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Roof Pressure Prediction in Coal Mine Based on Grey Neural Network

KE WANG[1,2]**, XINWEI ZHUANG**[1,2]**, XIAOHU ZHAO**[ID][3]**, WANRONG WU**[1]**, AND BING LIU**[1,2]
[1]School of Computer Science and Technology, China University of Mining and Technology, Xuzhou 221000, China
[2]Mine Digitization Engineering Research Center, Ministry of Education of the People's Republic of China, China University of Mining and Technology, Xuzhou 221000, China
[3]National Joint Engineering Laboratory of Internet Applied Technology of Mines, China University of Mining and Technology, Xuzhou 221000, China

Corresponding authors: Xiaohu Zhao (kewangcumt@163.com) and Bing Liu (shiyaocumt@126.com)

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ABSTRACT The prediction of roof pressure in mining area plays an important role in effectively preventing roof accidents and ensuring the safety of mine production. Because the roof pressure in the mine is affected by various natural and human factors, and there is a dynamic and fuzzy nonlinear relationship between the factors. At present, the lack of systematic management will seriously limit the analysis and judgment of the mine safety situation, and lead to the occurrence of mine accidents. In this paper, the compaction data of the roof of a mine return air working face in Xuzhou is taken as the experimental data, and an improved grey neural network model is proposed, which combines the grey theory with the neural network algorithm organically. It not only eliminates the shortcomings of the neural network model, but also makes up for the shortcomings of the grey network that cannot carry out self-feedback regulation. MATLAB is used to simulate and test the improved combined prediction model for roof pressure prediction, and the results are compared with those of single grey model and single BP neural network model. The simulation results show that the improved model not only improves the prediction efficiency, shortens the training time, but also improves the accuracy, so it is of great significance to the safety prediction of the mine roof.

INDEX TERMS BP neural network, background value optimization, GM (1, n) model, roof pressure.

I. INTRODUCTION

The purpose of monitoring the roof pressure of the mine is collecting and analyzing the factors that affect the mine safety. Therefore, it is important to determine what information should be collected is, what way in which to monitor roof pressure is and what way in which to process the collected information is. At the same time, the continuous collection of information, related to mine safety, is important to the continuous improvement of the theoretical system of the mine. The continuous improvement of the theory will also play a guiding role in the monitoring of the mine. In addition, it is necessary to pay special attention to the stress distribution features of surrounding rock, deformation features of surrounding rock, stress conditions of surrounding rock and roof damage of surrounding rock in the process of monitoring. It is important to utilize a variety of measuring instruments to collect and analyze data and utilize scientific mathematical analysis method to obtain valuable rule from

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the big data. Once we get the develop trend, we can solve the actual production problems question by using the data and the develop trend.

More and more intelligent algorithms are applied to various fields of different industries with the continuous improvement of computer network technology. Among these, using wavelet and chaos optimization to predict the roof pressure has achieved a better convergence. This method has the disadvantage of costing much time. The stability analysis of the roof state of the karst cave is carried out based on the fuzzy theory. The hierarchical model is utilized to determine the membership degree and the gray correlation degree is utilized to estimate the state based on calculating weight [1]. Grey model is applied to predict working face pressure, with PSO algorithm obtaining optimal parameters in the grey model, as a result, achieving good prediction effect [2]. The endless algorithm model is convenient for realizing coal mine safety production and understanding the change rule and mutual influence of the influencing factors, which are related to coal mine safety, improving the theory of coal mine safety production.

The current roof pressure monitoring system could help coal mine security production to some degree, it still has some shortcomings. These problems are mainly focus on information fusion processing [3]. As influencing factors which influence roof pressure are various and complex, it is necessary to deal with the monitoring data scientifically and reasonably. We need to carry out statistical analysis on the influence degree of the variables to explore their internal relevance after determining these variables, then, achieve strata movement of the mine. The future roof condition will be predicted through further monitoring and data analysis based in this way [4]. Method of data processing by combining multiply information is called data fusion. This method is conducive to extract valuable information from a large number of data according to a specific algorithm, ignoring the interference information, so as to achieve effective system monitoring and improving the accuracy of prediction. It also has great benefits for the discovery of internal association of big data [5].

At present, there are mainly the following methods for roof pressure safety monitoring in coal mine production.

(1) Qualitative analysis. Literature [6] uses qualitative analysis as a commonly used and most widely used analysis method. Its main principle is to compare and analyze the monitored data or parameters with the theoretical data or parameters, so as to draw a qualitative conclusion whether the monitored data is in the safe range or conforms to the change law. Literature [7] uses the relatively fixed theoretical calculation value as the criteria for judging the classification of roof state, compares the corresponding theoretical calculation value range of roof state observation value, obtains the corresponding safety or specific safety level evaluation, and makes early warning if necessary [8]. The state of roof is affected by many factors, and there are complex internal relations among them. How to reveal the relations among these factors and make a reasonable judgment for the state of roof is the key of qualitative analysis.

(2) Numerical analysis methods: nonlinear regression analysis, statistical regression, numerical average method, variance analysis, time series analysis, grey system, fuzzy system, neural network, etc. [6]. Among them, the development of artificial intelligence has greatly affected the development and design of coal mine safety system. A variety of intelligent algorithms are applied in the field of actual coal mine safety, and have good prediction performance [5], [7].

