TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.4, April 2014, pp. 2882 ~ 2889
DOI: http://dx.doi.org/10.11591/telkomnika.v12i4.4815

A Neural Network based Intelligent Method for Mine Slope Surface Deformation Prediction Considering the Meteorological Factors

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Abstract

Accurate mine slope surface deformation forecasting can provide reliable guidance for safe mining production and mine construction planning, which is also important for the personnel safety of the mining staffs. The mine slope surface deformation forecasting is a non-linear problem. Generalized regression neural network (GRNN) has been proven to be effective in dealing with the non-linear problems, but it is still a challenge of how to determine the appropriate spread parameter in using the GRNN for deformation forecasting. In this paper, a mine slope surface deformation forecasting model combining artificial bee colony optimization algorithm (ABC) and generalized regression neural network was proposed to solve this problem. The effectiveness of this proposed forecasting model was proved by experiment comparisons. The test results show that the proposed intelligent forecasting model outperforms the BP neural network forecasting model, BP neural network with genetic algorithm optimization (GA-BPNN) and the ordinary linear regression (LR) forecasting models in the mine slope surface deformation forecasting.

***Keywords**: slope deformation prediction, generalized regression neural network, artificial bee colony algorithm, optimization problem, parameter selection.*

1. Introduction

Mine slope surface deformation forecasting is an important part of management modernization of digital mine deformation monitoring systems, which has attracted more and more attentions from the academic and the practice. Mine slope surface deformation forecasting is of crucial importance to the safe mining production, the property of the mines and the safety of miners [1]. Accurate forecasting of mine disasters could ensure the safety of mine workers and improve the mine safety level. Therefore, accurate mine slope surface deformation forecasting with artificial intelligence method which is quite important for maintaining secure and stable production of digital mine deformation monitoring systems is needed. However, because mine slope surface deformation has complex and non-linear relationships with several factors such as terrain factor, geological factor, human engineering activities and meteorological factor. It is quite difficulty for forecasting deformation accurately [2].

Artificial neural network (ANN) [3] is a kind of intelligent computing technology which simulates biological neural network. It has the characteristics of self-learning, self-organizing, nonlinear dynamic process and high fault tolerance [4]. The significant advantage of ANN is that it possesses associative inference and adaptive capacity, and particularly it can be applied to processing various kinds of nonlinear problems. Studies show that GRNN has better function approximation performance than feed forward networks and other statistical neural networks on some datasets. Because of the strong non-linear mapping capability, the simplicity of network structure and high fault tolerance and robustness, the GRNN can effectively solve the non-linear problems, and it has been widely applied to a variety of fields including short-term load forecasting [5], medicinal chemistry [6], exchange rates forecasting [7], sales forecasting [8], wind speed forecasting [9], pattern recognition [10] and so on. However, it is very regretfully finds that the GRNN have rarely been applied to the mine slope surface deformation

Received September 11, 2013; Revised October 18, 2013; Accepted November 22, 2013

forecasting. This paper elucidates the feasibility of using the GRNN to forecast mine high-steep slope surface deformation.

The GRNN uses the radial basis function of nonlinear regression method based on the non-parametric estmation to train the neural network. However, due to the inherent defects of this method, the neural networks are prone to fall into local minimum. This disadvantage restricted the applications of the GRNN. Artificial bee colony algorithm (ABC) is a swarm intelligence-based optimization algorithm proposed by Karaboga [11] in 2005 for real-parameter optimization, which simulates the foraging behavior of a bee colony. This paper attempted to use the ABC to automatically select the spread parameter value of the GRNN for improving the forecasting accuracy of GRNN in the mine slope deformation forecasting.

In order to forecast the deformation of mine slopes in a practical manner, this work presents a new approach by the use of meteorological factors. The nonlinear mapping relationship between slope deformation and its meteorological influencing factors is established through a GRNN predictor. In addition, the ABC is applied to optimizing the GRNN to enhance the forecasting performance. Experimental tests have been carried out to evaluate and validate the newly proposed method for mine slope deformation forecasting.

2. The Proposed Algorithm

2.1. Generalized Regression Neural Network and Its Optimization

The generalized regression neural network (GRNN) uses the radial basis function (RBF). The core technique of the RBF is called kernel regression. Because of the following characteristics such as stronger approximation ability, faster learning speed and convergence velocity to the optimal regression surface, the GRNN has more remarkable superiorities than any other neural networks [12]. Even in the situation of the small sample data, the GRNN still has good forecasting performance.

