Research on Cognitive Engine Design for Cognitive Radio Networks

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杨艺

Contents

Chapter 1 Introduction

1.1 Research Backgrounds

1.1.1 Radio Spectrum Allocation and Utilization Status

Wireless communication is the fastest growing and most widely used technology in the field of information and communication in the past 10 years. The rapid development of wireless devices and applications is changing people's way of life and thinking. The continuous growth of the demand for wireless communication business has resulted in explosive growth in the amount of communication data in wireless communication systems. Fig 1-1 shows a data volume histogram for global mobile communications from 2010 to 2020 [1]. From Fig 1-1, it can be seen that the volume of mobile communication data in the world is increasing geometrically.

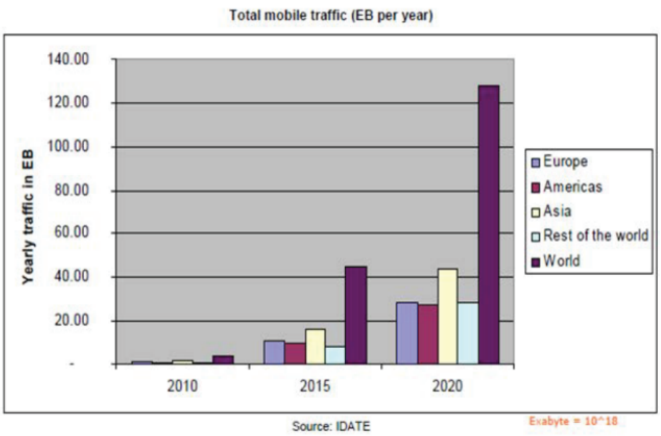

Fig.1-1 Predication of data requirement

The carrier of wireless communication is spectrum, but wireless communication can’t use every spectrum band arbitrarily. At present, the frequency of higher than 3000 GHz can’t be developed and utilized by mankind. Therefore, the available radio spectrum range is from 9 kHz to 3000 GHz arranged internationally. In the scientific community, the recognized radio wave was discovered in 1887 by the German physicist Hertz H.R. and proved that the electrical signals can spread in the air, laying the foundation for the invention of radio. In 1895, the Marconi G.W. as one of the founders of the radio communication invented the radio transmitter and successfully sent the radio telegraph with the carrier of the electromagnetic wave. In these more than 100 years since the wide application of wireless communication in 1907, radio communication technology has developed rapidly, and the demand for wireless communication is constantly changing. However, the improvement of transmission throughput and quality of service (QoS) are still the constant goals in the evolution of wireless communication technology.

Many properties and parameters of electromagnetic wave are related to frequency. In the low frequency band, the wireless electromagnetic wave has the characteristics of long transmission distance and small attenuation, but the amount of information that can be carried will be limited because of its narrow bandwidth. In the high frequency section, the performance of the radio electromagnetic wave is the opposite of the low frequency. Because of its larger bandwidth, the amount of information that can be carried is very large, but the transmission distance is greatly limited because of its larger attenuation. Therefore, the electromagnetic wave of 3KHz-300 GHz is usually used as a carrier for wireless communication. Table 1-1 shows the application of the corresponding frequency electromagnetic wave.

Table1-1 Application types of radio electromagnetic waves in different frequency bands

Frequency band	Applications
VLF	Underwater communication, navigation, wireless heart rate monitoring
LF	Navigation, time scale, amplitude modulation long wave broadcasting
MF	Amplitude modulation medium wave broadcasting and navigation
HF	Short wave radio, amateur radio
VHF	FM, TV broadcasting, radar, mobile communication
UHF	Television broadcasting, mobile communications, WLAN
SHF	Microwave equipment, mobile communications, WLAN, radar
EHF	Radio astronomy, high speed microwave relay

In table 1-1, VLF (very low frequency) ranged from 3 KHz to 30 KHz has 100-10 km wave length; LF (low frequency) ranged from 30 KHz-300 KHz has 10-1 km wave length; MF (medium frequency) ranged from 300 KHz to 3 MHz has 1000-100 m wave length; HF (high frequency) ranged from 3 MHz to 30 MHz has 100-10 m wave length; VHF (very high frequency) ranged from 30 MHz to 300 MHz has 10-1 m wave length; UHF (ultrahigh frequency) ranged from 300 MHz to 3 GHz has 100-10 cm wave length; SHF (super high frequency) ranged from 3 GHz to 30 GHz has 10-1 cm wave length;

EHF (extreme high frequency) ranged from 30 GHz to 300 GHz has 1-0.1 cm wave length.

