t) + k \cdot \sigma_x \cdot n(t) \tag{1}$$

where k is a coefficient that is represented by the ratio of white noise standard deviation and signal standard deviation. σ_x is signal standard deviation.

$X(t)$ is then decomposed by EMD and we get m IMFs and one RES. Repeat N times by adding different white noise every time.

$$X_N(t) = \sum_{i=1}^{m} IMF_{i,N} + RES \tag{2}$$

Be verified in literature [23], EEMD will get a better results when $k \in [0.1, 0.3]$ and $N = 100$. Hence, we set $k = 0.2$, and $N = 100$ in our model.

We calculate the average of each component, $IMF_i = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{N} IMF_{i,j}$ and $RES = \frac{1}{N}\sum_{i=1}^{N} RES_N$, respectively. And then, we get the equation of EEMD.

$$X(t) = \sum_{i=1}^{m} IMF_i + RES \tag{3}$$

***Step* 2.** We reconstruct these components into four terms by correlation analysis, which called high frequency term, intermediate frequency term, low frequency term and trend term, respectively. The correlation analysis reflects the degree of matching in different relative positions between two signals.

***Step* 3.** For both high frequency term and intermediate frequency term, LSSVR prediction model are built. In LSSVM model, there are several different types of kernel functions, while the RBF is by far the most popular option for kernel function types. Therefore, this study adopted a RBF kernel function, shown in equation (4), to apply to the LSSVR model.

$$f(x) = \sum_{i=1}^{l} a_i \times \exp\left(-\frac{x_i - x_j}{2\sigma^2}\right) + b \tag{4}$$

where x_i is the input vector, x_j and σ are the center and the parameter of the RBF kernel function, respectively.

***Step* 4.** For low frequency term, BP-MEC model is established. The flow chart of MEC-BP is shown in the red circle of Fig. 1. First, we determine the topology of BPNN, it includes five input nodes, five hidden nodes and one output node. Then, we optimize the weights, hidden layer thresholds and output layer threshold using MEC. The initial parameters of MEC are as follows: the size of the group is 200, the number of iterations is 10 times, the number of superior groups and temporary groups are 5, respectively. Finally, similartaxis and dissimilation operations are implemented. And we obtain the best values when the iteration stops, to apply to BPNN model. The main implementation process of MEC can be described as follows.

(1) In the solution space, generate a certain size of the individuals randomly, and search for a number of superior individuals and temporary individuals which has the highest scoring according to the score.
(2) Generate some new individuals around each individual which is the center of superior individuals and temporary individuals, respectively. Then we get a number of superior groups and temporary groups.
(3) Implement the similartaxis operation within each group until the group is mature, and use the best individual score in this group as the score of this group. Similartaxis is defined as a process that individual becomes a winner by competing within the group.
(4) After group is mature, we put the score on global billboard. Implement the dissimilation operation between these groups, then we get the best individual and it's

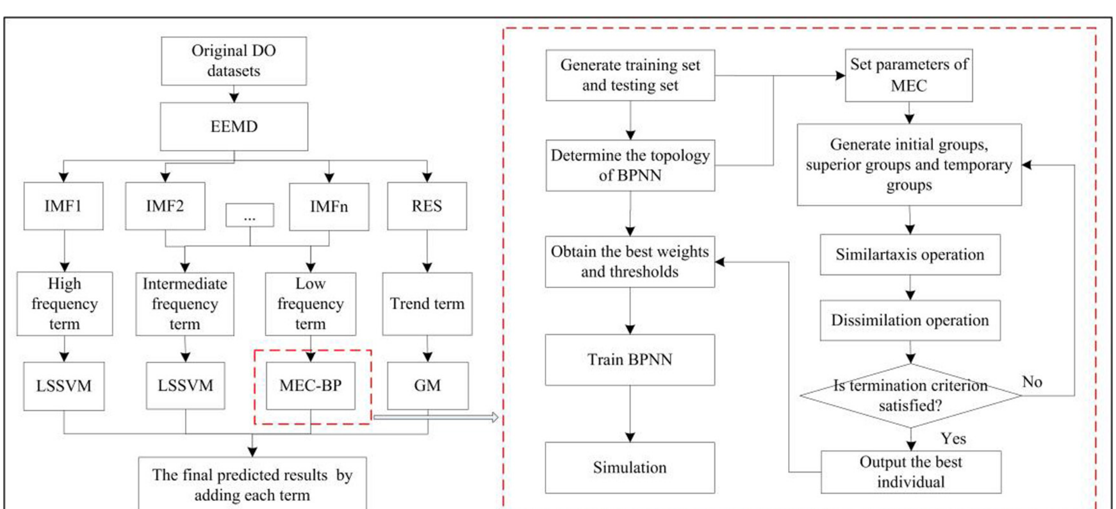

Fig. 1 – The flow chat of our hybrid algorithm.

score in the solution space. Dissimilation is defined as a process that if temporary groups' score is higher than superior groups', it will replace the superior groups. And the individuals in this superior groups will be released. If temporary groups' score is lower than superior groups', it will be abandoned and the individuals in this temporary groups will also be released.

