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Groundwater Level Prediction Based on BP and RBF Neural Network

Xu Chang[1,2], Jia Hui[1,2], Wang Rong[1,2], Wu Hao[1,2]

1-School of Environmental Science and Engineering, Chang'an University, Xi'an 710054, China
2-Key Laboratory of Subsurface Hydrology and Ecological Effect in Arid Region of Ministry of Education

Abstract::Groundwater level is an important indicator to measure groundwater resources and their exploitation amount. The accurate prediction of groundwater level is important for efficient use and management of groundwater resources. Because of mainly affected by natural and human factors, groundwater level has evident randomness. So, building stochastic model for prediction of groundwater level is of great significance in the evaluation of groundwater resources. In the paper, BP and RBF neural network models are built and they are applied in Yichang Irrigation District of Hetao Irrigation District in Inner Mongolia. Forecasting the groundwater level fluctuations in the irrigation district can provide references for many aspects, such as saving groundwater resources, restoring groundwater homeostasis in the region, establishing the optimum irrigation system of well irrigation, developing water-saving irrigation and promoting the sustainable development of agriculture and water resources. Overall, simulation results of the neural network models suggest that predictions of two models are reasonably accurate. The average absolute value of relative error of BP neural network is 5.28% and RBF neural network is 4.84%. Comparative analysis shows that RBF neural network is simpler, converges faster and has more stable prediction results.

Keywords: Groundwater level, prediction, BP neural network, RBF neural network

1. Introduction

Nowadays, water resources are seriously polluted in China. And in the most of places, surface water resources are scarce. In recent decades, along with the development of national economy, the development and utilization of groundwater resources are increasing. This leads to continual decline of groundwater level and results in many bad influences, such as land subsidence, ground fissures, water quality deterioration and seawater intrusion. Solving the problems of managing groundwater resources is very important. And it greatly depends on people to understanding the groundwater level dynamic. The groundwater level dynamic generally refers to the time variation of groundwater level, water quality and physical properties. Groundwater level is known as "the pulse of the earth" and the most important indicator of the groundwater dynamic (Cheng and Hong, 1988).

However, due to its randomicity and fuzziness, it is difficult to express complex non-linear relationship between groundwater level and its factors by a deterministic model (Li et al., 2001). Traditional prediction methods of groundwater level are deterministic mathematical model and random statistical methods, such as finite element method, finite difference method, regression analysis, spectrum analysis and time series analysis (Cheng and Hong, 1988). These methods based on linear theory and their prediction accuracy is not high.

*Corresponding author (e-mail: *xuch1988@126.com*)

Because of highly nonlinear characteristics between the groundwater level and its factors, artificial neural network is widely used in studying variation of groundwater level. Compared to the traditional prediction methods of groundwater level, artificial neural network model has strong nonlinear mapping ability, flexible network structure and is highly fault-tolerant. These make it be favored by many experts in the groundwater study. In this paper, BP and RBF neural networks are used in building groundwater level prediction model in Yichang Irrigation District of Hetao Irrigation District in Inner Mongolia. And the performances of the two neural networks are compared in simulation study.

2. BP and RBF Neural Network

2.1 BP Neural Network

In the 1986, Rumelhart and McClelland developed a Multilayer Feed-forward Neural Networks, which utilizes the error-back propagation (BP) learning algorithm and for that it is called BP neural network. BP neural network is a one layer or multilayer feed-forward neural network which consists of one input layer, one or several hidden layers and one output layer. An example of a three-layer feed-forward BP neural network is shown in Figure 1. The neurons of upper and lower layers are fully connected. But between neurons of same layer, there are no connections (Chauvin and Rumelhart, 1955; Wei, 2005). The standard BP algorithm is a gradient descent algorithm, in which the network weights are changed along the negative of the gradient of the performance function (Abdi H et al., 1996; Nguyen D and Widrow B, 1990). The main idea is to adjust the weights of the network to make total error minimum. In the forward process, the input signals are processed from the input layer to the output layer and the states of the layer's nodes can only influence the states of the next layer's nodes. At the output layer, the value of the output is compared with the anticipant value. If there is any error, the error will be returned along the quondam way, and the weight values of the nodes between layers are modified to reduce the error. So the error will be controlled in the range given in advance (Li, 2009).

