Prediction of Groundwater Level of Ji'nan Baotu Spring Using Grey Model and Elman Neural Network

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Abstract. Springs are the important resources of cultural, sightseeing and natural to Ji’nan, and it is very necessary to monitor, record, analyze and further to predict the groundwater level of Ji’nan springs in time. In this paper prediction model by month using Grey Model and Elman Neural Network were introduced respectively to implement accurate predict the groundwater level of Baotu Spring during the past last 12 months which from October 2013 to September 2014. The research results showed that the two prediction model can both achieve high prediction accuracy of groundwater level of the spring. The prediction accuracy of Grey Model is relatively even higher than that of Elman Neural Network after comparison of the two algorithms.

Keywords: Baotu Spring, groundwater level, prediction, Grey Model, Elman neural network.

1. Introduction

Ji'nan, the capital of Shandong Province and the world's largest city of springs as well, is well-known as the “Spring City” with the reputation of owning a large number of famous springs, especially for the Seventy-two Springs, such as Baotu Spring, Black Tiger Spring, Pearl Spring, etc. It can be said that the springs of Ji’nan are the soul and symbol of the city. However, in the recent decades with the rapid development of economy and society, water consumption of production and living and the greenhouse effect, water resources consumption, waste and pollution have been caused accordingly. Continuous year’s drought climate and water resource shortage lead to the overall decline of groundwater level of Ji'nan constantly, which result in most of Ji'nan springs dry up, many large reservoirs capacity low down sometimes. It is very important to monitor record and even predict the groundwater level of springs timely. Many experts and researchers have made intensive and wide-range relevant studies on Water Saving and Springs Protection and numerous meaningful and significant research achievements and results have been obtained already [1-8].

In this paper according to statistical and analytical work of the historical statistic data of groundwater level of Ji’nan Baotu Spring in the last 12 months, Grey Model (GM1, 1) and Elman Neural Network were proposed respectively to build the month prediction model of groundwater level of the spring, which can realize the accurate prediction of its groundwater level.

2. Methodology

2.1. Grey Model.

Grey Model (GM) is to build the model in the form of differential equations by using discrete random number changed into generating number whose randomness is significantly weakened and regularity is progressively showed [9]. Grey Model to predict has many types including GM (1, 1), GM (2, 1), DGM, etc. According to the analyzed question, here GM (1, 1) was introduced to build prediction model which represents first order differential equations and only contains one variable.

2.2 Elman Neural Network.

Elman neural network is very suitable for processing time series problem, so it is often used in prediction of one dimensional or multidimensional signal, and key applications on climate change, economic operating data and electrical equipment parameters, etc, all have satisfactory results [10].

All the algorithms mentioned above were programmed elaborately by using software MATLAB (Math works, USA, Version 2012a), and among these two approaches Elman neural network was built by calling the function of newelm or elmannet in MATLAB NNTOOL platform.

3. Results and Discussion

Historical statistical data of groundwater level of Baotu Spring in the last 12 months [11], i.e. from October 2013 to September 2014 [11], are shown in Figure 1.

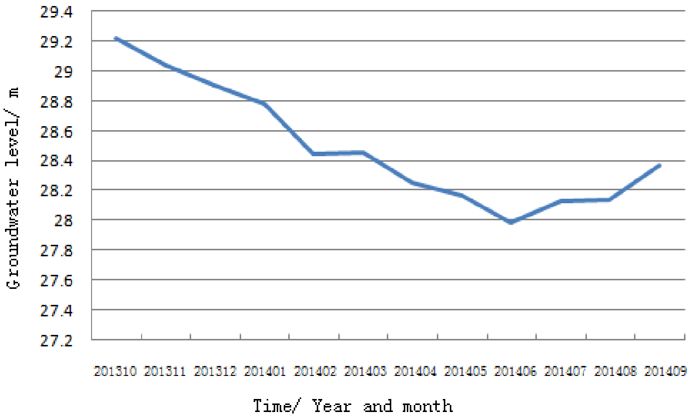

Fig. 1 Chart of groundwater level of Baotu Spring in the last 12 months

From Figure 1 it is obviously can be seen that the groundwater level of Baotu Spring is declined on the whole during the last 12 months. Therefore, in situation of Water Saving and Spring Protection is not so optimistic that it is imperative to pay close attention to the trend changes of groundwater level of the spring and to have the ability to accurate predict them in time.

3.1. Prediction Using Grey Model.

Modeling procedures of prediction using GM (1, 1) are given as follows:

(a) Data checking and preprocessing. The acquired raw data series is need to check for modeling reliability. Presume that the raw series is: $x^{(0)}=(x^{(0)}(1), x^{(0)}(2), \ldots \ldots, x^{(0)}(n))$, and if all the class ratio $\lambda(k)$ fall into the holding interval $\Theta=(e^{-\frac{2}{n+1}}, e^{-\frac{2}{n+1}})$, then raw data series $x^{(0)}$ could serve as GM (1,1) model data to predict. Here n is 12, so the interval of class ratio $\sigma(0)$ (k) must belong to [0.8574, 1.1536];

Calculated results of class ratio are 1.0064, 1.0044, 1.0043, 1.0120, 0.9994, 1.0071, 1.0031, 1.0066, 0.9949, 0.9997 and 0.9918, it is obviously that the interval of $\sigma(0)$ (k) meet the condition of class ratio λ (k);