Step **5.** For trend term which has the feature of near linear, the time series forecasting model GM(1,1) is suitable to predict this sub-sequence. Train datasets are used to build a model and then we can get the predicted values of test datasets.

Step **6.** Finally, the prediction values of the DO datasets are calculated by the sum of the forecasting values of four terms.

3. Experiments and discussion

3.1. Water quality data sets

Our data are collected from several ponds of Jingming aquaculture Ltd. in Dongying city, Shandong province, China. We select a total of 300 groups of samples to test including six factors: DO, water temperature (WT), pH value, salinity, electrical conductivity (EC) and turbidity. All of the five factors are closely related to DO. For example, the higher the WT, the lower the concentration of DO. The higher the salinity, the lower the concentration of DO, etc. The water quality data are split into two parts: the first 250 sets of water quality data are used for modeling training and the last 50 sets of data as testing data to analyze the prediction performance of our model. The original DO series is plotted in Fig. 2.

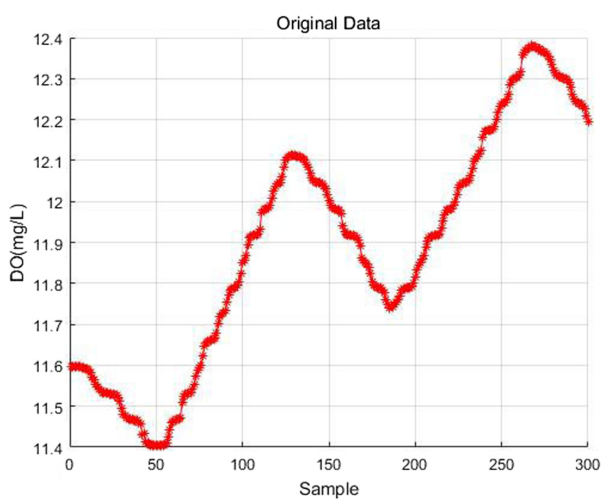

Fig. 2 – Original DO series.

3.2. Simulation results

Original DO datasets are regarded as a time series signal. Fig. 3 shows the decomposition process of the original DO datasets. The number of DO series is decomposed into 7 IMFs and a RES by EEMD.

We reconstruct these components in order to reduce the experimental complexity and the possibility of bigger error. In Fig. 3, most of the energy of the signal is concentrated in the RES component. This component reflects the change trend of the original DO datasets and called trend term. Then we calculate the correlation coefficient in Table 1 by analyzing correlation between 7 IMFs. We divide 7 IMFs into 3 reconstructive terms, which are high frequency term (IMF1, IMF2), intermediate frequency term (IMF3, IMF4) and low frequency term (IMF5, IMF6, IMF7), respectively. Fig. 4 shows four reconstructive terms.

High frequency term and intermediate frequency term have the characteristics of high volatility and complexity, we select LSSVR method which has high accuracy and adaptability to predict. The fluctuation of low frequency item is gentle, and the periodicity is obvious. BPNN is selected to predict this term. In order to improve the accuracy of BPNN, we optimize the initial weights of the neural network using MEC, PSO and GA, respectively. The MAE, MAPE, MSE, RMSE and running time of each optimization algorithm are given in Table 2. From Table 2 it can be observed that MEC-BP has the smaller running time and the similar prediction accuracy with PSO-BP and GA-BP. Thus, we select MEC-BP to predict low frequency term. Trend term is nearly linear, the GM is selected to fit the linear time series. Fig. 5 shows the predicted results of the reconstructive terms in the testing period.

The final predicted results are obtained by adding each reconstructive term and is shown in Fig. 6(a). To analyze and compare prediction performance, EEMD-ELM, EEMD-BP

