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Research Article

Optimization Algorithm of Communication Resource Allocation in a Complex Network Based on an Improved Neural Network

Haomiao Zhang [1] and Qing Liu [2]

[1] *School of Artificial Intelligence and Big Data, Chongqing College of Electronic Engineering, China*
[2] *School of Automation, Chongqing University of Posts and Telecommunications, China*

Correspondence should be addressed to Haomiao Zhang; zhanghaomiao0902@126.com

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The traditional optimization algorithm of communication resource allocation in a complex network has the disadvantage of weak antijamming ability, and the communication quality decreases obviously when the number of users is large. In China's large urban network applications, mobile phones and other networks can have problems such as reduced network efficiency when there are more access users at some communication base stations, thus affecting user network usage. An optimization algorithm of communication resource allocation in the complex network based on an improved neural network is proposed. Increase inertia improves the traditional BP neural network algorithm, using the average path length, clustering coefficient, and connectivity distribution index analysis of the complex network; the improved Hopfield neural network is utilized to confirm each user volume size; it is concluded that their users are able to get the number of subchannels, through the instantaneous channel coarse pair gain dynamic channel allocation, calculating bit load matrix at the same time, minimize transmission power, and achieve bit loading and power allocation and communication resource allocation optimization. Experimental results show that the proposed method has better application performance by introducing the improved neural network and suppressing the external interference on the basis of enhancing the communication effect.

1. Introduction

A complex network is characterized by a complex structure, a large number of nodes, and multiple connection patterns, which refers to a network in which scale-free parts, small worlds, attractors, self-similarity, self-organization, or all properties exist. Also, in complex networks, the connection weights between nodes are completely different from the directionality. Therefore, the relevant network evolution is manifested as the disappearance and generation of connections or nodes; with the complexity of dynamics, the node sets are likely to be in a nonlinear dynamic system; in the diversity of nodes, the nodes can represent anything in a complex network. When communicating in a complex network, communication resources cannot be evenly allocated due to the excessive complexity of the channel, and the information transmission is unstable, thereby causing poor user experience.

Therefore, according to the resource allocation problem generated when adding a cellular network based on D2D communication, literature [1] proposed a joint Hungary resource allocation method. By means of the transmission power and spectrum resource allocation problems for D2D users and cellular users, the algorithm of the proposed method can maximize the transmission rate in a heterogeneous network. Meanwhile, on the foundation of solving the incidence matrix, it is possible to transform into a nonconvex optimization problem through joint optimization and then obtain the solution through a continuous convex estimation strategy. Considering that the SpaceWire network is in the hotspot communication mode, literature [2] studies the cache resource allocation method, derives the method for analyzing the average delay and full-load probability of network routing nodes, and calculates the key communication nodes inside the network. According to the resource allocation scheme for D2D communication in millimeter wave 5G networks mentioned in literature [3], the large communication capacity can be realized through combining device-to-device (D2D) technology with mmWave. Thus, the combination of the above two technologies can help complete resource allocation in an outdoor millimeter wave environment. With the goal of maximizing throughput, the admission set of each D2D user is selected through a linear correlation method. Based on this, the power of communication users is controlled, the communication resource allocation optimized model is constructed via multistage matching algorithm of bipartite graph, and multiple KM algorithms are introduced to solve the allocation model. Although the above three traditional methods are effective, poor communication quality or even communication interruption may appear once the interference becomes strong.

To this end, an optimization algorithm for communication resource allocation in a complex network based on an improved neural network is proposed. Since the neural network is a multilayer feedforward neural network trained by the error backpropagation method, the error drops in the direction of the gradient as being influenced by the connection strength between the input node and the hidden layer node as well as the connection strength between the hidden layer node and the output node. By means of repeated learning and training, the network parameters corresponding to the minimum error can be confirmed, and the accurate allocation requirements can be obtained according to channel differences. For this reason, an inertia term is added to the algorithm so that the network can input information into similar samples, handle the minimum nonerror output error independently, and even transform information linearly to avoid insufficient resource allocation. As can be observed from the experimental results, the proposed improved Hopfield neural network can fully consider the bit loading in the complex network and dynamically realize optimal communication resources in subchannels based on the instantaneous channel gain.

2. Improved Neural Network Optimization Algorithm

2.1. BP Neural Network Algorithm. As a layered feedforward neural network, the BP neural network can be divided into an input layer, hidden layer, and output layer, of which the hidden layer is composed of one or more layers of hidden layer nodes [3], as shown in Figure 1.

