Water Temperature Prediction in Sea Cucumber Aquaculture Ponds by RBF Neural Network model

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Abstract—**Water temperature is considered as one of the most important parameters which influence the growth rate and development of sea cucumbers as well as their distribution within the pond environment. As the change process of water temperature is dependent on the complicated meteorological and geophysical conditions, artificial neural network with specific features such as non-linearity, adaptivity, generalization, and model independence will be a proper method for solving this problem. This paper presents a Radial Basis Function (RBF) neural network model based on nearest neighbor clustering algorithm and puts forward some improved methods aiming at looking for the defects of original algorithm, then integrated them into an optimization model and verified it on matlab platform. Finally, a comparison between RBF model and 1-D vertical model was made to confirm the excellent predictive performance of optimized RBF neural network model.**

Keywords- sea cucumber；water temperature；RBF neural network；nearest neighbor clustering algorithm

I. INTRODUCTION

Sea cucumber is a kind of traditional Chinese seafood with high edible and medicinal value. In recent years, due to the worldwide over-development of sea cucumber resources and the sharp decline of its population, sea cucumber artificial breeding is springing up(D.X.Yu, H.L.Sun, S.Q.Chen,et al.,2010).

Water temperature remains one of the most important parameters which determine the productive capacity of aquatic ecosystems. Water temperature influences the growth rate and development of sea cucumbers as well as their distribution within the pond environment. Sea cucumber has a specific range of water temperature that it can tolerate and high water temperatures can adversely affect it by limiting its habitat or can even result in sea cucumber mortality. Most stratification of water temperature occur in spring and summer, this natural process of heating and cooling of a poor is highly dependent on meteorological and geophysical conditions, which turns the bottom water where sea cucumbers survive into “dead water”. Therefore, it is extremely important to monitor and predict the water temperature at different depths in order to control the water temperature stratification during the process of sea cucumber breeding (F.Y. Wang, et al.,2008).

So far, the major methods of forecasting the water temperatures generally include empirical formulas, statistical models and numerical simulations. Under the assumption of periodical boundary conditions and with the 1-D thermal equations in hydrodynamics, the empirical formulas presented in Ref.[1](ZHU Bo-fang. Thermal stresses and temperature control of mass concrete[M]. Beijing: China Electric Power Press, 1999) can be employed to forecast the distribution of the water temperature along the depth. However, the use of the empirical formulas is limited to the flows in poors and the method may introduce errors of aliasing. In order to overcome the shortcomings of empirical formulas, recently, some researchers tried to study and solve this problem from different aspects. Li et al proposed a 1-D statistical model [2](LI Lan-tao, LUO Wen-sheng and LI Jin-jing. Study on water temperature forecasting of Danjiangkou reservoir near upstream dam face after dam height increasing [J].Water Resources and Power, 2006, 24(1): 52-54). Through taking the influences of the flow pattern and the other parameters into account, in the 1-D statistical model some different parameters were introduced for the empirical formulas, and the water temperature was calculated with.

Furthermore, with the development of the Frequency-division multiplexing (FDM) and Finite Element Method (FEM), numerical simulations have been extensively used to calculate the distributions of the water temperature by solving the vortex motion equations of incompressible viscous fluid. Compared with empirical formulas and statistical models, the amount for the numerical work is quite large. In addition, when there is numerical dispersion or oscillation due to some improper treatments about the convection terms, the prediction quality would be much more inferior to those of empirical formulas and statistical models.

Empirical models such as artificial neural networks (ANNs) have been used as a viable alternative approach to physical models (Maier and Dandy, 1997; Birikundavyi et al., 2002; Jain and Srinivasulu, 2004; Sahoo and Ray, 2008a). It has specific features such as non-linearity, adaptivity (i.e., learning from inputs parameters), generalization, and model independence (no a priori model needed). (G.B. Sahoo, et al, 2005). Jingyi and Hall(2004), Chen and Kim(2006), Hossam Adel Zaqoot, Ahsanullah Balocha,et al(2010) made a comparison between artificial neural networks and statistical

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methods in different areas, all the results showed that the predictions of neural networks were obviously better.

RBF neural networks have good characteristics of non-linear mapping, and they are particularly well suited for problems in which data sets contain complicated nonlinear relations among different inputs. By learning a large amount of data the RBF neural network can approximate nonlinear functions well. Jinsong Guo, Zhe Li (2008) built two artificial neural network (ANN) models, a feed-forward back-propagation (BP) model and a radial basis function (RBF) model, to simulate the water quality of the Yangtze and Jialing Rivers in reaches crossing the city of Chongqing, P. R. China. Finally, the results showed that RBF model calculated with a smaller mean error and fewer iterations.

