CHEMICAL ENGINEERING TRANSACTIONS

VOL. 51, 2016

A publication of
AIDIC
The Italian Association
of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Tichun Wang, Hongyang Zhang, Lei Tian

ISBN 978-88-95608-43-3; **ISSN** 2283-9216

DOI: 10.3303/CET1651093

Application of an Improved GA-BPNN Algorithm for Wireless Sensor Network in Hydrological Forecasting

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Hydrology is a variety of changes and motion laws of water in the nature. It is a key fundamental work for each country to understand the national geographic hydrology. It is particularly important to understand the hydrological data in the water conservancy project planning, management, drought prevention and flood control, as well as the protection and utilization of water resources. Due to the complexity of the influencing factors and the limit of the current level of science, hydrological forecasting accuracy is relatively low. How to improve the prediction accuracy attracts the concern of the hydrology scientists. Firstly, aiming at the difficulty of monitoring to the seawater hydrology, an online monitoring scheme composed of wireless sensor network and computer technology are proposed in this paper. Secondly, the neural network method is used to process the data collected by wireless sensors in order to forecast the related hydrological data. Thirdly, a hybrid algorithm combined with genetic algorithm and BP neural network is developed to improve the performance due to the defect of BP algorithm easily falling into local extremum in the process of training. In the section of simulation experiment, a designated wireless sensor networks for New York Harbor have been set up. This network is composed of a number of fixed wireless sensor network nodes in the upper reaches and the estuary of the river. This network combines the prediction model in this paper with the fixed-point data collection and data fitting to achieve the purpose of using wind velocity to predict hydrological information, which includes water level, water temperature, salinity, wave height and wave period. As can be seen from the experimental results, the improved BPNN algorithm is significantly better than the other two algorithms. It shows that the optimization of continuous space based on GA algorithm is very important for the number of hidden layers which affect the prediction accuracy of BPNN. It avoids the defects of the experience when the parameters are chosen, and the prediction accuracy is obviously improved.

1. Introduction

Hydrology is a variety of changes and the laws of motion of water in nature. It is an important basic work for each country to make the understanding of the geography of the country. It is particularly important to understand the hydrological data especially in the area of water conservancy project planning, management, drought prevention and flood control, as well as the protection of water resources. Hydrological monitoring is an important part of the hydrological work, and its core content is to collect the variation information of the water, which can be used for hydrological research and control of the flood disaster, rational allocation of water resources (Jiao, 2010; Tao, et al., 2003). With the development of social economy, the progress of science, technology and the increasing population make the hydrology monitoring work meet some new challenges and changes. Firstly, construction of various flood control projects and other artificial facilities together with the comprehensive treatment of water supply and demand make the hydrological conditions with new changes. Secondly, the application of new technology in hydrological monitoring put forward new requirements to the relevant hydrological monitoring workers. Thirdly, various human activities change the traditional mode of operation in the hydrological monitoring (Wang, et al., 2008; Jiang, 2007; Wang, et al, 2009; Du, et al., 2008).
Wireless sensor network is considered to be one of the most influential technology, and it has attracted great attention in both academia and industry. Similar to the satellite remote sensing technology in 1970s, WSN will have a revolutionary change to the earth system and environmental science(Hart and Martinez, 2006). At

Please cite this article as: Feng Y., 2016, Application of an improved ga-bpnn algorithm for wireless sensor network in hydrological forecasting, Chemical Engineering Transactions, 51, 553-558 DOI:10.3303/CET1651093

present, environmental monitoring has become an important research field of WSN, and many typical applications have been carried out. In the summer of 2002, the environmental monitoring project of Main Duck island has been proposed by Berkeley Laboratory of Intel Research Centre and Atlantic College (Polastre, et al., 2004). This project has a 4-month non-intrusive observation for light, temperature and humidity, pressure and information about infrared radiation elements according to the deployed 43 nodes. This project is used to study the nest build behaviour on the island. The sensing data is transferred to the base station in single hop wireless way, and can be accessed and downloaded by users with the help of the satellite communication link. In 2005, survival micro environment of a 70m-high redwood is studied by University of California at Berkeley according to WSN technology (Tolle, et al., 2005). This network includes 33 nodes, and each node collects air temperature, humidity and solar radiation information. Another monitoring project to study the relationship between light and the phenomenon of shrub cover up the grass also uses the WSN technology (Selavo, et al, 2007). The monitoring information includes the complex solar radiation intensity, temperature, humidity and CO_2 and other ecological factors.