Among them, in addition to the input layer nodes, the network also has one or more layers of hidden layer nodes with no connection in the same layer. The input signal is transmitted from the input node to the hidden layer nodes in sequence and then to the output node. That means that the output of each layer node will only affect the output of the next layer node. After removing the equal input and output in the input layer, the unit structure of the remaining nodes [4] is shown in Figure 2.

2.2. Improvement of the BP Neural Network Algorithm. Since there is no connection between the nodes in the same layer, it is difficult to cope with the intricate internal structure of the complex network. Meanwhile, the output result of the BP neural network only has a vertical influence, so neither the optimal output result can be obtained according to the neighboring nodes, nor the subtle requirement of channel resource allocation in complex network can be met. Therefore, the weights and thresholds are adjusted and improved in this research so as to obtain a new Hopfield neural network. The specific formula is

$$\begin{aligned} \Delta v_{ji}(N+1) &= a_1 d_t^{(k)} b_j, \\ \Delta \gamma_t(N+1) &= a_1 d_t^{(k)}, \\ \Delta w_{ji}(N+1) &= a_2 e_j^{(k)} x_i^{(k)}, \\ \Delta \theta_j(N+1) &= a_2 e_j^{(k)}. \end{aligned} \tag{1}$$

In the above formula, N represents the number of nodes in the network, Δv_{ji} represents the neural network asynchronous working method that reaches the threshold, $\Delta \gamma_t$ represents the neural network asynchronous working method that does not reach the threshold, Δw_{ji} represents the neural network synchronous working method that reaches the threshold, $\Delta \theta_j$ represents the neural network synchronous working method where the threshold is not reached, $d_t^{(k)}$ represents the neural network asynchronous coefficient, $e_j^{(k)}$ represents the neural network synchronization coefficient, b_j represents the neural network asynchronous threshold, and $x_i^{(k)}$ represents the neural network synchronization threshold.

During the actual learning process, the learning rates a_1 and a_2 have a greater impact. The greater the a_1 and a_2, the stronger the weight and threshold changes, which will lead to instability, namely, oscillation; the smaller the a_1 and a_2, the more stable it is, but the speed of convergence will be slower. In practical application, generally, the values of a_1 and a_2 should be large under the premise of not causing oscillation, and in order to make the learning speed fast and not easy to oscillate, an "inertia term" shall be added. The specific formula is

$$\begin{aligned} \Delta v_{ji}(N+1) &= a_1 d_t^{(k)} b_j + \eta_1 \Delta v_{ji}(N), \\ \Delta \gamma_t(N+1) &= a_1 d_t^{(k)} + \eta_1 \Delta \gamma_t(N), \\ \Delta w_{ji}(N+1) &= a_2 e_j^{(k)} x_i^{(k)} + \eta_2 \Delta w_{ji}(N), \\ \Delta \theta_j(N+1) &= a_2 e_j^{(k)} + \eta_2 \Delta \theta_j(N). \end{aligned} \tag{2}$$

The choice of a_i and η_i has a greater impact on the speed of network convergence, so the formula is

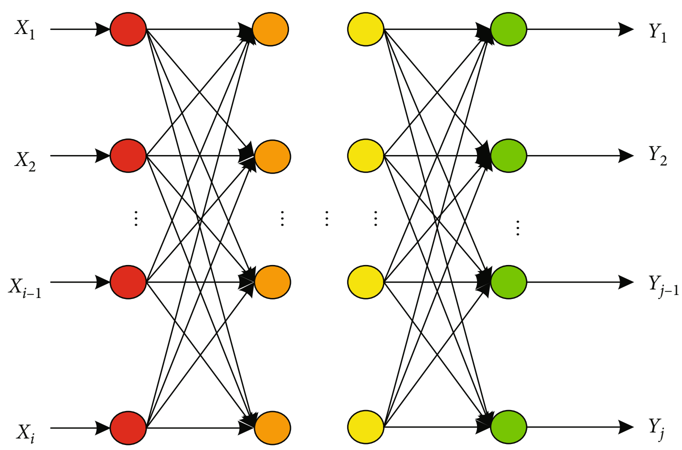


FIGURE 1: Schematic diagram of the structure of the BP neural network.

