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A three-dimensional prediction method of dissolved oxygen in pond culture based on Attention-GRU-GBRT

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ABSTRACT

Pond culture is an open water body, the distribution of dissolved oxygen in water is three-dimensional. The demand for dissolved oxygen in aquatic products living in different water layers is different. The traditional one-dimensional prediction at one single monitoring point can‘t reflect the real situation of dissolved oxygen in different spaces in the pond. To solve these problems, a three-dimensional prediction method of dissolved oxygen based on Attention-Gated Recurrent Unit (GRU) - Gradient Boost Regression Tree (GBRT) was proposed in this paper. Firstly, the environmental factors affecting the distribution of dissolved oxygen were collected, and the dissolved oxygen prediction model of the central monitoring point was constructed using Attention-GRU. The three-dimensional coordinate system with the central monitoring point as the origin was then established, and the GBRT algorithm optimized by the Random Search algorithm(RS) was used to predict the dissolved oxygen in any position of the pond water. In the one-dimensional prediction of dissolved oxygen at the central monitoring point, the Attention-GRU model proposed in this paper had MSE of 0.121, MAE of 0.219, and RMSE of 0.348, which was a big improvement compared with LSTM model, ELM model and CNN model. In the three-dimensional prediction of dissolved oxygen in the pond, the RS-GBRT model proposed had MSE of 0.097, MAE of 0.191, and RMSE of 0.313. Compared with the models such as ExtraTree model, RandomForest model, and Bagging model, each evaluation index had been greatly improved. The experimental results indicated that the proposed method can accurately predict the dissolved oxygen in the three-dimensional space of the pond.

1. Introduction

The pond aquaculture environment is the habitat on which aquatic products depend. The dissolved oxygen in the water is one of the most important ecological factors to measure the quality of the water. It is also the most important factor that causes the reduction of production and disease of aquaculture products (Culp et al., 2016). Due to the open breeding environment of the pond, the dissolved oxygen concentration of the pond is susceptible to a variety of ecological and environmental factors (Chen Y, et al, 2016), which will produce a difference in time and space distribution, showing a three-dimensional distribution characteristic (Muhammetoglu and Soyupak, 2000; Missaghi et al., 2017; Chen et al., 2018). The specific performance is that the dissolved oxygen concentration in different positions is different on the same horizontal surface of the pond, and it is also different on the same vertical surface but in different water layers. In the process of aquaculture, different aquatic products live in different water layers due to their different living habits, and the demands for dissolved oxygen are not the same. Therefore, it is very meaningful to carry out a three-dimensional prediction study in order to fully grasp the three-dimensional distribution law of dissolved oxygen in pond water, which is conducive to the intelligent regulation of pond culture water quality and effectively reduces the cost and risk of culture.

At present, there are some literatures that have conducted qualitative research on the distribution of dissolved oxygen in water (Yin et al., 2004; Antonopoulos and Gianniou, 2003; Li et al.,2011). Dai et al. (2013) conducted day and night monitoring of dissolved oxygen in different water layers of river crab ecological farming ponds. The measurement results showed that the dissolved oxygen in the pond water was the highest from 14:00–16:00 and the lowest from 4:00–6:00. The difference of dissolved oxygen between upper and lower layers in high temperature season was significant, but the difference in rainy days was

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small. In addition, under sunny conditions, the dissolved oxygen in areas with dense water plants was significantly higher than in areas with sparse water plants. Xie et al. (2009) analyzed the correlation between dissolved oxygen and temperature, salinity, chemical oxygen demand (COD), total organic carbon (TOC) and chlorophyll *a*, and obtained that the water surface dissolved oxygen content of Liusha Bay, southwest of Leizhou Peninsula, Guangdong, China was slightly higher than that in the bottom layer, and the dissolved oxygen and chlorophyll *a* showed a very significant positive correlation in winter. These studies explored the law of water quality change in pond culture from a qualitative perspective. However, the qualitative description only gives the changing trend of dissolved oxygen content, does not give the actual value, and has limited guidance for the actual production, cannot achieve accurate management. Therefore, it is necessary to quantitatively study the law of dissolved oxygen change in water.

Quantitative research on the law of water quality change mainly uses machine learning algorithms to predict water quality (Yang et al., 2014; Peng et al., 2017; Ta and Wei, 2017). At present, the research on dissolved oxygen prediction is mainly one-dimensional prediction (Khadr and Elshemy, 2017; Kang et al., 2017), that is, the prediction of dissolved oxygen from the time dimension. The commonly used methods include Fuzzy Neural Network(FNN), Support Vector Regression(SVR), Extreme Learning Machine (ELM), etc. (Duan et al., 2018; Khani and Rajaee, 2016; Li et al., 2018). Ren et al. (2018) proposed a dissolved oxygen prediction model based on FNN, and the genetic algorithm was used to optimize the center and width of the middle layer of FNN, determined the optimal parameter combination, and improved the efficiency and prediction accuracy of the model. Huan et al. (2018) decomposed the dissolved oxygen time series into a set of relatively stable subsequences through the overall empirical mode decomposition, then established the Least Square Support Vector Machine (LSSVM) model for each sequence and used Back Propagation (BP) neural network to reconstruct the predicted value of each component to obtain the predicted value of dissolved oxygen. These studies predicted the dissolved oxygen from the time dimension, and used the prediction data of one monitoring point as the predicted value of dissolved oxygen in the entire pond, without considering the three-dimensional distribution characteristics of the dissolved oxygen in the pond. To this end, some scholars have carried out a three-dimensional prediction study of dissolved oxygen, that is, a combination of time and space dimensions. At present, there are few studies on three-dimensional prediction of dissolved oxygen. Chen et al. (2016) proposed a three-dimensional short-term prediction model of dissolved oxygen in crab culture pond based on BP neural network. The BP neural network model optimized by particle swarm optimization (PSO) was used for data analysis and one-dimensional prediction, and the Kriging method was used to realize three-dimensional prediction of dissolved oxygen. However, the Kriging interpolation method requires a large amount of data, resulting in the limited application and generalization ability of the model, which can't be fully used in practical production.

