Design of underground mining wireless communication resource algorithm based on chaotic neural network

There are more and more applications of underground wireless communication in coal mines, such as coal mine video monitoring systems, coal mine dispatching systems, and coal mine safety data fusion systems. These coal mining systems require a large amount of data transmission, occupying a large amount of bandwidth, and the mine underground wireless communication resources are limited. It is necessary to allocate these resources reasonably to ensure the effective operation of these services. Coal mine underground radio resource allocation and optimization is the interface resources between the entire coal mine wireless communication system, such as communication bandwidth, signal spectrum and transmission time slot management, including channel multiplexing, packet scheduling, network optimization, load balancing and other related methods. The efficiency of the entire communication system is improved by maximizing the rational use of wireless network resources. In existing coal mine wireless communication resource optimization algorithms, there are adaptive feedback, wireless cooperative channel multiplexing technologies, etc. The existing wireless resource algorithms generally have high complexity, and there is still a certain space between the final calculation result and the optimal solution. This paper studies the existing coal mine underground optimization algorithm and optimizes and improves the existing chaotic neural network. It effectively reduces the complexity of the algorithm and makes the setting of parameters more consistent with the underground coal mine communication environment. At the same time, through a large number of tests, the parameter sets of chaotic neural network are provided, and a coal mine underground wireless resource optimization algorithm based on chaotic neural network is proposed, and the simulation results are given. The simulation results show that the algorithm proposed in this paper can effectively optimize the interface resources between the entire underground coal mine wireless communication system and improve the coal mine resource allocation rate.

Keywords: *Underground coal mine, mining wireless communication resource algorithm, chaotic neural network, OFDMA*

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1. Introduction

With the development and extension of large lanes, the existing systems can no longer meet the functional requirements of existing safe production and management [1-2]. In order to meet the needs of the underground auxiliary communication, the only solution at present is to upgrade the system. In order to upgrade and transform the existing system on the mine, all base stations in the mine must be replaced [3]. The main communication cables and the controllers of the core equipment in the equipment room need to be replaced [4-5]. The cost of upgrading the system and the cost of a new communication system are basically the same.

Coal mine underground is a special working environment [6]. Therefore, the mine wireless communication system is different from the general terrestrial wireless communication system and has the following features [7-8]. Coal mines have flammable gases such as gas and coal dust [9]. Therefore, the requirements for wireless communication devices are intrinsically safe and explosion-proof devices with good safety performance. The transmission loss is great. Coal mine underground space is small, roadway is inclined, there are corners and branches, rough roadway surface, and windy stations, locomotives and other obstacles, transmission attenuation and low transmission power [10]. The emission power of intrinsically safe explosion-proof electrical equipment is generally around 10mW-40mW. It has strong anti-interference ability. The underground space is small, the electro-mechanical equipment is relatively concentrated, the power is large, and the electro-magnetic interference is serious [11]. Therefore, the equipment should have strong anti-interference ability. With good protection ability, it should have dust, water, moisture, corrosion, mechanical impact resistance and other properties. It has strong resistance to failure. Coal mines are in poor conditions, equipment failure rates are high, and man-made destruction events occur from time to time [12-13]. Therefore, the mine wireless communication system should have strong anti-fault capability. When some equipment in the system fails, the remaining non-faulty devices can continue to work. It has large channel capacity. Coal mine underground is a mobile work environment, and the existing wired dispatch telephones are limited [14-16]. With the improvement of wireless communication system reliability, communication quality, function improvement, and cost reduction, it will play a major role in production scheduling, especially emergency rescue and disaster relief. Therefore, it needs to have a larger channel capacity. The moving speed is slow. The mobile speed of the handset in the mine wireless communication system is slow, which is mainly determined by the characteristics of mine personnel and transportation tools.

