Prediction of Dissolved Oxygen Content in Aquaculture of Hyriopsis Cumingii Using Elman Neural Network

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Abstract. Hyriopsis Cumingii is Chinese major fresh water pearl mussel, widely distributed in the southern provinces of China's large and medium-sized freshwater lakes. In the management of Hyriopsis Cumingii ponds, dissolved oxygen (DO) is the key point to measure, predict and control. In this study, we analyzes the important factors for predicting dissolved oxygen of Hyriopsis Cumingii ponds, and finally chooses solar radiation(SR), water temperature(WT), wind speed(WS), PH and oxygen(DO) as six input parameters. In this paper, Elman neural networks were used to predict and forecast quantitative characteristics of water. As the dissolved oxygen in the outdoor pond is low controllability and scalability, this paper proposes a predicting model for dissolved oxygen. The true power and advantage of this method lie in its ability to (1) represent both linear and non-linear relationships and (2) learn these relationships directly from the data being modeled. The study focuses on Singapore coastal waters. The Elman NN model is built for quick assessment and forecasting of selected water quality variables at any location in the domain of interest. Experimental results show that: Elman neural network predicting model with good fitting ability, generalization ability, and high prediction accuracy, can better predict the changes of dissolved oxygen.

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Keywords: prediction, dissolved oxygen, Elman neural network, Hyriopsis Cumingii

1. Introduction

Hyriopsis Cumingii is Chinese major fresh water pearl mussel, widely distributed in the southern provinces of China's large and medium-sized freshwater lakes. In recent years, aquaculture farmers to improve economic benefit in the production process, the use of livestock and poultry faeces or chemical fertilizer, lead to the water ecological unbalance, nitrogen and phosphorus excess water flooding, phytoplankton, nutrient runoffs, the serious influence of fresh-water cultured pearl's sustainable development. Lacking of dissolved oxygen water quality exacerbate in the ponds in summer easily causes freshwater mussel disease (G.F.Zhang, 2005). Therefore, real-time monitoring and forecasting of Hyriopsis Cumingii ponds' water quality has becoming a priority issues, specifically dissolved oxygen prediction.

Aquaculture water quality is a complex system. It affected by many factors such as environment, drugs, climate and bait etc. In this field, to prevent breeding water quality deterioration, forecasting DO value accurately has been quite an imperative subject at present. Prediction of water quality at home and abroad focused mainly in rivers, lakes, reservoirs, estuaries and other large waters using the gray system theory, polynomial regression, mathematical statistics, time series models and the neural network, etc (Xiaoyi Wang,2011; Yan-ping GAO,2008; LEE JHW,2003, LiangPeng Wang,2010; Xiao-ping Wang,2007; Wei-ren Shi, 2009; Zhi-xia Sun, 2009). Yu first made a prediction model for water quality based on improved BP neural network (Ch.X.Yu, 2008); Palani et.al. developed a neural network mode to forecast dissolved oxygen in seawater (Palani, Liong, Tkalich, 2009); Li established the BP and AR of the short-term forecasting model (F.F. Li, 2010); Zhang had adopted Elnman neural network model to forecast the SO2 in the atmosphere pollution index (Qi Zhang, 2009); Wang Ruimei predicted dissolved oxygen using the fuzzy-BP neural network (Ruimei Wang, 2010).However, limited water quality data and the high cost of water quality monitoring often pose serious problems for process-based modeling approaches. ANN provide a particularly good option, because they are computationally very fast and require many fewer input parameters and input conditions than deterministic models. ANN does, however, require a large pool of representative data for training. The objective of this study is to investigate whether it is possible to predict the values of water quality variables measured by a water quality monitoring program; this task is quite important for enabling selective monitoring of water quality variables.