With the research of deep learning, neural networks have been widely used in weather, finance, industry, agriculture, transportation and other industries. Among them, the Gated Recurrent Unit (GRU) neural network has a simple structure, and has strong ability to process multi-feature time series data. The Gradient Boost Regression Tree (GBRT) algorithm completes the learning task by constructing and combining multiple machine learners. In the case of few features and small amount of data, GBRT has higher data prediction accuracy, and is widely used in the fields of pattern recognition, computer vision, prediction and early warning.

Based on the above considerations, a three-dimensional prediction method of dissolved oxygen was established based on Attention-GRU-GBRT. Firstly, the environmental parameters affecting the distribution of dissolved oxygen were collected, and the dissolved oxygen prediction model of the central monitoring point was constructed using Attention-GRU. The three-dimensional coordinate system with the central monitoring point as the origin was then established, and the correspondence of dissolved oxygen concentration between the different positions of the pond and the coordinate origin was used to train a three-dimensional prediction model based on RS-GBRT. This method solves the problems of strong timing of water quality data and many influence factors on dissolved oxygen through the performance of GRU neural network for the prediction accuracy of time series data with multiple features and data volume. The GBRT algorithm has many nonlinear changes, strong expressive power, and can flexibly process a variety of discrete or continuous data, and it solves the problems of data dispersion and nonlinear changes faced by spatial prediction of dissolved oxygen. The method proposed in this paper made a comprehensive prediction of dissolved oxygen in the pond from the time dimension and the space dimension to provide support for intelligent production.

The remainder of this paper was organized as follows. Section 2 described materials and methods before Section 3 analysed the results. And Section 4 discussed the prediction results of the proposed method. Finally, Section 5 summarized the conclusions from this study.

2. Materials and methods

2.1. Data acquisition

In this paper, the experiment was carried out based on the data of the crab ponds in the aquaculture farm of Gaoteng Town, Yixing City, Jiangsu Province. The total area of the pond was 2.06 hm^2, the water depth was 0.8 m–2.0 m, and the breeding species was river crab. The appearance of the pond is shown in Fig. 1(a).

In order to collect the three-dimensional distribution data of dissolved oxygen in the entire pond, the pond water space needed to be described. To this end, a three-dimensional coordinate system of the pond water body with the central monitoring point as the origin, the south of the origin as the positive direction of the Y axis, the west of the origin as the positive direction of the X axis, and the point above the origin as the positive direction of the Z axis was established. The acquisition scheme was designed as shown in Fig. 1(b) and Fig. 1(c). In order to collect water quality data in real time, according to the pond water depth and topographic information, three remote locations were selected in the pond, and water quality sensors were installed at 20 cm (D1, E1, F1), 40 cm (D2, E2, F2) and 60 cm (E3, F3) underwater of these three locations respectively. The water level near point D2 was shallow, so it was impossible to install an underwater sensor at point D3.

The selection of the central monitoring point should meet the following conditions:

There should be a suitable water and grass density near the central monitoring point to facilitate the observation of the effect of chlorophyll content on the change of dissolved oxygen.

② The water depth of the central monitoring point cannot be too low or too high, which will affect the accuracy of the three-dimensional space prediction.

③ There should be sufficient light near the center point, not blocked, and not too much manual intervention.

To this end, this paper took point E2 as the central monitoring point, set it as the origin of coordinates, and constructed a three-dimensional coordinate system of the entire pond according to the positional relationship of Fig. 1(b). Multi-parameter water quality sensors were deployed at the E2 monitoring point, and the remaining monitoring points only had dissolved oxygen and water temperature sensors. At the same time, the dissolved oxygen content at points A, B, and C were also collected in three layers by manual measuring instruments. There were 17 collection points in the whole pond. In addition to water quality data, the meteorological sensors were installed around the pond to collect meteorological data of the same period. The experimental data from July 2019 to August 2019 was collected and the specific collection parameters are shown in Table 1.