Table 1-1 matches the corresponding transmission service according to the radio wave transmission characteristics of different frequency bands. At the same time, in order to avoid interference in the transmission process, the radio management departments of various countries use the static spectrum resource allocation method, and divide the radio spectrum into two kinds of spectrum: the authorized spectrum and the unauthorized spectrum. The authorized spectrum is a band that allows the authorized system to occupy exclusively in a specific area for a long time, such as the common radio and television frequency bands. Only the corresponding authorized users are allowed to access the authorized frequency bands for wireless transmission. In spectrum allocation, the method of authorized spectrum allocation dominates.

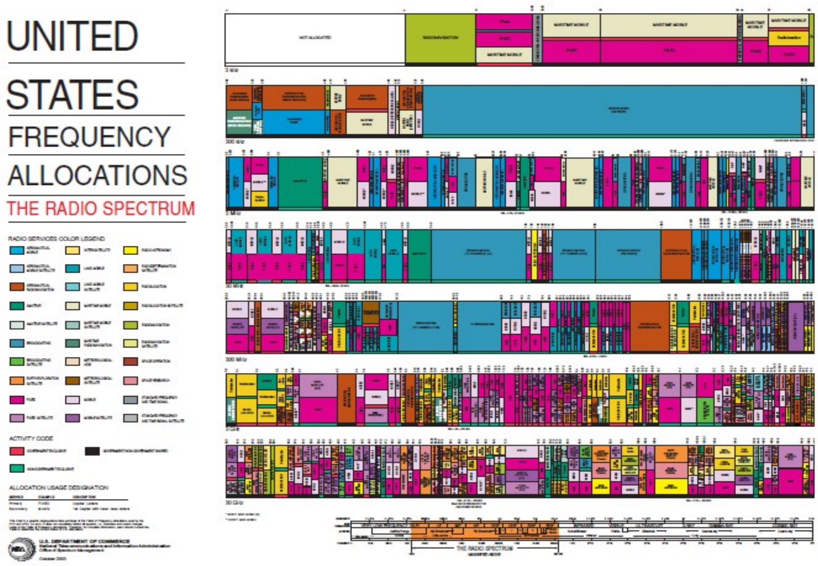

Fig.1-2 The allocation of the spectrum resource [2]

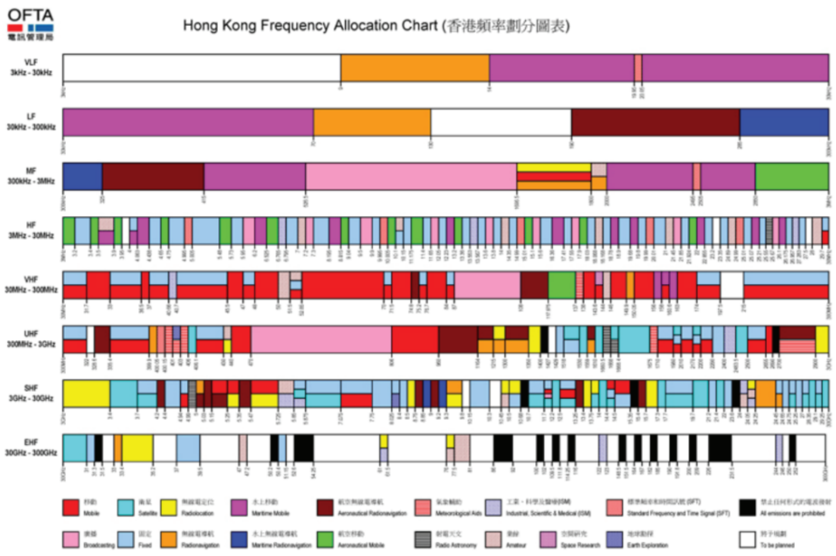

Fig.1-3 Radio frequency allocation chart of Hong Kong Special Administrative Region

Fig 1-2, Fig 1-3 respectively gives the spectrum allocation of the United States and the Hong Kong Special Administrative Region of China. Each color in the map represents the corresponding wireless communication system and business type. It can be seen from the graph that some frequency bands are allocated to the only applications, such as TV bands, radio broadcasting, space exploration and research, radio navigation, and the vertical fracture in some frequency bands is reused by many systems and services. The above facts show that the spectrum of 3 KHz-300 GHz suitable for wireless communication transmission has been divided by the authorized service, and the remaining distributable spectrum is very rare.

