A Hybrid Forecasting Model for Dissolved Oxygen Concentration in Shrimp Aquaculture: EMD-RF-LSTM Postprint

Authors: Yin Hang, Li Xiangtong, Xu Longqin, Li Jingbin, Liu Shuangyin, Cao Liang, Feng Dachun, Guo Jianjun, Li Liqiao

Date: 2023-02-17T00:00:00+00:00

Abstract

Dissolved oxygen (DO) concentration is a core indicator for water quality monitoring in shrimp aquaculture. To improve the prediction accuracy of dissolved oxygen concentration in shrimp aquaculture, this study proposes a hybrid prediction model for dissolved oxygen concentration in shrimp aquaculture based on Empirical Mode Decomposition, Random Forest, and Long Short-Term Memory neural network (EMD-RF-LSTM). First, Empirical Mode Decomposition (EMD) is employed to perform multi-scale feature extraction on dissolved oxygen concentration time-series data, obtaining Intrinsic Mode Functions (IMF) at different scales; then, Long Short-Term Memory neural network (LSTM) and Random Forest (RF) are respectively used to model the high-frequency and low-frequency IMFs at different scales; finally, a superposition model is constructed by combining the prediction results of each component to achieve comprehensive prediction of the dissolved oxygen concentration time-series data. The proposed model was tested and applied at the Nansan Island shrimp aquaculture base in Zhanjiang City, Guangdong Province. In performance evaluation based on real datasets, compared with the Extreme Learning Machine (ELM) model, the EMD-ELM model reduced the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) by 30.11%, 29.60%, and 32.95%, respectively. Based on Empirical Mode Decomposition, after using RF and LSTM to respectively predict the Intrinsic Mode Functions of different characteristic scales and then aggregating them by summation, the accuracy metrics of the EMD-RF-LSTM model prediction—MAPE, RMSE, and MAE—were 0.0129, 0.1156, and 0.0844, respectively. The key metric MAPE was reduced by 84.07%, 57.57%, and 49.81% compared with EMD-ELM, EMD-RF, and EMD-LSTM, respectively, indicating a significant improvement in prediction accuracy. The results demonstrate that the strategy of separately predicting high-frequency and low-frequency components after Empirical Mode

Decomposition can effectively improve overall performance, indicating that the proposed model possesses high prediction accuracy and can accurately predict dissolved oxygen concentration in shrimp aquaculture water bodies.

Full Text

EMD-RF-LSTM: Combination Prediction Model of Dissolved Oxygen Concentration in Prawn Culture

YIN Hang[1,3,4,6], LI Xiangtong[1,3,4,6], XU Longqin[1,3,4,6], LI Jingbin[2], LIU Shuangyin[1,2,3,4,5,6], CAO Liang[1,3,4], FENG Dachun[1,3,4,6], GUO Jianjun[1,3,4,6], LI Liqiao[2]*

[1]College of Information Science and Technology, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China
[2]College of Mechanical and Electric Engineering, Shihezi University, Shihezi, Xinjiang 832000, China
[3]Academy of Smart Agricultural Engineering Innovations, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China
[4]Smart Agriculture Engineering Research Center of Guangdong Higher Education Institutes, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China
[5]Guangdong Key Laboratory of Waterfowl Health Breeding, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China
[6]Guangdong Engineering Research Center for Agricultural Product Safety Big Data, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China

