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Prediction and application of mine roadway surrounding rock deformation based on AdaBoost-GA-ELM-model

Aiming at the shortcomings of one-sole-model with low accuracy and instability in the deformation prediction for mine roadway surrounding rock, this article comes up with an AdaBoost-GA-ELM model, which combines the ideas of AdaBoost algorithm, genetic algorithm and extreme learning machine, is proposed. The verification of engineering example about trough roof and floor section, I01091004 working surface, Tun-Bao coal mine shows that the AdaBoost-GA-ELM model has almost equal shares in the area of mine roadway surrounding rock deformation, which can bring gratifying prediction results, compared to GA-ELM, GA-BP and gray model, the prediction accuracy of which has a better effect, containing certain value for engineering application.

Keywords: *Mine roadway engineer; surrounding rock deformation; ELM; genetic algorithm; AdaBoost algorithm.*

1. Introduction

The mechanism of mine roadway surrounding rock deformation is supper complicated and there are enormous factors that could cast effects on it. As the deformation time series data of mine roadway surrounding rock under various internal and external factors, which is of great significance to study the stability of surrounding rock of mine roadway. Put the mine roadway surrounding rock deformation data as a time series, form a corresponding model to match which, so as to make it possible to predict the future development trend of mine roadway surrounding rocks[1-2]. In the perspective of disaster prevention and reduction, it is feasible to get the result of the development trend of mine roadway surrounding rocks through the establishment of the corresponding prediction model, and corresponding measures can be taken according to the staid result results, which is helpful to reduce the losses caused by the possible disasters.

In general, these researches on the deformation characteristics of surrounding rock of coal tunnel mainly focus on two aspects. On the one hand, physical deformation is measured by means of physico-chemical method, which provides reference and basis for design and construction [3-5]; on the other hand, some reasonable support and reinforcement are provided by intelligent calculation and forecasting. In the fields of intelligent calculation and numerical simulation, some scholars calculate the deformation prediction through the gray system [6-7]. Some scholars use the neural network to predict the deformation [8]. Some scholars promote the development through the combination of materialized means and intelligent computing [9-10].As a stand-out model of intelligent learning methods, neural network technology has shown good performance in dealing with complex nonlinear problems. And as a matter of fact, the neural network is essentially a black box model, which means you do not have to fully understand the inner mechanism of things when you form a modelling via the neural network, what you only need to do is to solve the problem by waiting on its mining data, which is a typical data-driven problem-solving method. Because of the above advantages of neural network technology, some scholars have applied this model to the study of mine roadway surrounding rock deformation problem [11-12], and achieved good results. However, the single neural network technology has some defects, such as local minimum and precision general. This single network technology is not effective in practical application and has certain difficulties in practical application.

In reality, the single network has a habit of presenting inconsistent mining degrees and focuses out of its every single training, which gives rise to the outputs coming with deviations. While in practical use, what it needs to learn is the prior knowledge, therefore, each single output is solid enough to reflect the partial pattern of samples in a certain

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sense, through getting every single network under the prior knowledge integrated, so as to make the goal of mining fully. Thus, this article, from the perspective of integration learning, proposes this AdaBoost-GA-ELM model aiming at mine roadway surrounding rock deformation prediction, which adopts AdaBoost algorithm, genetic algorithm (GA) and extreme learning machine (ELM), combined with outstanding global optimization ability and extreme learning machine faster learning speed, and by the method of AdaBoost algorithm, to get the overall generalization ability and prediction accuracy of the model. With the engineering example of the settlement of the surrounding rock of the I01091004 mine roadway working surface, Tun-Bao coal mine, this paper is set to prove the rationality of the proposed model in the last part.

2. AdaBoost-GA-ELM theory and model

2.1 GA-ELM model

2.1.1 Basic theory for ELM model

Extreme learning machine (ELM) is a network training method for single hidden layer feed-forward neural network, which has been currently applied in many engineering fields. The iterative method of traditional feed-forward neural networks, represented by the gradient descent method, has some shortcomings such as slow learning speed, which is as well as prone to fluctuating between over-learning and lack-learning. The extreme learning machine algorithm only needs one-step analysis and calculation, which is iteration-free, to find the network output weight, in this way, it makes the ELM equipped with a faster learning speed and generalization ability [13].

