Prediction method of mine gas emission based on complex neural work optimized by Wolf pack algorithm

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\textbf{ABSTRACT}

In view of the local extreme problem of the gradient descent algorithm, which makes the working face of mine gas emission prediction uncertainly, this paper combined Wolf pack algorithm (WPA) with complex neural network nonlinear prediction method to the established new prediction model. The WPA shows good global convergence and computational robustness in the solving process of complex high-dimensional functions. Working face in a coal mine as a case, this paper selects seven factors as input variables of the mine gas emission prediction, uses training data to mature prediction model and adopted it to predict six group gas emission data. Research results show that the mean absolute percentage value of the complex neural network model which has been optimized by WPA is 0.06%, the root mean square error value is 0.0191, the mean absolute error value is 0.0175 and the equal coefficient value is 0.9979. The prediction results are very close to the real value, and the change trend is highly consistent with the actual situation.

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\section{1. Introduction}

With the acceleration of coal mining, the mining area and mining depth gradually increase, and the gas emission problem is prominent. Gas accident seriously threatens the life safety of mine workers and also restricts the production capacity and economic benefits. How to prevent the gas accident in the mining face area has become an urgent problem. The prediction of mine gas emission is an important factor to guide the mining of coal seams in working face, and the accuracy of prediction will affect the judgment and response of mine accident risk directly. The gas emission prediction provides a theoretical basis for the rational guidance of the layout of the work, and saves time and cost for mine safety precaution. Adopting reasonable and effective preventive measures is the key to ensure the normal and orderly work of mining.

At present, the mine gas emission detection data was used as the research object, which is applied to the gas early warning. The amount of gas emission is related to various factors, and accurate gas emission prediction can guide gas disaster prevention and control, and improve the utilization rate of gas resource technology. The research of gas emission prediction method mainly includes different-source prediction method, GIS prediction, gas geology research prediction, grey theory (Zhou et al., 2016) and fractal theory. Different-source prediction method can analyse the gas emission law of the working face and predict the amount of gas emission in the protective layer (Dai, Wang, & Zhang, 2007). Some scholars use probabilistic method to study the relationship between coal gas desorption intensity and exposure time, and obtain the empirical formula for predicting the amount of coal gas emission from coal mining (Yang, 2008). Some scholars used regression analysis to establish the approximate function of gas emission and mining depth, and realize the exploration process to forecast the gas emission, or application of the stepwise regression analysis method to establish a mathematical model to forecast the gas emission (Cai, Yuan, & Qi, 2010; Du, Liu, & Chou, 2010; Guo, Zheng, & Ju, 2009; Xu & Hu, 2009). Some scholars used the grey relational degree analysis and residual identification method to establish the prediction model of gas emission volume (Wu, Tian, & Song, 2005). The fuzzy improved grey Markov prediction model was established by combining the improved grey prediction GM (1, 1) model and Markov model (Tao, Xu, & Li, 2007). The fuzzy
With the development of computer technology and data mining technology, many prediction methods are widely used in gas emission prediction, including neural network, fuzzy theory and support vector machine (SVM), and they have stronger nonlinear computing power. For example, some scholars constructed neural networks using three gas gushing sources, including the mining layer, the adjacent layer and the goaf, and used for the prediction of gas emission (Karacan, 2008; Zhu, Chang, & Zhang, 2007). Some scholars used chaos theory to analyse the emission characteristics of driving face and proposed a nonlinear combination prediction method based on SVM (Huang, Tong, & Ren, 2009; Shi, Song, & He, 2006). Some scholars establish the prediction model of gas emission combine wavelet transform (WT) with Genetic Algorithm – the Genetic Algorithm – SVM (Ma, 2009). Some scholars take a fuzzy fractal process (WT) with Genetic Algorithm – the Genetic Algorithm – SVM (Ma, 2009). Some scholars take a fuzzy fractal process of mine gas gushing time series, using backpropagation neural network of nonlinear relationship between the influencing factors of fitting (Zhang & Qiu, 2006), and fuzzy time series model is set up. The method of fuzzy data mining is used to process the gas monitoring data to realize the prediction of gas emission (Xu, Wang, & Wang, 2004).