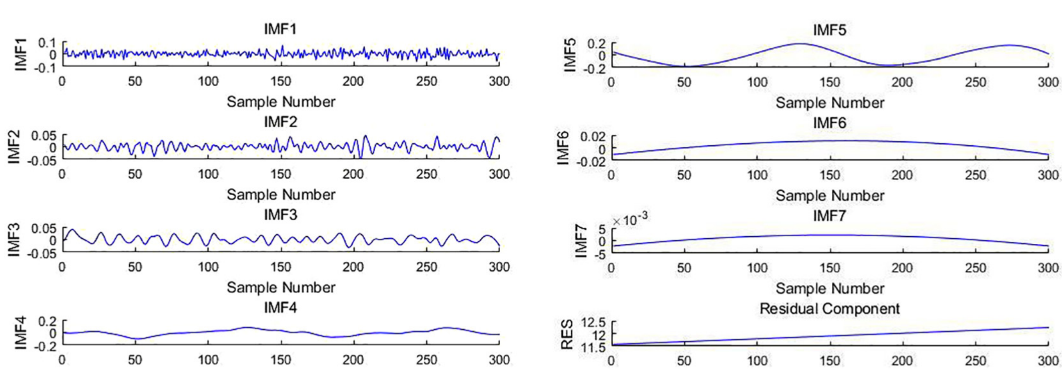

Fig. 3 – Decomposition by EEMD.

Table 1 – Correlation coefficient between 7 IMFs.

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
IMF1	1						
IMF2	0.0956	1					
IMF3	0.0544	0.0655	1				
IMF4	0.0063	0.0391	0.0770	1			
IMF5	0.0485	0.0910	0.0706	0.0433	1		
IMF6	0.0470	0.0339	0.0473	0.0101	0.0471	1	
IMF7	0.0066	0.0445	0.2600	0.2162	0.2389	0.3816	1

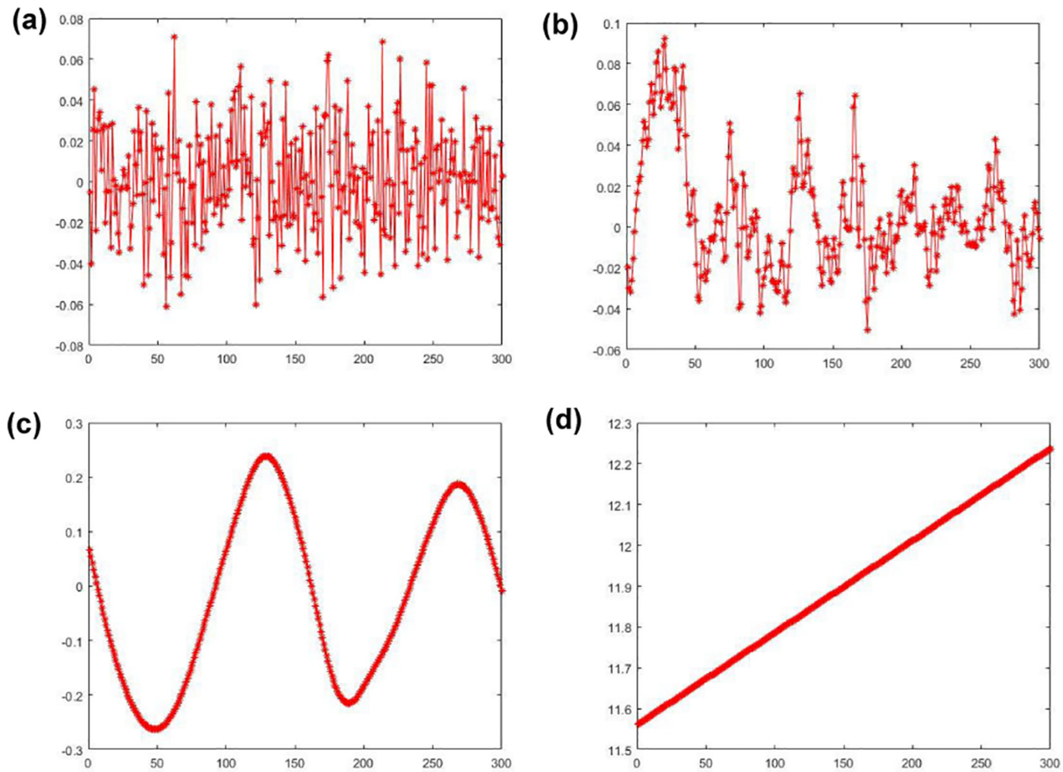

Fig. 4 – Four reconstructive terms (a) high frequency term (b) intermediate frequency term (c) low frequency term (d) trend term.

Table 2 – Optimization results of BP neural network based on different optimization algorithms.

	MAE	MAPE	MSE	RMSE (%)	Time (s)
BP	0.1396	0.0113	0.0217	14.73	1.3906
MEC-BP	0.0891	0.0073	0.0120	10.93	9.6250
PSO-BP	0.0863	0.0070	0.0135	11.63	971.8750
GA-BP	0.0010	0.0403	0.2279*e−04	0.48	1.8548*e+03

and MEC-BP models are used to forecast the sequence for the same datasets. The predicted results are shown in Fig. 6(b) (c) and (d), respectively. From Fig. 6 it can be seen that our algorithm has higher accuracy than EEMD-ELM, EEMD-BP and MEC-BP models.

