

Resource allocation algorithm design of high quality of service based on chaotic neural network in wireless communication technology

Yongfeng Cui¹  · Zhongyuan Zhao¹ · Yuankun Ma¹ · Shi Dong¹

Received: 10 August 2017 / Revised: 29 September 2017 / Accepted: 22 October 2017 / Published online: 16 November 2017
© Springer Science+Business Media, LLC 2017

Abstract With the rapid development of broadband wireless technology and the wide demand of multimedia mobile services, various broadband mobile multimedia services are coming into being. However, the limited radio resources do not adequately guarantee the quality of service requirements for these multimedia mobile services. In this paper, the improved chaotic neural network technology is applied to three typical broadband wireless communication systems. Through the theoretical analysis and the simulation, the proposed algorithm can make full use of the chaotic neural power to search the optimal solution, which can achieve the purpose of further optimizing the wireless resources. At the same time, it also make the positive attempt to promote cross-disciplinary integration.

Keywords Chaotic neural network · Hopfield neural network · Channel allocation

1 Introduction

With the development of the times and the development of the broadband wireless communication technology, the demand of the broadband mobile communication came has been growing up rapidly. To use 3G, LTE, WIMAX and W IFI or the other broadband wireless communication technology and to use a variety of portable terminals such as smart phones, tablet PCs and other network information for exchanging and processing, people can not only achieving the services of traditional voice, SMS and other services,

but also enjoy the services including microblogging, private letters, terminal positioning, send and receive e-mail, online games, music downloads and the video on demand and other broadband multimedia services. So the wireless LAN involves IT professionals and senior business managers. They need to be able to change LAN cabling flexibly and frequently throughout the site or within selected areas taken up by the owners and IT directors; any company whose location is not suitable for use with LAN cabling due to building or budget restrictions (such as buildings that are old, the space is leased or the location is temporary). Flexible and cost-effective to reach buildings within the field of view to buildings bridging devices can avoid costly trenching, line leasing, or routing problems over wireless LANs.

At present, the typical applications of wireless local area network include hospitals, schools, financial services, manufacturing, service, corporate applications, public access and so on. According to Gartner's global wireless LAN equipment forecast, in 2006 the global wireless LAN equipment market sales will reach 10.3 billion US dollars. In order to meet the multifarious needs of mobile Communication, a variety of broadband wireless communication technologies has appeared continually. However, these technologies are facing a serious problem commonly. That is, the limited radio resources have become a major bottleneck in the development of wireless communication technology. How to use limited wireless resources to provide both effective and reliable mobile broadband data services has become the common concern in academia and industrial circle.

In order to deepen the implementation of the “National Medium and Long-term Science and Technology Development Plan (2006–2020)”, giving full play to scientific and technological progress and innovation to accelerate the trans-

✉ Yongfeng Cui
cuiyf@zknu.edu.cn

¹ School of Science and Technology, Zhoukou Normal University, Zhoukou 466001, Henan, China

formation of economic development mode, in the “National ‘12th 5-Year’ Scientific and Technological Development Plan”, as the column, the “Demand-oriented major scientific issues in the field and direction “included ” Demand-oriented major scientific research areas and directions ”, and the communication and network theory, which focuses on energy efficiency priority and resource optimization, are clearly put forward. This fully shows that China has paid great attention to the optimal technology of radio resources which reflects the great significance of the development of national science and technology and the progress of social.

The radio resource optimization problem of the specific scene of the future wireless mobile communication system and the optimization model of the chaotic neural network are deeply excavated. In order to reduce the complexity, it will simplify the initial optimization problem and construct the chaos carefully. In order to reduce the complexity, we will simplify the initial optimization problem and construct the chaos well and we will simplify the initial optimization problem. It can be seen from the simulation results that although the solution is still the second best solution, it can meet the performance requirements of the system and the users well. Comparing with the existing literature, the proposed algorithm can further improve the radio resource utilization, which achieved the purpose of optimizing the radio resources.

1.1 Chaos network

Chaos theory, relativity and quantum mechanics are known as the most creative three revolutions of the twentieth century. Chaos theory is an important branch of the nonlinear science. In recent years, people have carried out extensive and in-depth study of chaos theory. Along with the rapid development of science and technology, chaos has become a frontier subject with far-reaching and rapid development. Chaotic features are as follows: aperiodic, randomness, initial value sensitivity, the overall stability of the local instability, ergodicity, singular attractors, bifurcation.

It is very difficult to give a very precise definition of chaos, and there is no unified scientific definition at present. The study of chaos by nonlinear dynamics is the most rigorous and systematic one. It has put forward some references for theoretical derivation and judgment from the point of view of physics and mathematics, and also provides a reference scale for practical measurement, which has laid a solid foundation for the research and the development of chaos. The most famous chaotic and mathematical definition is the Li-Yorke chaos definition [1] and the Devaney chaos definition [2].

The rational allocation of resources and the best use of resources in wireless communication systems are col-

lectively referred as the channel allocation issues (CAPs), with the aim of maximizing the use of spectrum resources. There are three types of channel allocation schemes: Channel Fixed Assignment Algorithm (FCA), Dynamic Channel Allocation Algorithm (DCA), Mixed Channel Assignment Algorithm (HCA). These algorithms require more or less information on the entire network and system-wide, often at the expense of frequent channel redistribution. In this paper, the literature [3] proposes a model which using a compatible matrix and defines a compatible matrix $C = c_{ij}$ (where n is the total number of community) and a channel demand the matrix $I \times n$ which is compatible with the c_{ij} in the matrix. The minimum interval of channels that can be used simultaneously between the community i and the community j is determined as follows: the channel demand matrix gives the number of channel requirements for each community channel allocation is essentially a NP-hard combinatorial optimization problem when the total number of channels and the channel requirements of each cell are determined.

1991 Kunz first application Hopfield neural network to solve CAP [4], the use of energy function that interference constraints and channel requirements, has some practicality, but it also does not consider the adjacent channel interference, the convergence process is easy to produce oscillation, and easy to fall into Local minimal and other shortcomings. In the literature [5], the fuzzy algorithm and the genetic algorithm are used to solve the CAP, but the search effect of the genetic algorithm is influenced by the genetic operator, and the fuzzy method is difficult to reflect the overall optimization performance of the channel allocation.

In recent years, chaotic neural network (CNN) has been widely used in the solution of combinatorial optimization problem because of its strong global search ability and superior ability than other neural networks. WANG Ling et al. Based on Euler discretization of Hopfield neural network (HNN), a chaotic neural network is constructed by introducing a large self-feedback term and introducing chaotic dynamics in HNN. A new chaotic neural network is proposed by using simulated annealing strategy Optimization algorithm, and used to solve the TSP problem, and achieved good results. The chaotic neural network is formed by introducing the chaotic noise generated by the external mechanism in HNN, which is another effective way to use chaotic neural network for combinatorial optimization.

1.2 Chaotic neural network

Chaos exists in the nonlinear system, is a unique phenomenon of the system, and the human brain itself is a very typical nonlinear system, obviously there is a chaotic phenomenon. Artificial neural network technology is precisely to simu-

late the human brain, naturally can not put aside the chaos. Although chaos and artificial neural networks each have their own characteristics, but in essence, there is a commonality between the two, that is, the nonlinearity of the system and the state of the simulation. Because of this, people are very natural to combine the two, the creation of a new intelligent information processing technology, that is, chaotic neural network.