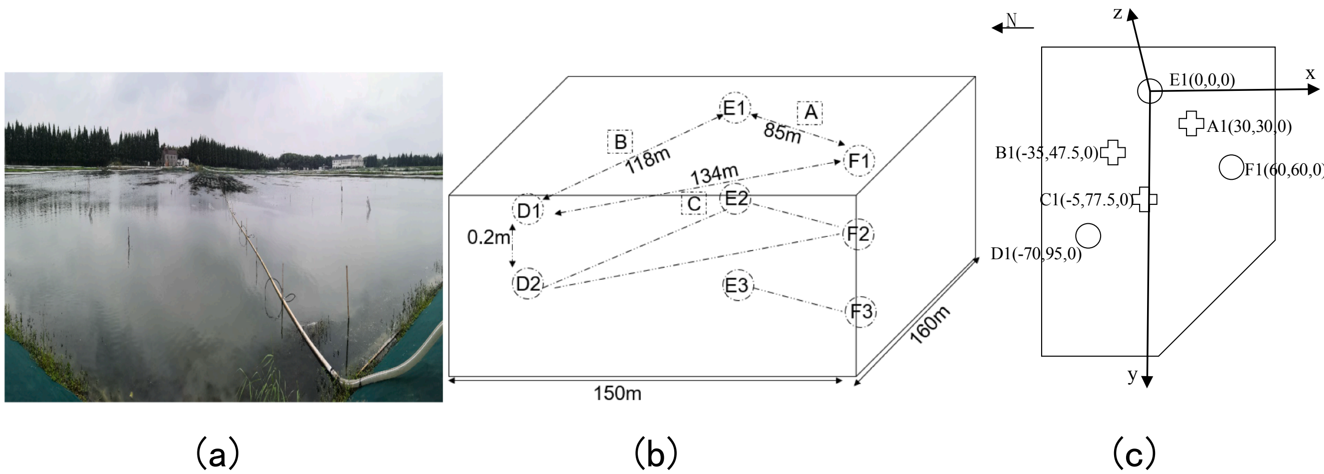

Fig. 1. The overall view of the pond and the installation of the collection point.

Table 1
Summary table of acquisition parameters.

Parameter type	Collection method	Parameter name	Number of collection points	Acquisition frequency (unit: min/time)	Number of collections (unit: piece)
Water quality parameters	Automatic acquisition	Water temperature, Dissolved oxygen, pH, Chlorophyll and Turbidity	8	10	67,552
	Manual acquisition	Water temperature and Dissolved oxygen	9	30	
Meteorological parameters	Automatic acquisition	Atmospheric humidity, Atmospheric temperature, Atmospheric pressure, Wind speed, Wind direction, Solar radiation and Rainfall	1	1	172,512

2.2. Overall process of our method

In this paper, a method based on Attention-GRU-GBRT was proposed to predict the dissolved oxygen in pond water. The overall process is shown in Fig. 2.

(1) Dissolved oxygen prediction at the central monitoring point based on the Attention-GRU model. The central monitoring point was a reference point for predicting the dissolved oxygen concentration in the three-dimensional space of the pond, and a multi-parameter sensor for water quality was deployed at this point. The prediction of dissolved oxygen in the whole pond was realized by establishing a mapping relationship of dissolved oxygen between the other positions in the pond and the central point.

(2) Three-dimensional prediction of dissolved oxygen based on the RS-GBRT model. The three-dimensional coordinate system with the central monitoring point as the origin was established to construct water quality data sets of multiple monitoring points of the pond, and the RS-GBRT prediction model was trained. The relative position information and environmental data based on the three-dimensional coordinate system of the pond were used as inputs to predict the dissolved oxygen at any position of the pond.

2.3. Dissolved oxygen prediction of central monitoring point based on the Attention-GRU model

The dissolved oxygen content of pond water is related to water quality and meteorological factors, but different environmental factors have different effects on dissolved oxygen content. In order to highlight the influence of different environmental factors on dissolved oxygen, the attention mechanism was used to calculate the feature vectors of different environmental factors. And a multi-parameter prediction model of dissolved oxygen based on GRU model was built to predict the dissolved oxygen at the central monitoring point. Attention is an attention distribution mechanism similar to the human brain (Zhou et al., 2018). By calculating the probability weights of different input parameters, some parameters can be paid more attention, thereby improving the quality of hidden layer feature extraction (Cinar YG et al., 2017; Gao et al., 2017). The advantages of attention are small complexity, few parameters, and each step of calculation does not depend on the calculation result of the previous step, and can be processed in parallel. The network unit corresponding to the GRU neural network has only two gates: update gate and reset gate. The advantages of the GRU model are simple model, few parameters, few tensor calculations, fast convergence speed, and short prediction time (Zhang et al., 2018b). The prediction process of Attention-GRU model proposed in this paper is as follows.

In Fig. 3, X_t indicates the input data, GRU indicates the GRU layer, h_t represents the state information at time t, a_t is the weight coefficient, $\widetilde{C}$ is the output vector after weighted averaging of h_t, and $\widehat{y}$ is the predicted value. A total of m feature parameters and n samples were input to the GRU layer for prediction. The update mode of the GRU layer is shown below (see Fig. 4).

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\widetilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h}_t \tag{4}$$

where, h_t denotes the state of the system at t time, z denotes the update gate, r denotes the reset gate, σ denotes the Sigmoid function, and W denotes a set of weights.