Supposed that there are N presets of training samples (X_i, t_i), $\boldsymbol{x}_i = [x_{i1}, x_{i2}, \cdots, x_{in}]'$, $\boldsymbol{y}_i = [y_{i1}, y_{i2}, \cdots, y_{im}]'$. ELM achieves the goal (Equation 2) of training network by minimizing the cost function (Equation 1).

$$\min \sum_{j=1}^{N} \left\| \boldsymbol{t}_i - \boldsymbol{y}_i \right\| \quad \ldots \quad (1)$$

$$H\beta = T \quad \ldots \quad (2)$$

In the formula: $H = \{h_{ij}\}$ (i = 1, 2,..., N; j = 1, 2, ..., K);

$h_{ij} = g(w'_j . x_i + b_j)$;

$\beta = \{\beta_{jk}\}$(j1, 1, ..., K; k = 1, 2, ..., m);

$T = [t_1, t_2, ..., t_N]'$; H stands for output matrix of hidden layers; $g(\cdot)$ stands for activation function of hidden layers; β stands for weight matrix from hidden layer to output layer; K stands for hidden layers; T stands for network output.

In ELM, input weights and hidden layer thresholds are given randomly. It can be solved by the method of least square analysis, that is:

$$\hat{\boldsymbol{\beta}} = \boldsymbol{H}^{+}\boldsymbol{T} \quad \ldots \quad (3)$$

In (3), H^+ is the Moore-Penrose of H, we can tell, from the above analysis process, that ELM does not need to iterate over node weights and thresholds, and only needs one-step calculation to complete the entire network training. Compared to the traditional neural network based on iterative training method, the training speed and generalization ability have been greatly improved.

2.1.2 GA-ELM model

Because ELM adopts the strategy of randomly assigning the input layer weights and hidden layer thresholds of the network, it is easy to cause the unstable operation of the algorithm, which limits the further application of the ELM in practical projects. In order to solve this problem, genetic algorithm (GA) is employed to optimize the initial parameters of the ELM (network input layer weights and hidden layer thresholds), so as to couple it into a genetic least learning machine (GA-ELM) model. The solution to this problem by genetic algorithm is described as follows [14]:

(1) Coding: The strategy of real encoding is employed to encode the optimal input weight and hidden layer threshold of ELM to generate the random number between [-1 1] as the initial solution.

(2) Initializing GA parameters: including population size and iterations.

(3) Setting fitness function: taking the network output value and the actual value of the absolute error and as GA fitness function.

(4) Executing selection operator, crossover operator and mutation operator sequentially.

(5) Judging the on or off of the algorithm (taking the strategy of reaching the maximum number of iterations).

(6) Outputting optimal parameter values (i.e., the optimal ELM input and threshold value of hidden layers).

2.2 AdaBoost integrating a single GA-ELM

AdaBoost is a typical integration algorithm. Past studies have shown that AdaBoost is not only effective for classification problems, but also performs well in regression prediction problems [15]. In the prediction problem, the AdaBoost algorithm considers a single prediction model as a "weak predictor", which tends to obtain a more accurate "strong predictor" by integrating weak predictors, and fully excavates the sample information by adjusting the corresponding weights of each sample, adding the weight to a sample with a large prediction error, while reducing the weight of the samples with small error, so as to obtain a new sample distribution. In this paper, AdaBoost is employed for the integration of a single GA-ELM to obtain a better strong predictor (AdaBoost-GAELM). The basic description by AdaBoost algorithm for this problem is as follows:

(1) Initialization: input the sample data $\{x_1, y_1)$, ..., $(x_m, y_m)\}$ and determine weak predictors' number n, set t=1, and

initialize the weight $D_t(i) = 1/m$..