The n-dimensional input vector of the GRNN is $X = [x_1, x_2, ..., x_n]^T$, the predicted value of the GRNN model is $Y = [y_1, y_2, ..., y_n]^T$, the joint probability density function of *X* and *Y* is $f(Y, X)$ and the expected value of the output Y is $E[Y/X]$. Thus, the GRNN model can be represented as:

$$E[Y/X] = \frac{\int_{-\infty}^{\infty} Yf(Y,X)dX}{\int_{-\infty}^{\infty} f(Y,X)dX} \tag{1}$$

The input layer, pattern layer, summation layer, and output layer constitutes the main structure of the GRNN as shown in Figure 1. The function of the input layer is receiving information and storing an input vector. After the process of input neurons feed the data of input layer to the pattern layer, the pattern layer possesses a non-linear transformation from the input space to the pattern space. The relationship between the input neuron and the proper response of pattern layer is memorized by the neurons in the pattern layer. At this process, the number of neurons in the input layer equals to the dimension of input vector and the number of neurons in the pattern layer equals to the number of input variables.

In the pattern layer, The *X* represents the input variable of the network, *s* represents the smoothing parameter, the X_i represents a training vector of the neuron *i* and the pattern function P_i is expressed as:

$$P_i = \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \quad (i = 1, 2, \cdots, n) \tag{2}$$

The S_s and S_w are two summations in the summation layer. S_s denotes the simple summation which calculates the arithmetic sum of the pattern layer outputs. S_w denotes the weighted summation which calculates the weighted sum of the pattern layer outputs. W_i denotes the weight of pattern neuron connected to the summation layer. The transfer functions S_s and S_w can be represented as Equation (3) and (4) , respectively:

$$S_s = \sum_{i=1} p_i \tag{3}$$

$$S_w = \sum_{i=1} w_i p_i \tag{4}$$

Through the input layer, pattern layer and summation layer, the data is fed into the output layer, and the output Y of the GRNN model can be calculated as follows:

$$Y = S_s / S_w \tag{5}$$

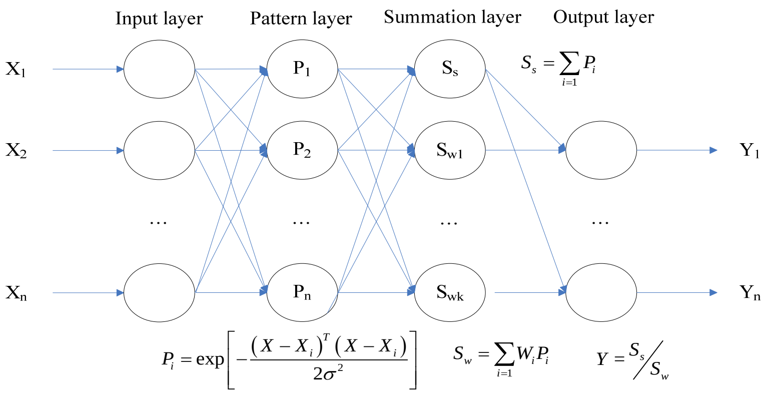

Figure 1. Schematic Diagram of the GRNN Architecture

The spread is the only one parameter of the GRNN model which needs to be determined. The important spread parameter for using GRNN for forecasting determines the generalization capability of the GRNN. The selection of the spread parameter is through the traditional method by priori knowledge or individual experience. They are not efficient for the forecasting program. Thus, an automatically efficiently method for selecting the appropriate spread parameter in the GRNN model is needed. In this experiment, it uses the artificial bee colony algorithm (ABC) to determine the spread parameter value of the GRNN model automatically.

Artificial bee colony algorithm (ABC) is a kind of new interactive evolutionary computation swarm intelligence method, which was proposed by Karaboga. The ABC is a new method for finding global optimization based on the honey finding behavior of the honeybee. The honeybee is superior to other species in vision and osphresis. The ABC-GRNN is an optimization algorithm combining the ABC with the GRNN. The radial basis function of nonlinear regression learning mechanism based on the non-parametric estmation often suffers from the local minimum. To overcome this shortcoming, the ABC is used to search the global optimal value to optimize the GRNN quickly. The detail of the theory of ABC can be referred to [13]. In this paper, the spread value of the GRNN is optimized by ABC. Figure 2. illustrates the solution procedure of the ABC optimized GRNN method for deformation forecasting of mine slope. According to the nectar finding characteristics of bee colony, the ABC can be divided into several steps:

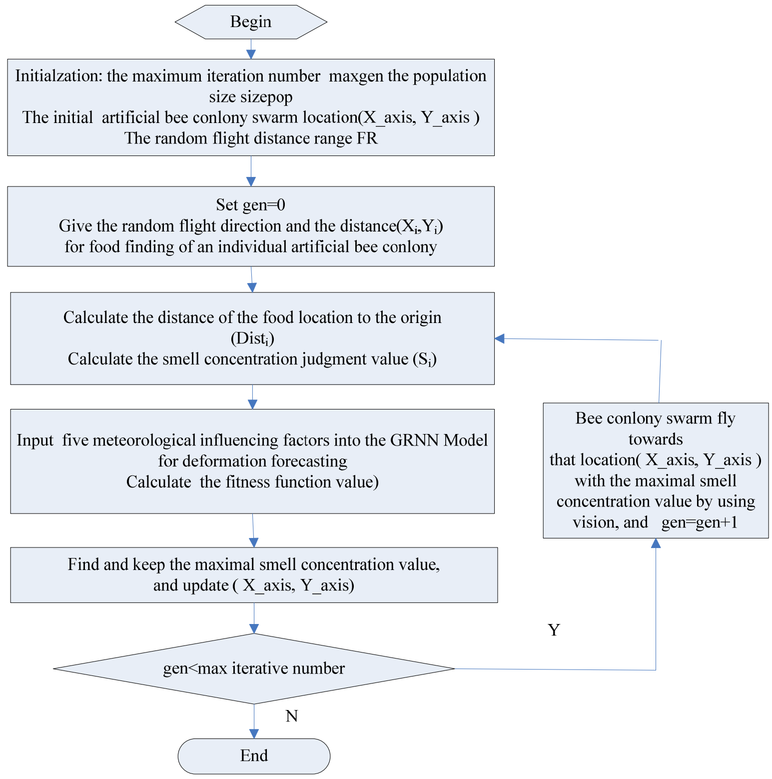

Figure 2. The Flow Chart of ABC Optimized GR NN Method

2.2. The Proposed Forecasting Approach

In this experiment, the proposed ABC-GR NN method uses the meteorological data to predict the deformation of the mine slope surface. The inputs of the GR NN are collected meteorological data such as the temperature, atmospheric pressure, cumulative rainfall, relative humidity and refractive index of the mining slope surface. The east coordinates, north coordinates and elevation coordinates of the monitored positions are as the output variables of the GR NN. Figure 3. illustrates the solution procedure of the ABC optimized GRNN method for deformation forecasting of mine slope.

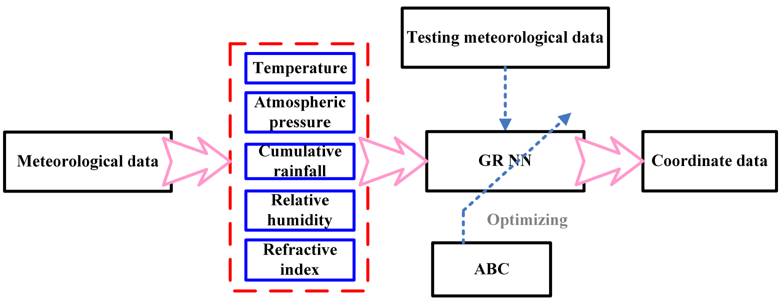

Figure 3. The Diagram of the Intelligent Forecasting Method

3. Research Method

3.1. Influence Mechanism of the Meteorological Factors

The meteorological factors, such as the rainfall and the temperature, etc., can provide significant evident to the deformation condition of the mine slopes. The surface runoff has the main erosion effect on the mine slope surface. The infiltration action along the slop top and surface decreases the soil cohesive force. The infiltration action along the slop fracture supplies the water level of the ground water. The seepage flow into the soil mass and the seepage flow inside the soil mass soften the soil mass. As a result, the rainfall could induce the slope landslide. Figure 4. shows the influence process of the rainfall action on the slope landside. As a result, the rainfall could induce the slope landslide.

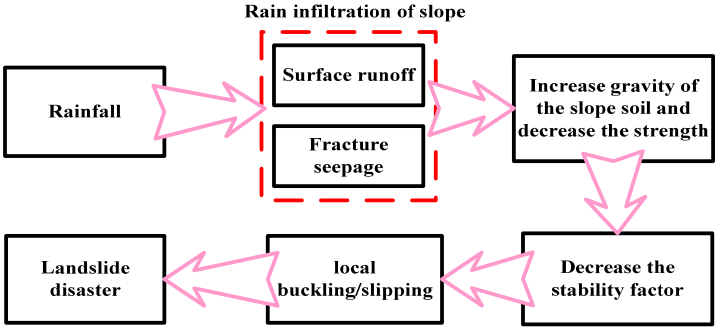

Figure 4. Influence Process of the Rainfall on the Slope Stability

Besides these two indicators, some other meteorological factors also have strong influence or/and connection to the deformation condition of mine slopes, such as the, atmospheric pressure, relative humidity and refractive index. All of them will be adopted to predict the deformation condition of mine slopes in this work.