Abstract

Dissolved oxygen (DO) concentration is a core indicator for water quality monitoring in prawn culture. To improve the prediction accuracy of dissolved oxygen concentration in prawn aquaculture, this study proposes a hybrid prediction model based on Empirical Mode Decomposition (EMD), Random Forest (RF), and Long Short-Term Memory (LSTM) neural networks. First, EMD is employed to perform multi-scale feature extraction on time-series dissolved oxygen data from aquaculture water, yielding Intrinsic Mode Functions (IMFs) at different scales. Subsequently, LSTM and RF models are separately applied to model high-frequency and low-frequency components. Finally, a superposition model is constructed by combining the predictions from each component to achieve comprehensive forecasting of dissolved oxygen concentration time-series data. The proposed model was tested and applied at a prawn culture base in Nansan Island, Zhanjiang City, Guangdong Province. Performance evaluation on real-world datasets demonstrated that compared with the EMD-ELM model, the EMD-RF-LSTM model reduced Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) by 30.11%, 29.60%, and 32.95%, respectively. After separate prediction of IMFs at different feature scales followed by summation, the MAPE, RMSE, and MAE metrics for the EMD-RF-LSTM model were 0.0129, 0.1156, and 0.0844, representing reductions of 84.07%, 57.57%, and 49.81% compared to EMD-ELM, EMD-RF, and EMD-LSTM, respectively. The key metric MAPE showed a significant improvement in prediction accuracy. Results indicate that the strategy of separately predicting high- and low-frequency components after EMD decomposition effectively enhances overall performance, demonstrating that the proposed model achieves high prediction accuracy and can reliably forecast dissolved oxygen concentration in prawn culture water bodies.

Keywords: prawn culture; dissolved oxygen concentration prediction; empirical mode decomposition; random forest; long short-term memory neural network

1. Introduction

Dissolved oxygen (DO) concentration is a critical parameter in aquaculture water quality monitoring, directly affecting the growth rate and survival rate of aquatic organisms, and serving as a key determinant of prawn quality and yield [1,2]. Currently, the average stocking density of typical *Litopenaeus vannamei* culture in China reaches 220–300 individuals/m^2, with 2–3 culture cycles per year. Due to stocking densities in prawn ponds being significantly higher than those in fish ponds and approaching industrial fish farming levels, monitoring requirements for dissolved oxygen concentration are more stringent.

Constructing an accurate model for dissolved oxygen variation in prawn culture environments and precisely predicting changes in water body dissolved oxygen concentration [3,4] is essential for achieving refined aquaculture management and regulation, scientifically determining optimal stocking densities and feed ratios, ensuring healthy prawn growth in stress-free environments, and improving culture economic benefits [5].

Current research on dissolved oxygen prediction methods in aquaculture has been extensively conducted by various research groups. Liu et al. [6] developed a dissolved oxygen prediction model using Wavelet Analysis (WA) and Cauchy Particle Swarm Optimization-based Least Squares Support Vector Regression, applied to DO prediction in crab culture. Xu et al. [7] employed wavelet analysis for multi-scale feature extraction and used weighted least squares support vector regression to model different scale sequences for DO prediction. Huan et al. [8] utilized Gradient Boosting Decision Trees and Long Short-Term Memory (LSTM) networks for aquaculture dissolved oxygen concentration prediction. Zhu et al. [9] optimized the loss function in LSTM backpropagation, proposing a Low-DO LSTM (LDO-LSTM) model that not only maintains overall DO prediction accuracy but also improves estimation precision for lower dissolved oxygen concentrations.

Previous studies have identified that dissolved oxygen in prawn culture water exhibits characteristics of long time-series, instability, and multi-scale nonlinearity [10,11], and is influenced by complex multi-factor coupling relationships [12], making it difficult to establish high-performance generalized models [13]. Due to sensor failures, noise interference, long time-series data [14], and spatiotemporal distribution differences among monitoring points [15], preprocessing such as denoising, multi-scale analysis, spatiotemporal classification, and feature extraction is required for dissolved oxygen time-series data from prawn culture water [16]. While wavelet analysis has been used for data denoising and feature extraction, it requires predetermined basis functions and involves human interference [17]. Empirical Mode Decomposition (EMD) can decompose nonstationary time-series data into low-coupling Intrinsic Mode Functions (IMF), effectively performing data denoising and anti-interference preprocessing [18-20].

