Prediction of coal mine gas emission based on Markov chain improving IGA-BP model

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Abstract

There are a lot of factors that affect the gas emission, and among those there is a complicated and nonlinear relationship, so a BP neural network model based on immune genetic algorithm (IGA) was constructed to solve the problem of the traditional BP neural network such as, slow training speed, easy to be trapped into local optimums, and the premature convergence. In order to further improve accuracy of the prediction, the Markov chain was used to modify the residual series for the sample of bigger error. The correction result is more close to the measured value. The results showed that both the prediction accuracy and convergence speed of the IGA-BP model are better than the BP neural network model. The prediction after modified by Markov chain was further improved, the absolute average relative error of the prediction of the IGA-BP model is 2.40%.

Keywords: gas emission, immunity genetic algorithm, BP neural network, Markov chain, prediction

1 Introduction

Gas is one of the important factors threatening the safety production of mine. The situation of safety in production of coal mine is becoming more and more serious. The security incidents occurred in small and medium sized coal mines are particularly frequent. According to statistics, more than 80% of the accidents are related to gas emission. Therefore, accurate prediction of gas emission become more important [1].

The gas emission is affected by geological structure, coal seam, coal seam thickness and other factors, various factors mutual restraint, is a nonlinear dynamic system, time-varying, makes it difficult to accurately predict the [2] of gas emission. In recent years, some scholars use BP neural network prediction of mine gas emission, and achieved good results, but BP neural network has slow convergence speed, easily falling into local minimum problems [3].

In order to solve these problems, this paper presents a BP neural network optimization algorithm -- the improved immune genetic algorithm BP neural network algorithm (Immunity Genetic Algorithm-BP neural network, referred to as IGA-BP), and to establish prediction model of underground gas emission of working face of dynamic prediction.

Although the improved algorithm better prediction results, but some relative error between predicted value and measured value is too large, so this paper use Markoff chain modified prediction error residual value, the correction value is more close to the measured values of [4].

2 Immune Genetic Algorithms (IGA)

In recent years, people began to biological immune technology into the bionic algorithm in traditional artificial immune algorithm, resulting in [5]. The theory based on this algorithm with immune operator, immune vaccination and immune selection operator has two aspects, the former is based on the prior knowledge of individual genes in the improvement, improve the individual fitness; the latter is testing the vaccine individual after inoculation, the individual fitness increased retention, or eliminated. The improved immune algorithm is applied to BP neural network design, use of biological immune technology in the concentration mechanism and individual diversity retaining strategy of immune regulation, effectively solve the premature convergence problem of [6].

IGA algorithm mainly uses the following features [7]:

1) immune system) ability to generate antibody diversity, the differentiated cells, the immune system produces antibodies to different antigens in many. Use this function to maintain the individual diversity of the evolutionary process, improves the global search ability of the algorithm, to avoid falling into local optimal solution;

2) self regulatory mechanism, balancing mechanism of immune system by promoting and inhibiting antibody, quantity can be self regulating necessary antibody inhibition concentration, individual this correspondence in genetic algorithm and the promotion, can improve the local search ability of the algorithm;

3) immune memory function and antibody producing cells will retain some memory cells, for the same antigen into the future, the corresponding memory cells can be

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rapidly stimulated and produced a large amount of antibody. Through this antigen memory recognition function in IGA algorithm, can speed up the search speed, improve the algorithm's search ability overall.

In general, the IGA algorithm is an improved genetic algorithm by biological immune mechanism is constructed, it will be practical to solve the problem of the objective function corresponds to the antigen, and the solution for the problem corresponding to the antibody [8]. The biological immune principle knowable, cell invasion of life body antigen immune system of division and differentiation, automatic produce antibodies to fight, this process was called immune response. In the process of immune responses, some antibodies as a memory cell to be preserved, when similar antigen invaded again, memory cells stimulated and rapidly produce large amounts of antibodies, the secondary response than the initial response more quickly, strong, reaction of the immune system and memory function. Combined with the antibody and antigen, destroys the antigen in a series of reaction. At the same time, mutual promotion and inhibition between antibody and antibody, used to keep the diversity of antibodies and immune balance, the balance is based on the concentration mechanism, namely antibody concentration is high, are inhibited; low concentration, is promoted by the reaction of the self-regulatory function, immune system.