With the continuous progress of computer network technology, more and more intelligent algorithms are applied to people's life and various fields of industry, such as using wavelet and chaos optimization to predict the roof pressure, which has achieved better convergence, but it costs more time and cost [9]. Based on the fuzzy theory, the stability analysis of the roof state of the karst cave is carried out. The hierarchical model is used to determine the membership degree, and the gray correlation degree is used to solve the weight method to estimate the state [10]. The grey model is applied to the prediction model of coal mine working face

pressure, and the PSO algorithm is used to select the optimal parameters in the grey model, so as to achieve good prediction effect [11].

Although the current roof pressure monitoring safety system to a certain extent provides help for coal mine safety production, there are also some shortcomings: that is, the problem of information fusion processing [12]. Considering that the roof pressure is affected by various factors, which are complex and interwoven.

This paper provides a scientific and reasonable way to deal with the monitoring data effectively. After determining the variables, first of all, we need to carry out statistical analysis on the influence degree of the variables, explore their internal not obvious relevance, and indirectly reflect the law of rock movement and roof pressure of the mine based on this relevance. On this basis, through further monitoring And analysis to predict the future roof condition [13]. This way of data processing by combining multiple information is called data fusion. This method is conducive to extract valuable information from a large number of data according to a specific algorithm and ignore the interference information, so as to achieve the effect of effective system monitoring and improving the accuracy of prediction. It also has great benefits for the discovery of internal association of big data [14]–[18].

The contributions of this paper are summaried as follows.

(1) This paper expounds the grey theoretical model, the concept and principle of the artificial neural network, and the typical BP neural network model in the artificial neural network, and discusses its applicable scene, advantages and disadvantages, with the emphasis on the analysis of the main shortcomings in the two models.

(2) A grey neural network model for roof pressure prediction is proposed. The single algorithm model is improved, and the fusion mode of the model also needs to be improved. The improved algorithm solves the problems in the previous single prediction model, and the solution can well match the monitoring condition of roof pressure under the special natural environment of the mine.

(3) According to the actual situation of a mine return air working face in Xuzhou and the improved grey neural network algorithm, the network topology and parameters are determined. Matlab simulation is used to verify the performance of the improved model. The simulation results of MATLAB show that the improved algorithm model can not only improve the efficiency of network prediction, but also has stable performance, good convergence and prediction effect.

The main contents of this paper are as follows: The first I introduces the research background and significance of this topic, including the research status of various technologies and algorithms in roof pressure prediction, as well as the overview of a variety of existing roof monitoring technologies and a variety of intelligent prediction algorithm models. The second II puts forward the improved hybrid grey neural network roof pressure prediction model, further analyzes

the advantages and disadvantages of its application in the algorithm, combines two models to build an improved algorithm, and analyzes in detail the reasons, improvement steps and the advantages of the improved model in theory. In section III, the performance of the system is verified. The experimental data is collected from a 1883 mine return air working face in Xuzhou area, and the algorithm model is realized by MATLAB program simulation, and the better prediction effect is achieved. Finally, Section IV concludes the paper.

II. HYBRID GREY NEURAL FORECASTING MODEL
A. DRAWBACKS FOR FORECASTING MODELS AND IMPROVEMENT STEPS
1) DISADVANTAGES OF PREDICTION MODEL

(1) BP neural network adopts the local search algorithm. It has the disadvantage of falling into the local optimum when it converges in the process of training. However, in many cases, the local optimum in a prediction system is not the same as global optimum. If we can't find the global best point, it will lead to training failure and can't get better training results.

(2) Training failure of BP neural network model is caused by another important factor that the setting of step length in the training process is hard. Generally speaking, when the step length is too large, the training results will diverge, resulting in the increase of model error and the failure of training results.

(3) In addition, the performance and efficiency of the network are also closely related to the size of the data sequence group. When building BP neural network, it is necessary to make statistical analysis on each group of training sample data, so as to adjust the weight and threshold value. Therefore, when the training sample is large, the direct consequence modeling time will be long, so the training efficiency will be low, which will eventually lead to the prediction result it takes too long.

2) ALGORITHM IMPROVEMENT STEPS

It improves the efficiency, accuracy and convergence of system data prediction.

Action1: Analyze the shortcomings of the model and adjust the model algorithm.

Action2: Analyze and use models and apply appropriate model algorithms.

Action3: Analysis model algorithm deficiency; Application combination algorithm; Circumvention deficiency.

After analyzing the shortcomings of the two single prediction algorithms, we design the algorithm improvement process as shown in Fig. 1 for the actual scene of roof pressure state prediction and overcome the shortcomings of the two single prediction models. We propose the improvement of the original grey theory model and the neural network model as the innovation of this topic to fit the task of predicting roof pressure, which mainly includes two aspects: (1) Increasing
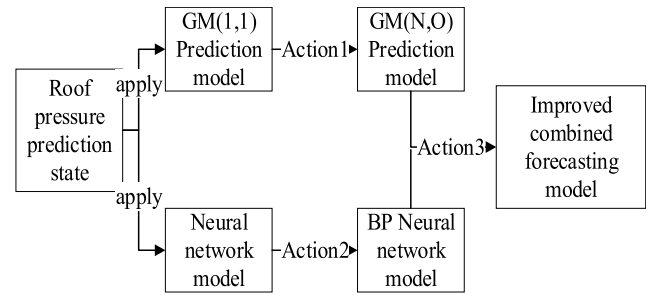

FIGURE 1. Sketch map of algorithm improvement procedure for hybrid forecasting model.

the background value parameters and dimensions for the grey prediction model and making it suitable for the prediction of the roof pressure environment; (2) By combining the advantages of each model, this method improve the grey model and modify BP neural network model, as a result, improving the efficiency of the algorithm, lifting the accuracy and improving the convergence of the prediction data.