Elman regression network is a kind of typical dynamic neural network, it in feedforward neural network on the foundation of basic structure, through the internal storage condition caused it to have the function of dynamic features mapping, so that the system has the ability to adapt to the time-varying characteristic, is a current of the most widely used type feedback neural network. This paper, we adopting Elman dynamic neural network to establish 1 hour dissolved oxygen predicting model in the Hyriopsis Cumingii ponds. This paper aims to find an effective way for prediction of in the Hyriopsis Cumingii ponds.

The remaining parts of this paper are organized as follow. Section 2 covers some related work including data collection and reprocessing methods the Elman neural network model, Elman NN parameter selection and model performance evaluation. the experimental results are shown and evaluated in section 3. Finally, Section 4 presents our conclusions.

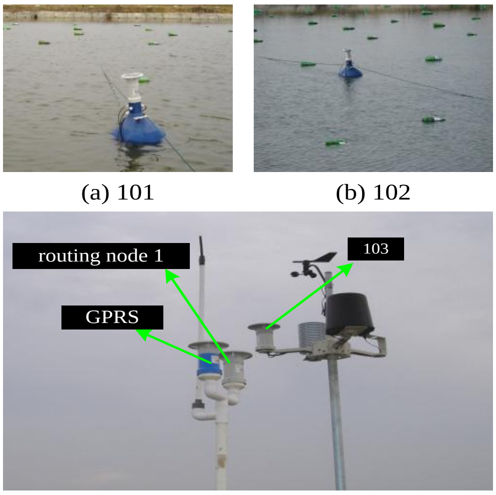
1 Relate work

In this section, we survey some related research techniques in the area of data collection, Elman NN architecture, Elman NN parameter selection, data pre-processing, model performance evaluation

1.1 water quality data collection

Ecological environment data of the Hyriopsis Cumingii aquaculture ponds are obtained by Digital Wireless Monitoring System of Aquaculture Water Quality (DWMS-AWQ) for real-time. It has been equipped at China Agricultural University-DuChang Aquaculture Digital System Research Center in DuChang city, Jiangxi province, China. The DWMS-AWQ consists of four parts: the data collection layer, the data transmission layer, the information processing layer and the application layer. The data collection layer directly connects to the intelligent sensor through RS485 connector and sends the data of intelligent sensor to routing node by wireless network. Then the routing node sends the data to the on-site monitoring center through a wireless network and to the remote monitoring center by GPRS.

In Hyriopsis Cumingii ponds, we installed two water quality data collection nodes101 and 102 collecting water level, water temperature, PH and DO at water level 1m and 2m, respectively, one meteorological data collection nodes 103 (collecting rainfall, temperature, humidity, wind speed, wind direction, solar radiation), routing node 1 and the GPRS module(Fig. 1).



(a) 101 (b) 102

(c)

Fig. 1. Hyriopsis Cumingii from breeding ecological environment data acquisition nodes

We refer to the knowledge of freshwater ecology to analyze the impact of dissolved oxygen factors, and choose water temperature(WT), solar radiation(SR), wind speed(WS), PH and dissolved oxygen(DO) five parameters of the ecological environment. The data used in this paper spanned 34 days, from July 2 to August 4, 2010. Data collection time interval is 1 hour. So we choose the dates every hour as the forecast value, which means 24 sets of data collected per day, the total samples is 816.

1.2 Structure of neural network model

1.2.1 Elman NN architecture

An artificial neural network (ANN) is a new generation of information processing system, which can model the ability of biological neural network by interconnecting many simple neurons. The neural network consists of layers of parallel processing elements called neurons; it is a simplified, simulation and abstract of human brain. They have the similarities in two main aspects: to acquire knowledge through learning from the external environment, and to store obtained knowledge use of the internal neurons. It is one of the well-known prediction models as it has excellent ability of mapping complex and highly nonlinear input-output patterns without the knowledge of the actual model structure. The feature of dealing with nonlinear problems makes ANN popular in many fields, such as financial signals prediction, language processing, biology, biochemical simulation and so on.