These studies have achieved good practical application effect, and have promoted the technical research of mine ventilation system optimization and gas disaster prediction and control. In recent years, the comprehensive prediction models and algorithms were also proposed (Tian, Li, Wang, & Wang, 2015), and the least squares SVM was selected as the prediction model (Tian & Li, 2017; Tian, Li, Wang, & Sha, 2017), and some models were applied to predict Wind power power prediction (Tian Zhongda, Li Shujuang, Wang Yanhong & Wang Xiangdong, 2018) and even apply to solve time-delay prediction problem of networked control system (Tian, Zhang, Li, Wang, & Sha, 2017) and Network Traffic prediction (Tian Zhongda, Li Shujuang, Wang Yanhong & Wang Xiangdong, 2017). But gas emission prediction technology is imperfect, and prediction accuracy is not high enough, and the accident that is not completely eliminate have threatened the lives of personnel safety, so that a new prediction method is needed urgently. This paper borrows a new complex neural network (Binguo, Xuedong, & Yongfa, 2015) and will not reinvent the wheel, and we will focus on the optimization of network weights and parameters. The paper is organized as follows. In Section 2, prediction network overview is introduced. In Section 3, Wolf pack algorithm is introduced. In Section 4, the steps of the new method are described. In Section 5, the experimental simulation is described. Finally, some conclusions are given.

2. Prediction network overview

In this section, we will briefly introduce the basic hierarchy of complex neural network models. The output of the system is \( d \), and it is a multi-input single output knowledge system. The decision rules of complex neural network system as follows:

\[ R^i_1: \text{if } \mathbf{x}_1 = u^i_1, \mathbf{x}_2 = u^i_2, \ldots, \mathbf{x}_m = u^i_m, \text{ and } y = d. \]

\[ \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m \text{ represent input variable of the complex neural network, which is precise condition attribute. } u^i_1, u^i_2, \ldots, u^i_m \text{ represent the output of the network. The output of the complex neural network is } y \text{, which is decision attribute. } i = 1, 2, \ldots, p, p \text{ represents the number of rules. } x_i \text{ corresponds to } r_i \text{ number of fuzzy sets, the number of decision attributes is } n. \]

\[ I^i_k = x_{ki} \]

\[ a^i_k = I^i_k (k = 1, 2, 3, \ldots, m). \]

The second layer is fuzzy layer. Each input variable \( x_i \) is discretized into \( r_i \) number of discrete values. Neuron functions of this layer are fuzzy membership functions corresponding to each discrete value.

\[ I^2_{ki} = a^i_k, \]

\[ a^2_{ki} = u^i_k = \exp \left( -\frac{(I^2_{ki} - a_{ki})^2}{\sigma_{ki}} \right), i_k = 1, 2, 3 \ldots r_k. \]

The third layer is the rule layer, and each node represents one rule. If the discrete value corresponding to the second layer of neurons is the front part of a certain rule, the connection weight between the neuron and the
The neuron of the rule layer is 1, otherwise 0.

\[ I^3_j = a_j = \omega^2_1 \cdot \omega^2_2 \cdot \ldots \cdot \omega^2_m, \]

\[ I^3_j = \omega^3(j = 1, 2, 3, \ldots, p). \]

The fourth layer is the conclusion layer. The number of nodes and the number of types of decision attributes are the same \( n \). The neuron of the third layer is connected with the neuron that represents the corresponding conclusion in this layer, meaning this rule generates some rule.

\[ I^4_j = \sum \omega^4_{jl} I^3_l, \]

\[ \omega^4_{jl} = \omega^4_l (l = 1, 2, 3, \ldots, n), \]

where \( \omega_{jl} \) represents confidence degree of rule. The initial value is confidence degree of corresponding rule. The confidence degree formula of decision rule is

\[ u(x_k) = \min \left\{ \frac{|[x_k]_1 \cap D_k|}{|[x_k]_1|} \right\} \]

where \( x_k \) represents the \( k \)th rule, \( D_k \) represents decision attribute type of the \( k \)th rule, \( R_k \) represents the type corresponding to the \( i \)th condition attribute of the rule. The fifth layer is the output layer, the number of nodes is the same with the number of decision attributes. This layer represents defuzzification, \( b_i \) represents the value of decision attribute of decision-making node, which keeps invariant in the training of network training.

\[ \hat{y}_i = \frac{\sum \omega^4_{jl} b_i}{\sum \omega^4_{jl}}, \quad \hat{y}_i = I^4_i. \]

The weights and parameters of the network are \( \omega_{kl}, \omega_{kl}, \omega_{oj} \).

