Prediction of Ground Water Level Based on DE-BP Neutral Network

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Abstract—**The continuous decline of ground water one of the important factors that affect developn national economy and society. Based on the DE-BP Propagation-Differential Evolution) neutral networ predicting model of ground water level is presente precision of the model is checked using the monitorii in Zhangjiakou area. The comparisons betwe predicted results of the three models (BP model, model and DE-BP model) and the monitoring data sh the precision of the present algorithm is high w maximum relative error being 0.17%.**

Keywords-ground water level; DE-BP neutral n prediction

I. INTRODUCTION

Groundwater is important water source for the economic and social development, but the exhaustive exploitation of groundwater contributed to several environ-geological problems, such as ground subsidence, ground crack etc, which affected development of human society seriously. Therefore, the research on ground water level monitoring is important to practical application.

A number of researches have been carried out on the prediction of ground water level. Decrease of ground water level is reduced to some factors such as rainfall, evaporation, exploitation. It often shows complex nonlinear characteristic, which tends to be described nonlinear model. Parameter identification of nonlinear model is a focus these days. Existing models include determinate and stochastic (regression model, time series analysis model, gray system model GM (1, 1), etc.)[1-3], that have some shortcomings. Reference [4] used artificial neural network [5] to study the dynamic prediction of groundwater and made certain progress.

At present, BP neural network is increasingly used to predict ground water level. BP neural network has many advantages, such as approximating optimal solutions, high predicting precision and so on [6]. However, it also has many disadvantages [7]. In order to overcome its shortcomings, this paper combines with DE (differential evolution) algorithm, puts forwards the prediction model based on DE-BP neural network, and checks the predicting precision using monitoring data.

II. PREDICTION MODEL OF DE-BP NEURAL NETWORK

A. BP Neural Network Model

The prediction model includes three parts: input layer, hidden layer and output layer, as shown in Fig.1:

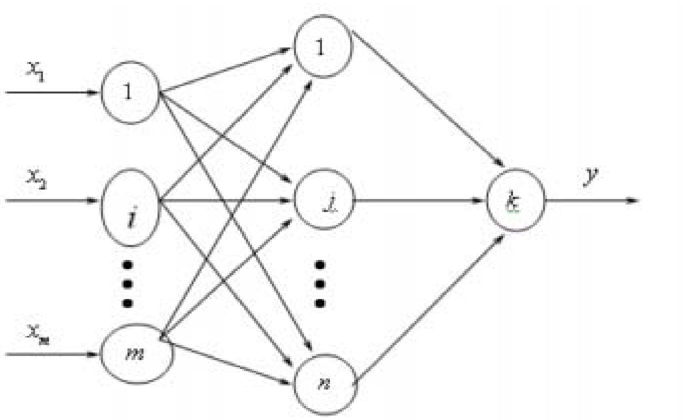

Figure 1. BP neutral network diagram of three-layered structure.

The nodes of input layer, hidden layer and output layer are $m, n, 1$. the weight and threshold of the model generate matrices and vectors:

1) *weight matrix* W *:*

$$W = \begin{bmatrix} \omega_{1,1} & \omega_{1,2} & \cdots & \omega_{1,n} \\ \omega_{2,1} & \omega_{2,2} & \cdots & \omega_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ \omega_{m,1} & \omega_{m,2} & \cdots & \omega_{m,n} \end{bmatrix} \tag{1}$$

2) *threshold matrix* T *:*

$$T = \begin{bmatrix} t_1 \\ t_2 \\ \vdots \\ t_n \end{bmatrix} \tag{2}$$

3) *weight vector* V *:*

$$V = [\upsilon_{1,k}, \upsilon_{2,k} \cdots \upsilon_{n,k}] \tag{3}$$

4) *threshold vector* S *:*

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$$S = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{bmatrix} \tag{4}$$

B. DE Algorithm

The operation process of DE algorithm includes species initialization, mutation, crossover, fitness function and selection. Concrete algorithms are as follows:

1) Species initialization: Mapping W, V, T and S into chromosome of DE yields:

$$\{\omega_{1,1}\ \omega_{1,2} \cdots \omega_{m,n}\ \upsilon_{1,k}\ \upsilon_{2,k} \cdots \upsilon_{n,k}\ t_1\ t_2 \cdots t_n\ s\} \tag{5}$$

$R_i(t)$ =chromosome i belongs to the generation of t.

$R_i(t) = (r_{i1}(t), r_{i2}(t), \cdots, r_{il}(t))$ $\quad i = 1, 2, \cdots, M$; $t = 1, 2, \cdots, t_{\max}$.

Where $t_{\max}$ =maximal evolutional generation;

l = chromosome length;

M = population size.