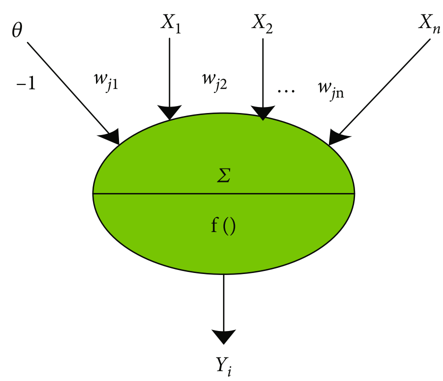


FIGURE 2: Schematic diagram of a single neuron.

$$\begin{gathered}
a_i = a_i \cdot \varphi,\ \eta_i = \eta_i,\ \Delta E(N) < 0\,;\ (i = 1, 2), \\
a_i = a_i \cdot \beta,\ \eta_i = 0,\ \Delta E(N) > 0\,;\ (i = 1, 2), \\
\Delta E(N) = E(N) - E(N-1), \\
\varphi > 1\, \beta < 1,
\end{gathered} \tag{3}$$

If $\Delta E(N) > 0$, it means that the learning error will increase, and the current output value is deviating from the expected value. At this time, the weight adjustment amount shall be reduced and learning efficiency shall be lowered to get rid of the inertia term. If $\Delta E(N) < 0$, it means that the gradient modification direction is correct, so adding the inertia term will increase the learning rate and improve the learning efficiency. The value of a_i and η_i shall be between 0 and 1 [5].

3. Optimization Algorithm for Communication Resource Allocation in the Complex Network

3.1. Communication Indicators in the Complex Network. A complex network mainly contains the following communication indicators:

(1) Average path length: the distance $d(x, y)$ between any two nodes in the network is the shortest path connecting the two nodes including the number of vector edges. The average path length is the average distance between all nodes in the network. The specific formula is

$$L = \frac{\sum d(x, y)}{N(N-1)/2}. \tag{4}$$

The average path length can reflect the length of the communication link between network nodes.

(2) Clustering coefficient/cluster coefficient: if there are at most $T(n) = k(n)[k(n) - 1]/2$ vector edges between the connection of a node n and the remaining $k(n)$ nodes in the network and if there are $E(n)$ vector edges between $k(n)$ nodes, then the clustering coefficient formula for node n is

$$C(n) = \frac{E(n)}{T(n)}. \tag{5}$$

The clustering coefficient is mainly used to measure the clustering of network nodes, and the clustering coefficient is to measure the nature of this network. The specific network clustering coefficient formula is

$$C = \frac{\sum C(n)}{N}. \tag{6}$$

The clustering coefficient can reflect the distribution characteristics of network nodes as a whole. Research has proven that regular networks have larger cluster coefficients and average distances, while random networks have smaller cluster coefficients and average distances [6].

(3) Distribution of connectivity $p(k)$: connectivity of network node n is the number of edges connected to this node vector $k(n)$. By randomly selecting a

node in the network, the probability of connectivity k is p. The function $p(k)$ where p value changes with the change of k is the connectivity distribution

3.2. Improvement of Neural Network Algorithm Input and Output Calculation. The Hopfield neural network is a continuous Hopfield neural network used based on the allocation model of interference resources. Its input and output relationship formula is

$$\begin{aligned} S_j &= \sum W_{ij} v_j + I_j, \\ a_j u_j &= -b_j \frac{du_j}{dt} + S_j \; a_j, b_j > 0, \\ v_j &= f(u_j) \; j = 1, 2, \cdots, n, \end{aligned} \tag{7}$$

The input weight S_j of the above neuron and the input state u_j of the neuron can be expressed by a dynamic equation, and the function of neuron transfer is usually represented by $f(u) = 1/(1 + e^{-\lambda u})$. W_{ij} represents the feedback weight of the output neuron j to the input neuron, and u_j represents the neuron, the output state of the element [7].

3.3. Energy Function and Stability. The definition formula of the Hopfield energy function is

$$E = -\frac{1}{2} \sum_i^n \sum_j^n W_{ij} \cdot v_i v_j - \sum_j^n v_j I_j + \sum_j^n a_j \int_0^{V_j} f^{-1}(v) dv, \tag{8}$$

In the above formula, $f^{-1}(u)$ represents the inverse function of u, that is, $f^{-1}(u_j) = u_j$.

If the network satisfies $W_{ij} = W_{ji}$, $W_{ij} = 0$, i, j represents the number of neurons, and f^{-1} represents a monotonically increasing function, indicating that the above-mentioned network is stable, and the function of network energy corresponds to the objective function, so that the optimal solution to the problem is obtained when the function converges to the minimum value.