Compared with the standard GA algorithm, based on the characteristics of the main IGA algorithm immune principles:

1) characterized by immune memory, this feature can improve the search speed, the ascension of the whole GA algorithm search function;

2) has the characteristics of antibody diversity, local search using this feature can improve GA algorithm;

3) has the ability of self-regulating, this function can improve the global GA algorithm search function, to avoid falling into local solution.

In short, the characteristics of IGA algorithm not only keeps the global GA algorithm parallel random search function, but also avoids the premature convergence problem in a certain extent, to ensure rapid convergence to the global optimal solution [9].

3 IGA-BP algorithm methodologies

Realization depends on BP neural network algorithm based on BP neural network IGA.

First, IGA receives an antigen (corresponding to a particular problem), followed by a set of randomly generated initial antibody (corresponding to the candidate solution); then calculates the fitness of each generation of the antibody, the antibody of crossover and mutation; groups through the concentration update strategy to generate the next generation of antibody group; until the termination condition is met, the algorithm ends. Which has the largest concentration of population is defined fitness or close to the number of antibodies and antibody ratio of total maximum fitness is.

Specific Methods IGA BP neural network optimization algorithm is as follows.

3.1 ANTIBODY CODING

BP neural network learning is a continuous parameter optimization process repeatedly, if you use a binary encoding, will lead encoded string is too long, and in the time and you want to calculate the antibody decoded into a real number, which may affect the accuracy of network learning and algorithm running time. Therefore, the use of real-coded way, each antibody corresponds to one network structure, the number of hidden nodes to the right of re-mixed and network real-coded.

3.2 ANTIBODY FITNESS FUNCTION

Assuming an amount of the antibody population, each antibody corresponds to a network, as a combined network structure. Corresponding to the error of each antibody as an antigen of IGA Therefore, the fitness function of the antibody to the antigen [10]:

$$F(i) = \frac{1}{E_i + const}, \tag{1}$$

$$E_i = \sum_p \sum_{out} (T_{p,out} - Y_{p,out})^2, (i = 1, 2, ..., n), \tag{2}$$

where *const* is greater than zero; $T_{p,out}$, $Y_{p,out}$ respectively the p training samples of the first two desired output and actual output; E_i antibodies corresponding to the i error.

3.3 GENETIC MANIPULATION

3.3.1 Cross

Use way cross at the intersection of two points, establish $X_1^l = [x_1^1, x_2^1, ..., x_n^1]$, $X_2^l = [x_1^2, x_2^2, ..., x_n^2]$ - the l-generation of two antibodies. In the i two arithmetic crossover point and j point, the next generation of antibodies is:

$$\begin{aligned} X_1^{l+1} &= [x_1^1, ..., x_i', ..., x_j', x_{j+1}^1 ..., x_n^1] \\ X_2^{l+1} &= [x_1^2, ..., x_i'', ..., x_j'', x_{j+1}^2, ..., x_n^2], \end{aligned} \tag{3}$$

The x_k' and x_k'' ($i \le k \le j$) is produced by the following linear combination:

$$\begin{aligned} x_k' &= \zeta x_k^1 + (1-\zeta) x_k^2 \\ x_k'' &= \zeta x_k^2 + (1-\zeta) x_k^1, \end{aligned} \tag{4}$$

type in the ζ ratio, moreover $\zeta \in [0,1]$.

3.2.2 The variation

Variation using the gauss mutation and the specific operation is the first antibody decoding into corresponding network structure. One by one according to the Equation (5) the ownership of the mutation network weight, mutated by hidden node components and weights to form a new antibody:

$$\Delta W = a\sqrt{F(i)}\mu(0,1), \tag{5}$$

where: $a \in [0,1]$; $\mu(0,1)$ is Gaussian operators.

3.4 BASED ON THE CONCENTRATION OF UPDATES

Concentration group to update the overall goal is to restrain high levels of antibodies, while ensuring the selected probability high fitness individuals a greater concentration of antibody is C, adjust the chance for individual choice:

$$p(i) = \alpha C\left(1 - \frac{F(i)}{F_{\max}}\right) + \beta \frac{F(i)}{F_{\max}}, \tag{6}$$

where: $\alpha, \beta \in [0,1]$; $F_{\max}$ is the biggest fitness or close to the largest fitness antibodies.

From the Equation (6), the antibody concentration is higher, the fitness of antibody is likely to be selected is smaller. Antibody concentration, the smaller the fitness of antibody the greater the chance of being chosen.