EMD has been applied in aquaculture and other fields. Xu et al. [21] combined EMD with Extreme Learning Machine (ELM) to construct a water temperature combination prediction model. Shi et al. [22] built upon Xu et al.' s work, combining Improved Genetic Algorithm (IGA) and Improved Extreme Learning Machine (SELM) to develop an EMD-IGA-SELM prediction model for improved water temperature prediction accuracy and stability. Yang et al. [23] proposed an EMD-LSTM prediction model, processing ammonia concentration time-series data with EMD to generate modal components at different time scales, then using LSTM to predict each component separately and summing the results to achieve a combined ammonia concentration model. Dai et al. [24] noted that LSTM adds hidden layers to traditional neural networks, effectively avoiding gradient vanishing and explosion, with good prediction accuracy and robustness. Zhao et al. [25] found in their research on prediction models based on frequency domain decomposition and deep learning algorithms that LSTM performs excellently on high-frequency component prediction but poorly on low-frequency components with fewer training samples. Qin et al. [26] constructed an EMD-RF model using empirical mode decomposition and random forest, achieving high accuracy and generalization performance across different frequency components.

Based on the above research, EMD-LSTM combination models have been applied to dissolved oxygen prediction, but the issue of poor performance on low-frequency components with limited training samples remains to be addressed, and combination prediction methods selecting appropriate models for different frequency domains require further investigation. To solve the problem of poor prediction accuracy for different frequency domain modal components after empirical mode decomposition of nonlinear time-series data with limited training samples, this study proposes a nonlinear combination prediction model for prawn culture dissolved oxygen based on EMD, RF, and LSTM. The model performs multi-scale decomposition of dissolved oxygen time-series data using EMD to obtain IMFs and residual components at different feature scales, then selects RF and LSTM to model low-frequency components, high-frequency components, and residuals respectively, and finally superimposes the predictions to forecast dissolved oxygen concentration in prawn culture water bodies.

---

2. Materials and Methods

2.1 Data Collection

To evaluate the proposed model' s performance in real-world environments, this study was conducted at the Nansan Island prawn culture base in Zhanjiang City, Guangdong Province, collecting real data from prawn culture ponds. The experimental prawn culture pond measured 38.0 m in length, 32.0 m in width, and 1.1 m in water depth. Multi-parameter water quality sensors, aerators, circulation pumps, and other water quality monitoring equipment were deployed at multiple points in the pond. The schematic diagram of the prawn culture pond monitoring layout and the experimental platform topology are shown in [Figure 1: see original paper].

The prawn culture environment monitoring and experimental platform includes functions for data collection, wireless transmission, data processing, and intelligent monitoring. The water quality parameters collected by the IoT-based data acquisition module include dissolved oxygen, pH, water temperature, electrical conductivity, and turbidity, with a collection frequency of 30 minutes.

2.2.1 Empirical Mode Decomposition (EMD)

EMD is an adaptive signal time-frequency processing method [18] that avoids human interference from presetting basis functions. It can adaptively decompose non-stationary, nonlinear original signals through multi-scale decomposition to obtain a set of IMFs with stationary and periodic characteristics and a residual component [20-24]. Denoting the original time-series dissolved oxygen data from prawn culture water as X(t), the EMD procedure is as follows:

(1) Using cubic spline interpolation, fit the upper and lower envelope curves of the dissolved oxygen original time-series signal, calculate the local maxima Xmax(t), minima Xmin(t), and mean M(t) as shown in equation (1):

$$M(t) = \frac{X_{\min}(t) + X_{\max}(t)}{2}$$

(2) Calculate the difference H(t) between X(t) and M(t) as shown in equation (2):

$$H(t) = X(t) - M(t)$$

If H(t) meets the requirements of an intrinsic mode function, it is added as an initial IMF component, denoted as C_1(t). If not, it replaces X(t) and the above steps are repeated until a new IMF component is obtained, ultimately constituting the high-frequency component of the signal sequence.