3.4. Communication Resource Allocation. First, the bit allocation plan and the subchannel allocation plan are confirmed. After the traffic size of each user and the instantaneous channel gain are known, the subchannels are allocated reasonably and dynamically to minimize the system transmission power p_T and then to complete bit loading as well as power allocation on each subchannel [8].

3.4.1. Dynamic Subchannel Allocation Analysis. Instead of considering the actual channel characteristics of all users, the traditional subchannel allocation solution only allocates the number of subcarriers based on users' size of traffic and allocates fixed subcarriers to each user, so it belongs to a static subchannel allocation method. In view that the actual channel characteristics of each user are not taken into account, the solution of dynamic subchannel allocation is realized in this research through the Hopfield neural network [9–11].

Table 1: Experimental data.

Experimental parameters	Experimental value
Radius of the cell (m)	600
Total bandwidth (MHz)	8
Path loss (dB)	128.1 + 37.6lgd
Noise power (dBm Hz^{-1})	-183
Base station to user SINR threshold (dB)	-10
User and user SINR threshold (dB)	-8.4
Base station to user distance (m)	100
Number of experiments	1000

The number of subchannels available to each user is identified by using the traffic size of each user, and then, the subchannels are dynamically assigned based on the instantaneous channel gain of each user (the required bit error rate is set to the same value for all users). The specific optimization function formula is

$$\min_{\rho_{k,n}} P_T = \min_{\rho_{k,n}} \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{P}{a_{k,n}^2} \rho_{k,n}, \tag{9}$$

where P represents the transmission power of the next channel symbol in the fixed modulation method, which is processed by normalization [12, 13]. The specific objective function p_T formula is

$$P_T = \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{P}{a_{k,n}^2} \rho_{k,n}. \tag{10}$$

And the formula for constraint condition is

$$1 = \sum_{k=1}^{K} \rho_{k,n}, \left(n \in \{1, 2, \cdots, N\}\right), \tag{11}$$

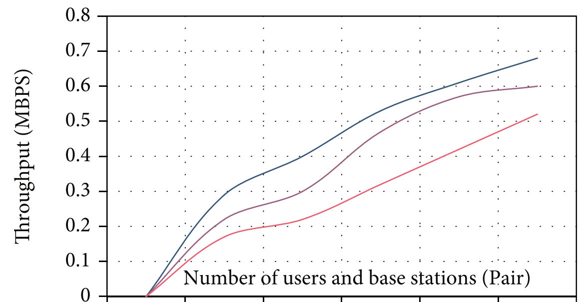
$$N = \sum_{n=1}^{N} \sum_{k=1}^{K} \rho_{k,n}. \tag{12}$$

Formula (11) satisfies that all subcarriers can only be used by one user, while formula (12) satisfies that all subcarriers can be used by users [14].

By combining the above algorithms, the subchannel distribution neural network energy function E is set; the specific formula is [15]

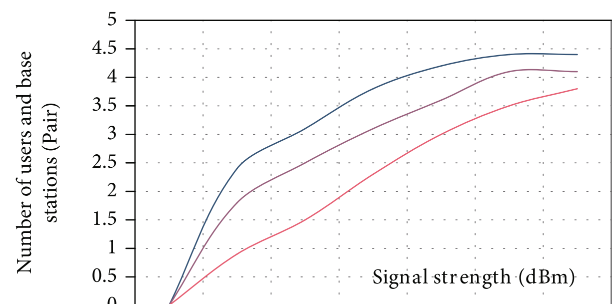
$$E = A \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{P}{a_{k,n}^2} \rho_{k,n} + \frac{B}{2} \sum_{n=1}^{N} \left(\sum_{k=1}^{K} \rho_{k,n} - 1 \right)^2 + \frac{C}{2} \left(\sum_{n=1}^{N} \sum_{k=1}^{K} \rho_{k,n} - N \right)^2. \tag{13}$$

The neural network motion formula for solving the allocation of subchannels is given as



	0	1	2	3	4	5
Method of this article	0	0.29	0.4	0.53	0.61	0.68
Reference (1) method	0	0.22	0.3	0.47	0.57	0.6
Reference (2) method	0	0.17	0.22	0.32	0.42	0.52

Figure 3: Comparison of throughput of different algorithms.