In the last century, in order to study and master the chaotic characteristics of biological neurons. K. Aihara, T. Takabe and M. Toyoda et al. proposed a chaotic neural network model for the first time, and established a neural network model with chaotic characteristics, which makes the artificial neural network have chaotic behavior and closer to the actual human brain neural network. Compared with the static neural network, the chaotic neural network has rich dynamic behavior, including stable equilibrium point, periodic bifurcation, chaos and so on. Therefore, chaotic neural network is considered to be one of the intelligent information processing systems that can realize its real world computing. It has become one of the main research directions of neural network, and opens up a new way of artificial intelligence information processing.

So far, people have put forward a variety of chaotic neural network, which is representative of: Aihara in 1900 on the basis of animal experiments proposed chaotic neural network model [6], 1991 Inoue and Kanoke proposed affinity chaos Neural network model and improved series of chaotic neural networks [7]. Among them, the series of chaotic neural network model which is introduced into chaotic power is one of the most representative models.

1.2.1 Chaotic neural network model

When constructing chaotic neural networks from chaotic neurons, several aspects are different from those of general neural networks: similar to Hopfield's feedback term from internal neurons: external input similar to BP algorithm; incoherence and threshold The We use the annealing strategy to control the chaotic dynamics, so we obtain the dynamic recursive equation of the chaotic neural network model

$$u_{xi}(n+1) = au_{xi}(n) + \beta \left(\sum_y \sum_j w_{xi,yj} v_{yj}(n) + I_{xi} \right) - z(n)(v_{xi}(n) - s) \quad (1)$$

$$v_{xi}(n+1) = \frac{1}{1 + \exp(-u_{xi}(n+1)/s) \times (1 + \eta(n))} \quad (2)$$

$$z(n+1) = \frac{z(n)}{\ln[e + \lambda(1 - z(n))]} \quad (3)$$

$$\eta(n+1) = (1 - \varepsilon) \cdot \eta(n) \quad (4)$$

In the formulas (1)–(4), $x, i, y, j = 1, 2, \dots, n; k = 1, 2, \dots, m$.

In the above equations, (1) is the dynamic equation of the chaotic network, (2) is the excitation function of the neuron, and the equations (3) and (4) are the annealing function. Among these, $W_{xj,yj}$ is the link weight of chaotic neurons, $u_{xi}(k)$, $v_{xi}(k)$ and I_{xi} are respectively the output, import and external offset of chaotic neurons, $\alpha(0 \leq \alpha \leq 1)$ is the attenuation factor of the neurons, $\beta(\beta > 0)$ is the proportional parameter, $\lambda(0 \leq \lambda \leq 1)$ $\varepsilon(0 \leq \varepsilon \leq 1)$ is the attenuation factor of the time variable, $z(n) < 1$ is the connection right of the self-feedback, s is the threshold or the plus amount of chaos which is set already. In order to effectively control the chaos, the variable $z(n)$ is a constant attenuation in time, it can make the network through a doubling period chaotic bifurcation process, so that the network gradually approaches a stable equilibrium point, which essentially corresponds to the temperature of annealing in the algorithm.

1.2.2 Channel allocation problem model

It is assumed that there are M community and N channels in a mobile communication system. The result of the channel can use one matrix of $M \times N$ to express, When assigning the J -th channel to the community i , $c_{ij} = 1$, otherwise $c_{ij} = 0$.

$$C = (c_{ij}), i = 1, 2, \dots, N; j = 1, 2, \dots, M \quad (5)$$

In the actual channel allocation, it often need to consider the following factors:

- (1) Channel demand (ROC) refers to the number of channels, it is expressed by the vector $D = \{d_i\}, i = 1, 2, \dots, m$ of channel demand, that is, the i -th community needs d_i channels;
- (2) Inter-field interference (CSC) means that in the same community, if multiple channels are to be allocated, these channels should have a minimum frequency interval; (3) the same / adjacent channel interference (CCC / ACC) refers that the same channels can not used in some community at the same time, adjacent communities also can not use the same channels.

The compatible matrix $C = (c_{ij}), i = 1, 2, \dots, M$ used to give the define between the communities, among these, C_{ij} represents the minimum frequency interval of channels which can be used in community i and j . Obviously, CCC and ACC can be described by, c_{ij} but CSC is characterized by c_{ij} .

The specific mathematical model is

$$\text{ROC} \sum_{i=1}^M x_{ij} - d_j = 0 \quad (6)$$

$$\text{CSC} \quad \sum_{j=(c_{ji}-1)}^{j+(c_{ji}-1)} V_{iq} \neq 0 \quad (7)$$

$$q = j - (c_{ji} - 1)$$

$$q \neq j, 1 \leq q \leq m$$

$$\text{CCC/ACC} \quad \sum_{p=1}^n \sum_{q=j-(c_{ip}-1)}^{j+(c_{ip}-1)} V_{pq} \neq 0 \quad (8)$$

$$p \neq i \quad 1 \leq q \leq m$$

$$c_{ip} > 0$$

To this end, the energy function which is to define the problem of defining the channels is

$$E = \frac{A}{2} \sum_{i=1}^n \left(\sum_{q=1}^m V_{iq} - d_i \right)^2 - B \sum_{i=1}^n \sum_{j=1}^m \left(\sum_{q=j-(c_{ij}-1)}^{j+(c_{ij}-1)} V_{iq} + \sum_{p=1}^n \sum_{q=j-(c_{ip}-1)}^{j+(c_{ip}-1)} V_{pq} \right) V_{ij} \quad (9)$$

$$q \neq j, 1 \leq q \leq m$$

$$p \neq j \quad 1 \leq q \leq m$$

$$c_{ip} > 0$$

by PS services) by 0 or 1 time slot and the difference between average (peak_gprs_ch) and max (peak_gprs_ch) is less than 15%, it is suggested to increase the carrier frequency of these districts.

2.1.3 GPRS radio channel resources optimized after the load check

As the (E) GPRS wireless channel resources are optimized to adjust the allocation of the resources which is under the PCU, the resource load of each PCU needs to be checked. Through the CDEF expansion network PCU load check, must be sure to make each PCU capacity load is less than 80% (Fig. 1).

2 Radio resource optimization process

2.1 Radio resource optimization process

2.1.1 Basic principles of CDEF optimization

It is limited to verify the GTRX number configuration by the result which is according to the multi-day and multi-period KPI—ava_44(average number of slots in the PS domain).For the number of time slots of those average PS domains which is greater than the number of times of the current CDEF that is set, The CDEF value is taken as the number of time slots for the actual average PS domain of the cell, which can reduce the number of unnecessary (E) GPRS upgrades.