(2) Iteration: the weak predictor is trained according to the weight distribution to obtain the mapping relationship between the input value and the output value. The error of each sample and the error ratio are calculated as follows:

$$e_t(i) = | f_t(x) - y_i| \quad ... \quad (4)$$

$$\varepsilon_t = \sum D_t(i)\, e_t(i) \quad ... \quad (5)$$

Adjust the weight of the sample according to the following formula D_t and calculate each weak predictor's weight w_t:

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \beta_t^{e_t(i)} \quad ... \quad (6)$$

$$\beta_t = \frac{\varepsilon_t}{(1-\varepsilon_t)} \quad ... \quad (7)$$

$$w_t = \frac{1}{2}\log\left(\frac{1}{\beta_t}\right) \quad ... \quad (8)$$

In the formula (6), Z_t stands for normalizing operation; after completing all-above steps, set $t = t+1$, till $t = n$.

(3) Output result: After the above steps are completed, the result of the predictor will finally be combined to obtain the final result:

$$y_{final} = \sum_{t=1}^{n} w_t f_t(x) \quad ... \quad (9)$$

In summary, the flow chart for AdaBoost-GA-ELM is given in Fig.1.

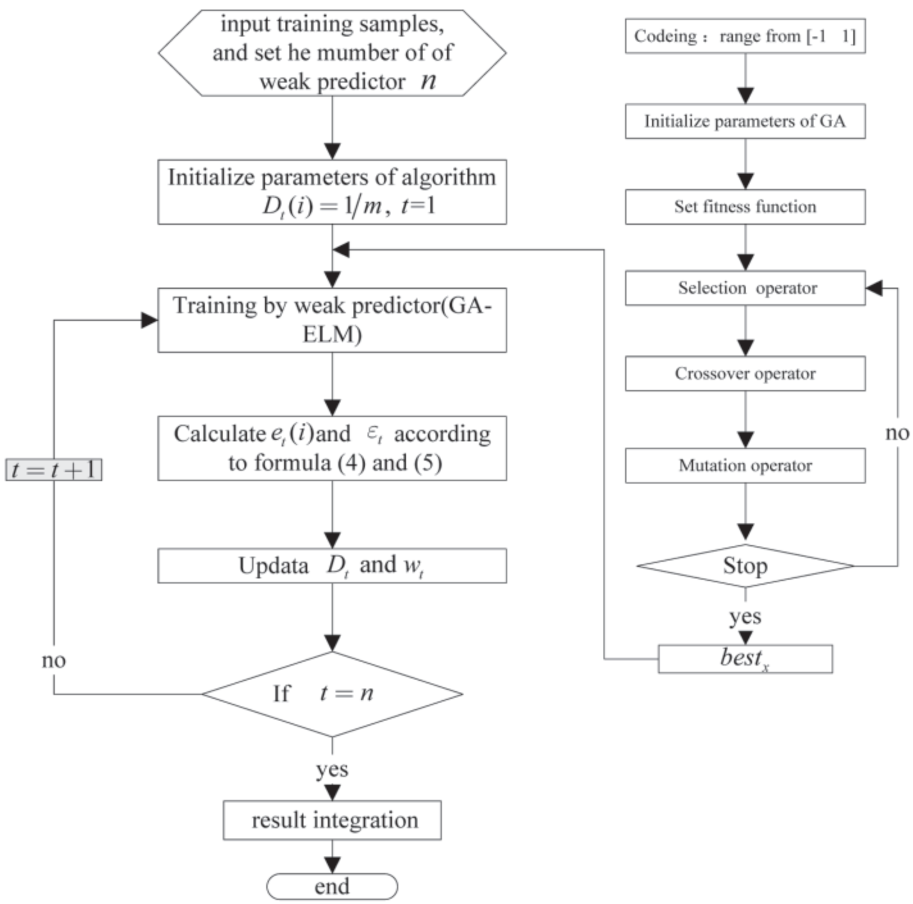

Fig.1 Flow chart of AdaBoost-GA-ELM model

3. Application for AdaBoost-GA-ELM model

3.1 Verification of engineer examples

Tun Bao coal mine is located in the west of sulfur mine ditch. It is a modern mine of a company, mine design capacity 1.2 million t/a, and the major system reserves 5 million t/a capacity expansion needs [3]. The mine can mine within the coal seam from top to bottom for the 4-5, 7, 9-10, 14-15. Minefield mining thickness is 31.23~46.48m, with an average total thickness of 38.24m, and the coal reserves are very rich. These rock formations of I01091004 working surface, Tun-Bao coal mine are relatively low in strength and have obvious stratification of strata with calcareous cements that are easily dissolved by groundwater. In addition, there are several geological faults distributed from east to west within the driving range, and most of them are normal faults, and the structural complexity is medium. The coal seam