### 3. Wolf pack algorithm

Wolf pack algorithm (WPA) is proposed by Wu, Zhang, and Wu (2013) in 2013. As a new swarm intelligence algorithm, the WPA shows good global convergence and computational robustness in the solving process of complex high-dimensional functions. In this paper, WPA is adopted to optimize the weights and parameters of the network. According to the hunting process of the wolves, the wolves are given three roles, namely, the head Wolf, the search Wolf and the capture Wolf. The head Wolf is always the most sophisticated Wolf in the pack, directing the pack to capture its prey and not to participate in the process of wandering, attacking and besieging. The search Wolf is the elite unit of the pack, responsible for searching the prey. The capture Wolf is the attack force in the Wolf pack. Once the head Wolf begins to howl, the capture Wolf quickly moves towards the head Wolf and approaches the prey. Whether it’s a walk or a rush, when a Wolf perceives a concentration of prey larger than the current one, we think the Wolf is more likely to catch prey. So the Wolf will replace the head Wolf and summon him, summoning the surrounding capture Wolf to the current position. When the prey is captured, the rules of reward are used, and the sooner the prey is captured, the more food the Wolf will get. This allows the wolves that have the ability to capture prey to maintain a system that is more likely to catch prey in subsequent hunting, thus ensuring the development of the wolves.

The variables of the WPA are defined as follows.

The total number of wolves is \( N \), and \( D \) is the variable should be optimized. The state of an artificial Wolf is expressed as \( X_i = (x_{i1}, x_{i2}, \ldots, x_{ip}) \), where \( x_{ip} \) represents the position of the \( i \)th artificial wave in the \( d \)-dimensional space. The objective function is \( Y = f(x) \), \( Y \) represents the intensity of the prey that a Wolf perceives, that is fitness.

1. **The generation of the head Wolf.** The head Wolf is the optimal value \( Y_{lead} \) in the initial solution. The head Wolf is not a particular Wolf, and each Wolf’s position is updated during the iteration. If there is a better solution, the head Wolf will be replaced by another Wolf.

2. **The process of migration of the search Wolf.** Among the \( N \) artificial wolves, the number of wolves is \( S_{num} \), and \( S_{num} \) is determined by \( \left[ N/(\alpha + 1) \right], N/\alpha \), where \( \alpha \) is the scaling factor of the search Wolf. The direction of the Wolf is \( h \), and the walking distance is \( Step_a \). The fitness value of the Wolf in the initial solution is \( Y_i \), and then the Wolf is based on the current position, which is further forward to the direction \( p (p = 1, 2, \ldots, h) \), and the position of the forward Wolf in the \( d \)-dimensional space is updated to

\[ x^p_id = x_id + \sin(2\pi \times p/h) \times Step_a^d. \]

At this point, calculate the target function value \( Y_{ip} \) of the search Wolf and select the direction with a larger value to go further between \( Y_{ip} \) and \( Y_i \). At the same time, the location of the search Wolf is updated, and the fitness value \( Y_{lead} \) of the current position of the search Wolf is compared with that of the head Wolf. If \( Y_{ip} > Y_{lead} \), the search Wolf will replace the head Wolf and summon the capture Wolf to the current position. Otherwise, keep going until it reach the maximum number of trips \( T_{max} \).

3. **The rushing of the capture Wolf.** Except for the search wolf and the head wolf, the remaining wolf is the capture wolf, and the number of the capture wolf is \( M_{num} \). When the capture Wolf receives the call information of the head Wolf, it runs in the direction of the head Wolf, and the step is \( step_b \). After the attack, when the Wolf in the \((K + 1)\) iteration, the position in the \( d \)-dimensional space is updated.
to
\[x_{id}^{k+1} = x_{id}^k + \text{step}_d^p \times (g^k_d - x_{id}^k) / |g^k_d - x_{id}^k|, \] (12)

where \(g^k_d\) is the place in the \(d\)-dimension space of the head Wolf among the \(K\)-generation wolves.

