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Simulation and Prediction of Water Level for Ji'nan's Baotu Spring Based on BP Neural Network Models

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ABSTRACT

The precipitation infiltration and the exploitation of ground water influenced a lot to the spring level. We take the precipitation of the present month, last month and last two months and average groundwater level, total exploitation of the present month and last month as input layer while the present month's average groundwater level as the output layer. Combining the genetic algorithm with BP neural network together we can use the sequences from February 2002 to December 2006 and sequences of months in 2008 as the training samples while the sequences of 2007 as test samples. The results showed that the predicted spring level using the neural network model differed a little with the measured data and the absolute error was between 0.01 m and 0.59 m. The relative error calculated according to relative elevation 27 m was between 2% to 34%. Since the relative error standard of unqualified is greater than 20% we know the predicted value in April, July and August were unqualified. The multiple regression analysis to the same sequences showed that the absolute error of predicted and measured spring level were between 0.05 m and 0.46 m. The relative error calculated according to relative elevation 27 m was between 4% to 119% which is obviously bigger. So the neural network model had better predicted accuracy.

KEYWORDS: Neural Network Model; Jinan's Baotu Spring; Exploitation Amount; Hysteretic effect; Simulation and Prediction

PREFACE

Many research results were achieved using the artificial neural network model to predict the groundwater level [1] [2] [3]. Many scholars such as Baoming Chi, Lan Lin and Yuanfang Ding [4] put forward groundwater dynamic predicted model based on the genetic algorithm with BP neural network. They made sure first the threshold of neural network by optimizing the genetic algorithm then used the LMBP algorithm to do the fine turning in the solution space to achieve the optimal solution or the approximate optimal solution. QiangXu. Longcang Shu, Guilian Yang[5] introduced the genetic algorithm based on wavelet neural network to solve the optimize. They also compared the BP and WNN models to predict the water level of deep confined water in Tianjin city, China. Zongzhi Wang, Juliang Jin and Zisheng Zheng. [6] put forward an improved BP neural network model which took the exploitation amount of the ground water, the groundwater level of previous year and precipitation the current year as input neurons while the topology was 3:3:1to predict the groundwater level in Ji'nan area. The model used the observation data of the whole year with large scale water level precipitation. It is necessary to use the observation data of months to set up a model based on BP neural network in order to forecast the spring flows and make the scheduling scheme to satisfy appreciation needs before spring utilization.

INFLUENCING FACTORS FOR THE *BAOTU* SPRING LEVEL

The spring groups around Ji'nan area whose total area is 1486km^2 have Dongwu fault zone in the east, Mashan fault zone in the west, carboniferous, Permian and igneous rocks in the north and surface watershed of Mount Tai in the south. Nowadays there are 108 spring groups in Ji'nan area which can be divided to four big groups in which Baotu spring is the most famous one. The origin of the groundwater for Ji'nan spring groups mostly is the precipitation infiltration quantity, underground runoff recharge amount, return percolation of irrigation and infiltration replenishment in river course. The drainage can be shown as the spring flow of Ji'nan spring groups, manual exploitation amount and quaternary pore water recharged upwards by karst water.

Precipitation Recharge Amount

The spring level and flow have close relationship with the precipitation. Ji'nan Investigation and Evaluation Report of Groundwater Resources [7] showed that the precipitation time mainly focused on July, August and September. Every year in the rainy season the karst water level and the spring flow generally increased. During April to June of the dry season the groundwater level is the lowest and the spring flow is the minimum. The dynamic curve of the groundwater level and spring flow with the precipitation distribution were very obvious. It also inflected a character that the karst water can be recharged by a short-term concentration supply for long term consumption.