2.1.2 Basic principles of GTRX optimization

According to the multi-day multi-period KPI—peak_gprs_ch (the number of slots of the minimum (E) GPRS in the busy time) to verify whether the GTRX number configuration is limited. When the max (peak_gprs_ch) differs from the number of (E) GPRS maximum time slots (GTRX are all occupied

2.2 Radio resource optimization technology based on chaotic neural network

Since the introduction of chaos has been imported into the neural network, the hybrid neural network is widely used in various combinations of optimization. In recent years, chaotic neural networks have been used in the optimization of radio resources, and have achieved rich research results. And discussing the application in detail of several representative pure neural networks in the optimization of radio resources.

In 1982, J.J. Hopfield and D.W. Tank, physicists at the California Institute of Technology, presented an interconnection network that could be used as an associative memory, a well-known Hopfield neural network model. The neurons in the model are connected to each other, from the output to the input with a feedback connection, which is a typical recursive network and also known as a recursive network [8]. HNN network has successfully solved the problem of Traveling Salesman Problem (TSP), and realized the function of the network with hardware [9, 10], which attracted wide attention in academia. Luonan Chen and Kazuyuki Aihara improve the HNN network, introduce the chaotic power generated by

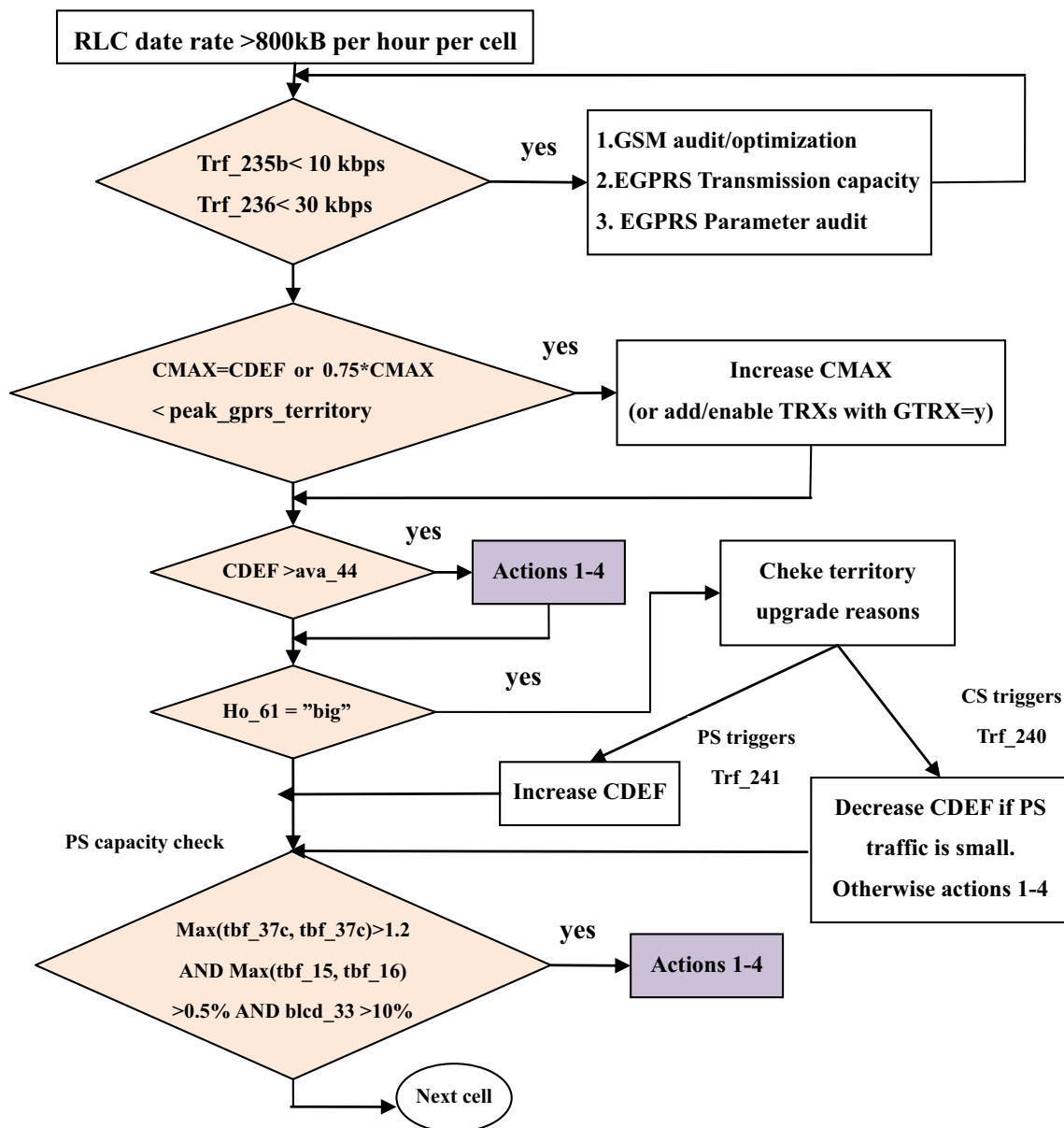


Fig. 1 Radio resource optimization process

transient, and propose the Transiently Chaotic Neural Network (TCNN) [11]. (SCS), also known as Noisy Chaotic Neural Network (NCNN) [12, 13], proposed a randomized chaotic simulated annealing algorithm based on TCNN, The Comparison of HNN and TCNN, NCNN

In the search ability and convergence speed has significantly improved, can be a good solution to the TSP problem. In order to improve the HNN series of chaotic neural networks, and apply them to the problem of communication optimization, the scholars have solved the problem of broadcast packet scheduling in the wireless network, the problem of spectrum allocation in the satellite communication, the

problem of multicast routing and the problem of large area Channel allocation.

Enrico et al. successfully solved the multi-cell dynamic channel assignment problem with HNN. By constructing a reasonable energy function and using the piecewise function as the neuron excitation function, the algorithm analyzes whether the vertex of the state space is a reasonable solution, and the relationship between the parameters in the energy function is discussed. By simulating the scene of 49 regular hexagonal cells, the results show that with the traditional static, channel assignment and other Compared with the dynamic channel assignment algorithm are used

in the literature, HNN with a large number of neuron parallel processing structures can obtain a good performance on the dynamic channel assignment problem, including the quality of solution and the speed of network operation [14]. Girma et al. proposed a distributed architecture based on HNN, which provides a distributed platform for the performance of dynamic channel allocation [15]. Yang et al. used the improved HNN network to study the power optimization problem of the perceptual radio system, and proposed a hybrid spectrum access method based on the total transmission power limitation [16]. Uykan et al. analyzed the problem of dynamic allocation of non-real-time traffic in wireless networks, and proposed a dynamic resource allocation algorithm for dual-S HNN networks based on the fast convergence [17]. Professor He Zhenya and others proposed a multi-step channel allocation method based on TCNN. The algorithm first assigns the channel to each cell according to the Bristle mechanism. If the result of the first step does not satisfy the optimal solution requirement, the second step will use the TCNN method. The simulation results show that the proposed algorithm has a significant improvement in performance compared with the existing algorithms [18]. The results also show that the proposed algorithm can improve the performance of the proposed algorithm. Wang et al. Used TCNN for multiuser signal detection in CDMA systems and achieved better results than HNN signal detection methods [19]. In ad-hoc wireless networks, the problem of multipath routing has been the focus of ad-hoc network research. Due to the mobility of wireless terminals, it is difficult to choose the best path dynamically. Sheikhan et al. Analyze the characteristics of ad-hoc networks, including the reliability of communication, balanced loading and Qos of business needs, using TCNN technology, proposed a reliable dynamic multi-path routing technology [20].