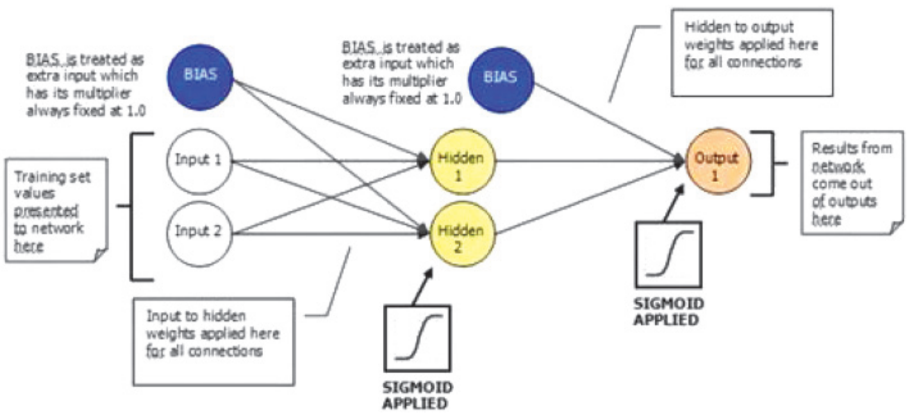

Fig.1 Neural network model with sigmoid function

The widely studied chaotic neural network model introduces a negative feedback term with chaotic characteristics in the Hopfield neural network, and then obtains the chaotic neural network model. Therefore, it is necessary to first introduce the Hopfield neural network before deeply researching the chaotic neural network. The American physicist J. J. Hopfield first proposed a single-layer feedback network system. This single-layer feedback network is called a Hopfield network. The nonlinearity and high dimensionality of feedback neural networks make it difficult to determine the state trajectory of existing tools, and even chaotic phenomena may occur. Due to the complexity of the neural network with chaotic characteristics, it has been widely studied.

2. The principle of chaotic neural network

Chaotic neural network can accurately find the balance point and periodic law in the communication network [17-18]. It is one of the most popular technologies in modern information processing technology and has good dynamic characteristics. The disadvantage is that the algorithm is easy to fall into the trap of local optimization, and the convergence of the algorithm is not high, and local optimization is needed. The chaotic neural network is a self-feedback recursive system [19]. Each time the calculation result is recalculated as the initial condition of the next iteration, the entire network becomes convergent. When the system reaches steady state, the iterative process ends.

The transient chaotic neural network model is as follows:

$$x_t(t) = f(y_i(t)) \qquad \text{... 1}$$

$$y_i(t+1) = ky_i(t) + \alpha\left[\sum_j W_{ij}x_j + I_i\right] - z_i(t)(x_i(t) - I_0) \qquad \text{... 2}$$

$$z_i(t+1) = (1-\beta)z_i(t) \qquad \text{... 3}$$

Hereinto, formula (1) is the excitation function of the neuron; x_i is the output of the i neuron; y_i is the input of the i neuron; W_{ij} is the coupling weight value from j neuron to i neuron; I_i is the replacement of the i neuron; I_0 is a normal number, α is the coupling strength between neurons, also known as the coupling factor; k is the nerve diaphragm damping factor, $0<k<1$; $\beta(0<\beta<1)$ is the simulated annealing parameters, $z_i(t)$ is the simulated annealing's initial value. Equation (3) is analogous to the simulated annealing algorithm function. As the number of iterations increases, this equation will gradually go to zero.

Formula (1) is not fixed as an excitation function, it can be a Sigmoid function, or it can be another function that is consistent with Sigmoid (Fig.1).

This paper uses the Sigmoid function, which is the model proposed by Chen and Aihara [1]. The Sigmoid function is shown in the following formula.

$$f(u) = 1/(1+\exp(-u/\varepsilon)) \qquad \text{... (4)}$$

In which, ε is the gain parameter.