(3) Subtract $C_1(t)$ from H(t) to obtain the residual term $r_1(t)$, which serves as a new signal sequence. Using the method in step (2), the remaining IMF components $C_2(t)$, $C_3(t)$, ···, C (t) and residual term r (t) are obtained. The original time-series X(t) can finally be decomposed and expressed as the sum of all components and the residual term, as shown in equation (3):

$$X(t) = \sum_{i=1}^{n} C_i(t) + r_n(t)$$

2.2.2 Random Forest (RF)

Random Forest (RF) is a machine learning method inheriting the Bootstrap Aggregation (Bagging) algorithm 思想 [27,28], using Classification and Regression Trees as weak learners. It comprises multiple independent decision trees with equal weights to form a decision forest. Compared with traditional decision tree methods, RF converges rapidly and effectively overcomes overfitting, demonstrating high accuracy for nonlinear, non-stationary, long time-series data prediction, with advantages in training speed, generalization capability, and predictive performance [29].

2.2.3 Long Short-Term Memory Neural Network (LSTM)

LSTM is a neural network model proposed by Hochreiter et al. based on Recurrent Neural Networks (RNN) [20,23-25]. LSTM replaces RNN hidden layer neurons with cell states and three gate structures, enabling the ability to remove or add control information to cell states, thereby overcoming RNN' s gradient vanishing, decreased learning capability, and long-term dependency problems [30,31].

LSTM uses input gates and forget gates to control information passed forward through cell states, while output gates control cell states for LSTM current value output, as follows:

$$\begin{gathered}
i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\
h_t = o_t \odot \tanh(C_t)
\end{gathered}$$

where i, f, o, and C represent the input gate, forget gate, output gate, and candidate vector, respectively; W denotes weights; b denotes biases; $\sigma(\cdot)$ is the sigmoid activation function; tanh(•) is the hyperbolic tangent activation function; i , f , o , and C represent the input gate, forget gate, output gate, and candidate vector update values at time t, respectively; Wc and bc represent the weight and bias of the candidate vector C; x is the sequence input at time t; and h is the output at time t.

---

3. Design of EMD-RF-LSTM Combination Prediction Model

3.1 Model Architecture

To address the problem of poor prediction accuracy for different frequency domain modal components after empirical mode decomposition of nonlinear time-series data, and to verify the effectiveness of separate prediction for high- and low-frequency components, this study designed an EMD-RF-LSTM-based combination prediction model for dissolved oxygen in prawn culture water, using dissolved oxygen concentration data as input. First, EMD performs multi-scale decomposition on the periodic, nonlinear dissolved oxygen time-series data from prawn culture, dividing it into high-frequency IMFs, low-frequency IMFs, and residual values (RES). The decomposed data then undergoes normalization and is split into training and testing sets. Low-frequency IMFs are used to train the RF model, while high-frequency IMFs train the LSTM model, with the Adam optimizer iteratively adjusting LSTM parameters. Finally, the testing set evaluates the model through comparison with standard models (ELM, RF, LSTM) and EMD-based decomposition models (EMD-ELM, EMD-RF, EMD-LSTM) to verify the proposed model' s performance for prawn culture dissolved oxygen prediction. The detailed steps are:

(1) Collect dissolved oxygen time-series data through water quality sensors and complete preprocessing;
(2) Perform EMD decomposition on preprocessed dissolved oxygen time-series data to obtain IMF components at different frequencies and normalize them;
(3) Divide the normalized prawn culture dissolved oxygen IMF components into high-frequency and low-frequency sets, and split into training and testing sets;
(4) Establish LSTM and RF models for high-frequency IMFs, low-frequency IMFs, and residual components, initializing model parameters and weights;
(5) Train the models using the training set, iteratively optimizing LSTM model parameters and weights to complete the EMD-RF-LSTM-based prawn culture dissolved oxygen prediction model;
(6) Evaluate the model using the testing set and compare with other models.

The constructed prediction model is shown in [Figure 2: see original paper].

3.2 Evaluation Metrics

To verify the EMD-RF-LSTM model's prediction performance for prawn culture dissolved oxygen concentration, this study conducted comparative experiments with other models. Three evaluation metrics were selected: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to assess the combination model' s performance.

