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Aquaculture Water Quality Dynamic Prediction Based on EDBD Algorithm Grey Neural Network Forecasting Model

Shiliang Zhang
Department of Computer Science,
Ningde Normal University, Ningde, Fujian, China 352100

***Abstract* – Due to the parameter of the random initialization network when using the grey neural network forecasting model, problems like falling into local optimum value and low prediction accuracy during the evolutionary process often occurs. Therefore, adoption of the optimal initial parameters of EDBD algorithm grey neural network is proposed, a prediction model based on EDBDA optimization grey neural network. Online monitoring of water quality indicators analyze, classify, predicts, determine the nonlinear relationship between its water quality indicators and other the affecting factors, research the distribution of water and quality changes in aquaculture water and discriminate for water quality fuzziness. Through experiments, comparative analysis are made on three forecasting models: the RBF neural network, the grey neural network and the EDBDA optimization grey neural network. In regards to stability of prediction performance, this model is significantly better than the conventional use of network prediction model. The results demonstrate the effectiveness of the proposed model to further improve the accuracy of grey neural network forecasting model.**

***Keywords* – Neural Network, EDBD Algorithm, GM (1,1), Forecasting Model.**

I. Introduction

Since 1969, JMBATES and C.WJ.GRANGER's first systematic presentation of the concept of combination forecast, the combination forecast has been popular amongst researchers due to its high accuracy, stability and reliability [1-3]. So far, the combination forecasting method has achieved several results, thus the emergence of a number of combination models, such as a combination of cluster analysis and neural networks, fuzzy neural networks, genetic neural network, chaotic neural network, grey neural network, as well as grey system combining grey system and genetic algorithms, grey Markov process, neural network and autoregressive integrated moving average model (ARMA) combination, grey support vector machine model, etc. [4]. In which the grey neural network model integrates the neural network and the grey model [5], possessing both the unique method for small samples of data modeling of a grey system and the advantageous adaptive ability in face of non-linear and imprecision of a neural network. Therefore, the idea of combining grey system and neural network to form the grey neural network has become a hot research topic in recent years [6]. Grey theoretical predictions studies the uncertainty system in "small samples" and "poor information". Its prediction method is based on the past and present known and unknown information to build a GM extended model extending from past to future. A small amount of data is needed to facilitate the prediction [7]. However, studies show that the grey model [8]: lacks self-learning, self-organizing and adaptive ability; the ability to process information is weak. Also, a theoretical flaw exists in the development parameters a and coordinate coefficients u of grey prediction model GM (1,1) which sometimes lead to large model errors. Neural network possesses advantages such as parallel computing, distributed-information storage, fault-tolerant and adaptive learning, etc. [9]. Its weakness is its network modeling accuracy is often affected by the randomness of data and sample size for prediction; the greater the randomness, the lower the modeling accuracy. In terms of a global network, prediction accuracy is difficult to achieve when there is not enough training samples. Given the RBF (Radial Basis Function) neural network is a local neural network [10][11], the demand for training samples will be less than the usual BP network, resulting in better accuracy than global network model. Therefore, RBF neural network is applied. Based on the analysis above, combine the grey modeling technology into the RBF neural network model, constructing the grey RBF neural network forecasting model [12]. On one hand it avoids the grey forecasting model inherent error, and on the other hand, due to the introduction of GM models AGO technology [13], it effectively reduces the randomness in the data implied, speeds up the neural network convergence speed and improves the accuracy of neural network modeling. Combination of the neural network and grey system forms a grey neural network system to facilitate solving the grey uncertain model. Under normal circumstances, mathematical methods can be applied to the neural network algorithm to solve the grey model in which the grey model and the neural network complement each other [14]. However, adapting the grey neural network for prediction usually allows falling into local optimum during network evolution, resulting in slow convergence and greater prediction accuracy problems.

In this paper, instead of using traditional orthogonal least squares method, the EDBD algorithm (EDBDA) will optimize the parameters of the neural network model, combine it with the grey model, establishing the grey RBF neural network forecasting model based on EDBDA, using an optimized network after training for prediction, getting better prediction results.

The structure of the rest of the paper is as follows: In Section 2, fundamental notions of the BPNN theory and EDBD algorithm is introduced. Then, an optimized grey neural network model base on EDBD algorithm is established in Section 3. In Section 4 present the empirical results of this analysis. Finally, some conclusions are obtained.