3.5 BASIC STEP

Step 1 randomly generated antibodies in a certain weight distribution interval of initial population, and each antibody denotes a BP network.
Step 2 calculate the fitness of each antibody according to each antibody coding to draw corresponding BP network and its connection weights.
Step 3 will assess whether or not the performance of the BP network can converge to the desired accuracy range, if can output optimal BP networks, good execution Step 4 if not.
Step 4 genetic operation to antibody group, crossover and mutation.
Step 5 choice based on the concentration of antibody, produce a new generation of antibody group, jump to Step 2 continue to cycle.

4 The establishment of the absolute gas emission prediction model

This article selects several main influencing factors of absolute gas emission [11, 12] as the input layer of the model: Mining layer primitive gas content (p_1), buried depth of coal seam (p_2), thickness of coal seam (p_3), coal bed pitch (p_4), mining height (p_5), working face length (p_6), working face production rate (p_7), adjacent layers of primitive gas content (p_8), adjacent layer thickness (p_9), interlayer lithology (p_{10}), mining intensity (p_{11}). The combined gas emission as output layer of the model.

Model of the topological structure of BP neural network in the form of the 11-16-1 (as shown in Figure 1), a total of 28 the activation function of neurons in hidden layer neurons are s-shaped function:

$$f(x) = \frac{1}{1+e^{-x}}, \tag{7}$$

Output layer neuron activation function using linear function:

$$f(x) = x, \tag{8}$$

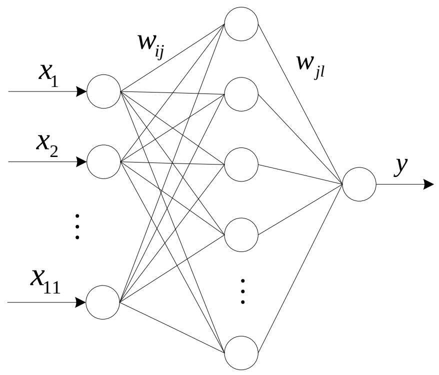

FIGURE 1 Topological structure of BF neural network

According to the characteristics of the immune genetic algorithm (GA), population size selected 50, type (1) = 0.001, (5) = 0.1, (4) = 0.5, the concentration of population in the total number of antibodies in the number and group is greater than 0.8, the ratio of evolution algebra for 200 generations.

5 Experimental studies

This paper selects kailuan mining group money mining camp in May 2007 to December 2008 working face of absolute gas emission quantity and influencing factors of statistical data (as shown in Table 1) as sample, 1~15 group of BP neural network model is used to IGA - training the BP model 16~18 group for testing, predictive results of the two models (see Figure 2) convergence contrast (as shown in Figure 3).

Through the experiment of Figures 2 and 3, the simulation curve can be seen that the BP neural network model of prediction in poor convergence speed, and the error is bigger; IGA - BP model is the improvement of BP neural network model, so the prediction curve can more accurately fitting the measured curve, precision and convergence speed are improved, but still part of the forecast error is bigger, so this article use Markov chain correction IGA - BP model prediction error of the salvage value, in order to improve the prediction accuracy.

TABLE l The statistical data of coalface gas emission influencing factors

Serial number	p_1 (m^3/t)	p_2 (m)	p_3 (m)	p_4 (°)	p_5 (m)	P_6 (m)	P_7	P_8 (m^3/t)	p_9 (m)	p_{10}	p_{11} (t/d)	T (m^3/min)
1	1.92	408	2.0	10	2.0	155	0.960	2.02	1.50	5.03	1	3.34
2	2.15	411	2.0	8	2.0	140	0.950	2.10	1.21	4.87	1	2.97
3	2.14	420	1.8	11	1.8	175	0.950	2.64	1.62	4.75	1	3.56
4	2.58	432	2.3	10	2.3	145	0.950	2.40	1.48	4.91	2	3.62
5	2.40	456	2.2	15	2.2	160	0.940	2.55	1.75	4.63	2	4.17
6	3.22	516	2.8	13	2.8	180	0.930	2.21	1.72	4.78	2	4.60
7	2.80	527	2.5	17	2.5	180	0.940	2.81	1.81	4.51	1	4.92
8	3.35	531	2.9	9	2.9	165	0.930	1.88	1.42	1.82	2	4.78
9	3.61	550	2.9	12	2.9	155	0.920	2.12	1.60	4.83	2	5.23
10	3.68	563	3.0	11	3.0	175	0.940	3.11	1.46	4.53	2	5.56
11	4.21	590	5.9	8	5.9	170	0.795	3.40	1.50	4.77	3	7.24
12	4.03	604	6.2	9	6.2	180	0.812	3.15	1.80	4.70	3	7.80
13	4.80	634	6.5	9	6.1	165	0.785	3.02	1.74	4.62	3	7.68
14	4.80	634	6.5	12	6.5	175	0.773	2.98	1.92	4.55	3	8.51
15	4.67	640	6.3	11	6.3	175	0.802	2.56	1.75	4.60	3	7.95
16	2.43	450	2.7	12	2.2	160	0.950	2.00	1.70	4.84	1	4.06
17	3.16	544	2.7	11	2.7	165	0.930	2.30	1.80	4.90	2	4.92
18	4.62	629	6.4	13	6.4	170	0.803	3.35	1.61	4.63	3	8.04