---

4. Experiments and Results Analysis

4.1 Data Preprocessing

The experiments used dissolved oxygen concentration data from the experimental pond at the Nansan Island prawn culture base in Zhanjiang City as the research object, with water quality data collected by the IoT data acquisition module serving as experimental samples. A total of 1,488 samples collected from July 20 to August 20, 2020, were included in the experimental dataset, with the first 1,344 data points used as the training set and the final 144 as the testing set. [Figure 3: see original paper] shows the raw data for the complete collection period, where the horizontal axis represents the data sequence collected at 30-minute intervals and the vertical axis represents dissolved oxygen concentration values. The real dissolved oxygen time-series data from the prawn culture site exhibits significant periodicity and nonlinearity.

To address data anomalies caused by water quality sensor failures, a mean smoothing method was applied. If the absolute difference between a parameter value and its mean exceeded three times its standard deviation, it was identified as an outlier and replaced with the average of its neighboring data points, as shown in equation (5):

$$P_t' = \begin{cases} \bar{P}_t & \text{if } |P_t - \bar{P}_t| > 3\delta \\ P_t & \text{otherwise} \end{cases}$$

where P is the dissolved oxygen parameter value collected at time t; $\bar{P}_t$ is the mean value; δ is the standard deviation; and P' is the value after outlier processing.

To improve prediction accuracy, reduce errors, and facilitate correlation analysis among prawn culture dissolved oxygen concentration data for better time-series information extraction, this study normalized the data using equation (6):

$$N'' = \frac{N - N_{\min}}{N_{\max} - N_{\min}}$$

where Nmax is the maximum dissolved oxygen concentration, Nmin is the minimum dissolved oxygen concentration (units: mg/L), and N" is the normalized value.

4.2 Development Environment and Tools

The experimental computing environment consisted of an Intel I7-7700K CPU, 8GB RAM, Windows 7 + Python 3.7 + MATLAB, with Anaconda3 as the integrated development environment. The EMD and ELM models were implemented using MATLAB toolboxes, the RF model using Anaconda' s Scikit-learn package, and the LSTM model built with the Keras framework. Experimental parameters were optimized using Leave-One-Out Cross-Validation (LOOCV) grid search.

4.3 Multi-Scale Decomposition of Dissolved Oxygen Based on EMD

To achieve more accurate prediction results and obtain high-precision prawn culture dissolved oxygen time-series components, this study first applied EMD to perform multi-scale decomposition on raw dissolved oxygen time-series data. The resulting components are shown in [Figure 4: see original paper].

As seen in [Figure 4: see original paper], the prawn culture dissolved oxygen concentration time-series data exhibits distinct multi-scale features after decomposition. The intrinsic mode functions IMF1–IMF7 each demonstrate different information characteristics, while the final residual component sequence is stable, reflecting the long-term variation state of total dissolved oxygen content in prawn culture water.

4.4 IMF Component Prediction and Parameter Settings

Based on literature [25], [30], and [31], this study employed a comprehensive experimental approach using LSTM and RF models to separately model and train IMF1–IMF7 and the RES component on the basis of empirical mode decomposition. The LSTM model parameters were optimized using extended stochastic gradient descent, while RF model parameters were optimized using grid search to identify the predictive performance of LSTM and RF models on components of different frequencies.

The standard LSTM model used 20 hidden layer nodes, a batch size of 32, and a time step of 5. The RF model used a learning rate of 0.1, a tree depth of 3, 500 trees, and a minimum leaf weight of 6. The LSTM and RF prediction results for each IMF and RES component are shown in and , respectively.

As shown in and , the RF model achieved a MAPE of only 1.1542 for high-frequency component IMF1 and 0.0154 for IMF4, both lower than the corresponding LSTM predictions. However, as component frequency decreased, the RF model' s prediction accuracy improved. In contrast, LSTM model prediction accuracy decreased with lower component frequencies. The comparison revealed that LSTM outperformed RF on high-frequency components IMF1-IMF4 in key metrics, while RF performed better on low-frequency components, confirming experimental expectations. These results indicate that low-frequency components are suitable for RF model training, while high-frequency components are appropriate for LSTM model training.