Wang et al. had improved the NCNN, proposed a variable threshold noise chaotic neural network algorithm, and successfully applied to satellite communication in the spectrum allocation problem [21]. Wang et al. used the chaotic neural network to calculate the propagation delay of multicast routing tree with delay limit by constructing reasonable energy function. The simulation results show that the method can find the multicast routing tree with the lowest delay and successfully solve the problem Multicast Routing Problem [22]. For the past three years, Sun et al. have improved the chaotic noise chaotic neural network to solve the multicast scheduling problem in packet wireless networks. A time division multiple access with minimum frame length, maximum channel utilization and minimum average delay is designed. (TDMA) frame structure [23]. Zhang et al. used NCNN to effectively solve the problem of subcarrier and power allocation for single-cell OFDMA downlink systems [24]. Sun et al. introduced a noise adjustment factor based

on the hysteresis noise chaotic neural network. This method is applied to the broadcast resource scheduling problem of wireless multi-hop network. The simulation results show that the method can further improve the performance of the system [25]. It can be seen that chaotic neural network has been widely applied and studied in the optimization of radio resource.

3 Regional about channel assignment and optimization based on NCNN

3.1 Technology about MBSFN

MBSFN technology is introduced into the E-MBMS system in order to improve the spectrum utilization, improve the signal quality of the cell at the edge of the cell, solve the problem of blind coverage, and meet the increasing demand of MBMs [26]. Although MBSFN technology can achieve greater performance improvement, but inevitably produce new problems. The primary problem is time synchronization. Therefore, the study of MBSFN from R9–R11 has never been interrupted, and the corresponding research literature is more and more. At present, the research on MBSFN technology mainly focuses on three aspects: synchronization technology, networking technology and wireless resource allocation and optimization [27].

3.2 Synchronization technology about MBSFN

Since the MBSFN mode is the same waveform for all cells at the same frequency in the MBSFN area [28]. To do this, the synchronization problem becomes a core issue of MBSFN technology, which requires time synchronization between cells And frequency synchronization. The primary problem is time synchronization. Time synchronization means that each base station sends the same MBMS service at the same time. Since the E-MBMS adopts the extended CP, it relaxes the requirement of time synchronization to precision, and is generally accurate to microsecond [29]. If each eNB can not transmit synchronously, the MBMS information received by the user from the different eNB may become the same frequency interference information, not only can not obtain the macro diversity gain, but will affect the user to the effective merger of these information, Will cause the information to be distorted and can not be received correctly. Frequency synchronization refers to the requirement that all eNBs within the MBSFN area send the same MBMS service on the same carrier frequency [30]. If the district can not be strict time and frequency synchronization, it will affect the performance of the entire MBSFN network.

3.3 Networking technology about MBSFN

MBSFN requires multiple neighboring cells to form an MBSFN area. So, what kind of cell is added to the MBSFN area, and how many MBSFN regions are suitable for the MBSFN area. These are the networking problems of MBSFN. Only through a reasonable MBSFN network, in order to reflect the advantages of MBSFN technology in order to ensure the overall performance of MBSFN network. At present, MBSFN technology network is mainly concentrated in the district to join the conditions and MBSFN network size on two issues.

Refers to a cell with what conditions to join the MBSFN area. The general judgment conditions include whether the user has the business requirements of MBSFN, the location relationship between the user and the MBSFN network, and the quality of the MBSFN signal received by the user. If the user needs MBSFN business, and the use of MBSFN network size problem is in the end how many cells to form an MBSFN area more appropriate. Generally with the cell size CP length, send power and so on. If the MBSFN area is too small and the number of cells is small, the diversity gain effect of the received signal is not obvious, and the advantages of MBSFN technology are not reflected. If the MBSFN area is too large, the same signal transmitted by multiple eNBs may reach the same user, which may exceed the length of the design CP, thus forming the same frequency interference, affecting the overall performance of the MBSFN network. Therefore, the size of MBSFN network needs a reasonable design, both to meet the user's MBMS needs, but also reflects the advantages of MBSFN, but also conducive to the realization of these are single-frequency network must solve the problem. Some papers and patents are used to study the networking of MBSFN, including topology, inactive area definition, intersecting region and reserved area definition, user counting judgment scheme and MBSFN network performance analysis.

3.4 Radio resource management about MBSFN

With the rapid development of wireless communication technology and a variety of multimedia business needs continue to grow, limited spectrum resources become increasingly scarce. Although MBSFN technology sends the same MBMS service at the same time in multiple cells at the same time by means of point-to-multipoint, which greatly saves the spectrum resources and improves the spectrum utilization rate. However, MBSFN technology also provides single-frequency network planning and radio resource allocation Has brought new challenges. In the case of scarcity of frequency resources, how to efficiently use limited spectrum resources for MBSFN transmission is particularly important. 3GPP has designed the M2 interface between the eNB

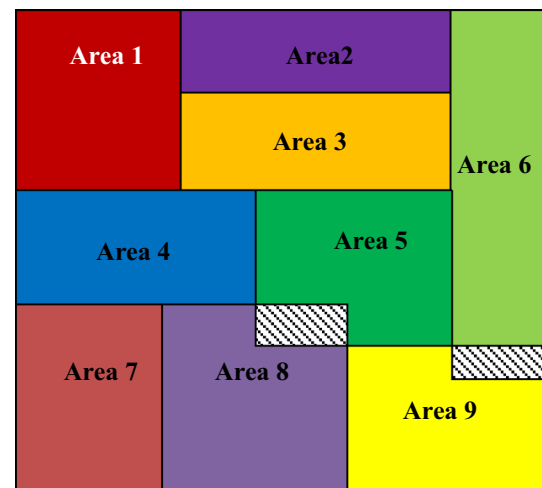


Fig. 2 MBSFN System model, *Note* the shade part of the figure is the intersection of two adjacent areas

and the MCE. The interface includes the MBMS scheduling information providing function and the M2 interference management function. The MCE provides the transmission permission and the radio resource allocation of the MBMS service to all the eNBs in the MBSFN area through the M2 interface. Transmits the control signaling related to the MBMS service to the eNB for radio resource management.

In recent years, MBSFN wireless resource allocation and optimization more and more attention by the industry. According to the characteristics of MBSFN network architecture and simultaneous transmission of the same service, the radio resource allocation algorithm can effectively utilize the radio resource allocation algorithm, which can not only avoid the interference of the adjacent MBSFN area, but also can reasonably reuse the frequency resources and reduce the channel needed by the MBSFN area Number, in the protection of the overall performance of single-frequency network under the premise of improving the spectrum utilization. At present, the research on the wireless resource allocation of MBSFN technology mainly includes the allocation of resources such as frequency and power.