2. Architecture and basic knowledge of Wireless Sensor Networks

The architecture of a wireless sensor network is shown in Figure 1. Sensor networks usually include sensor nodes, sink nodes and management nodes. Sensor nodes are arbitrarily distributed in a monitoring region, and node constitute to a network in form of self-organization. Then, the monitoring data will be transferred to the sink node through multi hop ways. Finally, monitoring information will be transmitted to a management node through the Internet or other means of communication network. Similarly, the user can release the order according to the management of the sensor nodes to inform the nodes to collect the monitoring information.

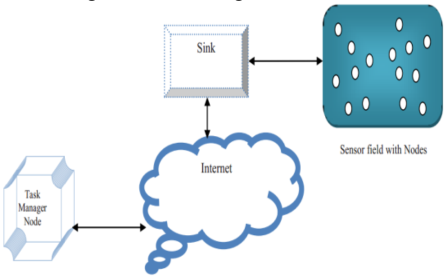

Figure 1: The Wireless sensor network

Compared to the traditional monitoring methods, wireless sensor networks have the advantages of less impact on the ecological environment, low cost and so on. Due to the limited sensing range of a single sensor node, certain coverage algorithm for waters in three-dimensional space should be taken to fix the position of the nodes in order to accurately detect physical parameters of each local water area. Intensive nodes deployment for important monitoring area is the basis of riverine and marine water environment monitoring.
The design of the database is mainly based on the daily sea water hydrology monitoring data while the scientific research and the special situation monitoring data are supplemented. The actual monitoring data is important supplemented with international and other sea water hydrology standards. Main hydrological monitoring is the main reference while the related factors is the supplementary. The system database consists of 4 basic tables, which are real-time data receiving table, monitoring point hydrological characteristic table, sea water level meter, and historical data table. Real-time data receiving table is the main database diagram which occupies most space. The content in the storage is water quality parameters which can be obtained in real-time. Therefore, items in the table include acquisition time, acquisition point position, temperature, pH value, dissolved oxygen (DO), COD.

3. An improved BPNN algorithm in WSN

3.1 Basic knowledge of BPNN

For hydrological data collected by wireless sensor which is introduced in Section 2, we use an improved BPNN model for processing so as to predict the related hydrological indicators. Here, we will introduce the basic knowledge of BPNN model. BPNN (Back Propagation neural network) is a Multilayer Feed-forward Neural Networks based on the error back propagation algorithm. The basic structure is shown in Figure 2.

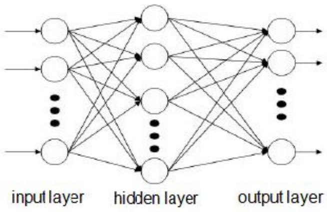

Figure 2: Specific process of the BPNN algorithm

Design input and output couple (X_p, T_p), $p = 1, 2, \cdots, P$, where p is the number of training samples, X_p is the p th sample input vector, M is the dimension of input vector; T_p is the p th sample output vector (expected output), $T_p = (t_{p_1}, t_{p_2}, \cdots, t_{p_N})$, and N is the dimension of output vector. The actual output vector of the network is $O_p = (o_{p_1}, o_{p_2}, \cdots, o_{p_N})$. The neural network adopts structure of single hidden layer, and the number of nodes of the hidden layer is H. w_{ij} is used to express the connection weight between the input layer and the hidden layer as well as the hidden layer and the output layer. w_{ij} is the connection weight between the i_{th} node in first layer and the i_{th} node in second layer. Sigmoid function is adopted as the transfer function between the hidden layer and output layer of the neural network. $f(x) = 1/(1+e^{-x})$, and the error function is $E = \frac{1}{2}\sum_{k=1}^{N}(t_k - o_k)^2$.

The three layer BP neural network program algorithm steps are shown as follows:
Output of hidden layer node:

$$y_j = f(net_j) = f(\sum_{i=1}^{M} w_{ij} x_i) \tag{1}$$

x_i is the input value of the i_{th} node of the input layer, y_{j} is the output value of the hidden node.
Input layer node o_k:

$$o_k = f(net_k) = f(\sum_{j=1}^{H} w_{jk} y_j) = f(\sum_{j=1}^{H} w_{jk} f(\sum_{i=1}^{M} w_{ij} x_i)) \tag{2}$$

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial net_j}\frac{\partial net_j}{\partial w_{ij}} \tag{3}$$

Define the descending gradient δ_j:

$$\delta_j = -\frac{\partial E}{\partial net_j} = -\frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial net_j} = -\frac{0.5\sum(t_k - o_k)^2}{\partial o_j} f^{'}(net_j) = (t_j - o_j) f^{'}(net_j) \tag{4}$$