B. LAMBDA-BASED GM (1,n) MODEL

Due to the parameter setting of GM (1,1) grey prediction model, this method has inevitable defects. Taking the prediction of roof pressure as an example, there are many factors affecting roof pressure, which are interrelated and highly complex. Therefore, in this case, only using GM (1,1) model to predict could not fully reflect the real characteristics of the system. Similarly, in all kinds of prediction problems in real life, the influencing factors are all multi-faceted and non-linear. Therefore, when solving the complex prediction problems with multi factor influence, we need to improve the original GM (1,1) model and increase the breadth of its parameters, such as using GM (m, n) model to represent the specific characteristics of more systematic and detailed practical problems. The prediction of roof pressure is affected by many factors in the scene, so we choose the dimension of the model as the dimension. The roof pressure state is relatively stable, so we use the first-order prediction model to describe it, that is, GM (1, n) model.

1) DATA PROCESSING

Set the original data sequence as $x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)]$, in which n is represented as the number of data. The following formula accumulates the original time series data sequence to weaken its volatility randomness and get the new data sequence:

$$x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)] \qquad (1)$$

In above formula, $x_t^{(1)}$ is represented as the accumulation of the previous data.

$$x_t^{(1)} = \sum_{k=1}^{t} x_k^{(0)}, \quad t = 1, 2, \cdots, n \qquad (2)$$

By integraling the above formula on the interval[k, k+1], we can get:

$$x^{(1)}(k+1) - x^{(1)}(k) + a \int_k^{k+1} x^{(1)}(t)dt = u \quad (3)$$

In the above formula k = 1, 2, ..., n−1, which is:

$$x^{(0)}(k+1) + a \int_k^{k+1} x^{(1)}(t)dt = u \quad (4)$$

So far, the data processing part of the improved GM (0, n) model is introduced.

2) BACKGROUND VALUE OPTIMIZATION

If $Z^{(1)}(k+1) = \int_k^{k+1} x^{(1)}(t)dt$ is set to the background value of $x^{(1)}(t)$ on the interval $x^{(1)}(t)$, there are:

$$x^{(0)}(k+1) + aZ^{(1)}(k+1) = u \quad (5)$$

However, the function $x^{(1)}(t)$ is still unknown, but according to the solution of the first order differential equation is an exponential function, we can get:

$$x^{(1)}(t) = Ce^{bt} \quad (6)$$

If the curve passes through point $(k, x^{(0)}(k))$ and point $(k+1, x^{(0)}(k))$, then:

$$x^{(1)}(k) = Ce^{bk}, x^{(1)}(k+1) = Ce^{b(k+1)} \quad (7)$$

From the above two formulas, we can get:

$$b = \ln x^{(1)}(k+1) - \ln x^{(1)}(k) \quad (8)$$

$$c = \frac{x^{(1)}(k)}{e^{bk}} = \frac{[x^{(1)}(k)]^{k+1}}{[x^{(1)}(k+1)]^k} \quad (9)$$

so the background value is:

$$
\begin{aligned}
Z^{(1)}(k+1) &= \int_k^{k+1} x^{(1)}(t)dt \\
&= \int_k^{k+1} ce^{bt} dt \\
&= \frac{x^{(1)}(k+1) - x^{(1)}(k)}{\ln x^{(1)}(k+1) - \ln x^{(1)}(k)}
\end{aligned} \quad (10)
$$

At this point, the process of background value solution and derivation is completed.

3) PARAMETER SOLUTION

Parameters a and u can be achieved by the least square method:

$$\hat{\Phi} = [\hat{a}, \hat{u}]^T = (B^T B)^{-1} B^T Y \quad (11)$$

Among them:

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -Z^{(0)}(2) & 1 \\ -Z^{(0)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(0)}(n) & 1 \end{bmatrix} \quad (12)$$

And $Z^{(1)}(k+1)$ is the background value determined by the formula

$$\frac{x^{(1)}(k+1) - x^{(1)}(k)}{\ln x^{(1)}(k+1) - \ln x^{(1)}(k)},$$

Therefore, the formula of model response time is:

$$\hat{x}^{(0)}(k) = (\hat{x}^{(0)}(1) - \frac{u}{a})e^{-a(k-1)} + \frac{u}{a}, \quad k = 1, 2, \ldots, n. \quad (13)$$

At this point, the pending parameters in the model are solved.

4) DATA PREDICTION

The grey parameters are brought back to the differential equation. Thus, the predicted data value can be obtained. After that, the predicted value of the original sequence can be obtained by subtracting the model

$$
\begin{aligned}
\hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\
&= (\hat{x}^{(0)}(1) - \frac{u}{a})(1 - e^a)e^{-ak}, \quad k = 1, 2, \ldots, n.
\end{aligned} \quad (14)
$$

Instead of the derivative of time, this is a derivation with high precision. When the derivative is in nature, both of them can achieve accurate prediction.