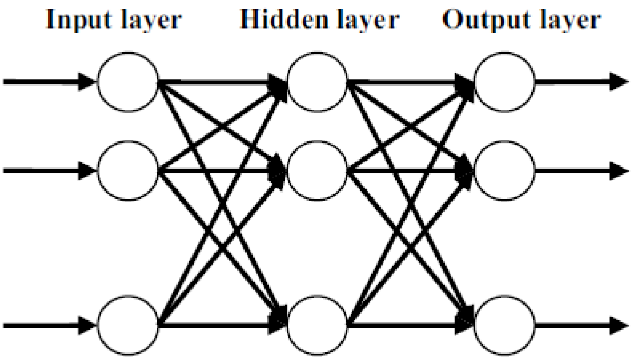

Figure 1: BP neural network architecture

2.2 RBF Neural Network

Radial basis function (RBF) method is a technique in high-dimensional space interpolation. In 1988, Broomhead and Lowe compared RBF with multilayer neural network and put RBF into designing neural network. RBF neural network is a typical three-layer feed-forward network and is made up of an input layer, a hidden layer and a linear output layer. Network hide-layer activated function can describe exactly the actual neuron activity characteristics. In the paper, the Gaussian function is used for network hide-layer activated function and it is defined in the following formula:

$$\varphi_i = \exp\left[-\frac{\left\|x - c_i\right\|^2}{2\sigma_i^2}\right] \tag{1}$$

Center value c_i and radius σ_i define the working range of base function with this center. The more close between input x and center, the bigger of output φ_i. The speed of this process is determined by σ_i and smaller σ_i makes function more sensitive to input changes (Cheng, 2008).

As the "base" of the hidden units, RBF constitutes a hidden space. Then, input vector can be mapped directly to the hidden space. When center value of RBF is determined, the mapping relationship will be determined. The transformation from hidden layer space to output space is linear. So, network output is linear weighted sum of hidden unit output and the weights are adjustable parameters of network (Li, 2009). The RBF network receives a k dimensional input vector x and outputs a scalar value using the general formula:

$$y_k = \sum_{i=1}^{q} w_{ki}\varphi_i \qquad (k = 1, 2, \ldots, L) \tag{2}$$

where ψ_i is the Gaussian function, w_{ki} is weighted value from node i of hide-layer to node k of output layer, and q represents the number of nodes in the hidden layer.

Overall, network is non-linear transformation from input to output. But network output is linear weighted sum of hidden unit output. Weights of network can be solved by linear equations. This can greatly speed up the learning and avoid local minimum value appearing.

3. Empirical Analysis

Yichang Irrigation District of Hetao Irrigation District is located in the drought Northwest Plateau of China. Yellow River and groundwater are the main irrigation water resources. Groundwater is in the majority. There are three irrigation periods every year in the Yichang Irrigation District: summer irrigation period (April to June), autumn irrigation period 1 (July to September) and autumn irrigation period 2 (October to November). According to data analysis, groundwater level is affected by many factors, mainly by rainfall, average temperature, evaporation, water diversion, groundwater exploitation and groundwater excretion. The data of six factors in every irrigation period were collected from government department. The data of all these parameters were available during the years 1990 to 2000. There were 33 samples data of 11 years. The samples data were divided into two parts: the first 27 samples data for training, the remaining 6 for predicting. The samples data for predicting were not involved in the training and screening parameters.

3.1 Empirical results of BP Neural Network

When training, the six impact factors of the first 27 samples data are selected as input data and groundwater level data are selected as output data. In the model, input vector is represented as: X=(x_1,x_2,...,x_{27}), and output vector is represented as: Y=(y_1,y_2,...y_{27}), where x_i
is represented as: x_i=(H_1,H_2,H_3,H_4,H_5,H_6) and H_i represent the six impact factors respectively.