In conclusion, the neural network model based on RBF algorithm is an advisable choice in the field of water temperature dealing with various complex physical processes. This paper first develops an adaptive RBF neural network model and quests the optimization method, then compares the results obtained by RBF model and 1-D vertical model, finally provides guidelines the use of optimized method for future water temperature prediction purposes.

II. MATERIALS AND METHODS

A. *Study area and data source*

The data used in this study were produced by Digital Wireless Monitoring System for Aquaculture Water Quality. The system has been installed at China Agricultural University-Dongying Aquaculture Digital System Research Center in Shandong province, where is near the Yellow River estuary. The area of each experimental pond is about 1300 m^2, and the water level is about 1-2m.

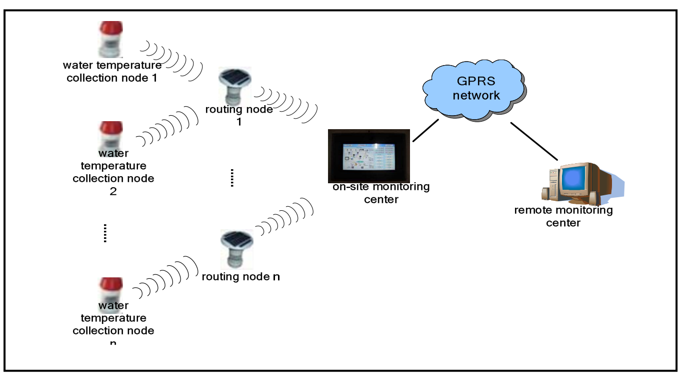

Figure 1. Structure diagram of Digital Wireless Monitoring System

The system consists of four parts: data collection nodes, routing nodes, on-site monitoring center and remote monitoring center. Each data collection node assembles a number of sensors and a RF modem, then fixed in sea cucumber aquaculture ponds by buoys. On-site monitoring center includes on-site TPC, Wireless Sensor Network (WSN) unit and GPRS unit, remote monitoring center is a computer with fixed IP address.

The working process of the system is as follows, data collection nodes send data to the on-site monitoring center through routing nodes. On-site monitoring center collects all the data then communicates with remote monitoring center through GPRS. From both on-site monitoring center and remote monitoring center, we can get the water quality data collected by data collection nodes.

The data used in the paper include water temperature data at 4 different depths and real-time meteorological data in Dongying from August 7 to August 13, 2009. Data collection time interval is 30 minutes, which means that there are 270 sets of data in total. We use first 220 data sets for neural network training and the latter 50 data sets for test.

B. *RBF neural network*

ANN uses a multilayered approach that approximates complex mathematical functions to process data. An ANN is arranged into discrete layers each layer consisting of at least one neuron. Each node of a layer is connected to nodes of preceding and/or succeeding layers but not to nodes of the same layer with a connection weight. Thus, as the number of layers and nodes in each layer increases, the process becomes more complex demanding more computational effort. In general hydrologic and environmental problems are complex and require a complex ANN structure for prediction purposes. The number of layers and nodes in each layer is problem specific and needs to be optimized (Maier and Dandy, 2000; Sahoo and Ray, 2006).

The RBF is a type of feed-forward neural network that learns using a supervised training method. RBF networks are three-layer networks, whose output nodes form a linear combination of the basis functions (usually of the Gaussian type) computed by the hidden layer neurons. Each neuron provides a significant non-zero response only when the input falls within a small localized region of the input space. The output neurons implement a weighted sum of hidden neuron outputs. The radial basis function is centered at the point specified by the weight vector associated with the neuron. Both the positions and the widths of these functions are learned from training patterns.