The increasing of the weight of nodes between the output layer and the hidden layer is proportional to the descending gradient, and the formula of weight updating can be expressed as following:

$$w_{ji}(t+1) - w_{ji}(t) = \eta \delta_i o_j \tag{5}$$

The defects of BP neural network algorithm are easy to fall into local minimum and slow convergence in the iterative process. In this paper, the additional momentum method and the adaptive learning rate method are used to solve these problems. The additional momentum method will add a value to the weight changes based on the back propagation method. This value is proportional to the change of the previous weight. The specific method is that a part of the previous weight adjustment amount is added to the weight adjustment amount according to the error calculation. The results of the specific method is adopted as the actual weight adjustment:

$$\Delta\omega_{ij}(n)=\alpha\Delta\omega_{ij}(n-1)+(1\text{-}\alpha)\eta\nabla f(\omega_{ij}(n-1)) \tag{6}$$

Where, η is the learning rate, n is the training times, α is the momentum factor, and $\nabla f(\omega_{ij}(n-1))$ is the gradient of the error function.

After the use of the additional momentum method, weight adjustment will change along the average direction of the bottom of the error surface. Condition of $\Delta\omega=0$ can be prevented when the network weights go into the flat zone, which makes the network jump out of the local minimum of error curved surface.

The basic idea of the adaptive learning rate method is that the learning rate is adjusted adaptively according to the variation of the error. In the training process, adaptive adjustment mechanism of the learning rate is shown as formula (7) which can increase the stability and improve the convergence speed.

$$\eta(n)=\begin{cases}1.2\eta(n-1) & E(n)<E(n-1)\\ 0.8\eta(n-1) & E(n)>1.1E(n-1)\\ \eta(n-1) & otherwise\end{cases} \tag{7}$$

Where, $E(n)$ is the error of the step n.

3.2 Using GA algorithm to optimize the parameters of BPNN

Genetic algorithm is an intelligent optimization algorithm, and it is also known as the modern heuristic algorithm. This algorithm has the advantages of high global optimization performance, generality, and suitable for parallel processing. This algorithm generally has a rigorous theoretical basis rather than simply relying on expert experience. Therefore, it can find the optimal solution or approximate optimal solution in a certain time.

The algorithm steps are as follows:

Step 1: Parameter initialization: including the determination of the size number of initial population of genetic algorithm, search space of $[u_{\min},u_{\max}]$, probability of crossover p_c and mutation p_m, learning rate β in the BP algorithm, and momentum factor α ;

Step 2: Determination of fitness function: reciprocal of the mean square error of the BP network is selected as the fitness function:

$$f(x)=\frac{1}{\frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{L}(d_{p_k}-o_{p_k})^2} \tag{8}$$

Step 3: Coding: the encoding of this genetic algorithm consists of two parts: control code of controlling the nodes number in the hidden layer and the weight code for adjusting the weight.

Step 4: Generation of the initial species groups: set appropriate number of populations, and the general population size is 30~100.

Step 5: Calculate the fitness of each individual: input the training samples and obtain the fitness of each individual according to the fitness function. According to the size of each individual fitness, the new population will be generated using the roulette selection method.

Step 6: Crossover and mutation: in this process, the control code won't be operated and the crossover and mutation process is only for weight code with real number to obtain new generation of groups.

4. Simulation experiment and result analysis

In this experiment, a number of fixed-point wireless sensor network nodes are set up in the New York port in the United States and its upper reaches of the river and estuary waters. Based on these nodes, an observation and prediction system for New York port has been constructed. This system achieves the purpose of predicting water regime by the wind velocity according to the combination of fixed-point data collection, data fitting and the prediction model in this paper. Hydrological information includes water level, water temperature, salinity, wave height and period. Firstly, as can be seen from Figure 3, we show the monitoring data of surface currents in January and February, 2016. The white squares in the figure 3 are sensors for monitoring hydrology. Overall, surface currents value of New York port increases with the increase of temperature. This shows that the weather conditions are the main factors that affecting the surface currents seasonal changes.