II. EDBD Algorithm

When BPN learns using a fixed learning rate, it often encounter two phenomena, namely the slowing phenomenon and the jumping phenomenon, its contents are as follows:

A. Slowing phenomenon

As Fig.1 shows, during the network learning process, a certain amount of link's weight change is in consecutive numbers, aka continuous positive or continuous negative, which means that the gap between the neurons of the link is continuously positive or negative. This phenomenon means the value of the error function that reaches a minimum weight value is not skipped. If the decline of the error function decreases, it is known as the slowing phenomenon.

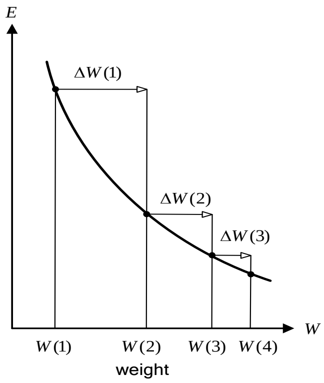

Fig.1. Slowing phenomenon

B. Jumping phenomenon

As shown in Fig.2, during the network learning process, a certain link's weight change is consecutively opposite, as in the signs are interspersed continuously, which means that the gap between the neurons are continuously interspersed with positive and negative signs. This phenomenon also means the value of the error function that reaches a minimum weight have been skipped. If the error function value is incremented, it is called the jumping phenomenon.

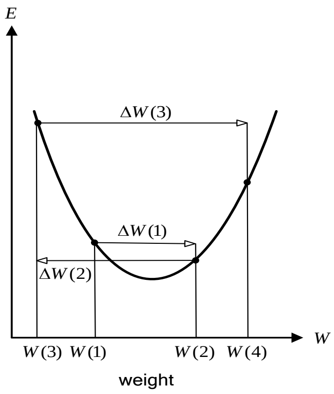

Fig.2. Jumping phenomenon

In order to improve these two phenomena, this study will refer to the EDBD algorithm[10-11] proposed by A.A. Minia and others so that the accuracy and rate will improve when the BPB learns, relevant principles of the EDBD algorithm is to add inertia to the amount of change in a learning weight of a neural network $\Delta W_{ij}(t)$ to improve the convergence process and shock during the process. (Eq. 1):

$$\Delta W_{ij}(t) = -\eta_{ij}(t)\frac{\partial E(t)}{\partial W_{ij}} + \alpha_{ij}(t)\cdot\Delta W_{ij}(t-1) \qquad (1)$$

where:

$\Delta W_{ij}(t)$ is represented by W_{ij} (representing the weights between the n-1th level and the ith neuron and the nth level and the jth neuron) the change during the tth time learning cycle, so on and so forth $\alpha_{ij}(t)\cdot\Delta W_{ij}(t-1)$. represents inertia; $\alpha_{ij}(t)$ represents inertia factors, controlling the inertia proportions, and $0 \le \alpha_{ij}(t) \le 1$. (Eq. 2):

$$\eta_{ij}(t+1) = Min\left[\eta_{max}, \eta_{ij}(t) + \Delta\eta_{ij}(t)\right] \qquad (2)$$

where:

η_{max} –represents learning rate limit. (Eq. 3):

$$\alpha_{ij}(t+1) = Min\left[\alpha_{max}, \alpha_{ij}(t) + \Delta\alpha_{ij}(t)\right] \qquad (3)$$

where:

α_{max} is the inertia factor limit. (Eq. 4-5):

$$\Delta\eta_{ij}(t) = \begin{cases} \kappa_l \exp(-\gamma_l\left|\bar{\delta}_{ij}(t)\right|) & \text{if}\,\bar{\delta}_{ij}(t-1)\cdot\delta_{ij}(t) > 0 \\ -\phi_l\eta_{ij}(t) & \text{if}\,\bar{\delta}_{ij}(t-1)\cdot\delta_{ij}(t) < 0 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

$$\Delta\alpha_{ij}(t) = \begin{cases} \kappa_m \exp(-\gamma_m\left|\bar{\delta}_{ij}(t)\right|) & \text{if}\,\bar{\delta}_{ij}(t-1)\cdot\delta_{ij}(t) > 0 \\ -\phi_m\phi_{ij}(t) & \text{if}\,\bar{\delta}_{ij}(t-1)\cdot\delta_{ij}(t) < 0 \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

where:

$$\bar{\delta}_{ij}(t) = (1-\xi)\cdot\delta_{ij}(t) + \xi\cdot\delta_{ij}(t-1),$$

$\delta_{ij}(t)$ –amount of change for the t times.