When $\alpha = 0$, the above three equations evolve into chaotic neuron models:

$$x(t) = f(y(t)) \qquad \text{... 5}$$

$$y(t+1)=ky(t)-z(t)(x(t)-I_0) \qquad \text{... 6}$$

$$z(t+1)=(1-\beta)z(t) \qquad \text{... 7}$$

3. Wireless OFDMA resource optimization model

The existing mine-based wireless communication system is mainly based on the multi-user OFDMA technology. Its resource allocation includes two modes: dynamic resource allocation and static resource allocation. The existing ones are based on dynamic allocation.

Suppose R_T is coal mine underground wireless communication system's signal transmission rate; P_i is the system transmit power; P_E is sum of multi-channel error rates; BER is the bit error rate of a single channel. The mathematical model of the optimization of signal bit, power and carrier load in the underground wireless communication in the coal mine is as follows.

The final optimization goal is

$$\max R_T = \max \frac{B}{N}\sum_{x=1}^{K}\sum_{i=1}^{N} V_{x,i}\log_2(1+\frac{P_i\left|H_{x,j}\right|^2}{BN_0/N}) \quad ...\ 8$$

$$\min P_T = \min \sum_{x=1}^{K}\sum_{i=1}^{N} V_{x,i}P_i \quad ...\ 9$$

And it shall meet

$$C_1:\ V_{x,j} \in \{0,1\}; \forall_x = 1,2,...K; i = 1,2,...N; \quad ...\ 10$$

$$C_2: \sum_{x=1}^{k} V_{x,j} = 1, \forall i \quad ...\ 11$$

$$C_3:\ P_i \geq 0, \forall i \quad ...\ 12$$

$$C_4: \sum_{i=1}^{N} P_i \leq P_T^{total} \quad ...\ 13$$

The above optimization problem for the radio resources on the mine forms different models for finding balance points through the conditions defined in Equation (10)-Formula (13), where Equation (9) represents the optimal formula for the transmission power of the wireless communication network. Equation (8) indicates the optimal solution to the maximum bandwidth of each business system. The conditional expression (10) represents the specific service range allocated to the sub-channel i. The condition (11) restricts a sub-channel to be used by only one specific service. Equation (12) indicates that the sub-channel transmission power is positive. The sum of the total powers of the services cannot be limited to exceed the maximum rated power, and Equation (13) represents the requirements for signal transmission rates of different services.

4. An optimization algorithm based on chaotic neural network

Chaotic neural networks use phase space to search quickly in the global scope. Compared to the previous algorithm, the disadvantages of falling into the local optimum are solved, and the convergence is greatly improved compared to before. The neural network-based maritime radio resource optimization model is as follows.

$$V_{x,j}(t) = \frac{1}{1+\exp(-U_{x,j}(t) * u_0)} \quad ...\ 14$$

$$U_{x,j}(t+1) = \lambda U_{x,i}(t) + a(\sum_{x,i\neq y,j} w_{x,i;y,j}(t)V_{y,j}(t) + b_{x,j}) - z_{x,j}(t)(V_{x,j}(t) - I_0) \quad ...\ 15$$

$$z_{x,j}(t+1) = (1-\beta)z_{x,j}(t) \quad ...\ 16$$

In the formula, $U_{x,j}(t)$ is the transient state of information processing element; $V_{x,j}(t)$ is the network element output at the moment t; u_0 is information processing unit weight factor coefficient; λ is the convergence damping coefficient; a is positive correlation scale factor; $w_{x,i:y,j}(t)$ is correlation coefficient between two information processing units; $z_{x,i}(t)$ is the recursive feedback factor; I_0 is the positive normal number; β is the feedback declining factor.

In the multi-service OFDMA wireless communication system on the mine, the signal modulation method adopts M-QAM, then each frame of the customers' business x contains $c_{x,i}$ bits at the sub-channel i, $M_T = 2^{cx,i}$. If the grain factor of the sub-channel i is $|H_{x,i}|^2$, the optimal value needed to transmit $c_{x,i}$ bits' transmission power is:

$$P_i = \frac{f(c_{x,i})}{\left|H_{x,i}\right|^2} \quad ...\ 17$$

$$f(c_{x,i}) = \frac{N_0}{3}\left[Q^{-1}(\frac{P_e}{4})\right]^2 (2^{c_{x,j}} - 1) \quad ...\ 18$$

In the formula, P_e is the error rate controlled by the system.