3.3. *Performance criteria*

We employ the MAE, MAPE, MSE and RMSE to evaluate the forecasting accuracy. The smaller the values of these errors, the better the performance of the forecasting model. The calculating formulas are as follows:

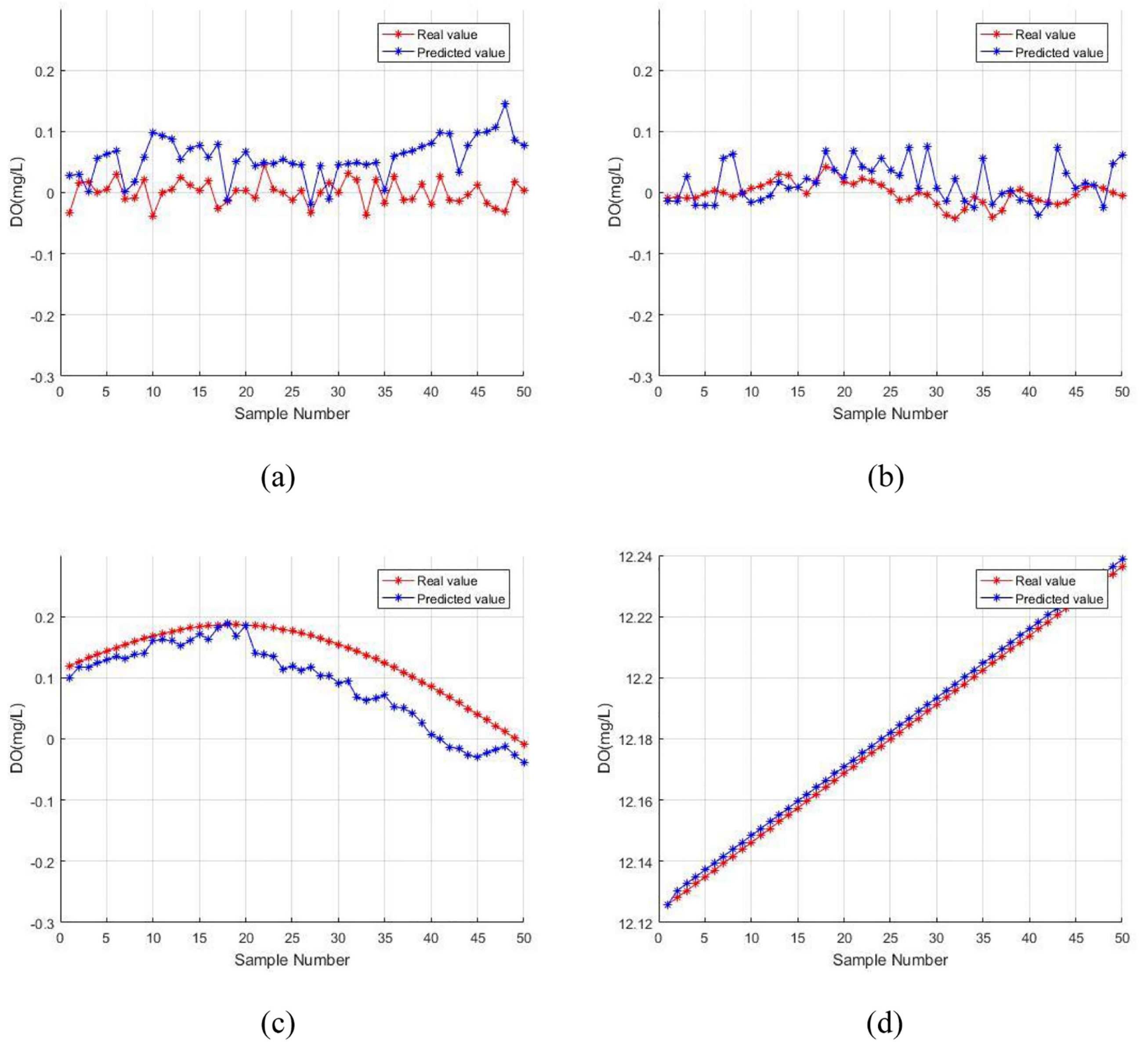

Fig. 5 – Predicted results of four reconstructive terms (a) high frequency term (b) intermediate frequency term (c) low frequency term (d) trend term.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{6}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{8}$$

In these formulas, N represents the number of samples, y_i represents the real values, and $\hat{y}_i$ represents the predicted values.