4.5 Combination Prediction Based on EMD-RF-LSTM

Based on the characteristics demonstrated in Section 4.4, LSTM and RF models were used to separately predict high-frequency components (IMF1-IMF4) and low-frequency components plus residual (IMF5-IMF7, Rn). The predictions from each component were then summed to achieve dissolved oxygen concentration prediction in prawn culture based on EMD-RF-LSTM.

To verify model performance, dissolved oxygen concentration predictions were conducted using standard models, modal decomposition models, and the proposed model on the same dataset. The standard ELM model used a sigmoid activation function with 8 hidden layer nodes. The dissolved oxygen concentration prediction results for different models are shown in [Figure 5: see original paper], with performance metrics presented in .

4.6 Results Analysis

4.6.1 Empirical Mode Decomposition (EMD) Analysis Analysis of prediction results reveals that empirical mode decomposition can multi-scale extract time-series information from prawn culture dissolved oxygen data. After decomposition, more intrinsic mode coefficient time-series signals are obtained while preserving original information. Taking the key accuracy metric MAPE as an example, EMD-decomposed ELM, RF, and LSTM models reduced MAPE by 30.11%, 70.40%, and 74.83% respectively compared to their corresponding standard models, demonstrating significantly higher prediction accuracy. This proves that multi-scale decomposition of time-series data based on EMD can effectively improve prediction performance.

4.6.2 Multi-Frequency Modal Component Combination Prediction Analysis Experimental results show that under the same dataset, the EMD-RF-LSTM model, which employs RF and LSTM for separate prediction of different feature-scale IMFs after empirical mode decomposition, achieved substantial improvements. Using the key metric MAPE, the proposed multi-frequency modal component combination prediction model reduced MAPE by 84.07%, 57.57%, and 49.81% compared to EMD-ELM, EMD-RF, and EMD-LSTM models, respectively, demonstrating significantly enhanced prediction accuracy. This confirms that the multi-frequency component prediction strategy can improve model performance.

4.6.3 EMD-RF-LSTM Combination Prediction Model Analysis The proposed EMD-RF-LSTM combination model integrates the advantages of

EMD' s multi-scale feature extraction, LSTM' s long time-series high-frequency data prediction, and RF algorithm' s low-frequency IMF information extraction. The model achieves high prediction accuracy for prawn culture dissolved oxygen concentration, with the prediction curve effectively fitting the nonlinear time-series variation trends of culture dissolved oxygen, yielding excellent prediction results.

---

5. Discussion and Conclusion

5.1 Discussion

Long-term monitoring of prawn culture water quality reveals that water quality parameters, particularly dissolved oxygen concentration, change relatively slowly, with minimal variation within 30 minutes as shown in literature [7] and [12]. Compared with data collection cycles, intervals, and training data volumes in literature [30], this study appropriately increased the data collection interval while maintaining the same one-month monitoring period to reduce the total number of training samples. As a time-series recurrent neural network designed to solve RNN' s long-term dependency problems, LSTM demonstrates good memory capability for time-series data and provides reasonable predictions even for shorter time-series. Literature [25] shows that LSTM performs excellently on high-frequency components after empirical mode decomposition but poorly on low-frequency components with limited training samples. Literature [31] validated training effects with limited samples by selecting 1,500 data groups for their proposed EMD-LSTM model, achieving good prediction results. Considering the relationship between variable quantity and total sample size, this study selected 1,488 dissolved oxygen concentration time-series data points collected over one month at 30-minute intervals as training samples to verify the EMD-RF-LSTM model' s performance under limited training data.

Under limited training sample conditions, this study first verified LSTM' s poor prediction performance on low-frequency components after empirical mode decomposition. Experimental results divided IMF1–IMF4 as high-frequency components suitable for LSTM modeling and IMF5–IMF7 plus Rn as low-frequency components appropriate for RF modeling, constructing the EMD-RF-LSTM combination model to improve prediction accuracy. Additionally, the model demonstrated good prediction results through cross-validation using historical data. Future work will incorporate actual field test results to further validate model performance under limited historical data and adjust sampling frequency during periods of potential dramatic dissolved oxygen changes, such as during feeding, morning/evening transitions, or weather changes.