A lot of measured data revealed that as the capacity of the karst water containing system the precipitation infiltration recharge had obvious hysteretic effects on the spring. Yefei Ji *et al*. [8] gave out the hysteretic time of the precipitation recharge to the spring as 1 a using the stepwise regression method with the years measured data. Fuchen Liu [9] considered the difference sequences periodically influenced by the precipitation, spring level and spring flow and the hysteretic time of spring flow to the precipitation was 3 months. Obviously the influence of a rainfall process to the spring level was very complex and the influence of the precipitation to the spring flow and spring level three months later was the minimum. The influence became smaller to disappear with the passage of time and the hysteretic time would be longer than 3 months.

Artificial Exploitation Amount

The exploitation amount of groundwater will influence directly to the dynamic change of spring. In history groundwater exploitation in Ji'nan spring groups experienced three stages. In the first stage since 1959 to 1980 the exploitation amount maintained below 310,000 m^3/d while the spring flow can be 100,000-500,000 m^3/d with high spring level between 20 and 30 m. In the second stage since 1981 to 2000 the exploitation amount rapidly increased to 410,000-640,000 m^3/d and the spring flow greatly reduced below 100,000 m^3/d with spring level dropped a lot even to dry up. In the third stage since 2001 to 2010 the exploitation amount decreased to 200,000-290,000 m^3/d by strengthening spring protection and artificial groundwater recharge so the spring level remained at 28 m high.

Lateral Recharge

Ji'nan spring groups is not an independent hydrology geology unit which accepted respectively the lateral recharge from the Changxiao and Baiquan spring groups in north of Changqing and Dongwu fault zone. The recharge amount of every month was 1,510,000 m^3 and the proportion of lateral recharge of the total recharge amount was relative less.

Percolating Recharge of Surface Water

According to the regional hydrogeology survey water is filled for years in the region of below the Yufu River, Beisha River and Balou River then it will percolate to the Ordovician limestone area. The river will dry up after the rainy season while the land surface became dry valley so the proportion of percolating recharge of surface water of the total recharge amount was relative less.

Return Percolation Amount in Irrigation

Agricultural irrigation basically located at the western suburb of agricultural area. The agricultural exploitation amount reached 27,707,520 m^3 every year not including the deep buried area of Yuqinghu reservoir. The recharge can be 4,156,130 m^3/a if the infiltration coefficient is 0.15.

In a word the influence of the precipitation recharge amount and exploitation amount of the groundwater to the groundwater dynamic was most obvious. Percolating recharge of surface water, return percolation for irrigation and lateral recharge both have close relationship to the precipitation while they cannot be considered separately when we used the neural network model or multiple regression analysis as the measured data was incomplete. So we can use 6 variables such as precipitation of current month, last month and last two months to simulate and predict the spring level. The variables can also be the exploitation of current month and last month and the spring level of last month.

SIMULATION AND PREDICTION FOR THE SPRING LEVEL USING THE BP NEURAL NETWORK MODEL

BP Neural Network Model and the Parameter Selection

We calculated with genetic algorithm and BP neural network method by optimizing the BP neural network weight with the genetic algorithm. It is discussed to introduce noise into input terminal and adjust in the weight modifying process to grasp the rules of the samples and stable convergence. The method also avoided the overfitting and oscillating phenomenon in the training process. The genetic algorithm was used to optimize the network's initial weight and the BP method partial accurate research. The initial network weight and threshold can be selected from the interval (-5, 5) at random. The population size can be determined as 20 by trial calculation as the training samples are less. In order to simulate the stable and rapid training process we add momentum term in and take the coefficient as 0.5 and the training rate as 0.01. The self adjustment coefficient can be selected as 0.95 for 4,000 times training rate which means that we must judge if the sum of squares of the sample error increased. If it get larger the training rate should be adjust to the 95% of the current value otherwise the rate should be kept invariant. In order to obtain the ideal results we take the minimum iteration number as 1,000,000 to avoid the overfitting and introduce noise term in. For example if the noise coefficient is 0.1 we should take random numbers between -0.05 and 0.05 as the input noise.