The Attention mechanism assigns the feature weights learned by the

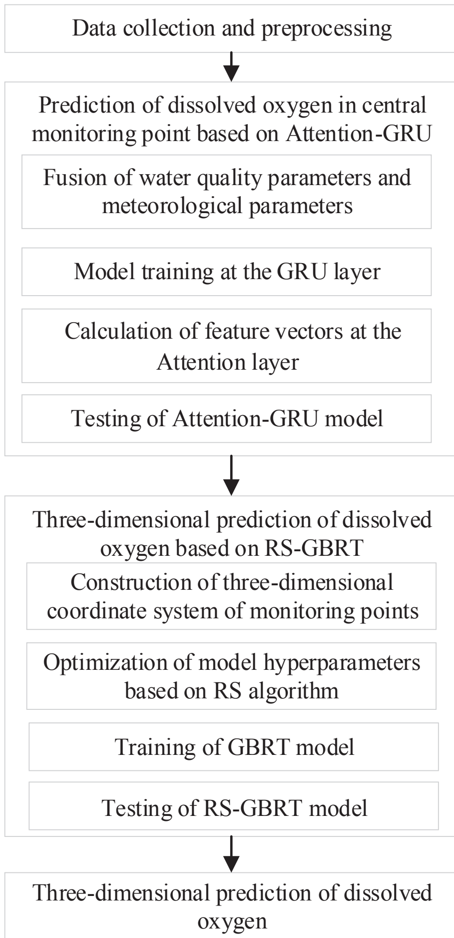

Fig. 2. Overall process of the proposed method.

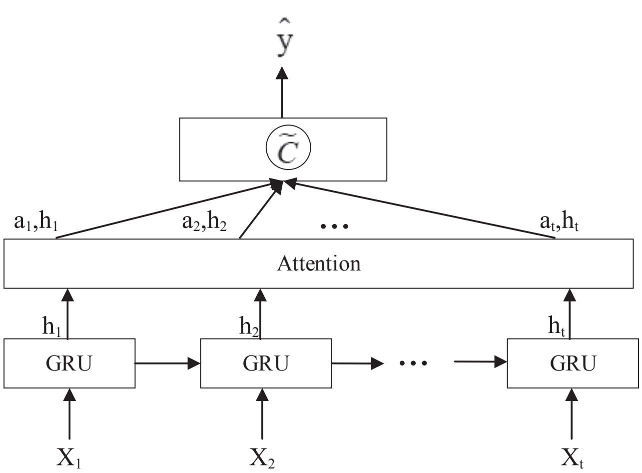

Fig. 3. Flow chart of the Attention-GRU model.

model to the input vector in the next time step, highlighting the impact of key features on the prediction of dissolved oxygen. The core of attention mechanism is to obtain the correlation between prediction target and input characteristics. In the process of processing a large number of input information, attention mechanism can be used to select and process some key input information, so as to improve the prediction efficiency. By adding attention mechanism after GRU layer to establish long-distance dependence between input sequences, the weights of different links are dynamically generated. All of the output of GRU layer are input into the attention layer, and the new output vector is obtained by weighted sum. Its essence can be described as a query to a series (key-value). The mapping is shown in Fig. 5. Each element in the sequence is assigned a weight coefficient. That is, the values of all the addresses (keys) are taken out, and the importance of the value is determined by the calculated similarity, and then the value is weighted according to the importance to get the attention value. The feature vector output from the Attention layer is passed through the fully connected layer, and then the final output layer is the dissolved oxygen content at the predicted time t.

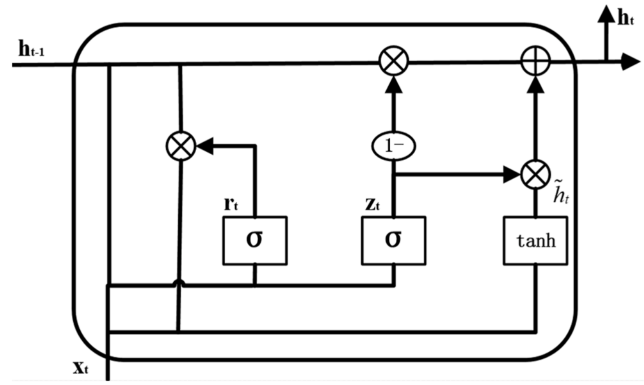

Fig. 4. Structure of GRU neural network.

2.4. Three-dimensional prediction of dissolved oxygen based on the RS-GBRT model

In this paper, the dissolved oxygen in the central monitoring point was combined with the three-dimensional coordinates to predict the dissolved oxygen concentration in the three-dimensional space of the pond. The reasons for this are as follows:

Due to the large difference in water temperature between the upper and lower layers, the phenomenon of thermal resistance was formed, resulting in a certain difference in dissolved oxygen content in different water layers of the pond. With the boundary of about 40 cm underwater, the dissolved oxygen concentration of the upper and lower layers were not the same, and there were obvious changes and fluctuations.

② The dissolved oxygen concentration at different monitoring points in the pond was not only related to time, but also had a certain mapping relationship with the distance from the point to the central point. In the daytime, the higher the water level, the higher the dissolved oxygen concentration, and the lowest dissolved oxygen concentration at the bottom. To this end, the dissolved oxygen in the three-dimensional space of the entire pond can be predicted through the central monitoring point.

Since the location information had no particularly obvious time-series features, and there were few features, for this reason, an integrated learning method that had better discrete and continuous data processing performance was considered for three-dimensional space prediction. GBRT is an iterative decision tree algorithm proposed by Friedman, the basic idea of GBRT is to build m weak learners, which are

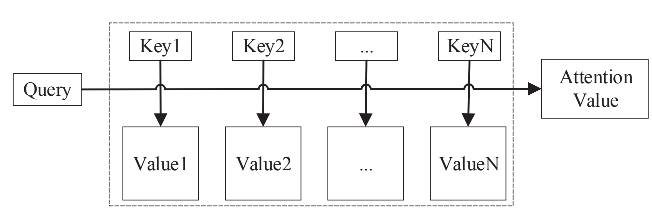

Fig. 5. Schematic diagram of Attention mechanism.

finally combined into a strong learner after several iterations (Wang et al., 2016; Li and Bai, 2016; Kang et al., 2019). GBRT has strong processing ability for different types of data, and it is very robust to deal with outliers out of space. It has obvious advantages in small number of features and small data set, and has high prediction accuracy.