The above facts show that the increasing demand for communication makes the spectrum resources suitable for wireless communication very short, which has become the main physical bottleneck restricting the further development and evolution of wireless communication. However, a large number of investigations have shown that the low spectrum utilization rate and even the idle spectrum resources are common because of inadequate radio service in the large number of authorized bands [3-5]. The reason is that there is a serious mismatch between the static spectrum planning system and the dynamic spectrum utilization. Figure 1-4 shows a statistical map of the average utilization rate of the frequency band below 3 GHz measured by the company named Shared Spectrum of the United States. From the diagram, we can clearly see that most of the wireless communications services have less than 25% spectrum utilization, most of the spectrum utilization is even less than 10%, and the average occupancy is only 5.2%. Because of the constraints of the relevant policies, the unauthorized users cannot access the idle spectrum for communication services even if no authorized users are using the authorized spectrum. In the background of extremely scarce spectrum resources, the serious low utilization of spectrum further aggravates the contradiction between the lack of wireless spectrum resources and the continuous growth of wireless communication demand.

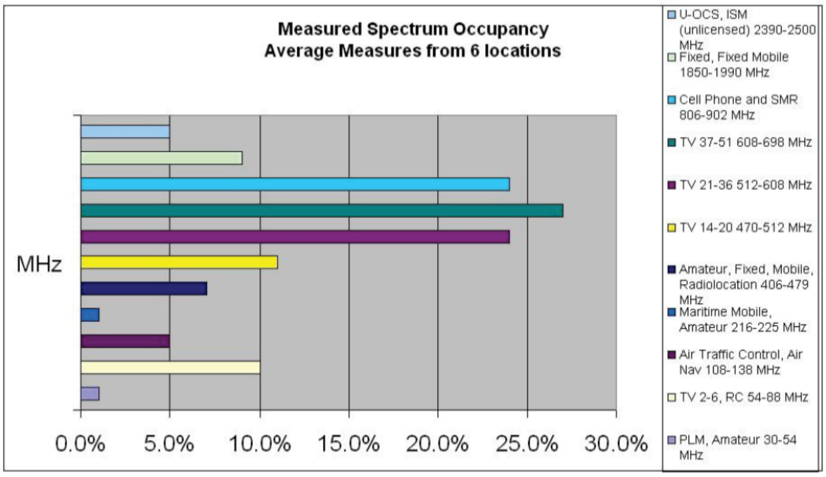

Fig.1-4 Measured spectrum utilization of some typical bands

With the scarcity of spectrum resources, it is difficult for new businesses and systems to obtain spectrum resources through static spectrum allocation. An unauthorized band is a frequency band that any user can use without authorization, such as the International Telecommunications Union (ITU) used by the International Telecommunications Union (ITU) for industry, science and medicine (Industrial, Scientific and Medical, ISM) without authorization. This open spectrum usage alleviates the problem of spectrum shortage due to the static allocation of spectrum. All kinds of wireless communication terminals have access to this band in a competitive way. However, more and more Bluetooth, wireless LAN and domain network users are trying to get the spectrum in the ISM band, which leads to more and more congestion in the ISM band. The limited wireless spectrum resources have been unable to meet the growing demand for wireless communication services and the new technology of wireless communication. How to solve the current scarcity of spectrum resources has become a problem to be solved urgently.

Under the static allocation of spectrum resources, the authorization of spectrum remains unchanged for a long time (usually decades), and given the authorized area and the specific business. However, the statistical distribution characteristics of different wireless communication services in time domain, airspace and frequency domain will affect the utilization of spectrum. In frequency domain, the utilization of some frequency bands is much higher than other frequency bands, such as the frequency segments of the operators' public mobile communication services. In the time domain, even if the average utilization rate is high, the utilization rate will change with time. For example, the user group of cellular services is also time regularity, with peaks and lows. In spatial domain, the spectrum utilization has a direct relationship with the geographical location. For example, the honeycomb band in the urban area is significantly higher than the cellular band in the suburb. Due to the unbalanced characteristics of the business distribution characteristics, the spectrum utilization rate under the static spectrum allocation mechanism is low, which is the motivation of dynamic spectrum access [6].