3.5 MBSFN channel allocation and optimization algorithm based on NCNN

Figure 2 simulates the geographical environment of a common city and constructs a square MBSFN propagation model. The single frequency network system model contains nine MBSFN areas. Each MBSFN area contains a number of adjacent neighbors, in the same area with the same transmission of MBMS business. According to the transmitted MBMS service, the number of channels required for each MBSFN

R_p area is determined, and the channel may be a subcarrier, and a resource block (consisting of a number of consecutive subcarriers). Requires the design of the algorithm to avoid a variety of interference in the case, the use of frequency reuse technology to improve the frequency of resource utilization.

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Intersecting matrix

$$\begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Adjacent matrix

$$\begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Non-adjacent matrix

(10)

The positional relationship of each MBSFN region is shown in Fig. 2, including intersecting, adjacent and non-adjacent two positional relations. Such as region 1 and regions 2, 4 and 5. Area 2 and region 5 intersect. Area 4 and area 7 intersect. Non-adjacent areas refer to two regions that are neither intersecting nor adjacent, such as region 1 and regions 3, 6, 7, 8 and 9 are non-adjacent. For the sake of expression and calculation, the MBSFN region position matrix is defined, and the rows and columns are MBSFN region numbers. The relation matrix is shown in Eq. (10). In the dynamic channel assignment, there are three types of electromagnetic compatibility restrictions, which must be considered when allocating radio channels to individual cells. These three types of constraints include:

- (1) Same channel restrictions (Co-Channel Constraint, CCC) means that the same channel can not be assigned to a cell located within the multiplexed distance at the same time.
- (2) Adjacent channel restrictions (Adjacent Channel Constraint, ACC) means that Adjacent channels can not be allocated to neighboring cells at the same time. That is, any pair of channels of adjacent cells must have a certain interval in the frequency domain.
- (3) The co-address restriction (Co-Site Constraint, CSC) means that there must be a certain frequency interval between the channels of the same cell. This interval is often greater than the interval required for the adjacent channel limit.

By the above three types of electromagnetic compatibility restrictions can be seen, it is because within the district and the existence of these three types of restrictions, it makes the dynamic channel allocation problem becomes more complex, especially in the composition of many small areas of the scene, the problem will be more complex. Although MBSFN technology uses the same content at the same time in the same MBSFN region, there are still three types of interference between the MBSFN region and the region, and because of the characteristics of the MBSFN network itself, the dynamic channel allocation problem and the traditional cell Dynamic channel allocation is not exactly the same, the following through the NCNN method to solve the MBSFN area of the dynamic channel allocation problem.

3.6 MNFN channel assignment and optimization algorithm based on NCNN

3.6.1 Energy function about NCNN

Since the same signal is sent at the same frequency in an MBSFN region, there are no more than three constraints between cells in an MBSFN region. However, the MBSFN region corresponds to a large cell, and there is still more than three in the MBSFN region. Interference. Therefore, we must consider these three kinds of electromagnetic interference restrictions when allocating the channel to the MBSFN region. On this basis, this paper puts forward the dynamic channel allocation and optimization method based on NCNN with energy function to avoid electromagnetic interference. Based on the characteristics of MBSFN,

- (1) Energy function about NCNN

After the full analysis of the various disturbances in the MBSFN region, it can be concluded that the energy function of the MBSFN region interference based on NCNN is:

$$\begin{aligned}
E &= \frac{B_e}{2} E_1 + \frac{C_e}{2} E_2 + \frac{D_e}{2} E_3 + \frac{E_e}{2} E_4 + \frac{F_e}{2} E_5 + G_e E_6 \\
&= \frac{B_e}{2} \sum_{p=1}^A \sum_{r=1}^C \sum_{s \neq r} V_{p,r} V_{p,s} f_{CAC}(r, s) \\
&\quad + \frac{C_e}{2} \sum_{p=1}^A \sum_{r=1}^C \sum_{\substack{q \in \text{adja} \\ q \neq p}} \sum_{s \neq r} V_{p,r} V_{p,s} f_{AAC}(r, s) \\
&\quad + \frac{D_e}{2} \sum_{p=1}^A \sum_{r=1}^C \sum_{\substack{q \in \text{over} \\ q \neq p}} \sum_{s \neq r} V_{p,r} V_{p,s} f_{OAC}(r, s) \\
&\quad + \frac{E_e}{2} \sum_{p=1}^A \sum_{r=1}^C \sum_{\substack{q \in \text{nona} \\ q \neq p}} V_{p,r} V_{p,s} f_{NAC}(p, q) \\
&\quad + \frac{F_e}{2} \sum_{p=1}^A \left(\sum_{r=1}^C V_{p,r} - R_p \right)^2 \\
&\quad + G_e \sum_{p=1}^A \sum_{r=1}^C V_{p,r} (1 - V_{p,r})
\end{aligned} \tag{11}$$

The normal number of the right side of the energy function equation $B_e, C_e, D_e, E_e, F_e, G_e$ is the weight coefficient of each of the energy functions. The first term indicates whether there is a channel interference in the same MBSFN area. If the channel r and s is assigned to the MBSFN region p at the same time, that is $V_{p,r} = 1, V_{p,s} = 1$, and the distance between the channels r and s is less than the interval $L = 3$, that is $f_{CAC}(r, s) = 1$, the three product is “1”, indicating that the current channel allocation has the same frequency interference, the item will be punished. On the other hand, if the product of the three terms is “0”, that is, if any of the three terms is “0”, the term “0” indicates that there is no interference in the same region.

The second term indicates whether there is a neighborhood interference between two adjacent MBSFN regions. If the channel r is assigned to the MBSFN area $p, V_{p,r} = 1$, the channel s is allocated to the adjacent area q of the area $p, V_{q,s} = 1$, and the distance between the channels is equal to 0 or 1, $f_{CAC}(r, s) = 1$, the neighborhood interference will be punished. In contrast, if the product of the three terms is “0”, that is, any one of the three terms is “0”, then the term “0” indicates that there is no neighborhood interference.

The third term indicates whether there is interference between two intersecting MBSFN regions. If the channel r is assigned to the MBSFN area p , that is $V_{p,r} = 1$, at the same time, the channel s is assigned to the intersection area q of the area $p, V_{q,s} = 1$ and the distance between the channels is

less than the interval, that is $f_{OAC}(r, s) = 1$, the intersection area interference will occur. On the other hand, if the product of the three terms is “0”, that is, if any of the three terms is “0”, the term “0” indicates that there is no intersecting area interference.

The fourth term indicates whether there is interference between two non-adjacent MBSFN regions. If the channel r is assigned to the MBSFN area $p, V_{p,r} = 1$, at the same time, the channel r is also allocated to areas p that are not adjacent to the area $q, V_{q,s} = 1$, and the distance D_{reuse} between regions p and q is less than the multiplexing distance, $f_{NAC}(p, q) = 1$. The same frequency interference happened between the two regions, the item will be punished. On the contrary, if any of the three terms is “0”, the term is “0”, indicating that there is no co-channel interference between non-adjacent MBSFN areas.

The fifth term indicates whether the total number of channels actually shared by each MBSFN area satisfies the channel requirements of the area. If each area meets the needs of the channel, the item is “0”, otherwise it will be punished. The last term is the accelerated convergence term, which is “0” when the output of all neurons is “0” or “1”, otherwise it will be punished.