2) Mutation operation: The main idea of mutation operation is using the vector difference of individual.If there is an current individual $R_i(t)$ .Three chromosomes ($R_{p1}(t), R_{p2}(t), R_{p3}(t)$, $i \neq p_1 \neq p_2 \neq p_3$) are selected randomly from $R_i(t)$. Let $R_{p_2}(t) - R_{p_3}(t)$, then scaling, yields:

$$u_{ij}(t+1) = r_{p_1 j}(t) + \eta\left(r_{p_2 j}(t) - r_{p_3 j}(t)\right) \tag{6}$$

Where η = zoom factor.

3) Crossover operation: $c_i(t+1)$ is yielded by the cross in the form of the discrete between the current individual and the variation individual . The component of j is expressed as follows:

$$c_{ij}(t+1) = \begin{cases} u_{ij}(t+1), rand_{ij}(0,1) \le CR \quad or \quad \mathrm{j}{=}rand(i) \\ x(t), rand_{ij}(0,1) > CR \quad or \quad \mathrm{j} \neq rand(i) \end{cases} \tag{7}$$

Where $rand_{ij}(0,1)$ = Random number in $[0,1]$;

CR =Crossover probability, $CR \in [0,1]$;

$rand(i)$ = Random integer in $[1, l]$.

4) Fitness function: The form of fitness evaluation is as follows:

$$f(R_i(t)) = 1/E = P \Big/ \sum_{i=1}^{P} \sum_{j=1}^{m} \left(\hat{y}_j^i - y_j^i\right)^2 \tag{8}$$

Where P = Training samples;

m = Number of nodes in input layer;

$\hat{y}_j$ = Actual output of node j ;

y_j = Ideal output of node j .

5) Selection operation: Comparing $c_i(t+1)$ with $R_i(t)$, the optimal selection result is as follows:

$$R_i(t+1) = \begin{cases} R_i(t) \ \ if \ \ f(R_i(t) > f(c_i(t+i))) \\ c_{i(t+1)} \ \ if \ \ f(R_i(t) \le f(c_i(t+i))) \end{cases} \tag{9}$$

2）—5）is repeated until $t_{\max}$.

C. DE-BP Prediction Neural Network

The combination of DE algorithm and BP neural network is used for the process of prediction. The operation of DE ensures the searching operation is done in the whole solution space and the solution is independent of the initial values. The operation of BP neural network ensures the precision of network weights. The process is shown in Fig. 2.

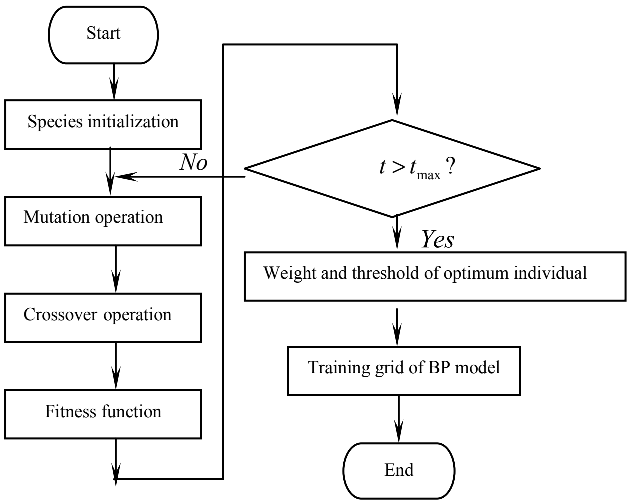

Figure 2. Schematics of DE-BP neutral network process

III. PPLICATIONS

Groundwater system is intricate. The components of system form an organic whole [8]. There are many natural factors and artificial factors, which affect groundwater level such as climate, soil, landform, hydrologic condition, natural disasters, artificial recharge and exploitation and so on.

According to previous study, the variety of groundwater level is mostly influenced by human activities (exploitation) and rainfall capacity in Zhangjiakou. The

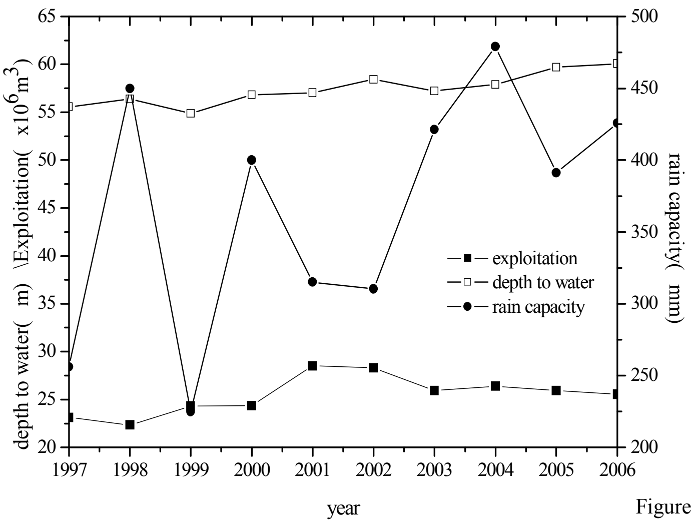

Figure 3. Annual tendency change of groundwater level exploitation rainfall

correlation between these factors is nonlinear, and artificial neural network has the ability to solve this problem.Therefore, the BP model is used in this study, which composes of 2 cells of import layer (the exploitation and rainfall capacity), and 1 cell export layer(groundwater level).The paper collected and arranged the local monitoring results of the exploitation and rainfall capacity (1997-2006),as shown in Fig.3.