There are nine parameters $\kappa_l, \phi_l, \gamma_l, \eta_{max}, \kappa_m, \phi_m, \gamma_m,$. α_{max}, ξ...etc in Eq. 1 to Eq. 5. Parameter values are chosen based on network characteristics of the user, generally through trial and error or experience to get a better combination of parameters. We can see how the EDBD algorithm is calculated from above: Each output neuron or hidden neuron has its own learning rate and inertia factor; using the exponential pattern to control the increase in amount, so that the learning rate will rapidly increase in flat areas (increasing the learning rate during small gaps), and during relatively large slopes, the rate of increase slows (reduce learning rate at large gaps). Thus flat areas have a greater learning rate increase with no risk of the jumping phenomenon happening. The inertia factor changes with the number of times learning. The Ceiling is defined as Eq. 2 and Eq. 3 to prevent with the value of unlimited inertia factor and learning rate increasing. Network learning updates its weights and thresholds every time a training example is added. When all the training examples are loaded once, a learning cycle is complete. At the end of each learning cycle, the network performs the MSE (Mean-Squared Error, MSE) calculation on the training examples and test examples, monitoring the completion of online learning. This study set learning examples and test examples into the network cycle learning process. If their MSE are less than 2.5% average, learning is completed.

III. Grey Neural Network Model Based on Optimized Build EDBD

Based on the comparison of neural network and grey prediction model, under the circumstances of little data, grey prediction model gets more accurate predictions. However, when the grey neural network random initializes network initial parameter, falling into the local optimal value often occurs during network evolution with lower accuracy and other issues will have some impact on the grey neural network predictions. In order to obtain more accurate predictions, first, accumulate once or multiple times on the original data generating new data, weakening the randomness of the original data, as training samples of neural network, radial basis function approximation is relatively easy, and then output data network for the whitening reduction process, the final output forecast results. Through trial and error, set nine RBF network data parameters $\kappa_l, \phi_l, \gamma_l, \eta_{max}, \kappa_m, \phi_m, \gamma_m, \alpha_{max}, \xi$ as 20, 0.7, 10, 0.1, 20, 0.7, 10, 0.1, 0.01. The value of the initial weight and threshold is set to a random value between -1 and 1, applying EDBD algorithm for the optimal values in space search, optimizing initial parameter values of the grey neural network, preventing the grey neural network falling into a local optimum during evolution, and improving the prediction accuracy of grey neural network. Its predictive model is shown in Fig. 3.

Main water quality indicators to be predicted include: temperature, pH, dissolved oxygen (abbreviated DO), Oxidative-Reduction potential (referred to as ORP), ammonia concentration (referred to as AC), salinity and so on. Among them, the dissolved oxygen can be used as an important indicator of the evaluation of organic pollution of water bodies and their degree of self-purification; ORP value is the measure of aqueous redox ability. According to changes in water quality and aquatic life physical activity impact, the input parameters are: (1) Water Quality Objectives (including more than 6 parameters) during a time period (1-8 days) as the training samples; (2) one day after the designated time period, the water quality indicators as training desired samples; (3) the remaining period as testing samples after network training; (4) water quality index before current time (1-8 days) as a predictor of the input sample.

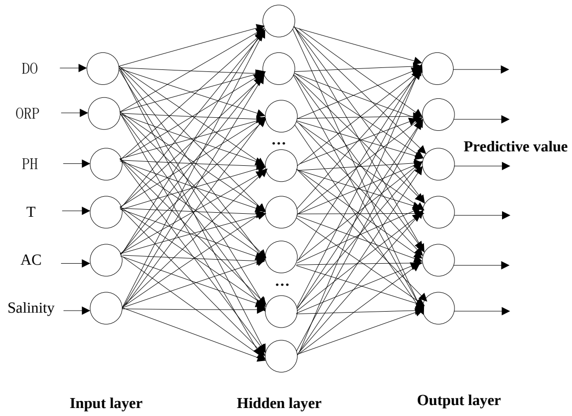

Fig.3. Prediction model for aquaculture water quality based on neural network

Its prediction algorithm is as follows:

Step 1: Set $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$ as the original series, after one or more times of accumulation, generates series $x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n))$, which $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, \cdots, n$

Step 2: Using the training data established in Step1 to train the grey neural network, EDBD algorithm instead of the least squares method for solving initial parameter values for grey neural network, allowing access to more accurate network connection weights;

Step 3: get G (1,1) whitening equation: $\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b$

Step 4: Solve a and b of the whitening equation, the solution yields G (1,1), model of the response function $\hat{x}^{(0)}(k+1) = (e^{-a} - 1)[x^{(0)}(1) - \frac{b}{a}]e^{-ak}, k = 0, 1, 2, ..., n$;

Step 5: Trained grey neural network predicts the test data;

Step 6: stop operation, compare and analyze the results predicted and actual values.