	0	90	86	82	78	74	70
Method of this article	0	2.4	3.1	3.8	4.2	4.4	4.4
Reference (1) method	0	1.8	2.5	3.1	3.6	4.1	4.1
Reference (2) method	0	0.9	1.5	2.3	3	3.5	3.8

Figure 4: Comparison of user communication under different signal strengths.

$$\begin{cases} \dfrac{dU_{k,n}}{dt} = -A\sum_k \dfrac{P}{a_{k,n}^2}\rho_{k,n} - B\left(\sum_{k=1}^{K}\rho_{k,n}-1\right) - C\left(\sum_n\sum_k \rho_{k,n} - N\right), \\ V_{k,n} = g(U_{k,n}) = \dfrac{1}{2}\left[1+th\left(\dfrac{U_{k,n}}{U_0}\right)\right], \end{cases} \tag{14}$$

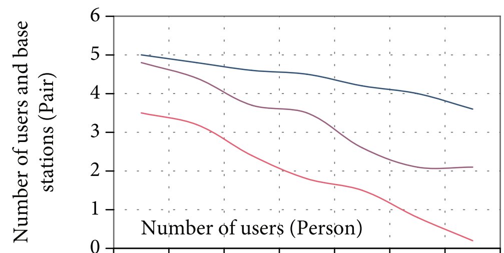
where A, B, and C represent the empirical output value [16], and the excitation function is $g(\cdot)$, which is a tangent function that approximates the S-shaped hyperbolic.

$$g(\cdot)\frac{\partial E}{\partial U_n} = -\frac{\partial U_n}{dt}. \tag{15}$$

The problem of dynamic subchannel allocation is confirmed via formulas (13) and (14). Starting from the network initial state U_0, the network data [11] is obtained through continuous iteration of the motion equation, which is the subchannel allocation matrix ρ.

3.4.2. Power Allocation and Bit Loading of Subchannels. The above problems are solved by the Hopfield neural network, and ρ, v, and l are used to jointly represent the bit loading matrix c [17]. $\rho_{k,n}$ represents the nth subchannel allocated by the kth user; $v_{n,j}$ represents the allocation of j bits in the nth subcarrier, and $l_{n,j}$ represents the number of bits to be allocated in the nth subcarrier. The calculation method of the bit loading matrix is described as follows:

(1) A new matrix npn can be obtained by multiplying the v and l matrices with the corresponding elements



	400	500	600	700	800	900	1000
Method of this article	5	4.8	4.6	4.5	4.2	4	3.6
Reference (1) method	4.8	4.4	3.7	3.5	2.6	2.1	2.1
Reference (2) method	3.5	3.2	2.4	1.8	1.5	0.8	0.2

Method of this article
Reference (1) method
Reference (2) method

FIGURE 5: Comparison of communication signals under different distances of users.

(2) A new matrix mpn [14, 18] can be obtained by multiplying the matrix of 1 row and j columns where all elements of 1 are with matrix npn

(3) The bit loading matrix can be obtained by expanding the matrix mpn into k rows and then multiplying the elements corresponding to ρ [19]

Through the bit loading matrix calculation method, the specific formula can be obtained as

$$\min P_T = \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{T\rho_{k,n}\left(2^{\rho_{k,n}v_{n,j}l_{n,j}} - 1\right)}{a_{k,n}^2}, \tag{16}$$

where $T = N_0/3[Q^{-1}(p_e/4)]^2$.
And the formula for constraint condition is

$$1 = \sum_{k=1}^{K} v_{n,j}, \tag{17}$$

$$N = \sum_{n=1}^{N}\sum_{j=1}^{J} v_{n,j}, \tag{18}$$

$$R_k = \sum_{n=1}^{N} \rho_{k,n} v_{n,j} l_{n,j}. \tag{19}$$

Formula (17) satisfies the fixed number of bits allocated by all subcarriers; formula (18) meets that all subcarriers can be allocated bits; formula (19) can meet the transmission rate of all users [20].