When the NCNN is running, the system starts at any of the initial values, and the output of the neurons will be disturbed by the above-mentioned various disturbances. The energy functions will be penalized. At this point, the energy function is very large, with the continuous operation of the network, the rich nerve power in the phase space continues to search for a comprehensive solution, resulting in the energy function of the value of the continuous decline in the energy function of the values are getting smaller and smaller, all restrictions tend to “0”, it is worth mentioning that the first few chapters of the energy function of the restrictions are ultimately “0”, and this chapter due to the special problem, the constraints in the system when the convergence is not really “0” (But rather “0” (described later in the simulation analysis) until a reasonable solution is found.

3.6.2 Kinetic energy equation of NCNN

Using the gradient method, we can get the dynamic ability of neurons of p, r . From equation 12:

$$\begin{aligned}
\frac{dU_{p,r}(t)}{dt} &= -\frac{\partial E}{\partial V_{p,r}} = -B_e \sum_{s \neq r} V_{p,r} f_{CAC}(r, s) \\
&\quad - C_e \sum_{\substack{q \in \text{adja} \\ q \neq p}} \sum_{s \neq r} V_{p,s} f_{AAC}(r, s)
\end{aligned}$$

$$\begin{aligned}
& -D_e \sum_{\substack{q \in \text{over} \\ q \neq p}} \sum_{s \neq r} V_{q,s} f_{OAC}(r, s) \\
& -E_e \sum_{\substack{q \in \text{nona} \\ q \neq p}} V_{p,r} f_{NAC}(p, q) \\
& -F_e \left(\sum_{r=1}^C V_{p,r} - R_p \right) - G_e (1 - 2V_{p,r}) \quad (12)
\end{aligned}$$

$U_{p,r}(t)$ is the internal state of the neuron of p, r , $U_{p,r}(t)$ is the output of neurons of p, r , Their relationship is as follows:

$$V_{p,r}(t) = \frac{1}{1 + \exp(-U_{p,r}(t) \times u_0)} \quad (13)$$

According to the Euler method, the continuous NCNN model is discretized, and the discrete NCNN model of (5–14) is established. By adding negative self-feedback to generate transient chaotic power, random noise is added to facilitate the jumping of the local minimum. The kinetic energy equation of NCNN is:

$$\begin{aligned}
& U_{p,r}(t+1) - \lambda U_{p,r}(t) - \alpha B_e \sum_{s \neq r} V_{p,r} f_{CAC}(r, s) \\
& - \alpha C_e \sum_{\substack{q \in \text{adja} \\ q \neq p}} \sum_{s \neq r} V_{p,s} f_{AAC}(r, s) \\
& - \alpha D_e \sum_{\substack{q \in \text{over} \\ q \neq p}} \sum_{s \neq r} V_{q,s} f_{OAC}(r, s) \\
& - \alpha E_e \sum_{\substack{q \in \text{nona} \\ q \neq p}} V_{p,r} f_{NAC}(p, q) \\
& - \alpha F_e \left(\sum_{r=1}^C V_{p,r} - R_p \right) - \alpha G_e (1 - 2V_{p,r}) \\
& - z_{p,r}(t) [V_{p,r}(t) - I_0] + n_{p,r}(t) \quad (14) \\
& z_{p,r}(t+1) = (1 - \beta_1) z_{p,r}(t) \quad (15) \\
& n_{p,r}(t+1) = (1 - \beta_2) n_{p,r}(t) \quad (16)
\end{aligned}$$

Equations 15 and 16 are simulated, β_1 and β_2 are the self-feedback and random noise attenuation factors, which are attenuated exponentially.

3.7 Simulation results and analysis

In this chapter, the total number of channels about C is reduced by the gradient. At each simulation time, we first

estimate a value and then simulate. If we can find a reasonable solution, we will gradually reduce the total number of channels until the solution is 0. Find the appropriate total number of channels, so as to improve the same frequency reuse rate. If there are many areas, the total number of channels required, you can take a similar dichotomy method to search for the appropriate value, the simulation steps are summarized as follows:

- (1) First determine the number of MBSFN areas, the total number of channels, the number of channels required for each district about R_p .
- (2) According to the MBSFN region of adjacent, intersecting and non-adjacent position relationship to determine the adjacent, intersecting and non-adjacent interference matrix.
- (3) Initialize the NCNN system model parameters and the various weight coefficients about E .
- (4) Start each simulation, according to the nature of NCNN Debugging each parameter.
- (5) Simulation 1000 times, count the simulation of the rate of understanding.
- (6) As long as the comprehension rate of the simulation is not 0, the search rule is updated according to the total number of channels, and the process returns to step 4), and the simulation is continued until the appropriate value is searched.

The initial setup parameters are as follows: 9 districts, 50 channels, $R_p = 5$, NCNN system model parameters and weight coefficients are as follows:

$$\begin{aligned}
& u_0 = 0.85, \alpha = 0.14, \lambda = 0.95, I_0 = 0.65, \\
& A_m = 2, z(0) = 0.85, \beta_1 = \beta_2 = 0.02 \\
& B_e = 8, C_e = 7, D_e = 7, E_e = 7, F_e = 10
\end{aligned}$$

Figure 3 depicts the energy function values E of the e system at $G_e = 0$. From the change curve, it can be seen that the value of the energy function changes greatly before the 60th step, especially before about step 40th, which also proves that the role of understanding is the rich noise of the chaotic neural force in the first stage of the search. After the 60th step, the line E can be swung out, and the function gradient can converge until it no longer changes, and the final value E is a relatively small positive number, but not 0, because the iteration stops the judgment that the conditional well is not “all the limit term in the star function is 0”, but when the change of the energy function is less than 5 consecutive times, the iteration is stopped. This also shows that the use of strong function to determine the stability of the system is reasonable and effective (see Fig. 4). In addition, from the change curve of F_e that is same as the curve of E , indicate

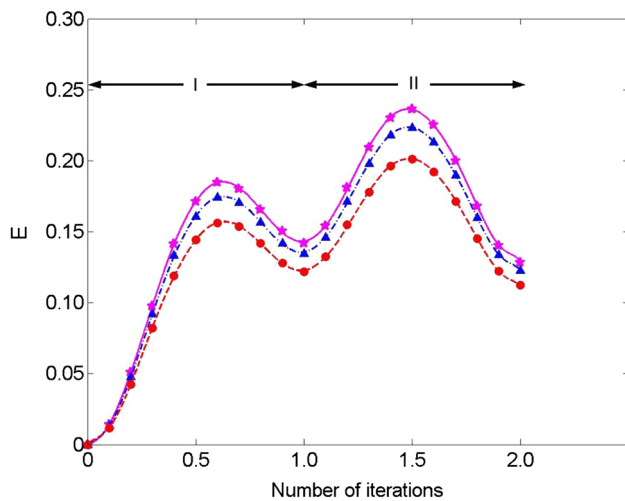


Fig. 3 The values of E and their items

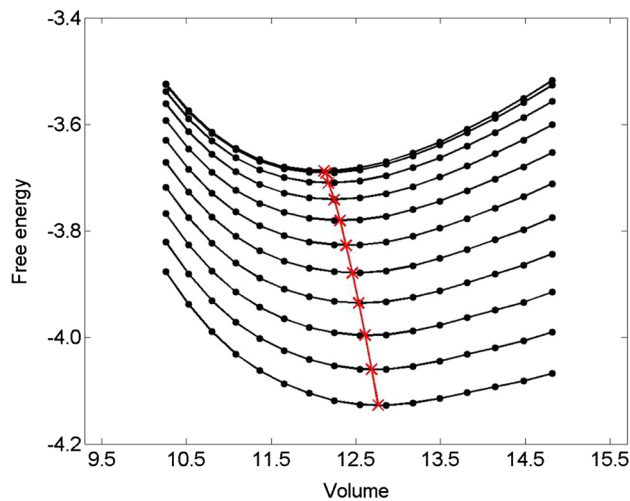


Fig. 4 The free energy as a function of volume

that the value of F_e is the item value of the energy function, the value of E changes with the value of F_e .