There are two ways to optimize the parameters. One is GridSearchCV (GS), which means that the learners are trained by the adjusted parameters to find the parameters with the highest accuracy in the verification set from all the parameters. The other is RandomizedSearchCV (RS), which uses the method similar to the GridSearchCV. However, it does not try all possible combinations, but selects a certain number of random combinations of a random value of each super parameter. For the hyperparameters whose search scope is distribution, random sampling is performed according to the given distribution. For the super parameters whose search range is list, the samples are sampled with medium probability in the given list. The more times it runs, the more parameters are selected, and the more likely it is to get the best result. And it is convenient to control the amount of calculation by setting the search times.

Since the RS algorithm has great performance in model with many parameters and has fast search speed, as well as great optimization effect, which can be well used in parameter optimization of GBRT (Bergstra and Bengio, 2012). To this end, the GBRT algorithm based on RS optimization was used to achieve three-dimensional prediction of dissolved oxygen in pond culture.

According to the collected water quality data, the time information, the location information of different monitoring points, and the predicted value of dissolved oxygen at the central monitoring point were used as feature vectors to construct a data set.

$$P_i = (X_i, Y_i, Z_i) \tag{5}$$

$$I = \begin{bmatrix} T_1 & O_1 & P_1 \\ T_1 & O_1 & P_2 \\ \cdots & \cdots & \cdots \\ T_1 & O_1 & P_q \\ T_2 & O_2 & P_1 \\ T_2 & O_2 & P_2 \\ \cdots & \cdots & \cdots \\ T_s & O_s & P_q \end{bmatrix} R = \begin{bmatrix} r_1 \\ r_2 \\ \cdots \\ r_q \\ r_1 \\ r_2 \\ \cdots \\ r_q \end{bmatrix} \tag{6}$$

where, i represents different monitoring points, X is the X-axis distance of monitoring point P from the origin, Y is the Y-axis distance of point P from the origin, Z is the Z-axis distance of point P from the origin, P is the position information of other positions relative to the central monitoring point, and T is the prediction time, O denotes the predicted value of dissolved oxygen at the central monitoring point, s is the length of time series, q is the number of monitoring points, I denotes the training set composed of characteristic vectors, and R denotes the label set of dissolved oxygen content at other locations.

The constructed data set was divided into a training set and a test set, the hyperparameters of the GBRT model were optimized by RS, and the optimal model was used to obtain the predicted values of dissolved oxygen at different locations in the pond. The prediction process of the RS-GBRT model is shown in the Fig. 6.

2.5. Method performance evaluation

The experimental development environment was as follows: The programming language was Python 3.6 (64-bit), and the integrated development environment was Anaconda 3.

The results of our experiments were evaluated by the mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE). They are calculated in Eqs. (7)–(9).

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

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \widetilde{y}_i\right| \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widetilde{y}_i\right)^2} \tag{9}$$

where yi is the true value, $\widetilde{y}i$ is the predicted value, and N is the number of predicted values.

To further verify the performance of the proposed Attention-GRU method, it was compared with the GRU model without Attention layer, the LSTM model with added Attention layer, the ELM model and the CNN model which were used in references. And in order to show the effectiveness of the RS-GBRT method, it was compared with the DecisionTree model, the RandomForest model and the Bagging model.

3. Experiments results

3.1. Prediction of dissolved oxygen at central monitoring point based on the Attention-GRU model

By reading the references (Fu R, et al., 2016; Zhang D et al., 2018) and actual modeling training, set the number of neurons in the input layer of the GRU model to 15, the number of hidden layer neurons was 7, and the number of output layer neurons was 1. Normal distribution random numbers were used to initialize the weights and variances. The activation function was “Rectified Linear Unit(relu)” and the number of iterations was 2000. The dissolved oxygen on July 28 in the test set was taken as an example, the predictive and actual values were shown in Fig. 7.

The method proposed in this paper was compared with GRU model, Attention-LSTM model, ELM model and CNN model, the results of calculating various prediction indexes of different models are shown in Table 2.

As shown in Table 2, the proposed method outperformed the non-

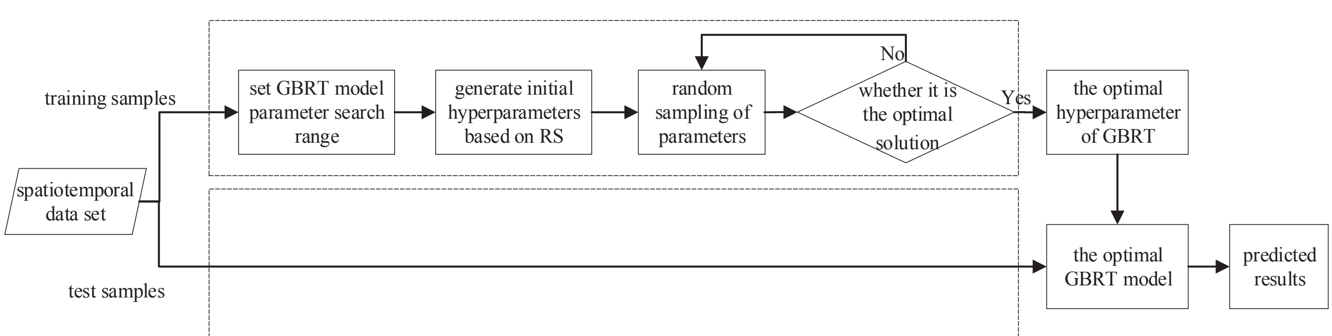

Fig. 6. Flow chart of the RS-GBRT model.