6 Markov correction error salvage value

Markov chain is a kind of probability prediction method about the incident It is based on the status of the current events to predict its future changes each time a forecasting method of [13]:

1) Markov chain state Spaces is established.

2) To determine the state transition probability and the state transition matrix. In the process of development and change of events, the state E_i after k step move to the state transition probability of E_j to P_{ij} [14]:

$$P_{ij} = \frac{m_{ij}^{(k)}}{M_i}, \qquad (9)$$

where: A total number M_i state E_i; $m_{ij}^{(k)}$ state step E_i by k to E_j ; m is the division of state. Markov step m transition probability matrix in $P(m)$:

$$P(m) = \begin{bmatrix} P_{11}^{(m)} \cdots P_{1n}^{(m)} \\ \vdots \qquad \vdots \\ P_{n1}^{(m)} \cdots P_{nn}^{(m)} \end{bmatrix}. \qquad (10)$$

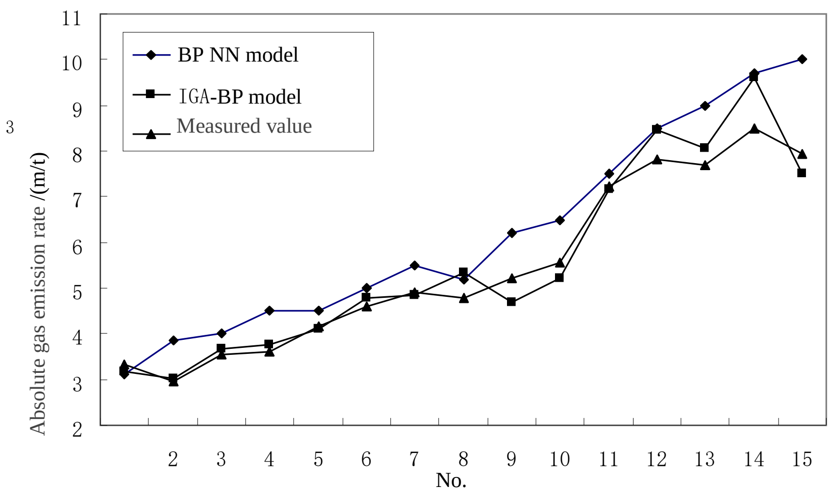

FIGURE 2 The prediction results of BP neural network model and IGA-BP model

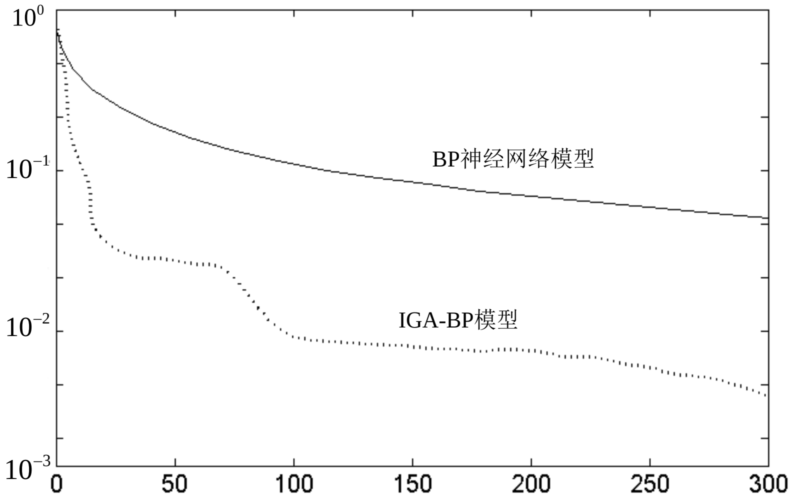

FIGURE 3 The convergence contrast of BP neural network model and IGA-BP model

3) IGA-BP model for Markov prediction results:

$$F = F_{IB}/(1-q)\,, \tag{11}$$

where IGA - BP model prediction; to the original state of boundary value of the range according to the situation of training sample relative error of prediction (as shown in Table 2. Markov chain state interval is determined according to the actual situation can be divided into three intervals divided on the basis for $E_1[0\quad \bar{x}-0.5s]$, $E_2[\bar{x}-0.5s\quad \bar{x}+0.5s]$, $E_3[\bar{x}+0.5s\quad 1]$ as sample mean square error.