5.2 Conclusion

This study addresses the instability and multi-scale characteristics of dissolved oxygen concentration data in prawn culture water, analyzing the problem of poor prediction accuracy for different frequency domain modal components after empirical mode decomposition of nonlinear time-series data with limited training samples. Using EMD for multi-scale decomposition of dissolved oxygen concentration data, LSTM for high-frequency component prediction, and RF for low-frequency component prediction, separate modeling was performed for different frequency bands. Real culture environment data experiments demonstrated that the proposed EMD-RF-LSTM combination prediction model achieved MAPE, RMSE, and MAE metrics of 0.0129, 0.1156, and 0.0844, respectively. Compared with EMD-ELM, EMD-RF, and EMD-LSTM models, the key metric MAPE decreased by 84.07%, 57.57%, and 49.81%, respectively. Under limited training sample conditions, the model demonstrates good prediction performance for prawn culture dissolved oxygen concentration, effectively improving prediction accuracy and robustness.

References

[1] YU D, SONG J, YE H, et al. Suggestions on the development of healthy shrimp culture under ecological framework[J]. Chinese Journal of Ecology, 2021, 40(2): 568-576.

[2] ZHU L, CHE X, LIU X, et al. Construction and experiment of simple industrial recirculating water shrimp culture system[J]. Transactions of the CSAE, 2020, 36(15): 210-216.

[3] WU J, LI Z, ZHU L, et al. Hybrid model of ARIMA model and GAWNN for dissolved oxygen content prediction[J]. Transactions of the CSAM, 2017, 48(S1): 205-210.

[4] CHEN Y, CHENG Q, FANG X, et al. Principal component analysis and long short-term memory neural network for predicting dissolved oxygen in water for aquaculture[J]. Transactions of the CSAE, 2018, 34(17): 183-191.

[5] SWETA B, AMBIKA H, MAHESHAWARI J. Simple rapid and on spot dye-based sensor for the detection of Vibrio load in shrimp culture farms[J]. Archives of Clinical Microbiology, 2021(1): 1-8.

[6] LIU S, XU L, JIANG Y, et al. A hybrid WA-CPSO-LSSVR model for dissolved oxygen content prediction in crab culture[J]. Engineering Applications of Artificial Intelligence, 2014, 29(3): 114-124.

[7] XU L, CHEN Y, ZHANG J, et al. Prediction model of dissolved oxygen in industrialized vannamei breeding based on wavelet analysis and weighted least squares support vector regression optimized by artificial bee colony algorithm[J]. Engineering Journal of Wuhan University, 2017, 50(4): 608-617.

[8] HUAN J, LI H, LI M, et al. Prediction of dissolved oxygen in aquaculture based on gradient boosting decision tree and long short-term memory network:

A study of Changzhou fishery demonstration base, China[J]. Computers and Electronics in Agriculture, 2020, DOI: 10.1016/j.compag.2020.105530.

[9] ZHU N, WU H, YIN D, et al. An improved method for estimating dissolved oxygen in crab ponds based on Long Short-Term Memory[J]. Smart Agriculture, 2019, 1(3): 67-76.

[10] CAO W, HUAN J, LIU C, et al. A combined model of dissolved oxygen prediction in the pond based on multiple-factor analysis and multi-scale feature extraction[J]. Aquacultural Engineering, 2019, 84: 50-59.

[11] RAHMAN A, DABROWSKI J, MCCULLOCH J. Dissolved oxygen prediction in prawn ponds from a group of one step predictors[J]. Information Processing in Agriculture, 2020, 7(2): 307-317.

[12] SHI P, KUANG L, YUAN Y, et al. Dissolved oxygen prediction for water quality of aquaculture using improved ELM network[J]. Transactions of the CSAE, 2020, 36(19): 225-232.