The forecasting results of four methods are shown in Table 3. The relative MAE, MAPE, MSE and RMSE differences between our algorithm and EEMD-BP model are 0.1061, 0.0086, 0.0242, and 11.22% in the test period, respectively. This result depicts our hybrid model has yielded significantly more reliable performance and higher prediction precision than EEMD-BP model. The relative MAE, MAPE, MSE and RMSE differences between our algorithm and EEMD-ELM model are 0.1602, 0.013, 0.0417, and 15.89% in the test period, respectively. It is clear that our hybrid model also has more accurate results than EEMD-ELM. Similarly, our model is also better than MEC-BP and the RMSE value is improved by 5.75%.

In order to verify the validity of our model, we repeat the experiment using the other two different groups of data. Fig. 7(a) and (b) shows two sets of data collected from the

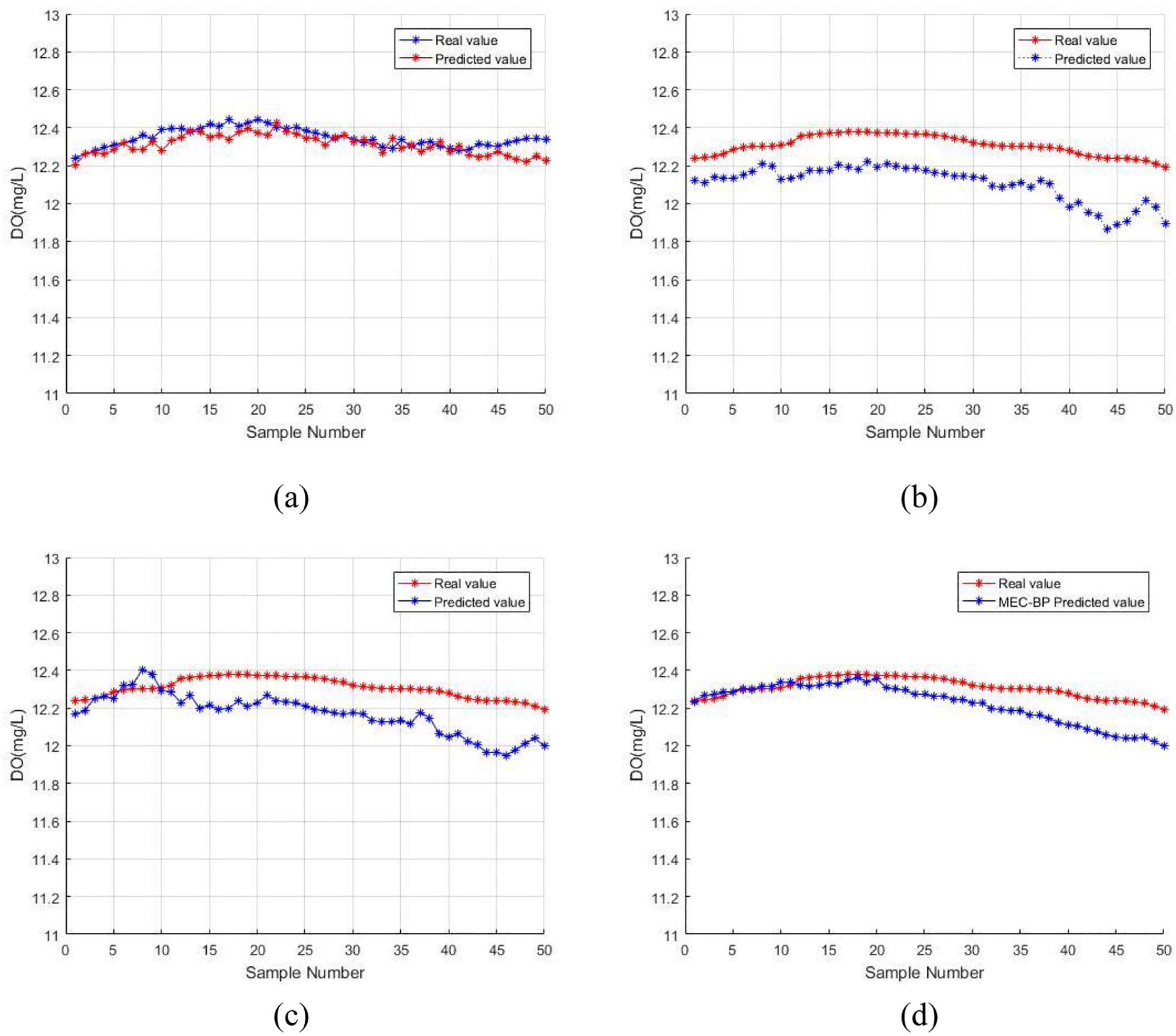

Fig. 6 – Final predicted results (a) Our algorithm (b) EEMD-ELM (c) EEMD-BP (d) MEC-BP.