At the same, the fitness value \(Y_i\) of the capture Wolf after rushing, if \(Y_i > Y_{\text{lead}}\), the capture Wolf will replace the head Wolf and summon the other capture Wolf to the current position. Otherwise, keep going until the distance of the head Wolf is less than \(d_{\text{near}}\). Enter the siege process of the prey, determine the distance \(d_{\text{near}}\) calculation formula is
\[d_{\text{near}} = \frac{1}{D \times \omega} \times \sum_{d=1}^{D} |\max_d - \min_d|, \] (13)

where \(\omega\) is the determinant and \([\min_d, \max_d]\) is the range of the \(d\)-dimension variable.

(4) The siege of prey. After rushing, the capture Wolf entered the siege stage with the search Wolf. The head Wolf is closest to the prey, the position of the head Wolf is regarded as the position \(g^k_d\) of the prey, and the wolves’ siege of the prey siege stage is stepc. The corresponding position is updated to
\[x_{id}^{k+1} = x_{id}^k + \lambda \times \text{step}_d^p \times |g^k_d - x_{id}^k|, \] (14)

where \(\lambda\) is the random number between [-1,1]. During the process of siege, when the current position of the artificial Wolf is more suitable than the original position, the position is updated. Otherwise, the location is not updated.

stepa, stepb, and stepc have the following relationship:
\[\text{step}_d^a = \text{step}_d^b / 2 = \text{step}_d^c \times 2 = |\max_d - \min_d| / S. \] (15)

(5) Wolves update. In order to maintain the number of good wolves in the pack and to maintain the diversity of wolves in the pack, choose the least adaptive \(R\) Wolf to eliminate, and randomly produce \(R\) new artificial wolves. Here \(R\) is determined by \([N / (2 \times \beta), N / \beta]\), \(\beta\) is the update scaling factor.

The detailed steps for WPA are as follows.
Step 1 Initialize work. The number of initial artificial wolves is \(N\), the position \(X_i\), the maximum number of iterations \(K_{\text{max}}\), the proportion factor \(\alpha\) of the Wolf, the maximum migration number \(T_{\text{max}}\), the value \(\omega\) distance determined by the step factor \(S\), and the update scaling factor \(\beta\).
Step 2 The search Wolf begins working, and the position is updated according to Equation (11) until that the fitness value \(Y_i\) of the search Wolf is greater than the fitness value \(Y_{\text{lead}}\) of the head Wolf, and exchange them. Otherwise, the search Wolf continues to run until the distance between the search Wolf and the prey is less than \(d_{\text{near}}\), and return to step 4.
Step 3 The capture Wolf carried out the attacking process and update the position of the capture Wolf by Equation (12), and if the fitness value \(Y_i\) of the capture Wolf is greater than the fitness value \(Y_{\text{lead}}\) of the head Wolf, exchange them. Otherwise, the capture Wolf needs to continue to attack until the distance between the capture Wolf and the prey is less than \(d_{\text{near}}\), and return to step 4.
Step 4 The search Wolf and the capture Wolf carried out the siege, update the position by Equation (15) and update the head Wolf at the same time.
Step 5 Update the pack.
Step 6 If the maximum number of iterations is reached and the optimization accuracy meets the requirements, output the optimal solution. Otherwise, return to step 2.

4. Improvement of the complex neural network

In view of the local extreme problem of the gradient descent algorithm, which makes the working face of mine gas emission prediction uncertainly, in this paper, the WPA is introduced. We use the global optimization ability of the WPA to find better weights and parameters for the prediction model of complex neural networks. The steps are as follows.