[13] REN Q, WANG X, LI W, et al. Research of dissolved oxygen prediction in recirculating aquaculture systems based on deep belief network[J]. Aquacultural Engineering, 2020, 90: ID 102085.

[14] LIU Y, ZHANG Q, SONG L, et al. Attention-based recurrent neural networks for accurate short-term and long-term dissolved oxygen prediction[J]. Computers and Electronics in Agriculture, 2019, 165: ID 104964.

[15] FAN Y, REN N, TIAN G, et al. Spatio-temporal prediction method of dissolved oxygen in ponds based on DeepAR-RELM[J]. Transactions of the CSAM, 2020, 51(S1): 405-412.

[16] RAO W, YANG W, WEI Y, et al. Temporal and spatial variability of water dissolved oxygen with influence factors in aquaponics system[J]. Transactions of the CSAM, 2017, 48(S1): 374-380.

[17] YU H. Research on prediction method of key factors of pond aquaculture water quality based on machine learning[D]. Beijing: China Agricultural University, 2017.

[18] HU N, CHEN H, CHENG Z, et al. Fault diagnosis for planetary gearbox based on EMD and deep convolutional neural networks[J]. Journal of Mechanical Engineering, 2019, 55(7): 9-18.

[19] YANG J, HAN S, ZHANG S, et al. Fault diagnosis for planetary gearbox based on EMD and deep convolutional neural networks[J]. Journal of Vibration Engineering, 2020, 33(3): 582-589.

[20] LIU Y, XU Z, DONG W, et al. Concentration prediction of dissolved gases in transformer oil based on empirical mode decomposition and long short-term memory neural networks[J]. Proceedings of The Chinese Society for Electrical Engineering, 2019, 39(13): 3998-4008.

[21] XU L, ZHANG J, LI Q, et al. Combined prediction model of water temperature in industrialized cultivation based on empirical mode decomposition and extreme learning machine[J]. Transactions of the CSAM, 2016, 47(4): 265-271.

[22] SI P, YUAN Y, KUANG L, et al. Water temperature prediction in pond aquaculture based on EMD-IGA-SELM neural network[J]. Transactions of the CSAM, 2018, 49(11): 312-319.

[23] YANG L, LIU C, GUO Y, et al. Prediction of ammonia concentration in fattening piggery based on EMD-LSTM[J]. Transactions of the CSAM, 2019, 50(S1): 374-380.

[24] DAI S, CHEN Q, LIU Z, et al. Time series prediction based on EMD-LSTM model[J]. Journal of Shenzhen University (Science & Engineering), 2020, 37(3): 265-270.

[25] ZHAO X, SU G, LI K, et al. Spectrum occupancy prediction model based on EMD decomposition and LSTM networks[J]. Computer Science, 2020, 47(S1): 294-298.

[26] QIN X, LYU S, LI Q. Recognition of EEG based on ensemble empirical mode decomposition and random forest[J]. Chinese Journal of Biomedical Engineering, 2018, 37(6): 665-672.

[27] ANNA C, SALAH S, BRETT W. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review[J]. Computers and Electronics in Agriculture, 2018, 151: 61-69.

[28] DHIVYA E, DURAI R, VISHAL S, et al. Forecasting yield by integrating agrarian factors and machine learning models: A survey[J]. Computers and Electronics in Agriculture, 2018, 155: 257-282.

[29] LIU J, HE X, WANG P, et al. Early prediction of winter wheat yield with long time series meteorological data and random forest method[J]. Transactions of the CSAE, 2019, 35(6): 158-166.

[30] CHEN Y, FANG X, MEI S, et al. Principal component analysis and long short-term memory neural network for predicting dissolved oxygen in water for aquaculture[J]. Transactions of the CSAM, 2020, 51(10): 284-291.

[31] JIN X, LIU Y, YU J, et al. Prediction of outlet SO2 concentration based on variable selection and EMD-LSTM[J/OL]. Proceedings of The Chinese Society for Electrical Engineering, (2021-04-19). http://kns.cnki.net/kcms/detail/11.2107.TM.20210416.1541.009.html.