We use the three-layer neural network structure for calculation and the hidden layer activation function use the nonlinear hyperbolic tangent function while output layer use the linear activation function. We input the neurons number as 6 and the monthly average groundwater level as the output layer. The input layer can be precipitation of present month, previous month and first two months also the exploitation of present month and previous month and the spring level of previous month.

Analysis on the Prediction Accuracy

We take the observation sequences from February, 2002 to December, 2006 and January to December in 2008 as the training samples while the sequences from January to December in 2007 as the testing samples. The testing results can be shown in table 1 and the spring level predicted by the BP neural network model differs a little with the measured value. The absolute error located between 0.01 m and 0.59 m in which the error in July and August are biggest. The relative error is between 0.04% and 2.05% if the spring level is calculated from absolute elevation. The size of the relative error cannot be reflected. In order to eliminate the effect produced by the absolute elevation water levels of Baotu spring can be calculated from relative level elevation. As the Baotu spring stop to spewing when the water level is 27.01 m so the water levels can be calculated from relative elevation 27 m as 2.08% to 33.91%. Since the standard of unqualified is greater than 20% we know the predicted value in April, July and August are unqualified.

Table 1: Contrast between the measured and predicted spring level (Neural network model)

Month	Measured spring level(m)	Predicted spring level(m)	Absolute error(m)	Relative error (%) (Water levels of Baotu spring is calculated from absolute elevation）	Relative error (%) (Water levels of Baotu spring is calculated from relative elevation 27m)
2007.1	28.09	28.01	0.08	0.28	7.34
2007.2	27.92	28.05	0.13	0.47	14.13
2007.3	27.64	27.74	0.10	0.36	15.63
2007.4	27.60	27.40	0.20	0.72	33.33
2007.5	27.48	27.49	0.01	0.04	2.08
2007.6	27.37	27.33	0.04	0.15	10.81
2007.7	27.96	27.67	0.29	1.04	30.21
2007.8	28.74	28.15	0.59	2.05	33.91
2007.9	28.72	28.88	0.16	0.56	9.30
2007.10	28.70	28.63	0.07	0.24	4.18
2007.11	28.50	28.56	0.06	0.21	4.00
2007.12	28.36	28.37	0.01	0.04	0.74

MULTIPLE REGRESSION ANALYSIS OF THE *BAOTU* SPRING LEVEL

We take the precipitation of current month, last month and last two months and exploitation amount of current month and last month also the spring level of last month as independent variable and Baotu spring level of this month as dependent variable to set up a prediction model for spring water level with multiple regression analysis.

$$y_i=0.730517+0.004697p_i+0.001262p_{i-1}-0.000613p_{i-2}+0.965929y_{i-1}+0.000724W_{i-1}-0.000916W_i \quad (1)$$

In the formula p_{i-2} stands for the precipitation of the last two months (mm); p_{i-1} stands for the precipitation of the last month (mm); p_i stands for the precipitation of the current months (mm); W_{i-1} stands for exploitation amount of last month (ten thousand m^3); W_i stands for exploitation amount of current month (ten thousand m^3); y_{i-1} stands for average spring level of last month (m). The multiple correlation coefficient of formula (1) is 0.97.

The measured and predicted Baotu spring level of January to December in 2007 can be shown in table 2. The spring level predicted differs a little with the measured value and the absolute error is between 0.05 m and 0.46 m. The biggest error appeared in January and June. The relative error can be calculated from relative elevation 27 m as 4.00% to 118.92% (June). Since the standard of unqualified is greater than 20% we know the predicted values in January and June are unqualified. So the relative error is bigger than the result calculated by the neural network thus the neural network method has better predict accuracy.