Step 1 Pre-treatment of mine gas related data. The data is divided into training samples and test samples.
Step 2 Parameter initialization of complex neural network. The weights and parameters of the network are encoded, and the algorithm parameters of the WPA are initialized.
Step 3 The search Wolf begins attacking, and the position is updated according to Equation (11) until that the fitness value \(Y_i\) of the search Wolf is greater than the fitness value \(Y_{\text{lead}}\) of the head Wolf, and exchange them. Otherwise, the search Wolf continues to run until the distance between the search Wolf and the prey is less than \(d_{\text{near}}\), and return to step 5.
Step 4 The capture Wolf carried out the attacking process and update the position of the capture Wolf by Equation (12), and if the fitness value \(Y_i\) of the capture Wolf is greater than the fitness value \(Y_{\text{lead}}\) of the head Wolf, exchange them. Otherwise, the capture Wolf needs to continue to attack until the distance between the capture Wolf and the prey is less than \(d_{\text{near}}\), and return to step 5.
Step 5 The search Wolf and the capture Wolf carried out the siege, update the position by Equation (15) and update the head Wolf at the same time.
Step 6 Update the pack.
Step 7 If the maximum number of iterations is reached and the optimization accuracy meets the requirements, output the optimal solution. Otherwise, return to step 3.
Step 8 The optimized weights and parameters are assigned to complex neural networks.
Step 9 Training network. After network training, input test sample to predict mine gas emission.
Step 10 Analyse the predicted results and make evaluations.

5. The experimental simulation

The experimental simulation environment of the paper is MATLAB 2015b, which is a very useful tool. Experimental environment: CPU, i7-8550u; 8G running memory; Windows 10 operating system. 26 sets of mining working face data in a Coal mine in Shandong province were as an example to forecast analysis and have monitoring of gas emission and the other factors, including Coal seam thickness, gas content, the daily output, buried the depth, length of working face, the extraction rate and propulsion. The number of artificial wolves is 50, the maximum number of iterations is 20, the proportion factor of Wolf detection is 4, the direction number of Wolf detection is 4, and the weights and parameters of the network to be optimized are $a_{ki}, \sigma_{ki}, \omega_{i}$. The original data of the 20 groups were used as training samples, and the original data of the latter six groups were used as the prediction samples (Liangliang, Lijun, & Shengli, 2017). The data table is as follows (Table 1).

To analyse the prediction accuracy of the model, in this paper, the prediction results of the complex neural network are compared with the prediction results of the improved network and use four indicators (mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE) and equal coefficient (EC)). The formula of MAPE and EC is as follows:

\[
\text{MAPE}(%)= \frac{1}{n} \sum_{i=1}^{n} \left| \frac{x_i - x_j}{x_i} \right| \times 100, 
\]

where $x_i$ is the actual value, $x_j$ is the predicted value, and $n$ is the sample size.

Table 1. The value of measured data.