In order to ensure that input data and output data are within 0-1 and to prevent some neurons from reaching saturation, the raw data need to be normalized processing. There are many normalization processing methods. In this paper, the following standardized method is adopted:

$$H_i' = \frac{H_i - H_{i,min}}{H_{i,max} - H_{i,min}} \tag{3}$$

After data processing, three-layer network model will be established. And the final structure of BP network model is: 6-15-1 (i.e., 6 input layer nodes, 15 hidden layer nodes and 1 output layer node). Training accuracy is 0.001 and training times is 1000. Levenberg-Marquardt algorithm is used to train the network. And the network is evaluated with the root mean square error (MSE). The number of hidden layer unit is determined according to the " method of trial and error " (Raman H and Sunilkumar N, 1995). When the training is beginning, small number of hidden layer unit is given first. After several training, if the accuracy cannot meet the requirement, it needs to increase the number of hidden layer unit. Repeat this process until the training results meet the requirements. In this paper, when the number of hidden layer unit is 15, training results are very good. And MSE is 8.56×10^{-6}. After training, groundwater level is forecasted according to the remaining 6 samples data.

Training and prediction results of BP neural network are shown in Figure 2 and Table 1. Figure 2 and Table 1 show that Training and prediction values are good agreement with the actual value. The average absolute value of relative error of training is 3.19% and forecasting is 5.28%.

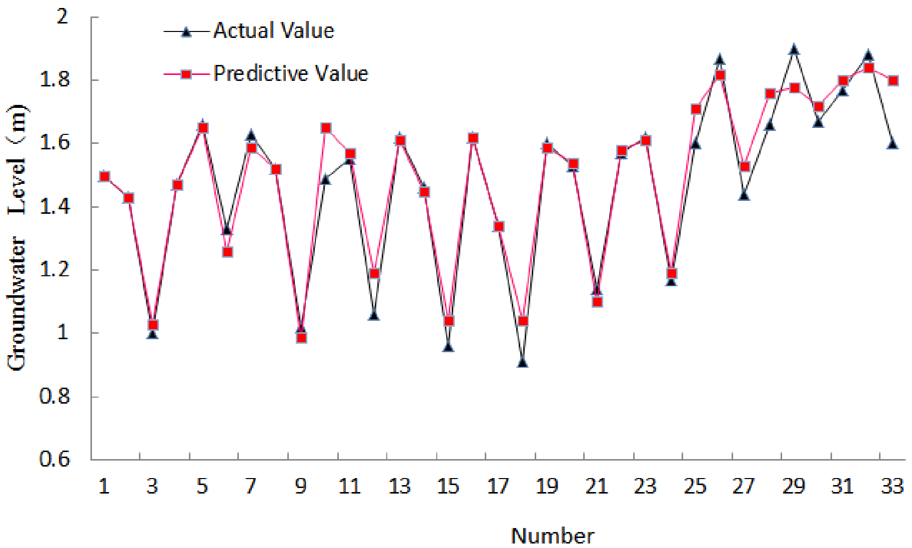

Figure 2: Plots of observed and computed water levels using BP neural network

Table 1: Predicted error using BP neural network

Time	Actual value (m)	Predicted Value (m)	Relative error (%)
1999 summer irrigation	1.66	1.76	6.02
1999 autumn irrigation(1)	1.9	1.78	6.32
1999 autumn irrigation(2)	1.67	1.72	2.99
2000 summer irrigation	1.77	1.8	1.69
2000 autumn irrigation(1)	1.88	1.84	2.13
2000 autumn irrigation(2)	1.6	1.8	12.5

3.2 Empirical results of RBF Neural Network

Using the MATLAB Neural Network Toolbox, the normalized data are used to design RBF network with function-newrb(). The function-newrb() can automatically increase the number of hidden layer neurons until the precision meets the requirement or the number of neurons reach the maximum. Its form is as follows:

$$net = newrb(\ P, T, GOAL, SPREAD, MN, DF) \tag{4}$$

where *P* is input sample, *T* is expected response, *GOAL* is training precision, *SPREAD* is a density of RBF and its default value is 1, *MN* is the maximum number of neurons, *DF* is the increasing number of neurons (Ge and Sun, 2007). Among these, *SPREAD* is an important parameter. Different values of spread influence the prediction performance of the model. Besides, the higher of the value, the smoother of the curve and forecast performance is far better. The opposite is reverse. After several trials, its optimal value is 6. *GOAL* is 0.001 and *MN* is 12 in the model.