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-t^2/2}dt_o \quad ...\ 19$$

Ultimately, the optimal transmit power of the channel occupied by each service is determined by N_0, P_e, $|H_{x,i}|^2$, and modulation methods.

In a specific mining wireless communication application scenario, the service can occupy multiple transmission sub-channels according to the required bandwidth. When the number of used channels is N, the total number of bits transmitted by the service x per unit time has the following expression.

$$R_x = \sum_{i=1}^{N} c_{x,i^o} \quad ...\ 20$$

5. Simulation

This paper simulates the resource optimization algorithm of OFDMA single cell wireless communication system based on chaotic neural network in Matlab platform. The base station is located in the center of the network and the carrier frequency is set to 2 GHz. The number of maritime communications services is 4. The number of users is 6, and the comprehensive priority is 1:2:2:3:4:4. The detailed parameter settings of the algorithm are shown in Table 1.

The chaotic neural network structure simulated in this paper is a two-dimensional model. The signal processing cell number distribution is $K \times N$, where K is the number of users and N is the number of services. The gain matrix of the entire maritime wireless communication channel is H, and the specific parameter $H_{x,i}$ is the gain coefficient of the service in the multipath channel. The entire chaotic network parameters are as follows: $u_0 = 7$, $a = 0.06$, $\lambda = 0.95$, $I_0 = 0.65$, $z(0) = 0.89$,

Table 1 Parameter setting

Parameter name	Range
System frequency/GH2	2
Selected channel model	Multi-fading channel model
Sub-channel frequency interval/kH_Z	15
Time slot/ms	0. 5
Number of data bits transmitted per timeslot	7
Communication system's rated bit error rate	10^{-4}
Comprehensive priority levels	1:2:2:3:4:4
Number of users	6
Number of multichannel Carriers	32, 48, 64, 80, 96, 112, 128
Signal modulation	M-QAM

Table 2 The number of 0 and 1 and ratio

Iteration times	The number of 0	The number of 1	The ratio of 0 and 1
2000	15884	16116	0.9856
5000	39502	40498	0.9754
8000	63047	64953	0.9707

Table 3. Run Characteristics

Run	N_0	N_1	N_0/N_1	Actual ratio	Theoretical Ratio
1	4283	4232	1. 012	0. 5118	0. 5000000
2	2168	2017	1. 074	0. 2515	0. 2500000
3	1014	1059	0. 957	0. 1246	0. 1250000
4	516	477	1. 081	0. 0596	0. 0625000
5	236	229	1. 030	0. 0279	0. 0312500

$A_e = 0.15, B_e = 2.5, C_e = 6, D_e = 2, F_e = 3.$

According to the above algorithm, three random hypothesis tests of Golomb were conducted. First, according to the Golomb hypothesis, the 0, 1 ratio of a pseudo-random binary sequence is 1:1.

Table 2 is the number of 0, 1 and ratio of multiple tests, take = 0.004, $I_0 = 0.1$, $k = 0.6$, $y(1) = 0.2$, $z = 0.1$. It can be seen from Table 1 that the 0, 1 ratio basically goes to 1.

Secondly, the run-length characteristic, i.e. the number of runs with L as the total number of runs, is $1/2^L$. Table 3 shows the test data when the value of the above parameter is used and the number of iterations is 2000.

It can be seen from Table 2 that since the statistical time series is limited, the actual ratio is close to the theoretical ratio, and it can be considered that the chaotic binary sequence accords with the run characteristics.