Table 3 – Accuracy analysis of four models.

Models	MAE	MAPE	MSE	RMSE(%)
EEMD-BP	0.1476	0.0120	0.0269	16.40
EEMD-ELM	0.2017	0.0164	0.0444	21.07
MEC-BP	0.0891	0.0073	0.0120	10.93
Our hybrid model	0.0415	0.0034	0.0027	5.18

same location with a pond at different times, and each group also has 300 samples.

Fig. 8 shows the forecasting results of the first set of data. The fitting accuracy of our hybrid model is higher than the other three models.

We calculate the mean MAE, MAPE, MSE and RMSE values of the two new sets of data in Table 4. Table 4 indicate that the MAE, MAPE, MSE and RMSE using our hybrid model are better than those of the EEMD-BP, EEMD-ELM and MEC-BP models. Moreover, our hybrid model has a significantly more reliable performance and a higher prediction precision than the other three models. Experiments show that our hybrid model has higher forecasting accuracy and is suitable for small sample prediction.

4. Conclusion

In order to solve the problems of lower accuracy in aquaculture dissolved oxygen prediction, this paper proposed a

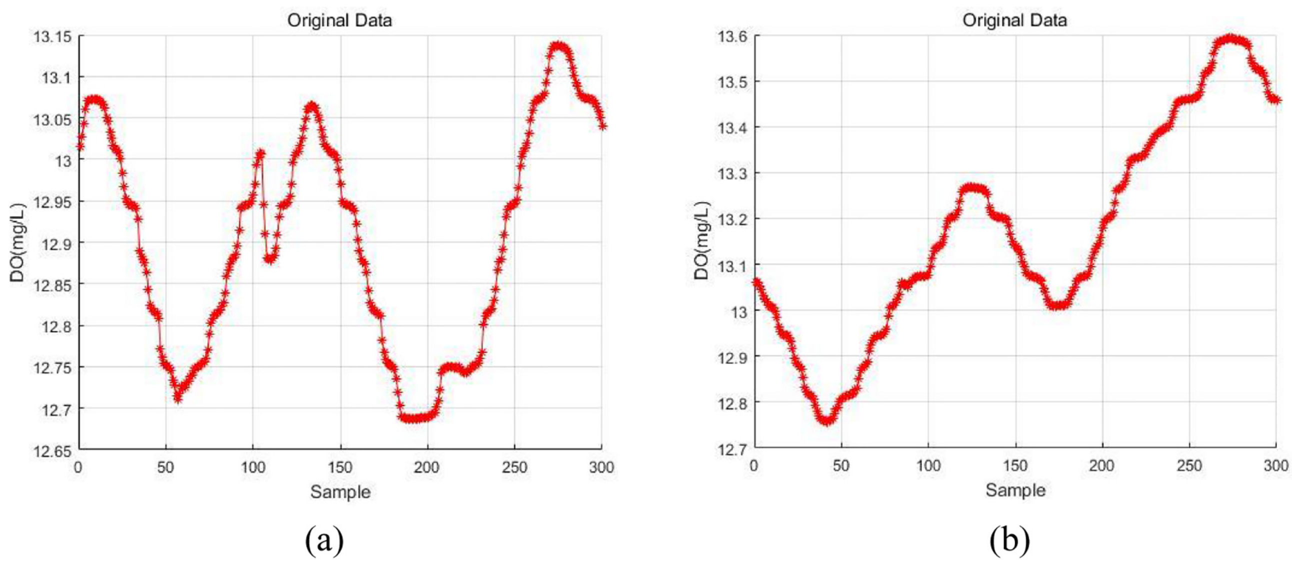

Fig. 7 – Two new sets of data.