1.1.2 Measures to Cope with the Spectrum Problem

In order to cope with the shortage of spectrum and low utilization rate, various countries and relevant organizations and agencies have put forward relevant plans and arrangements at the policy level. The United States' release broadband revolution was released in June 2010, indicating the National Telecommunication Industry Administration (NTIA), the National Telecommunications (National Tele-communications) and the Federal Communications Commission (Federal Communications Commission, FCC) will work together to free 500 MHz authorized and unauthorized spectrum is used for wireless broadband services. The Federal Communications Commission FCC has also readjusted the 335 MHz federated spectrum allocation scheme. In the Middle class tax relief and employment creation act 2012, the United States government has proposed a large number of spectrum related provisions. The legislation gives the Federal Communications Commission FCC the right to auction the spectrum of specific bands to wireless communication providers. The bill also authorizes the Federal Communications Commission FCC to allocate more spectrum resources for unauthorized systems (such as Wi-Fi) and innovative business applications, and to some extent mitigate the problem of commercial wireless service providers in the spectrum scarcity by increasing the proportion of Wi-Fi to occupy wireless data traffic. At the same time, in June 2013, through the presidential memo, the U.S. government pointed out that the federal

agencies should focus on increasing the utilization of the wireless spectrum and creating more available capacity to meet the rapidly rising demand for broadband users and enterprises. The presidential memo also pointed out that federal agencies should increase cooperation and data sharing with the private sector so that stakeholders can contribute their expertise to the maximization of spectrum utilization, which will enable wireless broadband providers and equipment suppliers to obtain more spectrum resources. In addition to the presidential memo, policies to cope with the scarcity of spectrum and low utilization include $100 million in federal investment in spectrum sharing and advanced communications technology. In view of the scarcity and low utilization of spectrum, a series of laws and regulations on spectrum management have been formulated and introduced, and it is clearly pointed out that the rational optimization of spectrum management method is one of the important means to improve the spectrum efficiency.

In order to break through the bottleneck caused by the scarcity of spectrum resources and the low utilization rate for the further development of wireless communication, in addition to the spectrum regulation policy, a new wireless communication technology, including dynamic spectrum access, dynamic spectrum sharing and high frequency spectrum efficiency, is also a feasible means to effectively alleviate the frequency spectrum resource shortage.

In order to cope with the shortage of wireless spectrum, the most direct idea is to develop and use higher frequency bands. Because of this reason, millimeter wave communication has become one of the research hotspots in the field of wireless communication in recent years [7]. Compared with traditional communication, the most prominent feature of millimeter wave communication is that the frequency band is very wide. Within the spectrum of 30GHz to 300GHz, only one percent of the relative bandwidth can technically achieve 100 gigabytes available bandwidth. So the millimeter wave communication technology will undoubtedly provide a powerful technique for the development of new wireless services and applications. IEEE has developed the IEEE802.15.3c standard to promote the application of millimeter wave communication technology. Although millimeter wave communication can play an effective role in alleviating the spectrum shortage problem, the particularity of its propagation characteristics also greatly restricts the application of millimeter wave communication. In the course of the propagation of millimeter wave signal, the wavelength of the electromagnetic wave is very short, it is very easy to be absorbed

in the propagation process, so it produces huge propagation loss. At the same time, because of the uniqueness of the electromagnetic wave in the millimeter wave communication, the design of the hardware circuit, the design of the power amplifier, the design of the antenna and the channel modeling are all the problems to be solved.

Ultra-wideband (UWB) wireless communication technology uses a spectrum overlapping mode to access the authorized spectrum and share the spectrum resources with the existing system, thus effectively improving the spectrum utilization rate [8]. In ultra wideband systems, high bandwidth and low power spectral density of non-carrier signals can be transmitted by transmitting extremely short nanosecond pulse to carry out high speed transmission, that is, impulse radio UWB (IR-UWB). Ultra wideband technology is restricted by indoor power due to strict restrictions on transmission power in various countries. High speed sampling, ultra wideband antenna design, weak signal reception and processing are prominent problems in UWB systems. At the same time, the interference of the existing communication system to the UWB system is also a technical barrier restricting its application and popularization.

Cognitive radio (CR) technology is regarded as an intelligent and dynamically reconfigurable radio system. The basic idea of cognitive radio technology is that secondary users observe the surrounding environment, obtain access to the spectrum resources called "spectrum holes", and access authorization frequency band by adaptive adjustment of the transmission parameter. "Spectrum holes" is a spectrum resource with multi-dimensional characteristics, that is, the spectrum resources that are not occupied by the primary user (PU) in the time, space and frequency domain, and can be access for secondary users. The emergence of cognitive radio technology provides a strong support for alleviating the current shortage of spectrum resources, improving spectrum utilization and realizing dynamic spectrum access. The difference between secondary users in cognitive radio networks and traditional radio devices is that each secondary user has the ability of cognition and reconfiguration. Cognitive ability refers to the perception of the surrounding environment and the ability to collect information, in which the information that is perceived and collected includes transmission frequency, bandwidth, power and modulation. Secondary users with this cognitive ability can detect the best available spectrum resources. Reconfiguration means that secondary users can quickly adjust the operating parameters according to the detected environmental information to achieve the purpose of optimizing the transmission performance and improve the spectrum utilization.