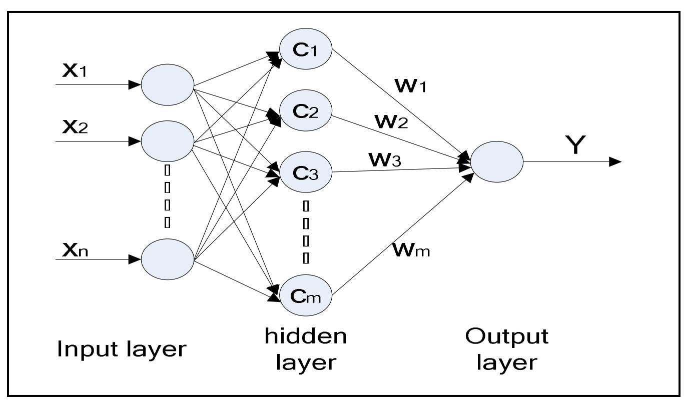

Figure 2. The structure of RBF neural network

There are several approaches used for training the RBF networks available in the literature (Haykin 1998; Moody and

Darken 1989). Most of these approaches can be divided into two stages. The first stage involves the determination of an appropriate set of RBF centers and widths. The second stage deals with the determination of the connection weights from the hidden layer to the output layer. Indeed, the selection of RBF centers is the most crucial problem in developing the RBF network architecture. These approaches are proposed to be located according to the demands of the data to be approximated.

Nearest neighbor clustering algorithm is an online adaptive dynamic clustering algorithm without confirming the number of hidden units in advance, which can obtain a optimal RBF network with a short learning time and a small amount of computation. Specific process of the algorithm is as follows:

1) Select an appropriate width r of Gaussian function, define a vector A(p) to store the sum of various categories of output vector, define a counter B(p) to calculate the number of each sample, in which p is the category number.

2) Taking the first data set (x^1, y^1) as beginning, create a clustering center on x^1 that $c_1=x^1$, $A(1)=y^1$, $B(1)=1$. Such RBF network has only one hidden unit which center is c_1, and weight vector form the hidden unit to output layer is $w_1=A(1)/B(1)$.

3) Considering the second sample data set (x^2, y^2), work out the distance between x^2 and c_1. If $|x^2-c_1|\leq r$, c_1 is the nearest neighbor clustering of x^2, and $A(1)=y^1+y^2$, $B(1)=2$, $w_1=A(1)/B(1)$; if $|x^2-c_1| > r$, take the x^2 as a new clustering center and make $c_2=x^2$, $A(2)=y^2$, $B(2)=1$. Then add a hidden unit into the network, and $w_2=A(2)/B(2)$.

4) Suppose the clustering center number of (x^k, y^k) is M, (k=3,4,…N), and the center is $c_1, c_2, \ldots, c_m$ respectively. There are M hidden units in the network as above-mentioned, then we calculate the distance of these clustering centers separately as $|x^k-c_i|$ (i=1,2,…,M). When $|x^k-c_j|$ is the smallest distance, c_j is the nearest neighbor clustering of x^k.

If $|x^k-c_j| > r$, take the x^k as a new clustering center and make $c_{M+1}=x^k$, M=M+1, $A(M)=y^k$, $B(M)=1$, keep the values of A(i) and B(i) in addition. (i=1,2,…,M-1). Then add M hidden units into the network as above-mentioned, and $w_M=A(M)/B(M)$.

If $|x^k-c_j| \leq r$, do the calculation as follows: $A(j)=A(j)+y^k$, $B(j)=B(j)+1$. When i≠j, i=1,2,…,M, keep the values of A(i) and B(i). The weight vector from the hidden unit to output layer is $w_i=A(i)/B(i)$.

5) The output of the RBF network as above-mentioned is

$$f(X^k)=\frac{\sum_{i=1}^{M} W_{i\varphi}(\|X^k-C_i\|)}{\sum_{i=1}^{M}\varphi(\|X^k-C_i\|)} \quad . \qquad (1)$$

In nearest neighbor clustering learning algorithm, the width r of gaussian function which determines the complexity of network is need to be predefined. The smaller of r is, the more clustering numbers are, the greater calculations are, and the higher precision is.

C. Network optimization

By studying and analyzing the nearest neighbor clustering learning algorithm, we have found 4 deficiencies:

1) It is not reasonable in some cases that only input information is used to determine whether a sample belongs to a clustering.

2) It is not appropriate with a fixed clustering radius when there is a big difference in sample distribution density.

3) In most cases, taking $C_j=\frac{1}{s}\sum_{j=1}^{k}x_j^k$ as a clustering is more reasonable, in which s is the sample number of subset k.

4) It doesn't take the learning errors as performance index to do the iterate in learning process, which will be limited on the occasions with high precision requirement.