Based on this problem, the neural network energy function E for power allocation and bit loading is set. The specific formula is

$$\begin{aligned} E = {} & A\sum_{k=1}^{K}\sum_{n=1}^{N} \frac{T\rho_{k,n}\left(2^{\rho_{k,n}v_{n,j}l_{n,j}} - 1\right)}{a_{k,n}^2} + \frac{B}{2}\sum_{n=1}^{N}\left(\sum_{n=1}^{J} v_{k,n} - 1\right)^2 \\ & + \frac{C}{2}\left(\sum_{n=1}^{N}\sum_{j=1}^{J} v_{n,j} - N\right)^2 + \frac{D}{2}\sum_{k=1}^{N}\left(\sum_{n=1}^{N}\sum_{j=1}^{J} \rho_{k,n}v_{n,j}l_{n,j} - R_k\right)^2. \end{aligned} \tag{20}$$

The movement of the neural network connected to the power allocation and bit loading is calculated. The specific formula is

$$\begin{cases} \dfrac{dU_{n,j}}{dt} = -A\sum_{k} \dfrac{T\rho_{k,n}\left(2^{\rho_{k,n}v_{n,j}l_{n,j}}\right)}{a_{k,n}^2}\rho_{k,n}l_{n,j}1n2 - B\left(\sum_{j} v_{n,j} - 1\right), \\ -C\left(\sum_{n}\sum_{j} v_{n,j} - N\right) - D\sum_{k}\left(\sum_{n}\sum_{j}\sum_{j=1}^{J}\rho_{k,n}v_{n,j}l_{n,j} - R_k\right), \\ V_{n,j} = g\left(U_{n,j}\right) = \dfrac{1}{2}\left[1 + th\left(\dfrac{U_{n,j}}{U_0}\right)\right]. \end{cases} \tag{21}$$

where D represents the value given by experience. The Hopfield neural network about the dynamic bit loading problem can be confirmed through formulas (20) and (21). Starting from the initial state U_0 [21], the network output v is obtained based on the continuous iterations of the network motion formula, and then, the transmission power can be obtained through formula (19), which is minimized to complete the optimal allocation of communication resources [22].

4. Verification of Experiment Simulation

4.1. Experiment Parameter. In order to verify the effectiveness of the proposed method, a base station is set in simulated community where users are evenly distributed and each user uses only one communication resource node. The simulation is completed via MATLAB, which requires 200 Kb/s of data rate, $B = 1$ MHz of bandwidth, $N = 64$ of the number of subcarriers, and BER $= 10^{-3}$ of the bit error rate. The data is randomly generated each time, and the average value is taken. The specific parameters are shown in Table 1: the unit of distance between the transmitter and the receiver is km.

4.2. Analysis of Experiment Results. The proposed method is compared with the approaches in literature [1] and literature [2], as shown in Figure 3.

According to Figure 3, in the process of constantly increasing the number of network communication user nodes, the proposed method can output the minimum linear result by improving the neural network algorithm and ensure the fine scheduling requirements of complex network without waste of resources, so its throughput is always better than that of the other two methods.

Under different communication signal strengths, the result of comparing the number of connections between users is constructed; the RSRP is valued between -90 and -70 dBm. The details are shown in Figure 4.

As can be learned from Figure 4, the results of the proposed method are superior to those of the other two methods because it calculates complex network communication indicators, clarifies the subfactors that affect communication quality, focuses on analysis, and effectively suppresses the influence of the outside world on the distribution method. When the RSRP value is -90, the user communication connection is not interrupted, so that the data-related information is successfully transmitted and the timeliness is achieved.

In order to further prove the effectiveness of the proposed method, the number of users in the complex network at the same time is increased, as shown in Figure 5.

Figure 5 shows that as the number of users increases, the number of communication connections gradually decreases, mainly because the demand for communication signals must be guaranteed by increasing the transmission power. In view of this, the original interference to the users will increase, thereby affecting the constructed user communication connection. However, by means of introducing the improved neural network algorithm, the proposed method can suppress external interference based on enhanced allocation, and its decline rate is much lower than that of the approaches proposed in literature. Therefore, it is proven that the proposed method has strong applicability and can cope with the continuous access as well as output of big data under complex networks.

5. Conclusions

In the network applications in China's large cities, take the cellular network as an example. Despite many numbers of cellular network base stations in large cities, the load of cellular network base stations varies greatly in different time periods and locations. For example, during office hours, there are more numbers of mobile phone network users in the city subway, office buildings, and other areas. During city off-hours, the number of cell phone network users increases in areas such as city residential buildings and hotels. This will lead to differences in the efficiency of network usage in the above-mentioned areas at different time periods, in order to improve the efficiency of complex network communication resource classification.

The proposed optimization algorithm for communication resource allocation in the complex network based on the improved neural network can properly allocate network communication resources with large network throughput and better communication effect. However, due to the influence of external interference factors, the communication connection in the proposed method will still be reduced, so further research is needed to achieve more reasonable allocation of communication resources.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors state that there is no conflict of interest.

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