There are many types of artificial neural networks. The Elman network is one kind of globally feed-forward locally recurrent network model proposed by Elman (J. Elman, 1990). It has a set of context nodes to store the internal states. Elman neural network is a kind of internal feedback, can store and use the last moments of the input and output information, and has a strong computing power. Elman neural network consists of four layers: the input layer (signaling effect), the hidden layer, the context layer. As shown in Fig. 2. There are adjustable weights connecting each two neighboring layers. Generally, it is considered as a special kind of feed-forward neural network with additional memory neurons and local feedback (P. S. Sastry, G. Santharam and K.P. Unnikrishnan, 1994). The self-connections of the context nodes in the Elman network make it also sensitive to the history of input data which is very useful in dynamic system modeling (J. Elman, 1990).

The basic structure of a multilayer feed-forward network model can be determined as consist of an input layer, one or more hidden layer and an output layer. The input layer neurons receive input patterns from the external environment and propagate them on to the first hidden layer neurons. In this layer any data processing is not carried out. Input values distributed from each of the input layer neurons are multiplied by each of the adjustable connection weights linking the input layer neurons to hidden layer neurons. At each neuron in the hidden layer weighted input values are summed and a bias value is added. Then combined input value is passed through a nonlinear transfer function like sigmoid to obtain the output value of the neuron. This output value is an input for the neurons situated in the following layer. Finally, the output layer neurons produce the output value of the network model (Fatih Ozcan. Cengiz D. Atiş. Okan Karahan. Erdal Uncuoğlu, 2009).

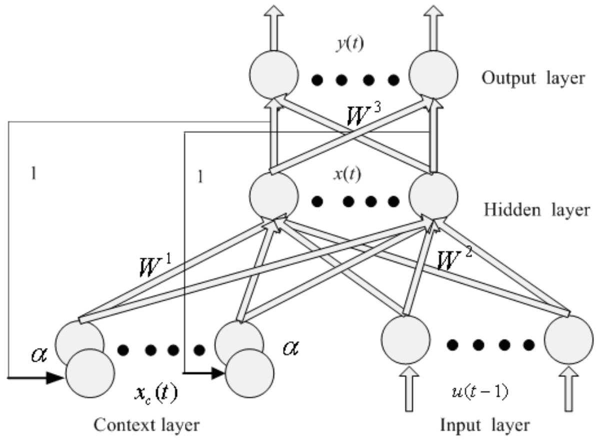


Fig. 2. Elman neural network architecture

Set x is the n-dimensional hidden layer node vectors, y is the m-dimensional output node vectors, u is the r-dimensional input vector, x_c is the n-dimensional feedback state vector; ω^1 is the weight matrix of the context layer to the hidden layer, ω^2 is the weight matrix of the input layer to the hidden layer, ω^3 is the weight matrix of the hidden layer to the output layer; $x(t)$, $x_c(t)$ and $y(t)$ are output of the hidden layer, context layer and output layer at time t, respectively. $\alpha(0 \leq \alpha < 1)$ is the self-connecting feedback gain factor, here set 0; $f(x)$ is the sigmoid function, such as the Formula 1. Elman neural network mathematical model shows in the following Eq.(2), (3), (4). Suppose the t^{th} step of real output of system is $y_d(t)$,desired output is y(t). The objective function of Elman neural network can be expressed as Eq. (5).

$$f(x) = 1/(1+e^{-x}) \tag{1}$$

$$y(t) = g(\omega^3 x(t)) \tag{2}$$

$$x(t) = f(\omega^1 x_c(t) + \omega^2 u(t-1)) \tag{3}$$

$$x_c(t) = \alpha x_c(t-1) + x(t-1) \tag{4}$$

$$E(t) = \frac{1}{2}(y_d(t) - y(t))^T (y_d(t) - y(t)) \tag{5}$$

1.2.2 Elman NN parameter selection

1.2.2.1 Hidden layers and nodes

Determining the number of hidden layers and nodes is a usually a trial and error task in ANN modeling. A rule of thumb for selecting the number of hidden nodes relies on the fact that the number of samples in the training set should at least be greater than the number of synaptic weights (Tarassenko, L., 1998). As a guide, the number of hidden nodes M should not be less than the maximum of I/3 and the number of output nodes O, where I is the number of input nodes. The optimum value of M is determined by trial and error.