Same as the BP neural network model, RBF model is also a three-layer network structure. The first 27 samples data are used to build the model. Then, the remaining 6 samples data are used to predict the groundwater level. Training and prediction results of RBF neural network are shown in Figure 3 and Table 2. The average absolute value of relative error of training is 3.49% and forecasting is 4.84%.

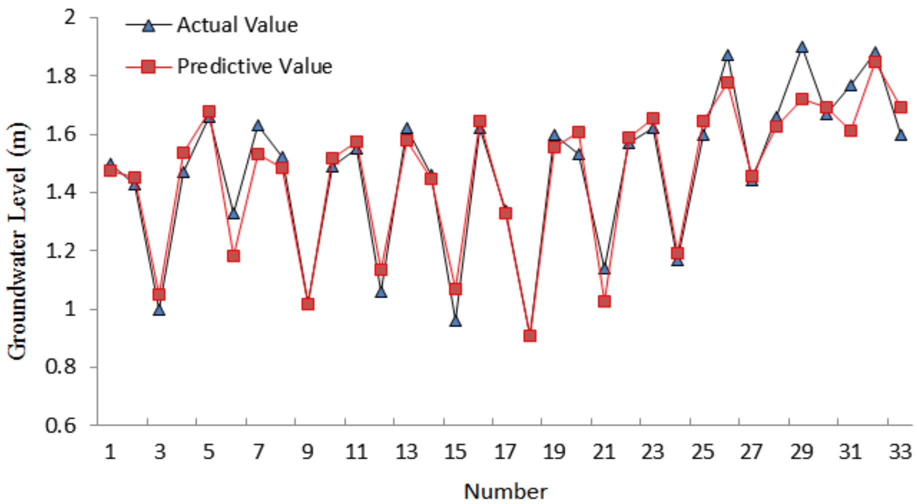

Figure 3: Plots of observed and computed water levels using RBF neural network

Table 2: Predicted error using RBF neural network

Time	Actual value (m)	Predicted Value (m)	Relative error (%)
1999 summer irrigation	1.66	1.63	1.81
1999 autumn irrigation(1)	1.9	1.72	9.47
1999 autumn irrigation(2)	1.67	1.69	1.20
2000 summer irrigation	1.77	1.61	9.04
2000 autumn irrigation(1)	1.88	1.85	1.60
2000 autumn irrigation(2)	1.6	1.69	5.62

3.3 Comparisons of BP and RBF models

In the paper, BP and RBF neural network models are built and used to predict the groundwater level. Results of the neural network models suggest that predictions of two models are reasonably accurate. Comparative analysis shows that the RBF network model structure is simpler than the BP network. Although they both have three-layer network structure, hidden layer neurons of the RBF network are less than BP. Under the same requirement of error (*GOAL* = 0.001), the convergence speed of RBF is faster. By comparing the empirical results of BP neural network with RBF neural network on predicting groundwater level, relative error of RBF is smaller than BP.

4. Summary and Conclusions

BP and RBF are very important neural network. They can approximate any linear or non-linear function. Because the impact factors of the groundwater level are random and fuzzy, there is a complex non-linear relationship between the groundwater level and its impact factors. When BP neural network and RBF neural network are used to predict groundwater level in the irrigation district, predictions of two models are reasonably accurate and predicted trend of groundwater level is consistent with the actual situation as long as right choice of impact factors. The more training samples are, the more accurate the model is. In the paper, BP neural network and RBF neural network are built to predict groundwater level and their prediction results are very accurate. And comparative analysis shows that RBF neural network is simpler, converges faster and has more stable prediction results.

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