Take 0.0001 as the initial training target error, 2000 as the initial maximum number of training. Train the constructive neural network upon the five water quality indicators during the designated time period, as well as speed up the convergence, consider normalizing learning samples and output targets so that all the samples, and output destination of each element are between [0,1], ensuring the sufficient input sensitivity and good fitting property from the network to the samples. Obtain network parameters after training and apply it on water quality parameters and performance prediction analysis.

IV. Experiment Results and Analysis

A. *Data Sources*

Test data samples are collected from Fujian Province Fisheries Ltd. Ningdeshenghai 1st larimichthys croaker breeding cage, length 200m, width of 62 m, an area of about 12,000 square meters, standard ecological aquaculture cage. The cage mainly breeds larimichthys croakers. A collection of sample data from the test site act as training and testing samples of neural network and the sampling period ranges from August 16, 2014 to August 25. The establishment of grey RBF neural network forecasting model based on EDBDA predicts the quality of information and analysis. For the first eight days, the indicators of water quality samples are training input data, sampling points for the day are 7: 00, 11: 00, 15: 00 and 19:00, with the ninth day of water quality parameter as test samples. Due to limited space, only data from one time point is cited (Table 1).

Table 1: Training and testing samples for the network（at 11 hour）

Time(day)	*ORP (mV)*	*PH*	*DO(mg/L)*	*T(℃)*	*AC(mg/L)*	*Salinity*
1	191.2	7.87	3.34	20.78	0.27	0.38
2	159.7	7.96	2.16	21.55	0.15	0.38
3	212.2	7.85	2.87	22.68	0.22	0.37
4	149.8	8.06	4.82	23.43	0.13	0.38
5	190.6	7.73	2.53	23.54	0.11	0.37
6	259.9	8.23	4.16	23.72	0.62	0.38
7	311.4	7.73	2.59	23.62	0.54	0.39
8	294.2	7.78	2.65	25.59	0.37	0.38
9	304.5	6.80	2.96	23.96	0.26	0.37

B. Comparative analysis of water quality indicators predictions

After training the network, predictions are made on the water quality index on the first 10 days, results are shown in Table 2 and Fig. 4. Salinity is not predicted due to its consistency.

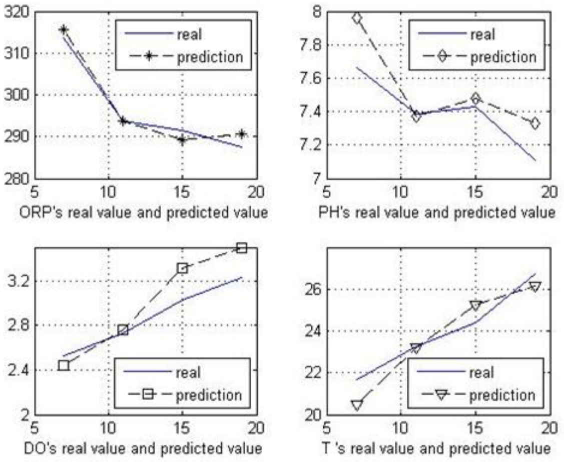

Fig.4. Comparison different variables between predicted values and real values

Fig. 4 and Table 2 demonstrates that the EDBD algorithm optimized grey neural network forecast model has a relative error less than 10%. In fact, other than dissolved oxygen, the other parameter presents errors less than 5%. The error between total real and predicted values are kept within a reasonable range.

In order to compare the performance of this algorithm model, the combined model in this paper, the traditional grey GM (1,1) model [17], the neural network model [18] as well as the grey neural network model [19] respectively, are given the same water quality sampling in 10 days to predict and calculate their respective relative errors. The results are shown in Table 3.