is partially loose and broken, which is a typical soft rock roadway with complex geological conditions. The roadway support of Tun Bao coal mine adopts the joint support of anchor rod, anchor net, steel strip and anchor cable. U-shaped steel shed supports are erected according to the site conditions when passing through the geological fault. There are slice help, bottom drum, the more serious roof in the mining affected sections. The cumulative value of displacement on both sides is up to 1.4m, and the accumulated displacement of top and bottom plates reaches 1.1m. Surrounding rock deformation and damage of arched section and rectangular section roadway of the mine area diagram is shown in Fig.2. In order not to affect the normal use of roadway, the mine had to take appropriate maintenance and rework measures on the roadway with serious damage. In order to ensure the safety and stability of the trough during the mining face and to grasp the steady state of the trough in real time, several parameters such as surrounding rock displacement, supporting structure pressure and surrounding rock loose ring are

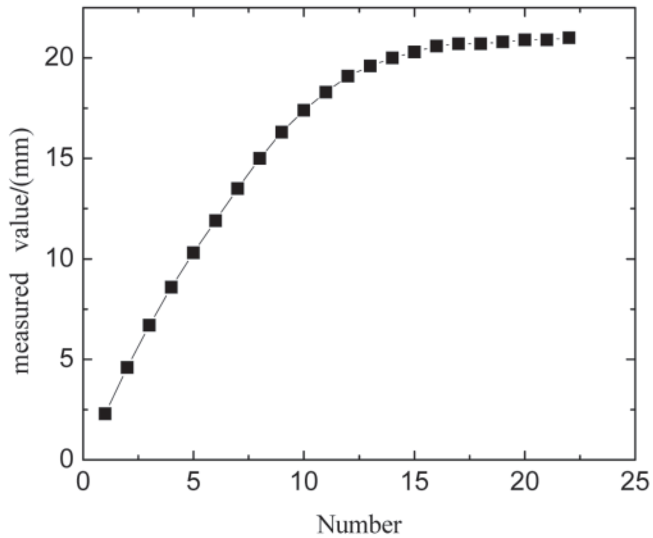

Fig.3 Vault settlement deformation measured data of Tun Bao coal mine roadway

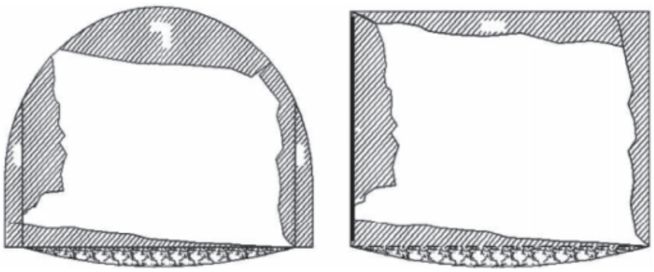

Fig.2 Arched section and rectangular section roadway of the mine area diagram

monitored for several sections of the roadway ahead of the mining face. In this paper, the monitoring data along the deformation of crown settlement of the surrounding rocks in the I01091004 working surface, Tun-Bao coal mine for 22 days is quoted to test the rationality of AdaBoost-GA-ELM method which is mentioned in Fig.3. The testing data of early 15 days is taken to form and train the model, and so as to predict the deformation data in the next 7 days. Among all, the major parameters of AdaBoost-GA-ELM are set as: 15 GA-ELM; 8 hidden layers of EML. In order to reduce the time consumed by the model, the GA parameter is set to a small value: GA's population number is set to 10, and the number of iterations is set to 20.