1.1.3 A brief introduction to cognitive radio

Cognitive radio technology was first proposed by Dr. Mitola on the basis of software defined radio technology [9]. Subsequently, Haykin and Goldsmith have expanded the definition and connotation of cognitive radio [10] [11]. Generally speaking, cognitive radio is an intelligent non spectrum authorized wireless communication system. Its basic idea is that cognitive radio systems can perceive the surrounding electromagnetic environment, and obtain cognitive information about the surrounding environment through learning and reasoning mechanism (e.g. spectrum frequency status and PUs' communication mode), once find a temporarily not occupied spectrum (spectrum hole), then access to this spectrum hole, also according to the perception information intelligently adjust the strategy of wireless transmission (Modulation mode, encoding and decoding mode, carrier spectrum, power, antenna direction and other parameters.) in real time, so as to ensure the validity and reliability of the communication of the cognitive radio system. It can be seen clearly that the cognitive radio system can access and use the authorized spectrum in the case of no harmful interference to the primary system, which can effectively improve the spectrum utilization. FCC and IEEE in the United States also promote the development and application of cognitive radio technology by formulating corresponding standards and regulations.

Cognitive radio is not only the key technology to achieve dynamic spectrum access, but also an effective solution to achieve heterogeneous network convergence. With the rapid development of wireless communication technology and the long-term coexistence of the second and third generation communication systems, in order to connect the existing networks to the future network seamless connection, the market puts forward the demand for universal terminals for various networks. Software Definition Radio [12], which can be reconfigured through software reconfiguration, has emerged as the times require, providing basic conditions for the realization of cognitive radio technology.

The cognitive radio proposed by Mitola is an architecture based on the cognitive cycle model, which includes a loop of observation, judgment, planning, decision and execution (Figure 1-5). At the same time, in this process, it involves the process of reasoning, processing, analyzing and predicting the contextual information [9]. The intelligence of cognitive radio is mainly embodied in a supervised and unsupervised learning process, which interacts with each step of the cognitive ring, learning and directing corresponding decisions. A prominent function of cognitive radio is to actively perceive ambient information. For example, it detects whether or not a certain type of event occurs (such as the presence of the main user signal); it determines the environment in which the cognitive wireless is located by analyzing information about GPS location information, light intensity, and temperature. The cognitive radio infers the urgency of the context task according to the analysis of the external observation information and the request of the internal task, and then determines the priority of the execution according to the urgency of the event request, and flexibly changes the transmission and receiving parameters of the communication stack.