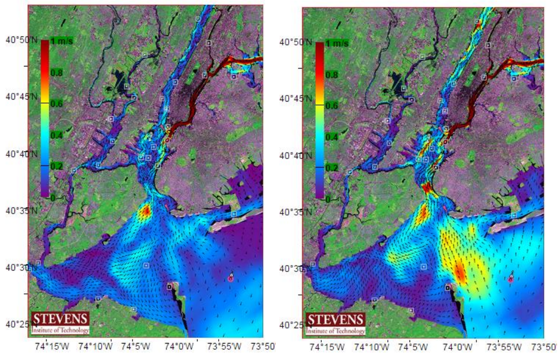

Figure 3: NY/NJ Surface Currents (m/s) on Jan 1, 2016 and Feb 1, 2016

Secondly, three kinds of factors of water environment are selected in this study. These factors include water temperature, water level and salinity. The main content of the experiment is to predict the water temperature, water level and salinity according to the wind speed. From figure 4, 5 and 6, we can see that the forecasting method of optimized BPNN with GA proposed in this paper can well fit the historical data of water level, water temperature and salinity changes according to the 72 points from January 1 to 3. In Figure 5, the blue curve is the fitting curve of the model.

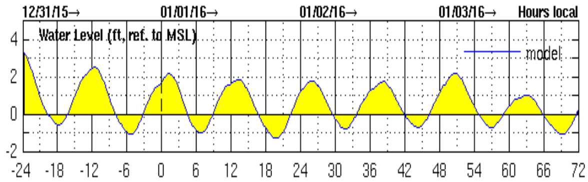

Figure 4: Fitting curve of water level variation

From Figure 3 and 5 we can see that the surface water temperature has changed significantly in the four seasons in this area, and temperature distribution of the surface water and the air flow is roughly the same while the shallow water area near the radial sand ridge is influenced by the temperature. Statistical results show that the surface water temperature have a significant correlation with air temperature and water depth, which shows that the temperature distribution on this sea surface region is strongly affected by temperature and water depth. From Figure 6 we can see that there are some differences in the distribution of temperature and salinity between bottom and surface in the offshore area, but the vertical distribution of salinity is relative uniform. This is due to the strong response of the shallow water area of the radial sand ridge to the temperature, and the salinity distribution is mainly affected by the evaporation, rainfall and circulation. In the Fig. 5 and 6, the red line and the blue line represent the bottom water and surface water in the sea.

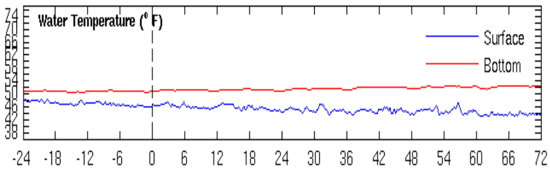

Figure 5: Relationship between surface and bottom(water temperature)

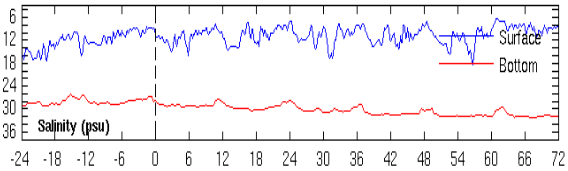

Figure 6: Relationship between surface and bottom(salinity)

Thirdly, we use three different methods to predict the value of water temperature in Jan 4. Then, by calculating the percentage of successful times and the number of samples, we can judge the success rate of the prediction algorithm. The improved BPNN algorithm, BP neural network algorithm and grey prediction method are analyzed and compared in the case of error threshold value between 1 ^{0}F and 5 ^{0}F . Figure 7 shows the 10 average success rate of the three prediction algorithms which are repeated 10 times that predict the water temperature in that area in January 4, 2016.

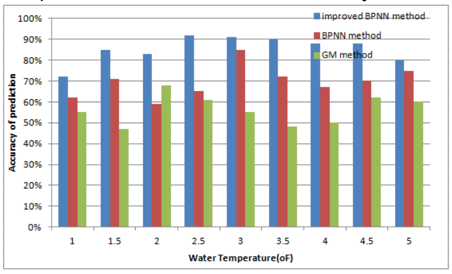

Figure 7: Comparison of the average success rate of the three prediction methods

As can be seen from Figure 8, the improved BPNN algorithm is significantly better than the other two algorithms. It shows that the optimization of continuous space based on GA algorithm is very important for the number of hidden layers which affect the prediction accuracy of BPNN. It avoids the defects of the experience when the parameters are chosen, and the prediction accuracy is obviously improved.

5. Conclusion

A new monitoring method for the hydrological information has been developed and applied. Firstly, an online monitoring scheme combined with wireless sensor network technology and computer technology is put forward aiming at the difficulty of monitoring sea water sampling. Secondly, the neural network method is used to process the data collected by wireless sensor, and then forecast the related hydrological data. Thirdly, aiming at the defect of BP algorithm easily falling into local extremum in the process of training, the paper has improved the performance of the hybrid algorithm according to the combination of genetic algorithm and BP neural network. As can be seen from the experimental results, the method of this paper avoids the defects of the experience when the parameters are chosen, and the prediction accuracy is obviously improved.

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