3.2 Discussion

In order to explain the rationality of AdaBoost-GA-ELM method in a further way, the author conducts a comparison among the results which are respectively from AdaBoost-GA-ELM's relative error, genetic algorithms (GA-ELM) and genetic BP neural network (GA-BP), Fig.4 shows us the comparison results of said methods. Seen from Fig.4, we can tell that it is an obvious fact that the prediction by AdaBoost-GA-ELM is better than the results by GA-ELM model and GA-BP, out of which, the average relative error of AdaBoost-

Table 1: Mine roadway surrounding rock deformation contrast of AdaBoost-GA-ELM model predicted and measured value

Number	Measured value/mm	Predictive value/mm	Error	Relative error
16	20.6	20.514	0.086	0.418%
17	20.7	20.631	0.069	0.334%
18	20.7	20.718	-0.018	0.088%
19	20.8	20.801	-0.001	0.003%
20	20.9	20.873	0.027	0.128%
21	20.9	20.878	0.022	0.106%
22	21.0	20.873	0.127	0.609%

See the comparison between the outputs of AdaBoost-GA-ELM and the actual values in Table No.1 (in Table No.1, the relative errors take the form of absolute values)

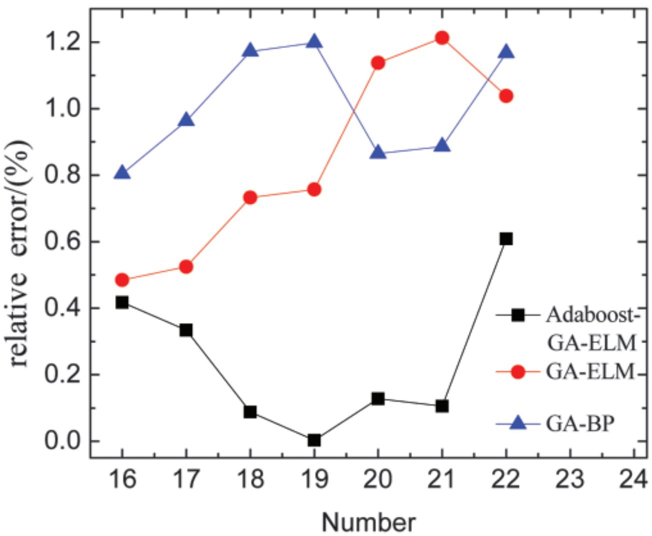

Fig.4 Relative error comparison of several models

GA-ELM model is 0.84%, while the GA-ELM comes out with 1%, and GA-BP is 1%, and the former's prediction accuracy was about 4 times of the latter two, which indicates that the AdaBoost-GA-ELM model is applicable to the deformation prediction of mine roadway surrounding rock, in practical project, it makes it feasible for us to achieve satisfactory results with AdaBoost-GA-ELM, in the case that requires the prior knowledge only.

4. Conclusion

(1) The mechanism of mine roadway surrounding rock deformation is supper complicated and there are enormous factors that could cast effects on it. As the deformation time series data of mine roadway surrounding rock under various internal and external factors, which is of great significance to study the stability of surrounding rock of mine roadway.

(2) The AdaBoost-GA-ELM model for mine roadway surrounding rock deformation prediction which is generated in this paper does not only absorb the strong ability of global optimization of genetic algorithm, but also

was born with the fast learning speed like ELM does, and what is more, The AdaBoost-GA-ELM model can ensure us an overall generalization ability and prediction accuracy.

(3) The verification of engineering example about crown settlement of the trough roof and floor section, I01091004 working surface, Tun-Bao coal mine shows that the AdaBoost-GA-ELM model can bring gratifying prediction results when a mine roadway surrounding rock deformation happens, which is almost the same with the actual monitoring deformation data of the project site, plus, compared to GA-ELM, GA-BP and gray model, the prediction accuracy has been greatly improved, which means that AdaBoost-GA-ELM model has great value in engineering application.

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