C. IMPROVED HYBRID GREY-NEURAL NETWORK MODEL BASED ON ROOF PRESSURE FORECASTING

1) COMBINATION MODEL PROPOSED

As a widely used forecasting method, combined forecasting model combine two single forecasting models into one model. Once combined forecasting model was proposed, it immediately received wide attention in many fields all over the world. Due to its outstanding advantages, it can combine the advantages of single estimation model together, enabling multiple models to complement each other and to make up for each other's defects, thus obtaining better prediction performance. All these were achieved by its comprehensive coverage of the system data that needs to be described in reality. In the 1970s, the importance of combined forecasting model has been highly valued due to its unparalleled advantages. It has been widely used in a variety of forecasting fields all over the world, and its related research results of combined forecasting algorithm model have also been reported [19].

At present, the research on the combined forecasting model mainly focuses on the following aspects:

The weighted concentration method: according to the way of weighted concentration, each single forecasting model is assigned with different weights. The results of the prediction are processed by centralized fusion. Among them, each single forecasting model is a mature forecasting model with stable performance and wide use, according to the applicable characteristics of a single mature model. The weighted concentration method will allocate the weight, so as to achieve the purpose of centralized advantage.

This forecasting method is also widely known as integrated forecasting or combination forecasting. Obviously, the key of the weighted set prediction method is how to assign a reasonable weight to a single prediction model, so that the prediction effect can reach a higher accuracy.

In addition, other widely used prediction algorithm focuses on the combination and reconstruction of models in the prediction process of prediction algorithm also exist., For example, data collection, data preprocessing (1-AGO transformation, normalization, etc.), training selected "training sample data", prediction model based on the input "test data", etc. The purpose is to combine the advantages of a variety of prediction algorithm models and avoid the disadvantages. At the same time, the comprehensive coverage of the data collected in practice is been paid more attention. The hidden correlation between various influencing factors that affect the prediction results was also paid much attention. In general, it is a relatively high coupling combination prediction algorithm.

Generally speaking, the combination method of this combination prediction method is the combination method of rough prediction and adjustment prediction. Different single prediction models are used as the part of rough prediction and adjustment prediction according to the characteristic. Obviously, rough prediction can estimate the approximate range and trend of prediction value. The main prediction part is a main part of error correction, naturally needs a model with advantages in error estimation to achieve satisfactory prediction results.

In recent years, researchers concerned and valued the second combination model widely and expected to achieve breakthrough research results. In order to achieve the relatively optimal effect, the relevant researchers focus on three aspects to design the combined forecasting model, and strive to make the combined forecasting model play its advantages to fit different application environments and play an excellent prediction performance.

The research content of this section is mainly based on the following parts: 1. For the main prediction model, the selection of the original mature prediction algorithm of the sub prediction model must refer to the advantages and disadvantages of a variety of prediction algorithms, and be determined according to the data characteristics of the actual situation and the characteristics of the influencing factors; 2. After determining the main and sub prediction model, we need to determine to embed the sub model into the main model;3. For a mature model, it is important to carefully decide whether its' structure needs to be adjusted according to the actual situation, as we want the model to perform best and realize all its potential. The model needs to be slightly improved, rather than simple application and combination.

Since the end of last century, China has also carried out a lot of meaningful research on combinatorial prediction model. Many researchers have made significant research results in this area, mainly including: Bayesian prediction model, Markov prediction model, hidden Markov prediction model,

fuzzy prediction algorithm, genetic prediction algorithm, which can be used in combinatorial prediction. It is of great significance for the improvement of intelligent prediction algorithm to study the combination of measurement model.

2) COMPOSITE MODEL STRUCTURE
According to the previous theory, followed are several combination methods of grey model and neural network model:

a: MILD ASSOCIATION FUSION
The grey theory model and the neural network model are separately used to predict and evaluate the complex systems with multiple factors which affect each other in different environments in this fusion relationship. However, the grey theory model is certainly more suitable for those complex systems which have relatively obvious grey characteristics, less data and poor regularity. Therefore, which system model was selected as a prediction model is judged according to the actual situation when it is necessary to predict the system data. The two models separately run, so they have couple weakly, which is called light correlation fusion.

b: MODERATE ASSOCIATION FUSION MODE I
Firstly, the multiple influencing factors that affect the final prediction results are taken as the data input part of the grey model to be separately grey predicted. Then the prediction results of the influencing factors are taken as the input part of the neural network prediction model, and the final prediction results are output by continuously adjusting and distributing the weights. The combination of the prediction model belongs to moderate association fusion. This model combines the advantages of the gray model with the neural network's weight distribution to improve the overall accuracy of the prediction system. The schematic diagram of the combination model is shown in Fig. 2:
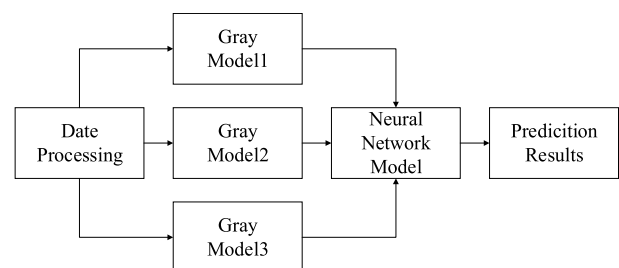

FIGURE 2. Moderate aggregation method I.