For neural network training, the appropriate number of nodes in hidden layer is very important. In dealing with more complex problems, use of too few hidden units, the network can not remember all of the input-output model, the training of divergence; if too many neurons, the network will not only lengthen the training time dramatically, may be "overfitting "phenomenon, and will greatly reduce the generalization. Therefore, the model must be taken into account the training speed and generalization ability, choose the best number of hidden layer neurons.

Let q for the output layer nodes, n nodes for the input layer, p hidden nodes for the common choice of several nodes in one hidden layer of valuation as follows:

(1) Maximum number of nodes in hidden layer p= q (n+1)

(2) Maximum number of nodes in hidden layer p=q×3

(3) Input nodes is larger than the output layer node p=（q×n）1/2

(4) $p = \sqrt{n+q} + a$ ，Where a is constant between [1,10]

In this study, a trial and error procedure for hidden node selection was carried out by gradually varying the number of nodes in the hidden layer.

1.2.2.2. Learning rate (eta) and momentum (alpha)

The models were calibrated using the back-propagation algorithm, as it has already been used successfully for the prediction of coagulant doses (van Leeuwen et al.,1999) and other water resources and environmental variables (Maier and Dandy, 2000) and, unlike second order optimisation algorithms, has the ability to escape local minima in the error surface (White, 1989). Optimal values of the parameters controlling the size of the steps taken in weight space as part of the back-propgagation algorithm (i.e. learning rate and momentum values) were found by trial and error. There is no specific rule for the selection of values for these parameters. However, the training process is started by adopting one set of values (i.e. $\eta = 0.2$, range 0 to 1, and $\alpha = 0.5$, range 0 to 0.9) and then adjusting these values as necessary (i.e. if the error reduction of the network is too slow or begins oscillating). The learning process in this study was controlled by the method of internal validation. Roughly 20% of calibration data was withheld and used to test the error at the end of each epoch. The weights were updated at the end of each epoch. The number of epochs with the smallest internal validation error indicates which weights to select. The ANN with the best performance when applied to the validation set was selected.

1.2.2.3. Initial weights

The weights of a network that is to be trained by BP must be initialized to some small, non-zero random values. If a network stops training before reaching an acceptable solution because a local minimum has been found, a change in the number of hidden nodes or learning parameters will often fix the problem; alternatively, we can simply start over with a different set of initial weights. When a network reaches an acceptable solution, there is no guarantee that it has reached the global minimum. The synaptic weights of the networks were initialized with normally-distributed random numbers in the range of -1to1.

1.2.3 Selection of input variables

According to the principles of ecological, there are three main sources of dissolved oxygen in the outdoor pond: production of phytoplankton photosynthesis, atmospheric oxygen dissolved in water, and increased by oxygen machine. Atmospheric oxygen dissolved in water is mainly affected by temperature, wind speed. But the gas in water diffusion is proceeding slowly, if not all kinds of mixed water masses (as well as horizontal flow fluctuations and vertical flow), this process limited to the surface. In the fertilizer ponds, the production of phytoplankton photosynthesis is the main source of oxygen; atmospheric dissolved oxygen played a secondary role.

Aquatic animals consume a large amount of oxygen when breathing. Aquatic plants in photosynthesis during the day also carry out respiration, but respiration rate much lower than the intensity of photosynthesis. At night, respiration of plants (especially algae) for water gas has a great influence. In addition, bacterial respiration is the oxygen consumption of the most important factor, both in the bottom water layers and bacterial decomposition of organic matter. When the dissolved oxygen super saturation in surface water, it may also occur oxygen escaping. Wind disturbance on the surface of the water can accelerate the process of escaping.