Table 2: Contrast between the measured and predicted spring level (Multiple regression analysis)

Month	Measured spring level(m)	Predicted spring level(m)	Absolute error(m)	Relative error (%) (Water levels of Baotu spring is calculated from absolute elevation)	Relative error (%) (Water levels of Baotu spring is calculated from relative elevation 27m)
2007.1	28.09	27.63	0.46	1.64	42.20
2007.2	27.92	27.80	0.12	0.43	13.04
2007.3	27.64	27.71	0.07	0.25	10.94
2007.4	27.60	27.66	0.06	0.22	10.00
2007.5	27.48	27.53	0.05	0.18	10.42
2007.6	27.37	27.81	0.44	1.61	118.92
2007.7	27.96	27.95	0.01	0.04	1.04
2007.8	28.74	28.60	0.14	0.49	8.05
2007.9	28.72	28.96	0.24	0.84	13.95
2007.10	28.70	28.56	0.14	0.49	8.24
2007.11	28.50	28.44	0.06	0.21	4.00
2007.12	28.36	28.22	0.14	0.49	10.29

CONCLUSIONS

(1) We can use 6 variables such as precipitation of current month, last month and last two months also the exploitation of current month and last month and the spring level of last month as the input layer to set up a BP neural network model while the monthly average groundwater level as the output layer. We calculated with genetic algorithm by optimizing the BP neural network weight with the genetic algorithm. It is discussed to introduce noise into input terminal and adjust in the weight modifying process. The network model got fast convergence and oscillating phenomenon can be avoided in the training process.

(2) The spring level predicted by the BP neural network model differs a little with the measured value. The absolute error located between 0.01 m and 0.59 m in which the error in July and August are biggest. The water levels can be calculated from relative elevation 27 m as 2.08% to 33.91%. The neural network method has better predict accuracy. Since the standard of unqualified is greater than 20% we know the predicted value in April, July and August are unqualified.

(3) The spring level predicted by the multiple regression analysis differs a little with the measured value and the absolute error is between 0.05 m and 0.46 m. The biggest error appeared in January and June. The relative error can be calculated from relative elevation 27 m as 4.00% to 118.92% (June).

So the relative error is bigger than the result calculated by the neural network. Since the standard of unqualified is greater than 20% we know the predicted values in January and June are unqualified.

REFERENCES

1. Shu-yan Zheng, Zhan-bin Li, Xi-an Li. Artificial Neural Network Method for Groundwater Level Forecast [J].Northwest Water Resources & Water Engineering, 2002(2):14-16.
2. Quan Ran, Sulin Xiang. Study on Artificial Neural Network Model for Groundwater Level Prediction [J]. Guizhou Chemical Industry, 2006(3):51-52.
3. Wenyi-Gao, Guang-sheng Chen, Mo Lin. Application of grey-BP Neural Network Integration Model for Groundwater Level Prediction in Yanji [J].Water Resources & Hydropower of Northeast China, 2008(7):30-32.
4. Bao-ming Chi, Lan Lin, Yuan-fang Ding. Application of BP Neural Network Model to Groundwater Dynamic Predication Based on Genetic Algorithms [J]. Geotechnical Investigation & Surveying, 2008(9):36-41.
5. Qiang Xu, Long-cang Shu, Gui-lian Yang. Application of Optimized Wavelet Neural Network Based on Genetic Algorithm in Groundwater Level Prediction [J].Journal of China Hydrology, 2010(1):27-30.
6. Zong-zhi Wang, Ju-liang Jin, Zi-sheng Zheng. Improvement of BP Neural Network Method and Application to Groundwater Level Forecast in Ji’nan City [J]. Hydro-Science and Engineering, 2005(4):71-74.
7. Ji'nan Investigation and Evaluation Report of Groundwater Resources. Groundwater Resources Survey [M]. Ji’nan Evaluation Report. 2008.
8. Ye-fei Ji, Jing Zou, Jin Gu. Determination of Precipitation Recharge Lag Time: Application in Spring Flow Simulation and Prediction[J]. Journal of Chinese Hydrology, 2008(12):30-32.
9. Fu-chen Liu,Ai-hua Sun,Wei Zhang. Hysteretic Effect and Spring Flow Forecast Analysis for Ji’nan’s Baotu Spring [J].Electronic Journal of Geotechnical Engineering, 2011(16/C):281-288.