3.2. Experimental Setup and Tests

The continuous experiment test has been carried out during 23th July to 29th July 2012. The mine slope of the China Coal Pingshuo group co., Ltd in North China was selected as the experiment test area. In the experiments, the meteorological factors data as well as the deformation data have been collected using a Image By SSR radar. The recorded meteorological factors contain the cumulative rainfall, relative humidity, atmospheric pressure, temperature and refractive index of the mining slope surface. The recorded deformation data includes the east coordinates, north coordinates and elevation coordinates of the monitoring probable deformation points. Then the collected data is used to establish a generalized regression neural network to forecast the deformation data of the mine slope surface.

Figure 5. The Topography of the Monitoring Area in the Experiments

Figure 5 shows the topography of the experimental strip mine. The monitoring mining area has several mining platform. The SSR-XT was installed at the platform of the southern part of the strip mine and was responsible for monitoring the northern part of the strip mine. The distance between the SSR radar to the monitoring area was 2km, which was a suitable range for the SSR radar.

The Weather Transmitter (WXT510) is the main actutor in the SSR-XT to collect the meteorological data. Figure 6 shows the WXT510. WXT510 consists of 3 wind transducers, a precipitation sensor, a pressure sensor and a humidity and temperature sensor; hence, it can measure six weather parameters, including the wind speed and direction, precipitation, atmospheric pressure, temperature and relative humidity. Herein, the precipitation sensor detects the impact of individual raindrops; then the volume of the drops is approximated to be proportional to the impact value to calculate the accumulated rainfall.

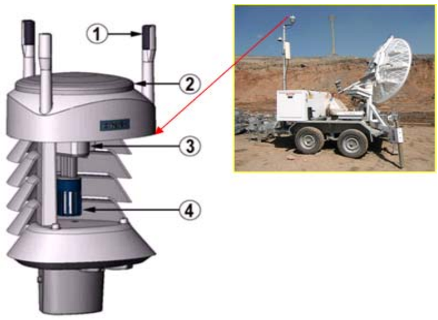

Figure 6. The Cut Away View of the WXT510: (1) the wind transducers, (2) the precipitation sensor, (3) the pressure sensor, and (4) the humidity and temperature sensor

The sensor unit of the SSR radar adopts real aperture radar technology to monitor the slope deformation continuously and obtain real-time coordinates deformation data. The collected coordinate data contains east coordinates, north coordinates and elevation coordinates of the monitored positions.

4. Results and Analysis

As mentioned above, the ABC optimized GR NN approach is proposed for the deformation forecast of the mine slope. The GR NN is capable for simulating the variation tendency of the mine slope deformation and dealing with the nonlinear mapping problem. The ABC seeks to improve the optimization ability of the GR NN by optimizing its spread parameter.

Figure 7. shows the performance comparisons of the prediction for the east coordinate among the fowling methods, MLR, BPNN, GA-BPNN, ABC-GRNN. It can be seen in the figure that the prediction precision of the ABC-GRNN is higher than that of others. The prediction error of the ABC-GRNN is much smaller than that of using other methods in the whole process. These comparisons indicate that taking the advantages of the ABC optimization, the GRNN could be trained well with high genelization ability and hence the forecasting performance is superior to the other methods.

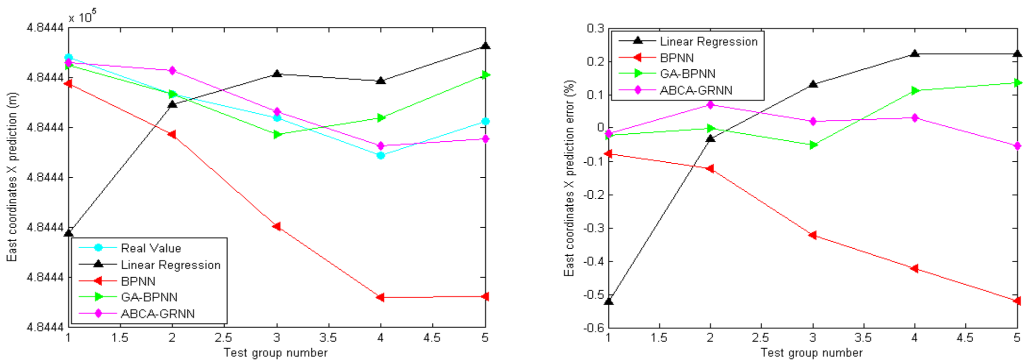

Figure 7. (left) The prediction data of MLR, BPNN, GA-BPNN, ABC-GRNN and Real Value, (right) The prediction error data of MLR, BPNN, GA-BPNN, ABC-GRNN