It can be seen from Fig. 3 that depth to water had increased year by year. There are rather apparent positive correlations between groundwater level and the former year. So in this paper about 70 percent of all cases (up to 432 cases) were selected randomly to form training samples (the data of 1997-2002) and forecast sample (the data of 2003-2006), on which DE-BP neural network were built. Then, comparing of monitoring results and predictive values of BP, GA-BP and DE-BP for depth to water of Huafeichang and Zuowei in 2003-2006 are shown in Fig. 4 and Fig. 5. The relative errors of the predicted results using the models of BP, GA-BP, DE-BP are listed in Tab.1.

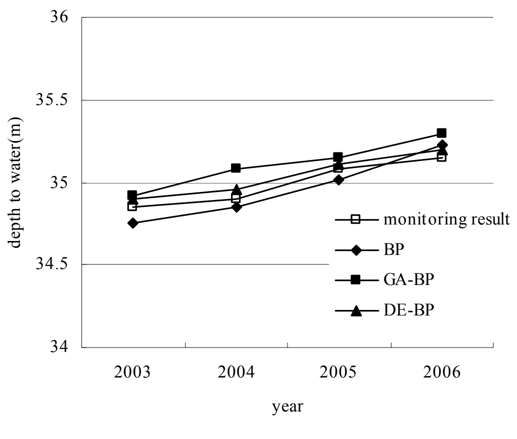

Figure 4. Comparison of monitoring results and predictive results of Huafeichang

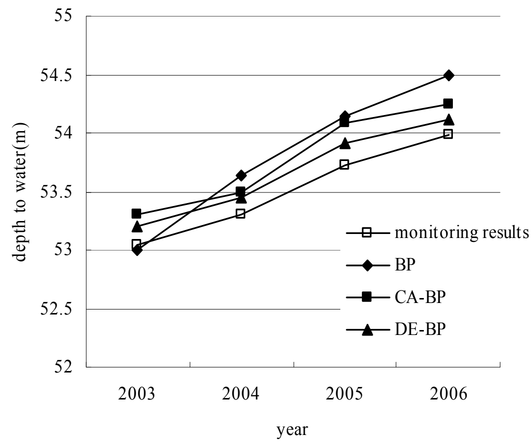

Figure 5. Comparison of monitoring results and predictive results of Zuowei

Comparison of monitoring results and predictive results of the depth to water of Huafeichang is shown in Fig. 4, the result shows that the predictive results by BP model and GA-BP model clearly deviation from monitoring results, and the predictive results by DE-BP model is most close to monitoring results, and the maximum relative error of 0.17%; Comparison of monitoring results and predictive results of the depth to water of Zuowei is shown in Fig. 5. According to the above result, relative error is 0.35%. From the Tab.1, the average maximum relative difference between the monitoring results and predictive results by BP model, GA-BP model and DE-BP model respectively is 0.415%, 0.365%, 0.165%.So the model of DE-BP neutral network can simulate the groundwater system, and the groundwater level can be predicted by the model reasonably good.

IV. CCONCLUSIONS

Based on analyzing the influencing factors of ground water level, a predicting method of ground water level based on DE-BP neural network is put forward. The predicting model can teach itself and adjust the efficiency of study automatically in the process of samples training. The performance does not depend on what people already know. The experimental results show that the predicting model has high precision. It is able to describe complicated system of ground water, and reveals nonlinear characteristics of ground water movement. In addition, according to the results, if water resources is still overexploited, the level will get lower. So strictly controling on exploitation must be imposed and effective measures shall be taken to protect groundwater resources and control land subsidence.

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TABLE I. RELATIVE ERRORS OF PREDICTION(%)

place / time	Huafeichang			Zuowei		
	BP	GA-BP	DE-BP	BP	GA-BP	DE-BP
2003	-0.29	0.18	0.14	-0.74	0.49	0.32
2004	-0.14	0.30	0.17	0.62	0.36	0.26
2005	-0.2	0.20	0.08	0.8	0.67	0.35
2006	0.23	0.22	0.14	0.96	0.50	0.24
average	0.21	0.23	0.14	0.62	0.50	0.29

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