In order to pass the role of the simulation test to accelerate the convergence, here, we firstly set $G_e = 0$, which means no item of G_e . In this paper, through repeated simulation and testing, the final result is shown in Eq. 17, including $C_{opt} = 35$.

$$V = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

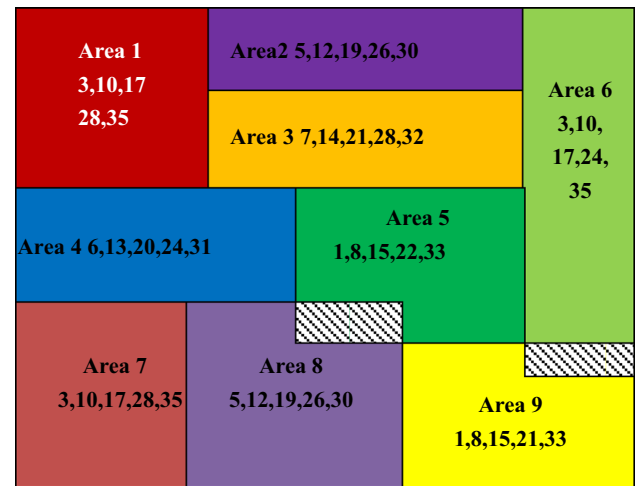


Fig. 5 MBSFN Area information distribution results

$$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \quad (17)$$

Annotated: This matrix is the ranks '9 × 35'

According to the value of the final channel assignment instruction matrix, the allocation result of each region is shown in Fig. 5. It can be seen that each MBSFN area is assigned five channels, and all meet the requirements of the restrictions, to avoid a variety of interference. It should be noted that, since this paper only involves nine regions, so the channel with the frequency reuse rate is not high, if the larger number of regional scenarios, the same frequency reuse rate will increase, and each area The number of letters required will also affect the same frequency reuse rate. In general, the greater the number of channels required for each zone, the greater the frequency reuse rate.

In order to more clearly see the effect of the same frequency reuse, Fig. 6 shows the number of multiple channels per multiple. As can be seen from the figure, there are five channels used three times, eleven channels used two times, eight channels used once. It is to be noted that in order to avoid various disturbances, a total of 11 channels of channels 2, 4, 9, 11, 16, 18, 23, 25, 27, 29 and 34 are not be used. The following method can be used to the further test whether it is appropriate for $C_{opt} = 35$. Place the unused channel in any of the MBSFN areas to see if it can be used. For example, the channel 16 is placed in the area 4, and since the area 1 has

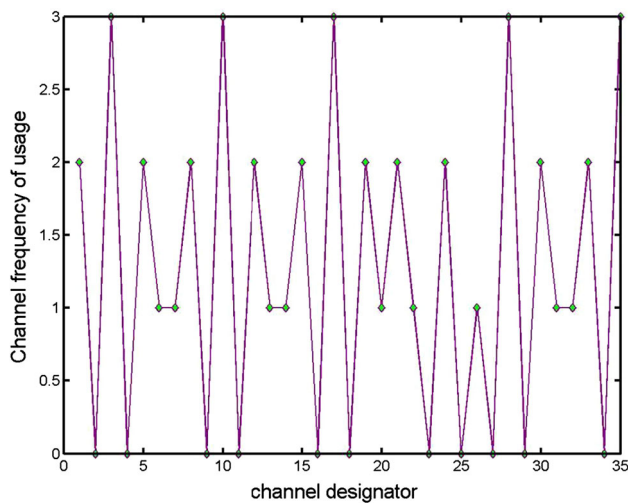


Fig. 6 The number of times each channel is used

the channel 17, the area 5 has the channel 15, the area 7 has the channel 17, there is an adjacent frequency interference, indicating that the channel 16 can not be used in the area 4. Or vice versa, for example, the channel 17 connected to the channel 16 is present in the regions 1, 6 and 7, indicating that the neighborhood of the three regions (2, 4, 5, 2, 3, 5, 8, 9, 5, 8) can not be used, otherwise there is adjacent frequency interference. Similarly, channel 15 exists in regions 5, 9, indicating that the neighborhood of the two regions (1, 4, 6, 7, 8, 6, 8, respectively) can not be used, otherwise there is adjacent frequency interference. Channel 16 and channel 14, 15, 17, 18 have interference in the same area and intersecting area. Therefore, the area where channels 14, 15, 17, 18 have been allocated and their intersecting regions can not be assigned channel 16, 5, 6, 7, 9, intersecting area 2, 4, can not allocate channel 16. In summary, channel 16 can not be used for any area. Through the above method, you can determine that any channel is not used can not be used, otherwise it will cause interference. This is also just to explain the rationality about $C_{opt} = 35$. In addition, since there is only 9 MBSFN areas in the simulation system model, 11 channels are not used, similar to “holes”. If the system has a large number of MBSFN areas, and each region requires more channels. You can avoid the “empty” problem, and the frequency reuse rate will be higher and higher.

4 Conclusion

Through the deep analysis of various optimization problems, combined with a variety of chaotic neural network technology, we carefully constructed the energy function of chaotic neural network. Which make full use of the rich chaotic neural power, successfully search the optimal solution of

structural problems, and effectively solve the Radio Resource Optimization. However, when the chaotic neural network technology is successfully applied to each specific application scenario, it is necessary to analyze the optimization problem in the specific scene deeply. The radio resource optimization problem of the specific scene of the future wireless mobile communication system and the optimization model of the chaotic neural network are deeply excavated. In order to reduce the complexity, it will simplify the initial optimization problem and construct the chaos carefully. In order to reduce the complexity, we will simplify the initial optimization problem and construct the chaos well and we will simplify the initial optimization problem. It can be seen from the simulation results that although the solution is still the second best solution, it can meet the performance requirements of the system and the users well. Comparing with the existing literature, the proposed algorithm can further improve the radio resource utilization, which achieve the purpose of optimizing the radio resources.

Acknowledgements This study was supported by the National Natural Science Foundation of China (Grant No. U1504602 and No. U1504613), Postdoctoral Science Foundation of China (2015M572141). The authors wish to thank the Science and Technology Plan Projects of Henan Province for contract 162102310614, under which the present work was possible.