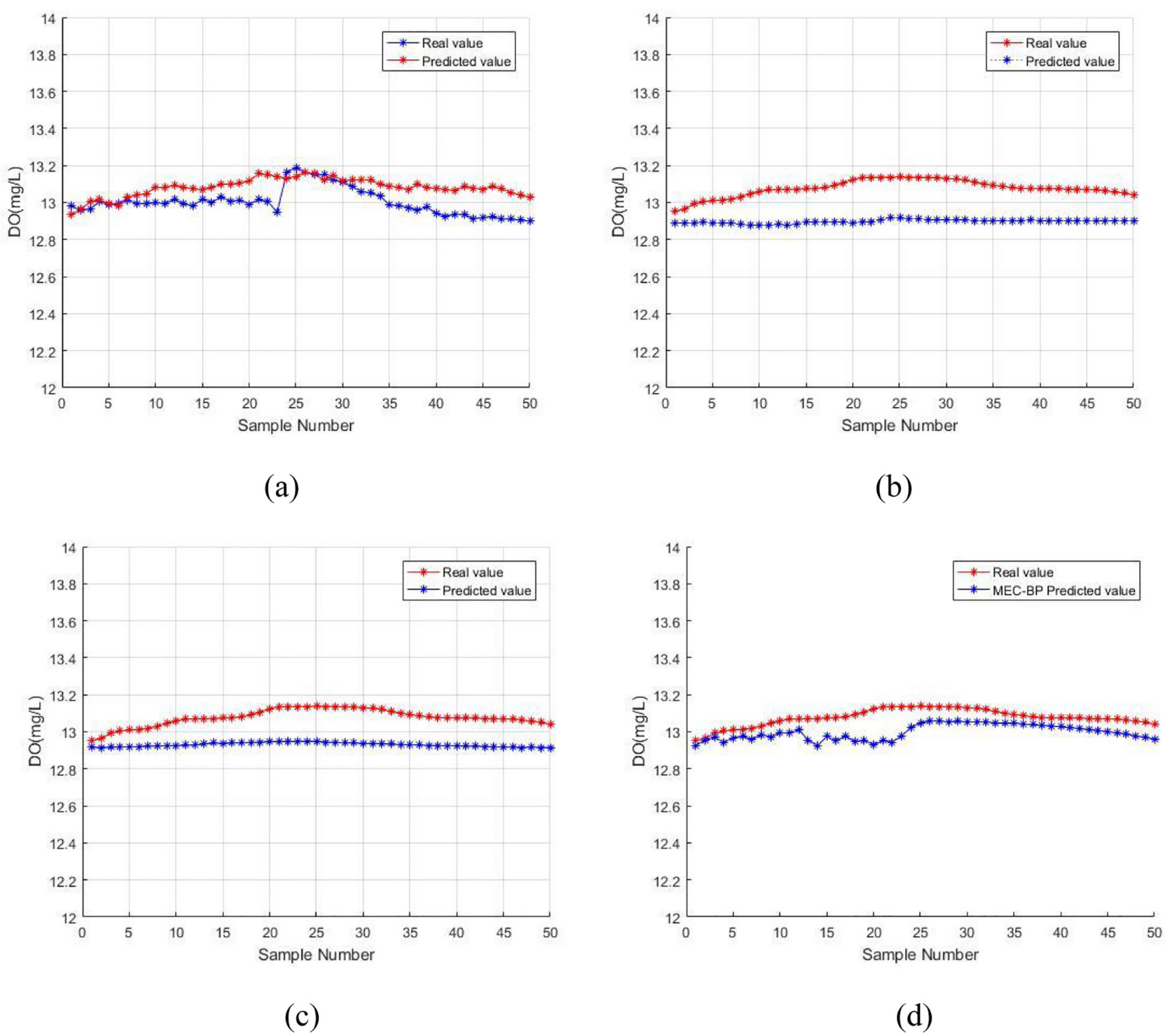

Fig. 8 – Final predicted results of the first set of data (a)Our algorithm (b) EEMD-ELM (c) EEMD-BP (d) MEC-BP.

Table 4 – The mean accuracy values analysis with two new sets of data of four models.

Models	MAE	MAPE	MSE	RMSE (%)
EEMD-BP	0.1844	0.0138	0.04625	20.77
EEMD-ELM	0.1951	0.01465	0.0446	20.96
MEC-BP	0.0967	0.00725	0.0241	10.83
Our hybrid model	0.08185	0.0078	0.00765	9.65

multi-scale forecasting method based on ensemble empirical mode decomposition. Original dissolved oxygen datasets were decomposed to 7 IMFs and a RES, and then, four terms are reconstructed by analyzing their correlation. The hybrid model was developed by combining three methods: least squares support vector regression, BP neural network optimized by mind evolutionary computation and grey model. Using actual experimental dissolved oxygen data from Jingming aquaculture factory in Dongying city, China, the simulate results show that compared with EEMD-ELM, EEMD-BP and MEC-BP, our hybrid model has better prediction performance, as measured by MAE, MAPE, MSE and RMSE.

Acknowledgements

This research is financially supported by National Natural Science Foundation Project of China (61471133)—"The research on combination model for water quality prediction in aquaculture based on dynamic multi-scale analysis".