Aiming at the defects of original algorithm, we have made corresponding improves, the specific steps are as follows:

1) Compute the distance d_{ij} (i , j =1, 2, 3, …, N, N is the sample total) between each sample and their average $\bar{d}$:

$$d_{ij}=\sqrt{\|x^i-x^j\|^2+\|y^i-y^j\|^2} \qquad (2)$$

$$\bar{d}=\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}d_{ij} \qquad (3)$$

Find out the nearest t samples to sample i, then set the distance as d_j respectively and work out their average distances.

$$\bar{d}_i=\frac{1}{t}\sum_{p=1}^{t}d_i^p \qquad (4)$$

2) Beginning from the first sample data set (x^1, y^1), create a clustering center on x^1 expressed as $\bar{x}^1$, then set $A(1)=y^1$, $B(1)=1$ and select a initial clustering radius r.

3) Suppose the clustering center number of (x^k, y^k) is m and the center is $\bar{x}^1,\bar{x}^2,\ldots,\bar{x}^m$ respectively, which means that there are m hidden units in the network as above-mentioned. Then find out the distance to these clustering centers respectively which expressed as $\left|x^k-\bar{x}^i\right|, i=1,2,\ldots,m$.

Set $\left|x^k-\bar{x}^j\right|$ as the smallest distance, the clustering j is the nearest neighbor clustering of sample x^k. Then make

$$r_k^*=\frac{r\bullet\bar{d}_k}{\bar{d}} \quad . \qquad (5)$$

If $$\sqrt{\|x^k-\bar{x}^j\|^2+\|y^k-\bar{y}^j\|^2}\leq r_k^* \quad , \qquad (6)$$

take the sample (x^k, y^k) into clustering j, and

$$A(j)=A(j)+y^k, B(j)=B(j)+1, \bar{x}_{tmp}^j=\bar{x}_{tmp}^j+x^k, \qquad (7)$$

$\bar{x}^j_{tmp}$ is clustering j and the sum of inputs belong to it. Otherwise, take the sample (x^k, y^k) as a new clustering center , and set

$$\bar{x}^{m+1} = x^k, m = m+1, A(m) = y^k, B(m) = 1 \ . \tag{8}$$

4) After determining the clustering, set $\bar{x}^i = \bar{x}^i_{tmp} / B(i)$ and put learning samples into network, then get the fitting error sum of squares E,

$$E = \sum_{k=1}^{N} e_k^2, e_k = f^k - y^k \tag{9}$$

f^k is the output when input is x^k, at this time we can adjust the network parameters according to general gradient algorithm,

$$\sigma = \sigma - \eta \frac{\partial E}{\partial \sigma} \tag{10}$$

η is learning rate.

5) The network output after learning is

$$f(x^k) = \frac{\sum_{j=1}^{m} A(j) \prod_{i=1}^{n} \exp\left(-((x_i - \bar{x}_i^j)/\sigma)^2\right)}{\sum_{j=1}^{m} B(j) \prod_{i=1}^{n} \exp\left(-((x_i - \bar{x}_i^j)/\sigma)^2\right)} \ . \tag{11}$$

III. IMPLEMENTATION, RESULTS AND DISCUSSION

TABLE I. COMPARATIVE ANALYSIS OF PREDICTIVE PERFORMANCE EFFICIENCY OF ORIGINAL RBF NETWORK, OPTIMIZED RBF NETWORK AND 1-D VERTICAL MODEL

Depth of Water	*Method*	*R*	*RMSE*	*ME*
20cm	original RBF network	0.981	0.538	0.197
	optimized RBF network	0.991	0.247	0.154
	1-D vertical model	0.979	0.423	-0.203
40cm	original RBF network	0.974	0.544	0.211
	optimized RBF network	0.989	0.297	0.159
	1-D vertical model	0.978	0.431	-0.205
60cm	original RBF network	0.971	0.651	0.218
	optimized RBF network	0.985	0.403	0.171
	1-D vertical model	0.977	0.439	-0.205
80cm	original RBF network	0.964	0.874	0.245
	improved RBF network	0.982	0.442	0.179
	1-D vertical model	0.974	0.450	-0.214

This paper constructs a RBF neural network using five factors: air temperature, air humidity, wind speed, solar radiation and the previous water temperature value as network inputs to predict the water temperature in sea cucumber aquaculture pond. The result of this model is the water temperature value one hour ahead, the predictive value should be in high coordination with the observed value.

In order to evaluate the performance of proposed algorithm effectively, we developed the original algorithm, optimized algorithm and 1-D vertical model on matlab platform respectively, then compared their algorithm complexity and prediction precision to analyze their advantages and disadvantages.