c: MODERATE ASSOCIATION FUSION MODE II
This model adopts parallel connection and series connection. First, two single models are used to predict the collected sample data respectively, and then the prediction result value is compared with the prediction result value of one model. In this way, the combination can perform better when one prediction model data is lost or the prediction deviation

is large correction effect. The schematic diagram of the combined model is shown in Fig. 3:
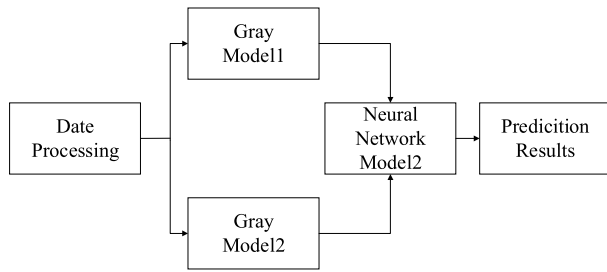

FIGURE 3. Moderate aggregation method II.

d: DEEP ASSOCIATION AND FUSION

Under this fusion condition, neural network model and grey theory model coupled deeply, and there are many specific combination methods. Here we only discuss two typical depth Association fusion methods: depth series and depth parallel. The fusion method of deep parallel is using the grey theory model and neural network prediction model to collect sample data respectively, getting the respective prediction data value, and then improving the prediction accuracy by reasonably adjusting the weight of each model to sum [20].

Another method of depth Association fusion is called series depth fusion. In this relationship, we utilize one prediction model to predict and estimate, and the other prediction model to predict and estimate the residual generation, and get the final combined model prediction results by correcting the first model prediction result [21]. In this paper, according to the characteristics of mine roof pressure and environmental analysis, we adopt the method of series depth fusion by combining improved grey neural network prediction model with neural network. The prediction schematic diagram of the model is shown in Fig. 4, and the prediction process of the model is analyzed as follows:
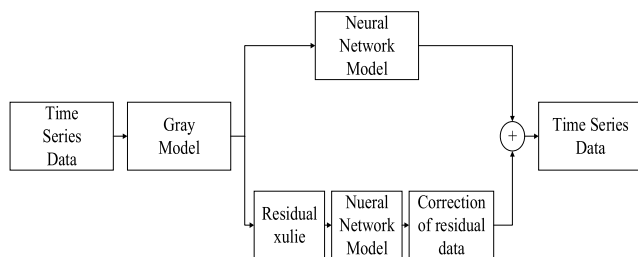

FIGURE 4. Deep aggregation method.

3) ESTABLISHMENT OF COMBINED GREY NEURAL NETWORK MODEL

(1) After research on the grey model and the specific application environment, the improvement of this model is supposed to focus on the following aspects. The GM (1, 1) model is improved respectively, on the basis of which,

the multi-dimensional input grey model is changed to adapt to various influencing factors of the roof. However, we use the multi-dimensional Grey Markov equation to predict the relevant influencing factors due to the influencing factors' complexity, and take the prediction results as the input data of neural network. In this way, the single grey model becomes an important part of the combined model.

(2) Improvement of grey model: there are many kinds of grey model, such as GM (0, n), GM (1, n), GM (2, 1), SCGM (1, n), ERC_GM (1, 1) model, etc. [22].

(3) Due to the BP neural network's advantage, for example, capable of processing non-linear data, it has special superiority on fitting complex relation between factors which used to predict roof pressure. Yet, it has two main disadvantages. The learning efficiency and convergence speed are too slow and it is easy to fall into local minimum convergence. So we made several improvements to the neural network. Firstly, we make the model have a faster convergence speed through directly modify the initial value. The second improvement is the adaptive variable-speed sample learning training method. Through optimization processing, the model can learn at a faster speed when the error value is large, so that the neural network can complete the sample training quickly. Afterwards, when the error is reduced to the optimal value, the speed begins to slow down gradually. The network sample training will not be too fast because of the training learning speed, so that the model is divergent. Fast network sample training will cause the failure of training.

(4) By analyzing and comparing two single mature models, we adjust their shortcomings and combine their advantages to obtain a combined model which can achieve better prediction performance in prediction efficiency and accuracy.

This chapter improves the grey neural network in the following aspects to better analyzing pressure state of the mine roof and achieve the rule, according to the disadvantage and advantage of the model:

(1) The research content of this topic is to predict the state of the roof pressure of the mine. Because there are many factors that affect the state of the system, a single grey prediction model is not suitable for direct prediction. However, this feature meets the needs of our combined model. Using the grey neural network model to model the system, can achieve good results with the multi factor data as the target data.

(2) Parameter initialization improvement: we improve the original random assignment method in the auxiliary prediction model for network initializing. The initial weight matrix and threshold matrix in the network are defined randomly, which will result in unstable network test performance, so it is impossible to objectively evaluate the network test performance. In addition, the uncertain initial value also makes the model unable to converge due to the improper assignment, which causing training failure. Therefore, when choosing the initialization matrix, this paper adopts the method of fixed value selection to ensure the stability and convergence of the system.

TABLE 1. Roof pressure data in working surface.