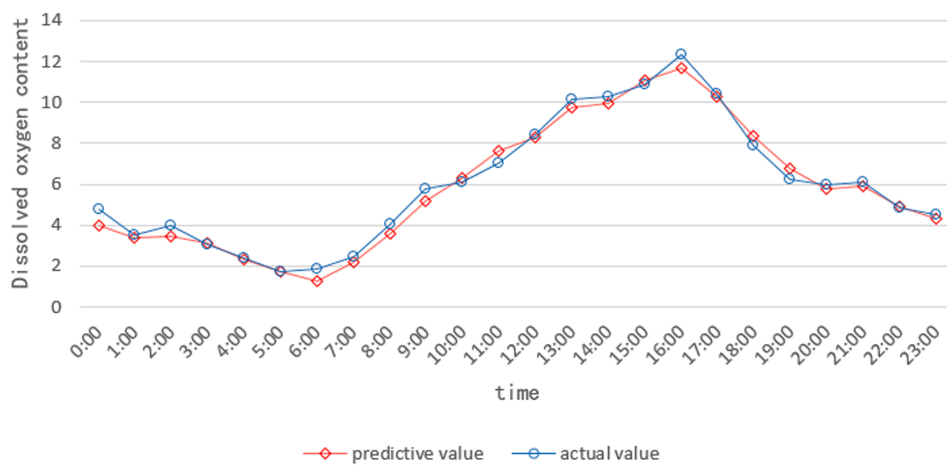

Fig. 7. Comparison of predictive and actual values of dissolved oxygen at the central monitoring point.

Table 2
Comparison of prediction indexes of central monitoring points in different models.

Models	MSE	MAE	RMSE
Attention-GRU	**0.121**	**0.219**	**0.348**
GRU	0.165	0.281	0.406
Attention-LSTM	0.145	0.248	0.380
ELM	0.202	0.332	0.445
CNN	0.278	0.408	0.527

attention GRU model by 26.7% in terms of MSE, 22.1% in terms of MAE, and 14.3% in terms of RMSE. Compared with the Attention-LSTM model, the improvements were 16.6%, 11.7%, 8.4%, respectively. Compared with the ELM model, the improvements were 40.1%, 34.0%, 21.8%, respectively. Compared with the CNN model, the improvements were 56.5%, 46.3%, and 34.0%, respectively. It can be seen that the accuracy of the GRU model by adding attention algorithm had been greatly improved compared with other methods.

3.2. Three-dimensional prediction of dissolved oxygen based on the RS-GBRT model

The RS-GBRT model proposed in this paper was used for three-dimensional prediction, and the GBRT hyperparameters were optimized by RS algorithm to obtain the optimal n_estimators = 73, learning_rate = 0.19, and max_depth = 9. The prediction results of the model on some data sets are shown in Table 3.

The RS-GBRT model was compared with the DecisionTree model, the RandomForest model and the Bagging model. The prediction error curves of each model prediction on part of the test set were shown in Fig. 8.

As shown in Fig. 8, the horizontal axis represents different test set samples, and the vertical axis is the prediction error. The closer the error curve is to the 0 axis, the smaller the prediction error. The absolute value of the prediction error of the RS-GBRT model was kept within 0.2, and the curve fluctuation was small, indicating that the prediction accuracy of the model was high and the prediction results were stable. At the same time, each evaluation index for the prediction of dissolved oxygen by each model was calculated as shown in Table 4.

As shown in Table 4, the proposed method outperformed the DecisionTree model by 66.3% in terms of MSE, 20.9% in terms of MAE, and 25.1% in terms of RMSE. Compared with the ExtraTree model, the improvements were 48.3%, 12.4%, and 28.1% respectively. Compared with the RandomForest model, the improvements were 27.1%, 14.1%, and 14.7% respectively. Compared with the Bagging model, the improvements were 32.0%, 16.7%, and 17.5% respectively. It can be seen that the model proposed in this paper can maintain a high prediction accuracy when predicting the dissolved oxygen content at different positions in three-dimensional space.

Table 3
Dissolved oxygen content in different positions of pond.

Point	Depth	Coordinate	Actual value	Predictive value
A	20 cm	(30,30,0.2)	12.23	11.96
	40 cm	(30,30,0)	11.0	11.23
	60 cm	(30,30,−0.2)	8.45	8.40
B	20 cm	(−35,47.5,0.2)	12.67	12.58
	40 cm	(−35,47.5,0)	9.46	9.45
	60 cm	(−35,47.5,−0.2)	7.85	7.77
C	20 cm	(−5,77.5,0.2)	11.38	11.40
	40 cm	(−5,77.5,0)	8.88	8.56
	60 cm	(−5,77.5,−0.2)	6.96	5.68
D	20 cm	(−70,95,0.2)	10.39	10.42
	40 cm	(−70,95,0)	9.2	9.15
E	20 cm	(0,0,0.2)	15.63	15.32
	40 cm	(0,0,0)	13.45	13.44
	60 cm	(0,0,−0.2)	8.08	8.12
F	20 cm	(60,60,0.2)	15.5	15.51
	40 cm	(60,60,0)	11.5	11.08
	60 cm	(60,60,−0.2)	8.62	8.23

Note: the water level near point D was shallow, and there was no sensor installed at 60 cm underwater.