Therefore, the factors affecting pond dissolved oxygen is mainly reflected in the impact factors of photosynthesis. Solar radiation intensity, water temperature, air temperature are the most important factors affecting photosynthesis. Cooperation with the intensity of light with the intensity of solar radiation, water temperature, air temperature increases, reaching saturation values will decline.

Phytoplankton photosynthesis, biological respiration and decomposition of organic matter led to changes in pH value. In summer, when water phytoplankton blooms, they tend to happen: the night at the deep water layer, in the biological process of respiration, due to the accumulation of carbon dioxide, pH value will decrease. High fishing pond, high aquatic life, strong biological photosynthesis and respiration more strongly, the variation of pH value is large[1]. This shows that pH is an important sign of reflecting the dissolved oxygen content.So in this paper we choose solar radiation(SR), air temperature(AT), water temperature(WT), wind speed(WS), PH and oxygen(DO) six parameters as Elman neural network input parameters.

1.2.4 Data pre-processing

In order to improve the training speed and accuracy, all data are normalized in this paper. Standardized function used in this paper is as follows Eq. (6).

$$x' = \frac{(y_{\max} - y_{\min})(x - x_{\min})}{x_{\max} - x_{\min}} \tag{6}$$

Where x denote the original data point here, xmin and xmax are the minimum and maximum values in the data set, respectively. Here, we set ymax is 1, and ymin is -1. In this way, all the input signals are changed to the interval [-1, 1].

1.2.5 Model performance evaluation

A model trained on the training set can be evaluated by comparing its predictions to the measured values in the overfitting test set. These values are calibrated by systematically adjusting various model parameters. The performances of the models are evaluated using the root mean square error (RMSE) [Eq. (7)], the mean absolute error (MAE) [Eq. (8)], the Nash–Sutcliffe coefficient of efficiency (R2) [(Eq. (9)], and the correlation coefficient (r). Scatter plots and time series plots are used for visual comparison of the observed and predicted values. R2 values of zero, one, and negative indicate that the observed mean is as good a predictor as the model, a perfect fit, and a better predictor than the model, respectively. Depending on sensitivity of water quality parameters and the mismatch between the forecasted water quality variable and that measured; an expert can decide whether the predictability of the Elman NN model is accurate enough to make important decisions regarding data usage.

$$RMSE = \sqrt{\frac{1}{N}\sum(X_{observed} - X_{predicted})^2} \tag{7}$$

$$MAE = \frac{1}{N}\sum | X_{predicted} - X_{observed} | \quad (8)$$

$$R^2 = 1 - (\frac{F}{F_0}) \quad (9)$$

$$F = \sum (X_{observed} - X_{predicted})^2 \quad (10)$$

$$F_0 = \sum (X_{observed} - X_{mean-observed})^2 \quad (11)$$

where N is the total number of observations in the data set.

2. Results and discussion

The Elman NN model was developed to simulate every hour DO concentrations in the Hyriopsis Cumingii freshwater pond with training of variable learning rate momentum gradient descent algorithm. The quality of a neural network, is different with the traditional least square fitting evaluation (mainly based on residuals, goodness of fit, etc.), not reflect in the data fitting on the existing capacity, but a later predictive ability (the ability of generalization). Predictive ability of the network (also known as generalization ability) and training capacity (also called approximation ability, learning ability) is contradictory. In general, training is poor, the forecasting ability poor, and to some extent, with the ability to improve training, improve forecasting ability. However, this trend has a limit, when reached this limit, with the training capability, predictability declines and that the so-called "over-fit" phenomenon. At this point, samples of learning too many details, but the law does not reflect the sample contains. In this paper we use the methods of data classification and disrupting to improve Elman neural network generalization and avoid over-fitting phenomenon. We selected first 4 days of 96 sets of data as the Elman NN as training data, and the fifth day data sets data as the variable data, and 24 sets of data as test data. The variable data play a role in preventing over-fitting.