	Daily report of mine pressure in driving face											
	Roadway section				Anchor cable (rod) dynamometer (MPA)				Roof separation meter (mm)			
Num ber	Initial value		Measured value		Initial pressure value		Measured pressure value		Initial value		Measured value	
	Height (mm)	Width (mm)	Height (mm)	Width (mm)	Main anchor rope	Reinforcing anchor rope	Main anchor rope	Reinforcing anchor rope	Deep part	Shallow part	Deep part	Shallow part
1	3600	5000	3459	4990	10	20	10	20	10	20	15	51
2	3700	5000	4352	4850	18	10	20	12	15	15	19	48
3	4000	5100	3413	4995	10	15	5	22	20	20	85	115
4	3600	5000	3498	4850	15	12	20	12	30	30	45	95
5	3600	5000	4403	4985	20	21	20	bad	25	30	30	63
6	4800	5100	4521	4742	22	20	58	60	25	15	105	145
7	3700	5000	3481	4532	35	15	58	26	40	20	76	115
8	3750	5200	3436	4588	40	35	78	70	30	25	100	145
9	4000	5300	3050	4953	30	25	80	56	35	30	135	155
10	3800	5200	2842	4634	21	22	40	44	25	30	80	125
11	3700	5200	3077	4839	22	12	32	19	30	20	70	105
12	3600	5400	3422	5236	17	26	30	34	60	40	85	100
13	3600	5300	3487	5013	10	23	17	43	40	20	64	98
14	3750	5350	3520	5000	20	30	38	44	30	20	75	108
15	3600	5100	3584	5051	28	18	52	54	60	60	65	70
16	3700	5100	3341	5073	15	22	5	25	20	20	40	65
17	3750	5250	3657	5071	25	30	20	20	30	25	45	70
18	3800	5300	3667	5206	22	25	38	25	50	60	60	90

(3) In addition, we also improved the fusion mode of the combined prediction model. In this paper, we build the improved roof prediction model by using the combination mode of deep series fusion of two single mature models. Main and secondary sub models build up the whole model together, which respectively estimate the influencing factors of roof pressure and the residual value of roof pressure. Among them, the main prediction model performs a rough estimation and outputs the approximate prediction result and the corresponding residual sequence. The auxiliary prediction model predicts the residual sequence by the formula. Therefore, we can obtain the final target result value by modifying the rough estimation value. Obviously, in this combination mode, the auxiliary prediction model is modified as a residual correction model and belongs to the auxiliary module. It takes a lot of time, so it is very important to control the efficiency and performance of the sub model. Based on the adjustment of the original neural network model, we control the training time of the neural network model, obtain the satisfactory prediction and ensure the system operation efficiency.

4) STEPS OF IMPROVING GREY NEURAL NETWORK ALGORITHM

The prediction process of the combined model is as follows:

(1) the grey model predicts the sample data and outputs the grey model to predict the sample sequence.

(2) using the formula to calculate the residual sequence value;

(3) build the neural network model, determine the input data sequence and output data sequence of the neural network model: take the influence factor data sequence sample of roof pressure as the input data of the neural network model, and take the residual sequence value from the grey model as the target data value (actual target value).

(4) the neural network model is established through training. The trained model is used to predict the target data error value. Then the final prediction value of the model can be calculated by formula.

III. SIMULATION OF ROOF PRESSURE FORECASTING FOR XUZHOU HUIFENG COAL MINE

A. DATA SAMPLE PROCESSING

The data used in MATLAB simulation is displayed in Table 1 (partial data shown). From the analysis of the third chapter, it can be seen that among the influencing factors of mine safety monitoring which affect the state of roof pressure, the six top factors that have great influence on each other are: the measured values of roadway section height and width, the measured values of main anchor element and reinforcement anchor element, the measured values of roof separation instrument depth and shallow part value. These factors were the input of prediction model, as shown in Table 2.

The residual value calculated by the main prediction model is taken as the target value of the auxiliary prediction model. This method respectively predict each part by taking the data collected from March 1, 2014 to April 27, 2014 as sample data and the data from April 28, 2014 to May 10, 2014 as forecast data,. Table 2 shows the construction sample set needed to establish the grey model.

B. SIMULATION RESULTS AND ANALYSIS

1) ESTABLISH GREY MODEL

Various, fluctuating and unstable factors affect the roof pressure of the mine, so we use the data at current time to

TABLE 2. Sample data for roof pressure forecasting.

Serial number	Roadway section (measured value)		Anchor dynamometer (measured pressure value) (MPa)		Roof separator (measured value) (mm)		Roadway section shrinkage (mm)
	Height (mm)	Width (mm)	Primary anchor	Reinforcing anchor	deep	shallow	Roof pressure
1	3605	5255	36	38	50	70	60
2	3720	5020	22	24	50	55	50
3	5615	4935	21	23	60	60	60
4	3750	5155	24	30	40	50	35
5	3605	5255	36	38	50	70	60
6	3720	5020	22	24	50	55	50
7	5615	4935	21	23	60	60	60
8	3750	5155	24	30	40	50	35
9	3552	4955	13	23	15	51	36
10	3652	4966	21	13	19	48	37
11	3946	5061	15	19	23	60	43
12	3561	4969	18	16	34	55	29
13	3551	4965	22	23	30	62	37
14	4758	5075	24	22	33	35	28
15	3629	4950	38	19	46	75	61
16	3688	5164	44	40	42	65	52
17	3949	5266	35	33	37	68	40
18	3768	5158	23	25	34	45	24
19	3665	5149	25	18	33	38	21

TABLE 3. Influencing factors contributing to roof pressure in coal mine.