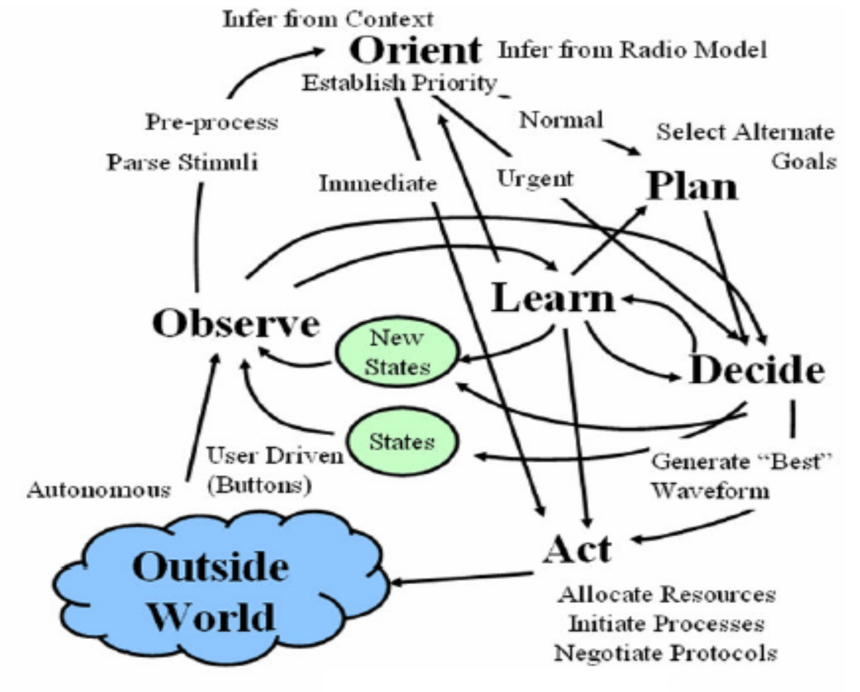

Fig 1-5 Cognitive cycle proposed by Mitola

Simon Haykin has proposed another representative cognitive radio model [10]. Simon Haykin believes that cognitive radio is an intelligent wireless communication device based on software radio, which can perceive the surrounding environment and use relevant methods to learn and adapt to the statistical changes in the environment. It is believed that cognitive radio has two main objectives: firstly, it is highly reliable communication whenever and wherever possible, followed by the effective use of spectrum resources. Haykin also proposed a cognitive loop model similar to Mitola (Figure 1-5), which mainly includes three basic problems of cognitive radio: 1) analysis of wireless environment, including detection of spectrum holes and estimation of interference, 2) channel state estimation and prediction modeling, 3) emission power control and spectrum management.