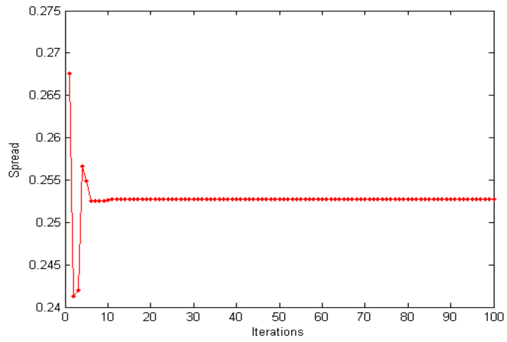

Figure 8. The Changing Process of the Node Density of GRNN

Figure 8. shows the process of the variation of the node density of GRNN. The experiment sets up the total number of the iteration times is 100. From Figure 8., it can be seen that the final spread value is about 0.2525 after about 7 steps iterations. The spread value is the only parameter need to be regulated for the GRNN. That is the advantage of using the GRNN to forecast the mine slope surface deformation.

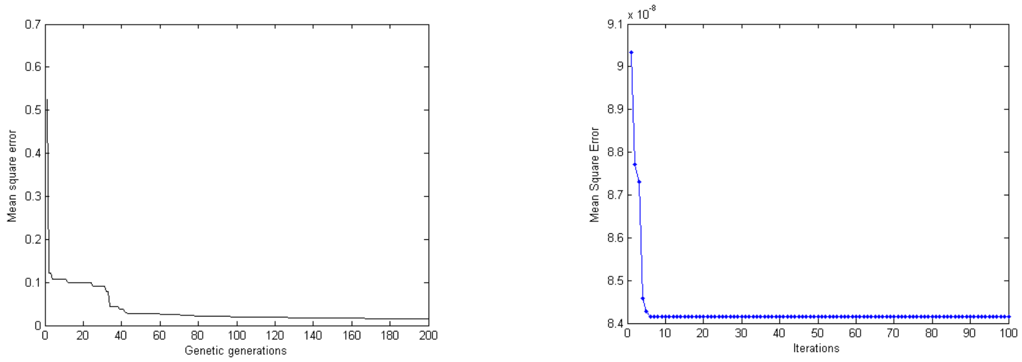

Figure 9. (Left) The convergence curve of the GA optimization, and (Right) The changing process of Mean Square Error of ABC-GR NN comparing with the Real value

Figure 9 (left) shows the convergence curve of the GA optimization. Figure 9 (right) shows the changing process of mean square error of GRNN comparing with the real value. It can be seen in the figure that the mean square error value of GRNN is very small in the process of the entire 100 iterations. After about 7 steps iterations, the ABC algorithm gains the lowest mean square error while the GA algorith needs 40 steps. It's known that the faster the lowest mean square error of the algorithm gains, the stronger the convergence ability of the algorithm has. Hence the ABC-GRNN can help the neural network increase the convergence speed. From Figure 7-9 it can be seen that the ABC optimization not only increases the convergence speed of the GRNN in the training process but also the genelization ability. Thus the ABC-GRNN could provide satisfactory performance in the prediction of the mine slope deformation.

5. Conclusion

In this work, our purpose was to compare the effectiveness of the proposed forecasting method ABC-GRNN with those of other well-known intelligent forecasting methods such as MLR, BPNN, GA-BPNN in the experimental investigation. The analysis results on experimental data demonstrate that, ABC-GRNN forecasting method has the most accurate predicting outcomes and the least mean square error. The ABC-GRNN is the best choice of forecasting the mine slope deformation and it is feasible and efficient for the forecast of the mine slope deformation. The proposed forecast approach in this work may provide practical utilities for mine slope deformation forecasting.

Acknowledgements

This project is sponsored by the grants from the National High Technology Research ,Development Program of China and Natural Science Foundation of China (863 Program) (No. 2013AA122301) (No.41371373).

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