In order to show the three-dimensional prediction results more clearly, the dissolved oxygen prediction data at each collection point at 14:30 on July 20, 2019 was used as an example to show the change rule of dissolved oxygen in water quality as follows.

Fig. 9 shows the distribution of dissolved oxygen in three-dimensional space. According to the distribution, the concentration of dissolved oxygen can be seen clearly, which is of great significance to understand the change law of dissolved oxygen in ponds.

4. Discussion

In order to show the three-dimensional distribution of dissolved oxygen in water more clearly, this paper showed the variation of dissolved oxygen in the vertical and horizontal directions.

(a) Change trend of dissolved oxygen in the vertical direction

In order to show the correlation between the dissolved oxygen in different water layers, the change curves of dissolved oxygen in different water layers near the central monitoring point on July 19, 2019 were drawn, as shown in Fig. 10.

From the above figure, the following changes in dissolved oxygen can be obtained:

Fig. 8. Changes of three-dimensional prediction error curves of different models.

Table 4
Prediction indexes of different models.

Models	MSE	MAE	RMSE
RS-GBRT	**0.121**	**0.219**	**0.348**
DecisionTree	0.359	0.277	0.599
ExtraTree	0.234	0.250	0.484
RandomForest	0.166	0.255	0.408
Bagging	0.178	0.263	0.422

On the same vertical plane, the dissolved oxygen content in the middle and lower layers was lower than that in the upper layer due to the combined effects of aquatic plants' respiration and meteorology. And the extreme value of dissolved oxygen in different water layers was different.

② In the early morning and night, the dissolved oxygen content of each water layer was very low. The dissolved oxygen content of the upper water level decreased faster and the dissolved oxygen content was lower.

③ During the daytime, due to the weather and photosynthesis of aquatic plants, the dissolved oxygen in the upper layer rose rapidly, and the extreme value appeared around 16:00. However, due to the deeper water level of the middle and lower layers, the time when the extreme value of dissolved oxygen appears was delayed, around 17:30 and 19:00 respectively, and the dissolved oxygen content rose slowly. These laws were consistent with the dissolved oxygen change law obtained by the traditional mechanism model and the actual breeding situation (Chen Y et al, 2016).

(b) Change trend of dissolved oxygen in the horizontal direction

The dissolved oxygen prediction data at each collection point at 14:30 on July 20, 2019 was used as an example to show the change rule of dissolved oxygen in water quality as follows.

In Fig. 11 (a), (b) and (c) represent the distribution of dissolved oxygen in the same horizontal plane at 20 cm, 40 cm and 60 cm underwater respectively. From the Fig. 10, the horizontal change of dissolved oxygen can be obtained as follows.

At 20 cm underwater, when the water layer was shallow, the three-dimensional distribution of dissolved oxygen in pond culture was mainly related to meteorological factors, and the content of dissolved oxygen was generally high, the overall performance was that the content of dissolved oxygen in point E and point F was high, followed by that in point A and point B, the content of point C was low, and the content of point D was the lowest. Among them, point E and point F were located in the southeast of the pond, in the direction of the air inlet, and the water temperature was high at noon, so the dissolved oxygen content of the two points was relatively high.

② At 40 cm underwater, the content of dissolved oxygen was closely related to the weather and photosynthesis of aquatic plants. The three-dimensional distribution of dissolved oxygen in pond culture showed that the content of dissolved oxygen in point E was higher, followed by

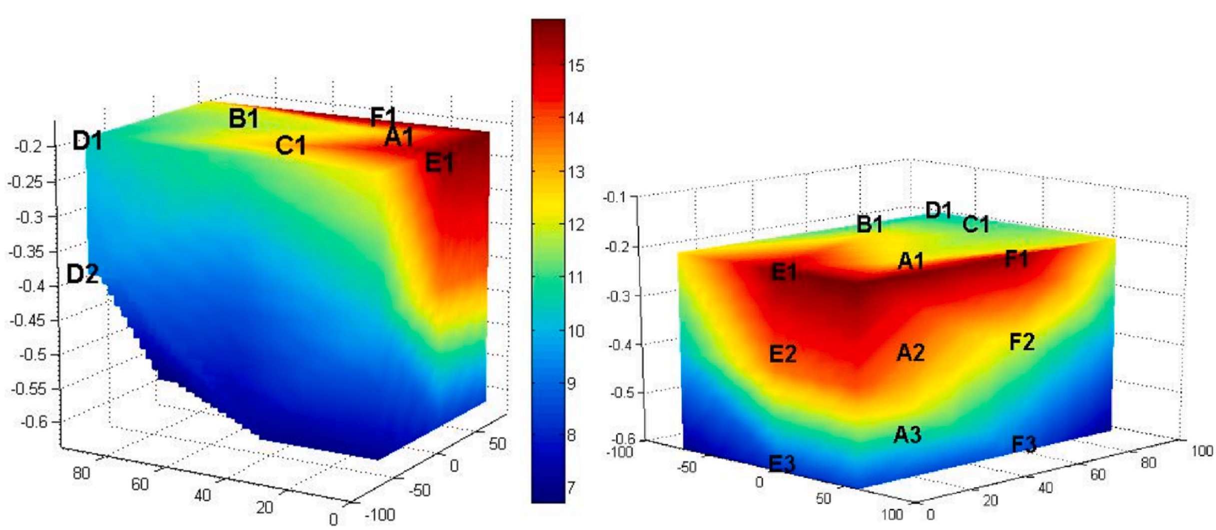

Fig. 9. Distribution of dissolved oxygen at different levels of pond.