Again, auto-correlation and cross-correlation. Set

$$\bar{x} = \lim_{N\to\infty} \frac{1}{N} \sum_{i=0}^{N-1} x_i \tag{21}$$

The auto-correlation function is

$$\mathrm{ac}(m) = \lim_{N\to\infty} \frac{1}{N} \sum_{i=0}^{N-1} (x_i - \bar{x})(x_{i+m} - \bar{x}) \tag{22}$$

The cross-correlation function is

$$\mathrm{cc}(m) = \lim_{N\to\infty} \frac{1}{N} \sum_{i=0}^{N-1} (x_{1_i} - \bar{x})(x_{2(i+m)} - \bar{x}) \tag{23}$$

Hereinto, x_{1i} and x_{2i} refer to a binary sequence corresponding to the chaotic time series generated from iterations starting from two different initial values; m denotes the correlation interval.

The quantified chaotic binary sequence was tested for correlation characteristics. The length of the sequence was 2000, and the correlation interval was –500 to 500. The aperiodic auto-correlation and cross-correlation properties were shown in Figs.2 and 3. From the experimental results, it can be seen that the chaotic sequence has sharp auto-correlation properties and very small cross-correlation values.

Through the above analysis, it can be seen that the chaotic binary time series is pseudo-random and can be

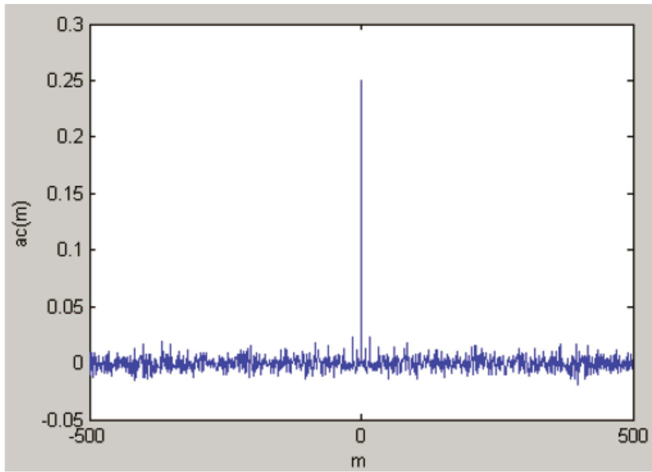

Fig.2 Self-correlation property map

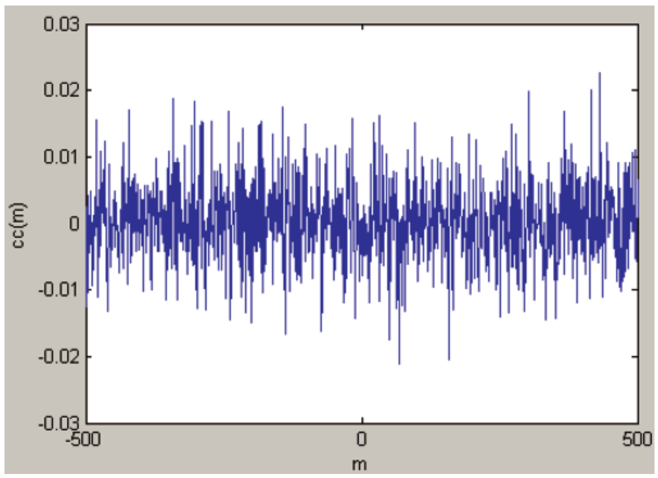

Fig.3 The cross correlation diagram

applied to stream cipher encryption.

6. Conclusion

In the field of wireless communication in underground coal mines, with the increase of services and users, its wireless resources have become more and more tense. How to allocate resources and make rational use of resources efficiently is the key to ensuring the operation of all businesses. The existing algorithms for optimizing wireless communication resources on mines include adaptive feedback, wireless cooperative channel multiplexing, etc. The ubiquitous algorithm has high complexity, and there is a certain degree between the final calculation result and the optimal solution. space. The algorithm proposed in this paper can effectively optimize the interface resources between the entire underground coal mine wireless communication system and improve the coal mine resource allocation rate.

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