Typical Elman NN DO prediction model results are shown as Table 1. 24 group training in the use of data fitting Elman NN prediction model, select a different number of hidden layer neurons, the model has a different fitting precision

Table 1. The performance for different number of hidden layer neurons

	3	4	5	6	7	8	9	10	11
RSME	0.24	0.29	0.29	0.23	0.29	0.30	0.30	0.30	0.30
MSE	0.23	0.23	0.23	0.29	0.24	0.24	0.24	0.24	0.24
R	0.23	0.20	0.18	0.17	0.16	0.15	0.14	0.14	0.13

The Elman NN model of DO in freshwater pond was successful in simulating patterns in measured DO concentrations that result from seasonal temperature variations, periodic blooms of phytoplankton (production of DO), and point-source discharges of oxygen-consuming substances like ammonia and BOD. In tropical ponds where there are frequent phytoplankton blooms to increase DO levels, DO concentrations fluctuate and supersaturate during these blooms. The DO models simulate the dynamics of the measured concentration and are within the range of the measured values. Elman NN models were successful in predicting patterns in the hourly DO data, and they can be applied on daily, weekly, monthly, and seasonal time scales. The Elman NN model's performance was good, but the outdoor environment is complex and the measuring system has the larger error.

More data sampling is thus required, and future work should recalibrate and revalidate the models to generalize our conclusions. The DO predicting model for freshwater will be further fine-tuned for higher accuracy by more accurate data. The result of the Elman NN DO predicting model was shown in Fig. 3(hidden layer neurons:8).

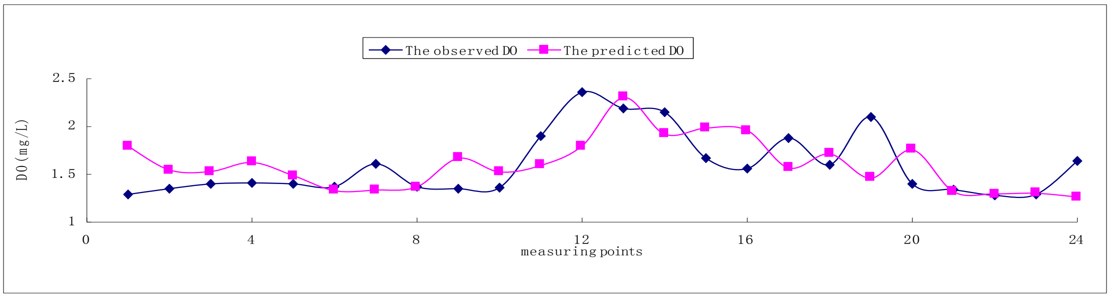


Fig. 3. The test curve of Elman prediction model

3.Summary and conclusion

Elman NN model was developed to predict dissolved oxygen in Hyriopsis Cumingii pond waters both temporally and spatially using continuous measurements of water quality variables. In spite of largely unknown factors controlling pond freshwater quality variation and the limited data set size, a relatively good correlation was observed between the measured and predicted values. The Elman NN modeling technique’s application for dynamic pond freshwater quality prediction was presented in this study. The Elman NN model has tremendous potential as a forecasting tool. An Elman NN prediction capability was tested and found to be faster than that from a process-based model with minimal input requirements.

In particular, we observed that the Elman NN methods were able to ‘‘learn” the mechanism of convective transport of water quality variables quite well. Based on the ‘‘best performance” in water quality parameter forecasting, we observed that Elman NN method with 7 or 8 hidden layer nodes is the better architecture for DO models, but the accuracy is not better for DO models. Also, the front part and last part of the forecast test data has a marked disturbance, which is Elman neural network inherent problem. The limitations of this study include its limited data set. The available data size is relatively small, reasonably good results were obtained for the water quality prediction of unseen validation dataset at locations separate from the training dataset stations. If more data become available, the proposed approach should provide better predictions3.

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