Serial number	height	width	Primary anchor	Reinforcing anchor	deep	shallow
1	3605	5255	36	38	50	70
2	3720	5020	22	24	50	55

TABLE 4. Parameters obtained by improved gray neural network mode.

parameter	height	width	Primary anchor	Reinforcing anchor	deep	shallow
a	0.0125	0.0127	0.0121	0.019	0.0068	0.0075
u	125.4113	137.5074	117.7724	137.1344	113.8365	106.2283

TABLE 5. Portion of forecasting results.

sequentially	height	width	Primary anchor	Reinforcing anchor	deep	shallow
2014.3.1	3735	5140	24	30	40	60
2014.3.1	4055	5260	25	32	35	60
2014.3.2	3720	5020	22	24	50	55
2014.3.2	5615	4935	21	23	60	60
2014.3.3	3735	5140	24	30	40	60
2014.3.3	4055	5260	25	32	35	60

predict the prediction value of the next time when we carry out the grey modeling. Also, we calculate their parameters, which are shown in Table 3, Table 4 and Table 5:

The original data was conveyed as input into the prediction model for prediction. The results are shown in Table 5:

2) ESTABLISH NEURAL NETWORK
We form independent variables by extracting the data of six influencing factors of grey model prediction test results, and

the corresponding roof pressure is taken as the target output. After that, we divided the data into training samples and test samples: in 1883, the total amount of data collected from the roof of a mine return air working face was 420 groups, among which we used the first 350 groups of data as training samples for model training, and the remaining 70 groups of data for testing the prediction effect of the improved model, in which the samples used were selected according to the roof at the time point. It is selected according to the sequence of pressure, so it has the feature of good sequence and consistency. Because "training" and "testing" need to consider randomness, the same sample is trained and tested many times, and we obtain prediction value the average value of the final prediction.
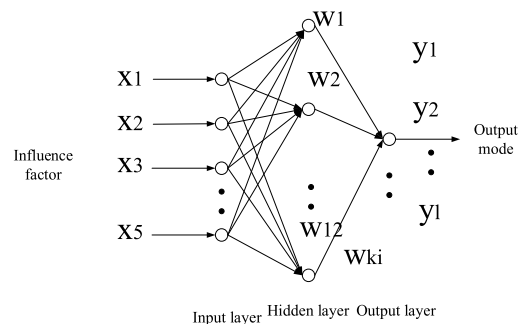

FIGURE 5. Topological structure of BP network.

Fig. 5 shows the topology of a BP network. Next, in order to maintain the stability of the prediction model performance test, we need to normalize the input training data. In MATLAB, we use the function to normalize the input vector of the training sample and the output target value to the interval $[-1, 1]$. In a certain operation, the error

reduction curve of training under different step sizes is shown in Fig. 6 and Fig. 7 respectively. After the test, the actual output value is re normalized to normal data. The comparison between predicted value and real value is shown in Fig. 8 ~ Fig. 11. It can be seen that the training network has a very good fit to the training data itself. Fig. 12 shows the residual. The mean square error between the actual output and the real value of the network. In order to better test the prediction performance of the prediction model, we compare its similar prediction model (including GNMM model, grey prediction model, neural network model) with it in many aspects. The prediction results of different simulation experiments of the three models are shown in the figure:

FIGURE 8. Output comparison of different forecasting model (1).

FIGURE 6. Sample error declining curve (100 epochs).
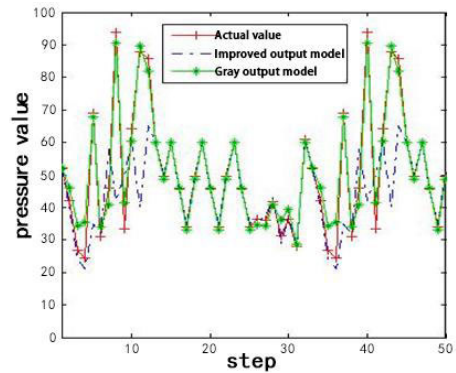
FIGURE 9. Output comparison of different forecasting model (2).

FIGURE 7. Sample error declining curve (200 epochs).
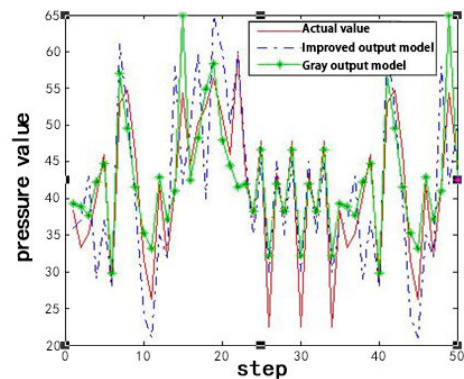
FIGURE 10. Output comparison of different forecasting model (3).

In each iteration, one sample is randomly selected from the sample and input into the network for training. After operation, the accuracy is 87%, the residual error is as shown in Fig. 12, the mean square error MSE = 32.367921, and the average relative error of the test sample is 5.35%, indicating that the network performance is good.

(3) According to the above experimental simulation results, it is not difficult to draw the following conclusions: on the whole, the improved grey neural network model in this topic can largely avoid long training time when directly connecting two models (grey theory and neural network). At the same time, it can reduce the prediction error of
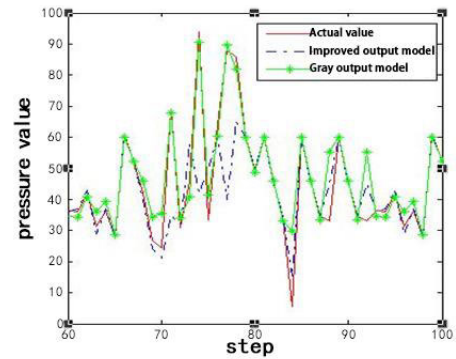
the model generated in a certain training time. Based on improving the prediction effect, this method also optimizes the generalization performance of the prediction system model to a certain extent. Therefore, compared with the single grey model, neural network and simple nested grey combination model has obvious advantages.