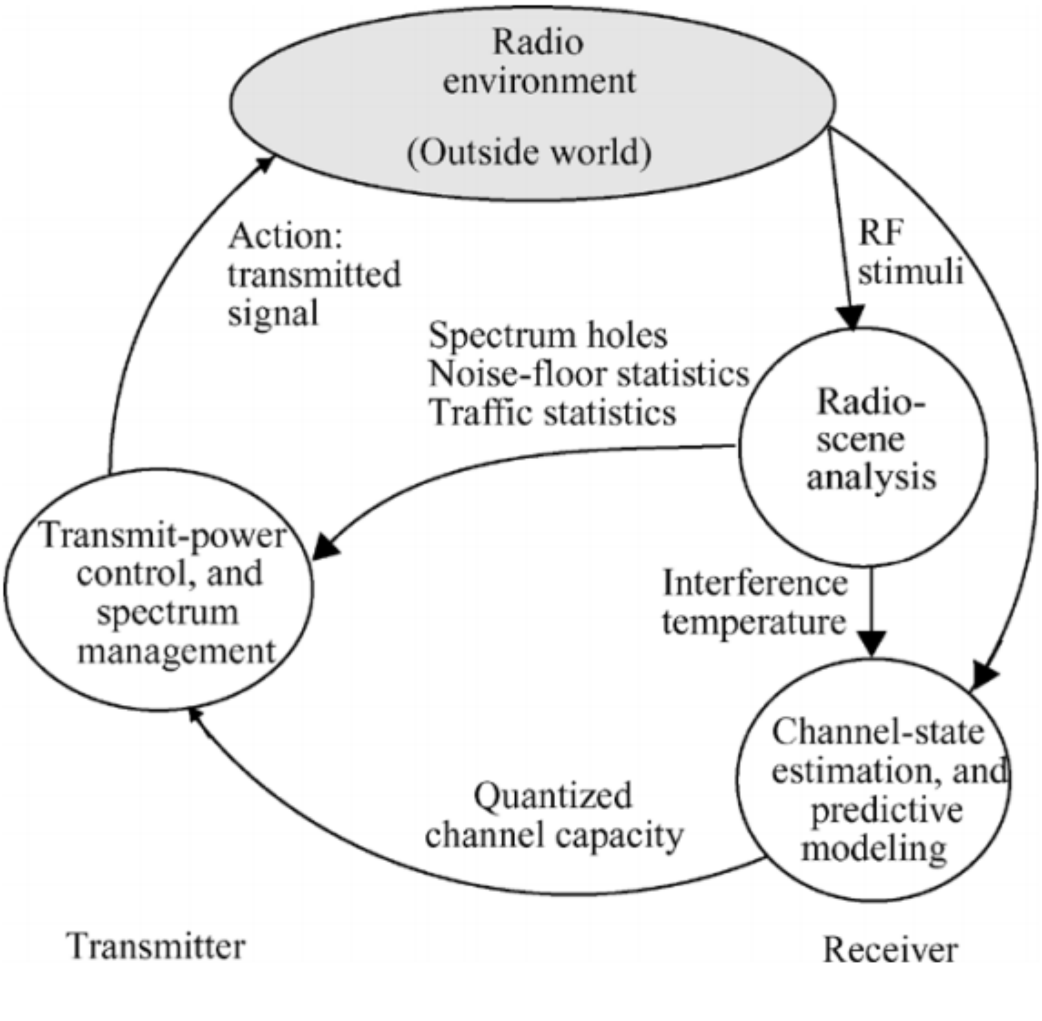

Fig 1-6 Cognitive cycle proposed by Simon Haykin

It's not only in academia, but also in some management entities and standardization organizations cognitive radio have different definitions. For example, the software radio forum thinks that cognitive radio is a wireless system with the following characteristics: 1) sense the changes of the external environment, 2) adaptively cope with these changes in some way, and improve the system performance by changing the working parameters. FCC describes a cognitive radio as a wireless node or network that can identify the frequency segments that are not used and use these bands to communicate, thus improving the efficiency of the utilization of spectrum resources. Therefore, the definition of FCC can be regarded as a simplification of the cognitive radio defined by Mitola, in which the cognitive radio mainly takes into account the radio spectrum information in the setting and adjusting of the transmitting and receiving parameters, and does not specify a learning reasoning ability.

In order to effectively use a spectrum, each layer needs cooperation and coordination. A radio node can make intelligent decisions and configuration through the interaction of each layer of the communication stack and the environment information. Where, the perception and policy modules are mainly used to detect the availability of spectrum, and they also drive learning and reasoning functions. No matter which cognitive models and definitions are used, the basic goal of cognitive radio is to improve the utilization of spectrum resources. The basic feature is that it has the ability of environmental perception. In the case of not causing harmful interference to the main user signal, it can intelligently adjust the parameters of the system to carry out dynamic spectrum access.

1.2 State of the Art Related Work

Under the premise of dynamic spectrum access, dynamic spectrum resource allocation can further enhance the utilization of wireless spectrum. Cognitive radio networks can allocate spectrum resources to secondary users through the combination of spectrum sensing results and spectrum allocation optimization objectives. The secondary system needs to consider the characteristics of the spectrum's central frequency, bandwidth, interference level, path loss and duration when analyzing the perceived spectrum resources. In establishing the target for the allocation of spectral resource allocation, the total throughput of the secondary user system should not only be considered, but the secondary user SUs needs to be considered. The system parameters include fairness, QoS and user interference constraints.

By using the utility function abstracted from the secondary user requirements as the target function of the spectrum sharing decision, the decision problem of the allocation of spectrum resources can be transformed into an optimization problem. Common solutions include water filling algorithm [13] [14], convex optimization algorithm [15] [16] [17], heuristic algorithm [18] [19], graph theory [20] [21] and so on. In [22], on the premise of not affecting the performance of the primary user, the author uses the distributed update process to allocate the power of the secondary user to maximize the throughput of the secondary system, and allocate the spectrum resources by centralized algorithm. Research in [23] simplifies the allocation of spectrum resources into the matching problem in weighted graphs, and maximizes the revenue of the whole system in spectrum decision making. In document [20], based on graph theory, the problem of spectrum sharing is modeled as a multi-objective optimization problem, which aims at maximizing the bandwidth revenue of the system and maximizing the fairness of secondary users, and simplifying it to coloring problem. At the same time, the particle swarm optimization (PSO) algorithm is used to solve the NP-hard problem, and the tradeoff between system bandwidth gain and secondary user fairness is achieved. Document [24] models the behavior of secondary users competing for spectrum resources to maximize their respective fitness functions in the form of game theory. In document [25], the power control problem of secondary users is abstracted as a distributed game problem. Secondary users can maximize their respective utility functions by adjusting the transmission power as players of the game. When the Nash equilibrium is reached, the secondary user system can get the maximum total system throughput. Literature [26] aims at the problem of distribution of dynamic spectrum resources in distributed cognitive radio networks. Secondary users carry out carrier allocation, power allocation and the choice of modulation mode according to the maximum its own fitness function. The goal of each secondary user is to minimize transmission power on the premise that the transmission rate and transmission power are guaranteed. It is modeled by game theory and verified to converge to the Nash equilibrium point.

1.3 Main Contributions and Framework of the Thesis

This thesis focuses on cognitive radio's cognitive engine design both in centralized systems and distributed systems.

Chapter 2 introduces a normal adaptive resource allocation process and our proposed modified particle swarm optimization algorithm.