| Serial number | Coal seam thickness (m) | Buried depth (m) | Gas content (m$^3$) | Extraction rate (%) | Production (t) | Working face length (m) | Daily progressivity (m) | Gas emission |
|---------------|-------------------------|------------------|---------------------|---------------------|----------------|-------------------------|------------------------|-------------|
| 1             | 4.2                     | 480              | 5.26                | 93                  | 2738           | 154.7                   | 2.9                     | 4.58        |
| 2             | 4.4                     | 470              | 5.45                | 93                  | 2991           | 154.7                   | 3.1                     | 4.58        |
| 3             | 4.1                     | 480              | 5.42                | 92                  | 2627           | 154.7                   | 2.8                     | 4.78        |
| 4             | 4.7                     | 471              | 5.54                | 93                  | 3117           | 154.7                   | 3.0                     | 4.32        |
| 5             | 4.8                     | 475              | 5.20                | 92                  | 3156           | 154.7                   | 3.0                     | 4.26        |
| 6             | 4.9                     | 471              | 5.46                | 93                  | 3363           | 154.7                   | 3.2                     | 4.34        |
| 7             | 4.2                     | 471              | 5.32                | 93                  | 3432           | 154.7                   | 3.4                     | 4.19        |
| 8             | 4.3                     | 471              | 5.05                | 92                  | 3488           | 154.7                   | 3.4                     | 4.64        |
| 9             | 4.5                     | 471              | 4.83                | 93                  | 3461           | 154.7                   | 3.6                     | 4.04        |
| 10            | 4.4                     | 471              | 5.04                | 93                  | 3410           | 154.7                   | 3.6                     | 4.68        |
| 11            | 4.2                     | 470              | 5.35                | 93                  | 3402           | 154.7                   | 3.6                     | 4.50        |
| 12            | 4.5                     | 470              | 5.01                | 93                  | 3427           | 154.7                   | 3.6                     | 4.60        |
| 13            | 4.3                     | 470              | 5.30                | 93                  | 3534           | 154.7                   | 3.7                     | 4.50        |
| 14            | 4.6                     | 470              | 5.35                | 93                  | 3147           | 154.7                   | 3.2                     | 4.68        |
| 15            | 4.4                     | 470              | 5.20                | 92                  | 3110           | 154.7                   | 3.2                     | 4.55        |
| 16            | 4.2                     | 474              | 5.02                | 93                  | 3112           | 154.7                   | 3.2                     | 4.42        |
| 17            | 4.4                     | 473              | 5.00                | 93                  | 3412           | 154.7                   | 3.6                     | 4.68        |
| 18            | 4.5                     | 473              | 5.01                | 93                  | 3412           | 154.7                   | 3.6                     | 4.52        |
| 19            | 4.5                     | 472              | 5.11                | 92                  | 3414           | 154.7                   | 3.6                     | 4.54        |
| 20            | 4.7                     | 470              | 5.35                | 93                  | 3425           | 154.7                   | 3.6                     | 4.36        |
| 21            | 4.7                     | 481              | 5.84                | 93                  | 3240           | 154.7                   | 3.5                     | 4.68        |
| 22            | 4.6                     | 481              | 5.82                | 92                  | 3440           | 154.7                   | 3.6                     | 4.62        |
| 23            | 4.6                     | 481              | 5.79                | 92                  | 3460           | 154.7                   | 3.6                     | 4.62        |
| 24            | 4.7                     | 481              | 4.85                | 93                  | 3480           | 154.7                   | 3.6                     | 4.68        |
| 25            | 4.6                     | 481              | 4.74                | 91                  | 3480           | 154.7                   | 3.7                     | 4.61        |
| 26            | 4.7                     | 480              | 4.84                | 93                  | 3510           | 154.7                   | 3.7                     | 4.65        |

Figure 1. The prediction results.
Table 2. MAPE, RMSE, MAE and EC.

| Prediction model | MAPE  | RMSE  | MAE   | EC     |
|------------------|-------|-------|-------|--------|
| The original model | 0.0014 | 0.0427 | 0.0390 | 0.9946 |
| The improved model | 0.0006 | 0.0191 | 0.0175 | 0.9979 |

\[
EC = 1 - \frac{\sqrt{\sum_{i=1}^{n} (x_j - x_i)^2}}{\sqrt{\sum_{i=1}^{n} x_j^2 + \sum_{i=1}^{n} x_i^2}}
\]  

where \( x_j \) is the real value and \( x_i \) is the prediction value.

The improved complex neural network model was used to predict the amount of gas emission in the mining area. The results are shown in Figure 1.

It can be seen from Figure 1 that the prediction effect of mine gas emission quantity based on WPA is higher than that of the original model. The prediction error of the complex neural network prediction model based on the WPA is reduced significantly, and the error sequence is more stable.

Table 2 shows that the value of MAPE is 0.0014 and 0.0006 respectively, the value of RMSE (root mean square error) is 0.0427 and 0.0191 respectively, the value of MAE (mean absolute error) is 0.0390 and 0.0175 respectively, and the value of EC is 0.9946 and 0.9979 respectively. This fully demonstrates that the improved network model has higher precision and better stability.

6. Conclusion

In this paper, WPA has been introduced into the prediction model of complex neural network, and the weights and parameters of the network are optimized. The model selects seven factors as input variables and predicts six group data of mine gas emission. Compared with the original model, the prediction results of the model are very close to the real value, and the change trend is highly consistent with the actual situation. Research results show that the MAPE value of the model is 0.06% and the EC value is 0.9979. Therefore the WPA has been found the weight and parameters of the network better, but the improved network operation time needs to be further optimized and improved.

Disclosure statement

No potential conflict of interest was reported by the authors.

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