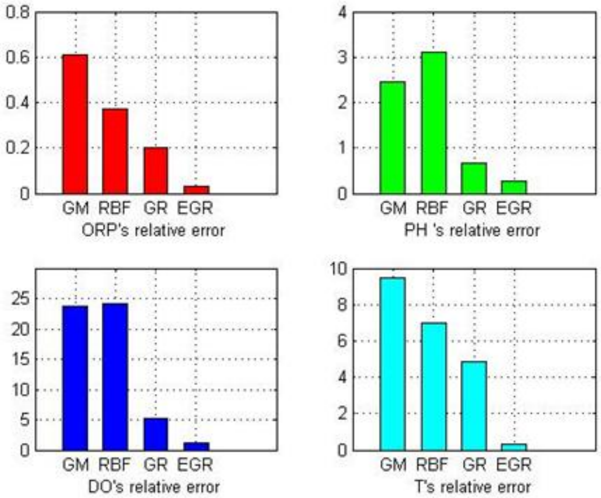

Fig.5. Relative error of different model

Table 2: The networks prediction result（10th day）

time	*ORP (mV)*			*PH*			*DO*			*T*		
	R	*P*	*PE*	*R*	*P*	*PE*	*R*	*P*	*PE*	*R*	*P*	*PE*
7:00	313.7	315.6	0.61	7.66	7.96	3.92	2.53	2.44	3.56	21.67	20.47	5.54
11:00	293.8	293.7	0.03	7.39	7.37	0.27	2.73	2.76	1.100	23.27	23.19	0.34
15:00	291.5	289.2	0.79	7.43	7.48	0.67	3.03	3.31	9.24	24.38	25.23	3.49
19:00	287.4	290.7	1.15	7.11	7.33	3.09	3.23	3.49	8.05	26.72	26.17	2.06

NOTE: **R**- Real value; **P**- predictive value; **RE**- relative error (%).

Table 3: Prediction and result values by different models

Model	ORP (mV)			PH			DO			T		
	R	P	PE	R	P	PE	R	P	PE	R	P	PE
GM	293.8	295.6	0.61	7.39	7.57	2.44	2.73	3.38	23.81	23.27	25.47	9.45
RBF	293.8	292.7	0.37	7.39	7.62	3.11	2.73	3.41	24.91	23.27	24.89	6.96
GR	293.8	293.2	0.20	7.39	7.44	0.68	2.73	2.87	5.13	23.27	22.14	4.86
EGR	293.8	293.7	0.03	7.39	7.37	0.27	2.73	2.76	1.10	23.27	23.19	0.34

Note: R- real value; **P**- predictive value; **RE**- relative error (%); **GM**-GM (1,1) model; **RBF**- radial neural network model; **GR**- grey RBF model; **EGR**- EDBD algorithm based Grey RBF model.

Compare the combined model with traditional grey GM (1,1) model, neural network model and grey neural network model in Fig.5 and Table 3. We can see that both single models, grey model and neural network model presents lower prediction accuracy than the grey neural network forecasting model. The EDBD optimization algorithm grey neural network model improved the predicting average accuracy 1% and the network predictions match the real values with high precision, indicating that EDBD based grey neural network model can be used to predict the indicators of dynamic aquaculture water quality.

V. Conclusion

This paper analysed the water quality monitoring indicators through water quality prediction models established by neural network. In this model, the water quality indicators are network input samples to study the real-time output of each prediction object. Instead of the traditional method of least squares, EDBD algorithm optimize the parameters of neural network, making it impossible to fall into local optimum, successfully achieving global optimization and greatly improving prediction accuracy. Combining the grey GM (1,1) model and neural network model, establishing grey RBF neural network forecasting model based on EDBDA, effectively combines the data sequence weakening characteristic of the grey theory and nonlinear adaptive information processing ability of the neural networks, making up the defect of inaccuracy of a single prediction method. The model is simple with strong anti-interference ability and does not need non-linear functions, etc. Through training of the network, the average prediction error is less than 5%, meeting the environmental management needs. The test results show that the neural network water quality prediction method is fast learning with stable learning process, has high prediction accuracy and other characteristics. Not only did it achieve accurate real-time prediction of aquaculture water quality, but it also avoids the excessive demands of past mechanistic studies on the basis of data [20], improving the practicability and automation. It promotes the use of aquaculture production, helps conserve water resources, improves product quality, improves water environment, and maintains sustainable and stable development of aquaculture. Therefore, researches on water quality, from intensive aquaculture evaluation, prediction to warning serves great practical significance.

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AUTHOR'S PROFILE

Shiliang Zhang

who was graduated from Department of Physics of Fujian Normal University in 1996 and received Master degrees from Information Engineering College of Jiangxi University in 2008. He is now a vice Professor of the Department of Computer science, Ningde Normal University and as a visiting scholar in Peking University. He has presented more than a dozen of papers and managed participated more than a dozen of projects. He has a lot of experience about project development, especially has researched a lot in electronic map and 3D simulation and gets many achievements.