Due to the hierarchical sequence must be positive, you must first make use of the equation:

$$\tilde{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}\,. \tag{12}$$

Normalized relative error sequence to [0, 1], between state interval.

According to the above formula of three state Markov state set respectively $E_1[0, 0.5458]$, $E_2[0.5458, 0.7021]$, $E_3[0.7021, 1]$ Using Equation (12) reduction divided interval, thus can be concluded that the relative error for sequence of three kinds of state. $E_1[-0.2892, -0.0988]$, $E_2[-0.0988, -0.0443]$, $E_3[-0.0443, 0.0596]$. According to the division of the state of the set of probability transfer matrix are obtained:

TABLE 2 The state of relative error distribution

Serial number	gas emission quantity(m^3/t)		absolute error/relative error (%)	The normalized relative error (%)	Status
	measured value	*predictive value*			
1	3.34	3.19	4.54	83.05	E_3
2	2.97	3.01	1.32	82.88	E_3
3	3.56	3.66	2.83	82.84	E_3
4	3.62	3.75	3.54	82.82	E_3
5	4.17	4.10	1.66	82.97	E_3
6	4.60	4.79	4.09	82.80	E_3
7	4.92	4.86	1.29	82.96	E_3
8	4.78	5.35	11.85	82.58	E_1
9	5.23	4.70	5.96	83.09	E_3
10	5.56	5.23	4.91	83.06	E_3
11	7.24	7.17	0.95	82.95	E_3
12	7.80	8.46	8.42	82.68	E_2
13	7.68	8.05	4.77	82.78	E_2
14	8.51	9.61	12.87	82.55	E_1
15	7.95	7.50	5.60	83.08	E_3

TABLE 3 Prediction of IGA-BP model and Markov chain revised

Serial number	measured value /(m^3/t)	IGA-B model		Markov	
		predictive value (m^3/t)	*relative error (%)*	*modified value (m^3/t)*	*relative error (%)*
16	4.06	4.26	-4.96	3.97	2.23
17	4.92	5.89	-19.63	4.96	-0.81
18	8.04	10.08	-25.36	8.47	-5.36

$$P(1) = \begin{bmatrix} 0.5714 & 0.1429 & 0.2857 \\ 0.6667 & 0.3333 & 0 \\ 0.0909 & 0.1818 & 0.7273 \end{bmatrix},$$

$$P(2) = \begin{bmatrix} 0.4477 & 0.1812 & 0.3711 \\ 0.6032 & 0.2063 & 0.1905 \\ 0.2393 & 0.2058 & 0.5549 \end{bmatrix},$$

$$P(3) = \begin{bmatrix} 0.4104 & 0.1918 & 0.3978 \\ 0.4996 & 0.1896 & 0.3109 \\ 0.3244 & 0.2037 & 0.4719 \end{bmatrix}.$$

So the Markov revised as shown in Table 3. As you can see from the result of modified Markov correction IGA - BP model can improve the prediction accuracy to make revised more close to the measured values With the actual and estimated values of the maximum relative error is 5.36%, the minimum relative error is 0.81%, the average relative error was 2.40% to prove the author proposed method of residual error correction effect is obvious.

7 Conclusion

This paper presents a BP neural network based on IGA is applied in gas emission prediction IGA in Gaussian mutation genetic algorithm on the basis of introducing and updating strategy based on antibody concentration regulation mechanism, on the basis of effectively keep the diversity of antibodies, both retained the characteristics of global convergence of genetic algorithm, and can avoid the premature convergence problem in the very great degree, improves the convergence efficiency. By experimental verification show that IGA-BP model has a faster convergence speed and strong global convergence On this basis, the salvage value correction of Markov chain is applied to forecast error, the accuracy of IGA – prediction of BP model is further improved. Therefore, based on IGA-BP and Markov chain of coal mine gas emission prediction has certain application value.

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