The predictive performances of all three methods are measured using four different statistical efficiency criteria to evaluate the relative strength and weakness of the various models developed. These are R, mean error (ME), mean relative error (MRE) and root of mean square error (RMSE). Each term is estimated from the predicted and observed water temperature (targets). All of these efficiency terms are unbiased as they use error statistics relative to the observed values. Overall, predictions are considered more precise if values R, ME, MSE, and RMRE are close to 1, 0, 0, and 0, respectively.

Table 1 shows the comparative analysis of predictive performance efficiency of original RBF network, optimized RBF network and 1-D vertical model. Firstly, we can see that the prediction precision of RBF neural network has a slight decline with the increase of depth, 1-D vertical model has no apparent change correspondingly. This is because the input factors of neural network we used (meteorological factors mainly) have a gradually diminished influence on water temperature with the increase of depth. Fortunately, the tiny change does not have a big impact on prediction result.

Secondly, data in table 1 indicates that the optimized RBF network has a better prediction performance than 1-D vertical model. Although 1-D vertical model can predict the distribution of the water temperature along the depth effectively, errors of aliasing that introduced by it are hard to be eliminated. However, the optimized RBF network can take learning errors as performance index to do the iterate in learning process, which will ensure a high prediction precision.

Finally, table 1 shows that the optimized network has a obviously better result than original network, these results are displayed not only in the prediction precision, but also in training time, as shown in table 2.

TABLE II. THE COMPARISON OF PREDICTION RESULTS BETWEEN ORIGINAL AND OPTIMIZED RBF NETWORK

Depth of Water	*Method*	*MRE*	*Training Time*
20cm	original RBF network	0.76%	9.1s
	optimized RBF network	0.39%	7.9s
40cm	original RBF network	0.83%	9.1s
	optimized RBF network	0.41%	8.0s
60cm	original RBF network	0.99%	9.3s
	optimized RBF network	0.55%	8.1s
80cm	original RBF network	1.22%	9.7s
	optimized RBF network	0.74%	8.3s

In order to explore the effect of each optimization method deeply, we try to analysis it with optimization process mentioned before and obtain comparative data in table 3 through simulation.

TABLE III. COMPARATIVE ANALYSIS OF PREDICTIVE PERFORMANCE EFFICIENCY OF EACH OPTIMIZATION METHOD

Method	*MRE*	*Training Time*
original RBF network	0.95%	9.3s
optimized RBF network by adding output information	0.86%	9.2s
optimized RBF network by adding adaptive adjustments	0.67%	7.9s
optimized RBF network by replacing the final clustering	0.83%	9.1s
optimized RBF network by gradient optimization	0.74%	9.4s
final optimized RBF network	0.52%	8.1s

The optimized algorithm adds influence of output information in the process of judging whether a sample can form a new clustering (formula 6) , which makes the determination of clustering more reasonable. Adaptive adjustments of new clustering radius based on sample density (formula 5) not only improves precision, but also shortens the training time greatly. Meanwhile, we replace the final clustering input by clustering input and the input centers of samples belong to it (formula 7 and step 4) , so the clustering can reflect and replace the samples belong to it more accurately. In addition, we only adjust one-dimensional parameters in process of gradient optimization (formula 10), as a result, there is little effect on learning speed with a big precision increase. At last, this paper develops a prediction network with optimal performance by integrating all the optimization modes (formula 11).

IV. CONCLUSION

Based on nearest neighbor clustering learning algorithm, a RBF neural network model of predicting the water temperature in sea cucumber aquaculture ponds has been established. In order to maximise the prediction precision and shorten learning time of network, some improved methods aiming at the defects of nearest neighbor clustering learning algorithm have been put forward. Then we integrated these methods reasonably after comparing the effects of each improved method and achieved an optimal optimization performance.

The results show that RBF neural network is a proper method for modeling a heat transfer problem due to the lack of information about internal process and boundary conditions. The optimized network has a better predictive performance than 1-D vertical model, but the prediction precision of RBF neural network has a slight decline with the increase of depths, which owing to the input factors of neural network we used (meteorological factors mainly) having a gradually diminished influence on water temperature with the increase of depths.

This paper proposed four improved methods, then contrasted and integrated them by experiments respectively, finally obtained an optimization algorithm with 0.43% decrease in MRE and 1.2s decrease in training time compared with the original algorithm. Restricted by the monitoring data, we can only estimate the water temperature stratification conditions by predicted value of water temperature at the four different depths, which needs to be improved in the future. Moreover, because the nearest neighbor clustering can not reflect the average value of samples, it is a feasible way to create a new kind of clustering algorithm aiming at this defect.

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