REFERENCES

[1] Kayacan E, Ulutas B, Kaynak O. Grey system theory-based models in time series prediction. Expert Syst Appl 2010;37(2):1784–9.
[2] Deng W, Wang G, Zhang X. Water quality prediction based on a novel hybrid model of ARIMA and RBF neural network. In: International Conference on Cloud Computing and Intelligence Systems IEEE. Shenzhen, China; 2015: p. 33–40.
[3] Li X, Song J. A New ANN-Markov chain methodology for water quality prediction. In: International Joint Conference on Neural Networks IEEE. Killarney, Ireland; 2015: p. 1–6.
[4] Chaochin C, Chen HH, Chinghua T. Grey prediction fuzzycontrol for pH processes in the food industry. J Food Eng 2010;96(4):575–82.
[5] Khotimah WN. Aquaculture water quality prediction using smooth SVM. Iptek J Proc 2015;1(1):342–5.
[6] Yan JX, Yu LJ, Mao WW, Cao SQ. Study on prediction model of dissolved oxygen about water quality monitoring system based on BP neural network. Adv Mat Res 2014;912–914:1407–11.
[7] Liu SY, Xu LQ, Li DL. Dissolved oxygen prediction model of eriocheir sinensis culture based on least squares support vector regression optimized by ant colony algorithm. Trans CSAE 2012;28(23):167–75.
[8] Liu SY, Xu LQ, Li ZB. Forecasting model for pH value of aquaculture water quality based on PCA-MCAFA-LSSVR. Trans CSAM 2014;45(5):239–46.
[9] Liu SY. Prediction and early-warning of water quality in aquaculture based on Computational Intelligence. Doctor thesis. China Agricultural University. 2014.
[10] Xue HP, Wang L, Li D. Design and development of dissolved oxygen real-time prediction and early warning system for brocaded carp aquaculture. Int Fed Info Proc 2013;392:35–42.
[11] Liu SY, Tai H, Ding Q, Li D, Xu L, Wei Y. A hybrid approach of support vector regression with genetic algorithm optimization for aquaculture water quality prediction. Math Comput Model 2013;58(3–4):458–65.
[12] Ahmed AM. Prediction of dissolved oxygen in Surma River by biochemical oxygen demand and chemical oxygen demand using the artificial neural networks (ANNs). J King Saud Univ-Eng Sci 2014;29(2):151–8.
[13] Ahmed AM, Shah SM. Application of adaptive neuro-fuzzy inference system (ANFIS) to estimate the biochemical oxygen demand (BOD) of Surma River. J King Saud Univ-Eng Sci 2017;29(3):237–43.
[14] Liu SY, Xu LQ, Jiang Y, Li DL, Chen YY, Li ZB. A hybrid WA–CPSO-LSSVR model for dissolved oxygen content prediction in crab culture. Eng Appl Artif Intel 2014;29(3):114–24.
[15] Cheng JS, Zhang K, Yang Y, Yu JD. Comparison between the methods of local mean decomposition and empirical mode decomposition. J Vib Shock 2009;28(5):13–6.
[16] Wang XL, Li H. One-Month Ahead Prediction of Wind Speed and Output Power Based on EMD and LSSVR. In: International Conference on Energy and Environment Technology IEEE Computer Society. Washington, DC, USA; 2009: p. 439–42.
[17] Wang LJ, Dong L, Gao S, Liao XZ. Short-term wind power prediction with signal decomposition. In: International Conference on Electric Information and Control Engineering IEEE. Wuhan, China; 2011: p. 2569–73.
[18] Zheng ZW, Chen YY, Zhou XW, Huo MM, Zhao B, Guo MY. Short-term wind power forecasting using empirical mode decomposition and RBFNN. Int J SGCE 2013;2(2):192–9.
[19] Liang L, Yu D, Chang X. Research on multi-step prediction of the short-term information by empirical model decomposition to abnormal state road traffic information. In: International Conference on Computer Science & Service System IEEE. Washington, DC, USA; 2012: p. 2034–7.
[20] Chen SY, Chou WY. Short-term traffic flow prediction using EMD-based recurrent Hermite neural network approach. In: International IEEE Conference on Intelligent Transportation Systems IEEE. Anchorage, AK; 2012: p. 1821–6.
[21] Liu X, Zhang A, Shi C, Wang H. Filtering and Multi-Scale RBF Prediction Model of Rainfall Based on EMD Method. In: First IEEE International Conference on Information Science and Engineering IEEE Computer Society. Washington, DC, USA; 2009: p. 3785–8.
[22] Liu SY, Xu LQ, Li DL. Multi-scale prediction of water temperature using empirical mode decomposition with back-propagation neural networks. Comput Electr Eng 49(C);2016: p. 1–8.

[23] Huang NE. The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. Proc Math Phys Eng Sci 1971;1998(454):903–95.

[24] Wu ZH, Huang NE. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Adv Adapt Data Anal 2011;1(1):1–41.

[25] Sun CY, Sun Y, Xie KM. Mind-evolution-based machine learning: an efficient approach of evolution computation. Intell Contr Automat 2000;1:118–21.