In this section, the improved grey neural network theory is used to analyze the roof weighting of a mine return air working face in Xuzhou. The prediction results with high accuracy value are obtained and the better performance of the improved grey model is verified.
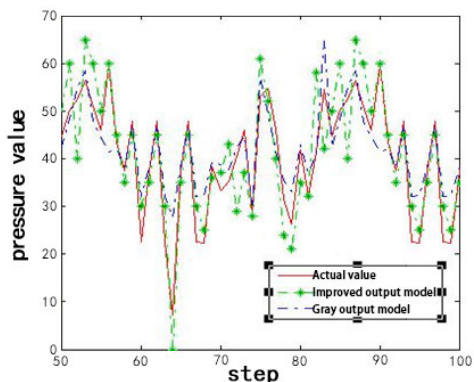
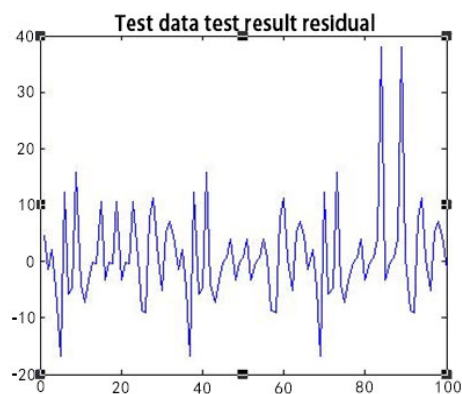**FIGURE 11.** Output comparison of different forecasting model (4).

FIGURE 12. Residual error for testing data by foresting model.

IV. CONCLUSION

Based on the analysis of grey model and neural network, this paper improves the single model, combines and improves the method of deep integration, and makes the following conclusions. First, by analyzing the research background and significance of a variety of roof pressure prediction models, we introduce the influencing factors and influencing laws of roof stress, and the domestic and foreign research survey of a variety of typical intelligent algorithm models. We summarize the grey theoretical model, the concept and principle of artificial neural network, and the typical BP neural network model in artificial neural network. We also apply the scenarios and advantages to it. The shortcomings of the two models are discussed, and the main shortcomings of the two models are analyzed. Second, the grey theory model and the neural network model have their advantages and disadvantages and their application scenarios. In order to better construct the optimization prediction model, according to the analysis of roof pressure state and environment, we combine the advantages of the two single models to avoid its shortcomings, and thus propose an improved algorithm – the grey neural network prediction model for roof pressure prediction. To begin with, we have analyzed some mainstream model algorithms in detail, especially the outstanding performance of the two single models in the

roof pressure of coal mine. In view of the disadvantages of single model and the characteristics and laws of mine roof pressure, we proposed an improved grey mental network model, and made the following improvements: improving the single algorithm model, and merging the model. The formula also needs to be improved. The improved algorithm solves the problems in the previous single prediction model, and the solution can well match the monitoring condition of roof pressure under the special natural environment of the mine. Third, according to the actual situation of a mine return air working face in Xuzhou and the improved grey neural network algorithm, we determine the network topology and parameters. In the case analysis, we collect the roof pressure data of a mine return air working face in Xuzhou area as the algorithm verification data, summarize the situation of the mine area and discuss the significance of using the improved grey neural network model to predict the roof pressure, and finally use MATLAB simulation to verify the performance of the improved model. The simulation results of MATLAB show that: compared with the single prediction model before, the improved grey neural network model has a significant improvement in training time, training and prediction effect, in which the training time is reduced by 20%, and the prediction accuracy of the samples is improved by 70%.This shows that the improved algorithm model can not only improve the efficiency of network prediction, but also has stable performance, good convergence and prediction effect.

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XINWEI ZHUANG received the B.S. degree in computer science and technology from the School of Computer Science and Technology, China University of Mining and Technology, Xuzhou, China, in 2019, where he is currently pursuing the master's degree with the School of Computer Science and Technology.

His main research areas include virtual reality, three-dimensional animation, and the mining IoT.

XIAOHU ZHAO received the B.S. degree in industrial automation, and the M.S and Ph.D. degrees in control theory and control engineering from the China University of Mining and Technology, Xuzhou, China, in 1998 and 2007, respectively.

He is currently an Associate Professor with the School of Information and Telecommunications, China University of Mining and Technology. His main research areas include the mine Internet of Things, mine communications, monitoring and control, computer networks, and intelligent computing.

WANRONG WU received the B.S. degree in computer science and technology from Xuzhou Normal University, Xuzhou, China, in 2006, and the M.S. degree from the School of Computer Science and Technology, China University of Mining and Technology, Xuzhou, in 2009.

KE WANG received the B.S. and M.S. degrees and the Ph.D. degree in mining engineering from the China University of Mining and Technology, Xuzhou, China, in 2001, 2004, and 2011, respectively.

He is currently an Associate Professor with the School of Computer Science and Technology, China University of Mining and Technology. His main research areas include virtual reality, three-dimensional animation, and the mining IoT.

BING LIU received the B.Sc., M.Sc., and Ph.D. degrees from the China University of Mining and Technology, Xuzhou, China, in 2002, 2005, and 2013, respectively.

He is currently an Associate Professor with the School of Computer Science and Technology, China University of Mining and Technology. His current research interests include nonlinear dimensionality reduction, broad learning, compressed sensing, and sparse machine learning methods.

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