References

- Li, T.Y., Yorke, J.A.: Period three implies chaos. *Am. Math. Mon.* **82**(10), 985–992 (1975)
- Banks, J., Brooks, J., Cairns, G., et al.: On Devaney’s definition of chaos. *Am. Math. Mon.* **99**(4), 332–334 (1992)
- Giortzis, A.I., Turner, L.F.: Application of mathematic programming to the fixed channel assignment problem in mobile radionetworks. *IEEE Proc. Commun.* **144**(4), 257–264 (1997)
- Kunz, D.: Channel assignment for cellular radio using neural networks. *IEEE Trans. Veh. Technol.* **40**(1), 188–193 (1991)
- Sung, C.W., et al.: Channel assignment and layer selection in hierarchical cellular system with fuzzy control. *IEEE Trans. Veh. Technol.* **50**(3), 657–663 (2001)
- Aihara, K., Takabe, T., Toyada, M.: Chaotic neural networks. *Phys. Lett.* **144**(bl7), 334–340 (1990)
- Yu, Q., Wang, Y.: The new direction of intelligent simulation neural network development. *Pattern Recognit. Artif. Intell.* **12**(3), 313–319 (1999)
- Hopfield, J.J.: Neural networks and physical systems with emergent collective computational abilities. In: *Proceedings of the National Academy of Sciences of the United States of America*, pp. 2554–2558 (1982)
- Hopfield, J.J.: Neurons with graded response have collective computational properties like those of two-state neurons. In: *Proceedings of the National Academy of Sciences of the United States of America*, pp. 3088–3092 (1984)
- Hopfield, J.J., Tank, D.W.: Neural computation of decisions in optimization problems. *Biol. Cybern.* **52**(1), 141–152 (1985)
- Chen, L., Aihara, K.: Chaotic simulated annealing by a neural network model with transient chaos. *Neural Netw.* **8**(6), 915–930 (1995)

12. Wang, L.P.: Noisy chaotic neural networks for solving combinatorial optimization problems. In: Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks **4**, 37–40 (2000)
13. Wang, L.P., Li, S., Tian, R.Y., et al.: A noisy chaotic neural network for solving combinatorial optimization problems: stochastic chaotic simulated annealing. *IEEE Trans. Syst. Man Cybern. Part B* **34**(5), 2119–2125 (2004)
14. Re, E.D., Fantacci, R., Ronga, L.: A dynamic channel allocation technique based on Hopfield neural networks. *IEEE Trans. Veh. Technol.* **45**(1), 26–32 (1996)
15. Lazaro, O., Girma, D.: A hopfield neural-network-based dynamic channel allocation with handoff channel reservation control. *IEEE Trans. Veh. Technol.* **49**(5), 1578–1587 (2000)
16. Yang, M., Jiang, M.Y.: Hybrid spectrum access and power allocation based on improved hopfield neural networks. *Adv. Mater. Res.* **588**, 1490–1494 (2012)
17. Uykan, Z.: Fast-convergent double-sigmoid hopfield neural network as applied to optimization problems. *IEEE Trans. Neural Netw. Learn. Syst.* **24**, 990–996 (2013)
18. He, Z.Y., Zhang, Y.R., Wei, C.J., et al.: A multistage self-organizing algorithm combined transiently chaotic neural network for cellular channel assignment. *IEEE Trans. Veh. Technol.* **51**(6), 1386–1396 (2002)
19. Wang, B.Y., Nie, J.N., He, Z.: A transiently chaotic neural-network implementation of the CDMA multiuser detector. *IEEE Trans. Neural Netw.* **10**(5), 1257–1259 (1999)
20. Sheikhan, M., Hemmati, E.: Transient chaotic neural network-based disjoint multipath routing for mobile ad-hoc networks. *Neural Comput. Appl.* **21**(6), 1403–1412 (2012)
21. Wang, L.P., Liu, W., Shi, H.X.: Noisy chaotic neural networks with variable thresholds for the frequency assignment problem in satellite communications. *IEEE Trans. Syst. Man Cybern. Part C* **38**(2), 209–217 (2008)
22. Wang, L., Liu, W., Shi, H.: Delay-constrained multicast routing using the noisy chaotic neural networks. *IEEE Trans. Comput.* **58**(1), 82–89 (2009)
23. Sun, M., Zhao, L., Cao, W., et al.: Novel hysteretic noisy chaotic neural network for broadcast scheduling problems in packet radio networks. *IEEE Trans. Neural Netw.* **21**(9), 1422–1433 (2010)
24. Zhang, H.B., Wang, X.X.: Resource allocation for downlink OFDM system using noisy chaotic neural network. *Electron. Lett.* **47**(21), 1201–1202 (2011)
25. Sun, M., Xu, Y., Dai, X., et al.: Noise-tuning-based hysteretic noisy chaotic neural network for broadcast scheduling problem in wireless multihop networks. *IEEE Trans. Neural Netw. Learn. Syst.* **23**(12), 1905–1918 (2012)
26. Alexiou, A., Bouras, C., Kokkinos, V. et al.: Communication cost analysis of MBSFN in LTEI. In: IEEE International Symposium on Personal Indoor and Mobile Radio Communications, pp. 1366–1371 (2010)
27. Tenny, N.E.: Poway, method and apparatus for reinforcement of broadcast transmissions in MBSFN inactive areas. In: United States, Patent application publication, US2010/0056166 A1, Mar. 4, (2010)
28. Lei, X., Jie, M., Zhu, H.S.: Improved cell reselection in an MBSFN system. In: International Application Published Under the Patent Cooperation Treaty (PCI), World Intellectual Property Organization International Bureau, W02009J113918 A1, (2009)
29. Ericsson.: Overlapping MBSFN areas[R], 3GPP TSG-RAN WG2 #66, San Francisco, USA, R2-093099, 4th May–8th May (2009)
30. Motorola, SFN areas and the MBMS coordinating function [R], 3GPP TSG-RAN-WG2 Meeting #54, Tallinn, Estonia, R2-062155, 28th August–1st September (2006)



Yongfeng Cui received the BS degree in Computer Science and Technology from Henan Normal University and the MS degree in Computer Application Technology from Huazhong University of Science and Technology, China in 2000 and 2007 respectively. He is currently researching on Computer Application Technology (CAT).



Zhongyuan Zhao Graduate student, Henan University of Technology. Received the BS degree in computer science and technology from Zhoukou Normal University, China in 2009. He is currently researching on Computer Application Technology (CAT). E-mail: zhaozy@zkn.edu.cn.



Yuankun Ma received the BS degree in South-Central University for Nationalities and the MS degree in Shandong University of Science and Technology, China in 2011 and 2014 respectively. He is currently researching on Machine Learning and Big Data Analytics.



Shi Dong received the M.E. degree in computer application technology from University of Electronic Science and Technology of China in 2009 and the PhD in computer application technology from Southeast University in 2013. Currently, he is a lecturer in the School of Computer Science and Technology at Zhoukou Normal University and he also works as post-doctor researcher in Huazhong University of Science and Technology, visiting scholar (postdoc researcher) in Washington University in St Louis. He is member of China Computer Federation. His research interests include distributed computing, network management.