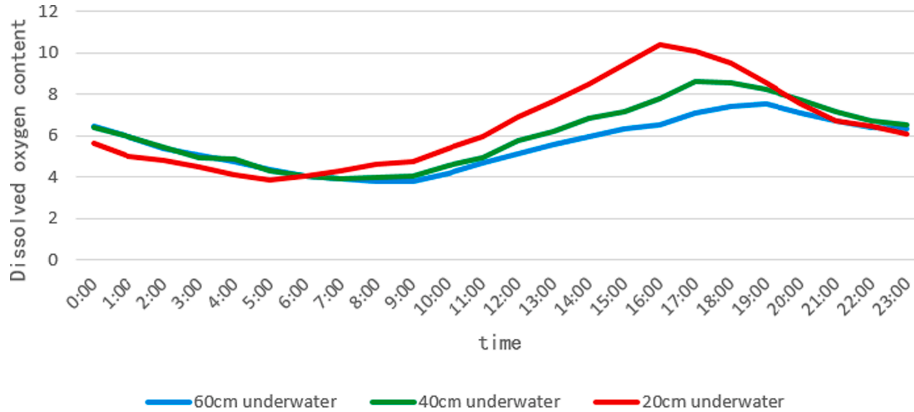

Fig. 10. Change of dissolved oxygen in different water layers in a single day.

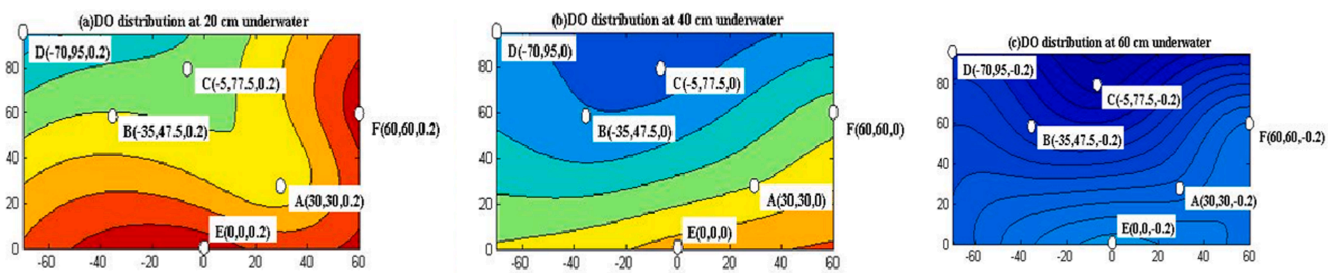

Fig. 11. Distribution of dissolved oxygen at different levels of pond.

that in point F and point A, the content in point B and point D was lower, and the content in point C was the lowest. The water grass around the pond was dense, while in the middle of the pond was sparse, manifested as the content of dissolved oxygen near point C was lower than point D.

③ At 60 cm underwater, the photosynthesis of water plants with dissolved oxygen content was more closely related. The content of dissolved oxygen was lower than the content of the upper water level. Specifically, the content of dissolved oxygen near point E was higher, followed by that at point F and point A, the content of dissolved oxygen at point B and point D were lower, and the content at point C was the lowest, which was almost consistent with the distribution of dissolved oxygen at 40 cm underwater. The results showed that the model had high prediction accuracy and can meet the actual production needs.

5. Conclusion

A three-dimensional prediction model of dissolved oxygen in pond culture based on the Attention-GRU-GBRT model was proposed in this paper. Firstly, the dissolved oxygen content of the central monitoring point was accurately predicted by the Attention-GRU method. Secondly, the three-dimensional prediction model of dissolved oxygen content based on RS-GBRT was constructed by combining the location information and time information to accurately predict the three-dimensional distribution of dissolved oxygen of the whole pond. The conclusions are as follows.

(1) Based on the Attention-GRU prediction model, the key features that affected the dissolved oxygen content were extracted through the Attention mechanism algorithm, which in turn improved the accuracy of dissolved oxygen prediction. This method achieved better prediction results on real data sets. Compared with the Attention-LSTM model, ELM model and CNN model, the evaluation indicators of this method had been greatly improved.

(2) The RS-GBRT-based dissolved oxygen three-dimensional prediction model fused position information and time information, and optimized the GBRT model hyperparameters through the RS algorithm to achieve accurate prediction of the three-dimensional distribution of dissolved oxygen throughout the pond. Compared with DecisionTree model, ExtraTree model and Bagging model, this method showed higher prediction accuracy and had higher practical value.

CRediT authorship contribution statement

Xinkai Cao: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing - original draft. **Ni Ren:** Formal analysis, Methodology, Software. **Ganglu Tian:** Data curation, Resources, Investigation. **Yuxing Fan:** Validation, Writing - review & editing. **Qingling Duan:** Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105955.

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