(b) Model prediction using GM (1, 1). Build GM (1, 1) model follow the steps and method in reference [9], first change raw data series $x^{(1)}$ to series $x^{(1)}$ by Accumulated Generating Operation (AGO), then establish whitenization first-order linear differential equation or its discreet form about $x^{(1)}(k)$. The white differential equation can be given in equation (1):

$$\frac{dx^{(1)}}{dt}e^{-ak}+ax^{(1)}=b \tag{1}$$

In the equation (1) above a is developing coefficient and b is grey action quantity, solve the equation about $x^{(1)}(t)$ and white response of Equation (1) could be obtained according to equation (2):

$$x^{\wedge(1)}(k+1)=(x^{(0)}(1)-\frac{b}{a})e^{-ak}+\frac{b}{a}, k=0,1,\ldots\ldots,n-1 \tag{2}$$

The undetermined coefficients of Equation (2) are a=0.0031, b=28.9982, and so the response is $x^{\wedge(1)}(k+1)$=9464.45-9435.23*e$^{-0.00306391t}$;

(c) Model checking (Check residual errors and difference of class ratio). The recuperating values of raw data series are obtained according to the following formula:

$$x^{\wedge(0)}(k+1) = (x^{\wedge(0)}(k+1) - x^{\wedge(0)}(k), k = 0, 1, ..., n-1 \quad (3)$$

Here $x^{(i)}(k)$ is actual value and $x^{\wedge(i)}(k)$ is model prediction value.

Residual error and difference of class ratio are given as following:

$$\delta^{(i)}(k) = \frac{x^{(i)}(k) - x^{\wedge(i)}(k)}{x^{(i)}(k)} 100\%, k = 0, 1, ..., n-1 \quad (4)$$

The running results of prediction model using GM (1, 1) are shown in Table 1.

Table1 Results of prediction model using GM (1, 1)

Serial number	Year and month	Actual value	Prediction value	Residual error	Relative error	Difference of class ratio
1	201310	29.2200	29.2200	0	0	—
2	201311	29.0347	28.8644	0.1703	0.0059	-0.0033
3	201312	28.9074	28.7761	0.1313	0.0045	-0.0013
4	201401	28.7848	28.6881	0.0967	0.0034	-0.0012
5	201402	28.4429	28.6003	-0.1575	0.0055	-0.0089
6	201403	28.4600	28.5128	-0.0528	0.0019	0.0037
7	201404	28.2603	28.4256	-0.1653	0.0058	-0.0040
8	201405	28.1732	28.3387	-0.1654	0.0059	0
9	201406	27.9887	28.2520	-0.2633	0.0094	-0.0035
10	201407	28.1323	28.1655	-0.0333	0.0012	0.0081
11	201408	28.1407	28.0794	0.0613	0.0022	0.0034
12	201409	28.3720	27.9930	0.3785	0.0133	0.0112

From Table 1 it is clearly can be seen that prediction accuracy can reach very high level, there are rather small residual error between actual values and prediction ones and its relative error is far less than 0.01 in most cases. Meanwhile, difference of class ratio is much small and its value is as well below 0.01 in general. It can be concluded that model constructed by Grey Model is very reliable.

3.2. Prediction Using Elman Neural Network.

It should takes one part of samples as train data set before using the other part as test data set to predict when using Elman Neural Network.

Modeling procedures of prediction using Elman Neural Network are briefly described as follows:

(a) Data normalization after loading the data matrix which need to process;

(b) Create Elman network utilizing train data set after setting some key parameters, such as iteration steps, training function and so on;

(c) Initialize and train Elman network;

(d) Predict the time series with test data set by using the created network.

In this work the main setting parameters of Elman are set as follows, transfer function select 'tansig' one for hidden layers, and 'purelin' for output layer and iteration steps are 500. Choose the first half series data as train set and the second half series data as test one, and meanwhile take every continuous 2 month data as input and view the third one as expectation output. Because there are somewhat small difference of running results after every program executing, so take one running results of prediction model using Elman Neural Network as an example, see Table 2.

Table 2 Results of prediction model using Elman

Serial number	Year and month	Actual value	Prediction value	Residual error	MSE of test set
1	201406	27.9887	28.3275	-0.3770	0.0590
2	201407	28.1323	28.4153	-0.2830	
3	201408	28.1407	28.2418	-0.1011	
4	201409	28.3720	28.3127	0.0593	

From Table 2 it is easily can be seen that prediction accuracy of Elman Neural Network is relatively much high and residual error between actual value and prediction one and MSE of test set are both rather small.

3.3. Models Comparison.

Although the two prediction algorithms can both implement high accurately predict, there are some differences between them after carefully comparison. For model built by Grey Model it can get more precise and more complete prediction data. While, with regard to the model constructed by Elman network its accuracy prediction is relatively lower and it only realize to predict a part of the whole raw time series data due to the division of the whole data into 2 parts and continuous moving forecast by the former ones when its training and testing.

4. Conclusions

Both the two prediction methods, Grey Model and Elman Neural Network, can reach the goal of high accuracy prediction of groundwater level of Baotu Spring by month, and their speed of program implementation are very fast. Compared with Elman network model, Grey Model could obtain further higher prediction accuracy and can get more comprehensive prediction data.

Acknowledgements

This work is financially supported by Basic Scientific Research Special Funds for the Central Universities of China (No. KYZ200921) and Open Project of Jiangsu Key Laboratory of Large Engineering Equipment Detection and Control (Project No. JSKLEDC201204).

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