Chapter 3 Cognitive Engine Design for Centralized Cognitive Radio Systems. We consider the communication networks is LTE-A frame. We designed an adaptive resource allocation algorithm for cognitive radio in LTE-Advanced communication frame.

Chapter 4 in this chapter, we focused on the distributed cognitive radio system. In distributed communication system, because the lack of central controller it's difficult to optimization the system's resource effectively. We designed a cooperative spectrum sensing strategy and a learning scheme for distributed cognitive radio to improve the spectrum utility.

Chapter 2 Adaptive Resource Allocation and Particle Swarm Optimization

In order to better understand the resource allocation scheme designed for cognitive radio communication systems in LTE-A frame, this chapter starts with the general problem of adaptive resource allocation, and carries out mathematical modeling and analysis of the problems in this practical application. Through the design of objective function and penalty function, the mathematical model of adaptive resource allocation is simplified. The simplified adaptive resource allocation problem is decomposed into two sequential optimization problems. Then the particle swarm optimization (PSO) algorithm is introduced to solve the optimization problem in this paper, and the original particle swarm optimization algorithm is improved according to the complementary characteristics of the particle swarm optimization and genetic algorithm.

2.1 The general model of adaptive allocation

Adaptive resource allocation in wireless communication systems is a technology that aims at different frequency selective fading between users, adaptively allocates subcarriers and power, so as to obtain user diversity gain, improve system performance and utilization of spectrum resources.

The following is the analysis of adaptive resource allocation based on K users N subcarriers multiuser multi carrier wireless communication system. In this system, $\rho_{k,n}$ is a discrete binary number with [0,1] value. Let Ω_k denotes a subset of subcarriers allocated to user k, then $\rho_{k,n} = \begin{cases} 1 & n \in \Omega_k \\ 0 & n \notin \Omega_k \end{cases}$; N is the number of available subcarriers in the communication system; N_0 is the single sideband power spectral density of additive Gauss white noise. B is the total system bandwidth. $h_{k,n}$ is the channel gain of the user k on the subcarrier n; Γ denotes the system SNR gap, which means the gap between the actual channel capacity and the theoretical channel capacity. In this chapter, $\Gamma = \frac{N_0}{3} Q^{-1}\left(\frac{BER_{\min}}{4}\right)^2$; $BER_k^{\lim}$ represents the minimum bit error rate requirement for user k.

From the definition of adaptive resource allocation algorithm, it can be seen that the goal of adaptive resource allocation is to obtain the diversity gain of the user, thus maximizing the total throughput of the communication system $\sum_{k=1}^{K}\sum_{n=1}^{N} R_k(n)$, where $R_k(n)$ denotes the throughput of the user k on the subcarrier n.

$$R_k(n) = \frac{\rho_{k,n}}{N}\log_2\left(1+\frac{p_{k,n}h_{k,n}^2}{\Gamma N_0 B/N}\right) \tag{2-1}$$

Maximizing the system capacity of communication systems is based on the classical water-filling allocation [27]. This allocation will cause the users with good channel conditions to occupy the majority of the sub-carriers and transmit power resources. The users of the poor channel condition will get very small amount of resources and may even be unable to be served, which should be avoided as far as possible in the actual communication system. Therefore, in the actual communication system, the adaptive resource allocation problem is bound to exist constraints, to a certain extent, to protect the needs of the system and users. It mainly includes:

(1) Fairness between users

Fairness among users in communication systems is one of the most important indicators of system performance. The fairness between users in the system ensures that users who are far away from the base station (usually have poor channel condition) can enjoy the same QoS as other users in the process of resource allocation. At the same time, dynamic adjustment of user fairness is also one of the goals of dynamic adjustments such as access control and load balancing. In the communication system based on orthogonal frequency division multiplexing, the fairness between users is defined as follows:

$$\Phi = \left(\sum_{k=1}^{K}\frac{R_k}{\gamma_k}\right)^2 \Big/ K\sum_{k=1}^{K}\left(\frac{R_k}{\gamma_k}\right)^2 \tag{2-2}$$

Where $R_k = \sum_{n\in\Omega_k} R_k(n)$ represents the channel capacity of user k in resource allocation. γ_k represents the channel assignment weights of user k in channel assignment. In document [28], the understanding of γ_k is the transmission rate of business expectations. $0 < \Phi \le 1$, and when $R_1 : R_2 : \ldots : R_K = \gamma_1 : \gamma_2 : \ldots : \gamma_K$ is established, the fairness of the system reaches the maximum $\Phi = 1$.

(2) Minimum bit error rate limitation:

This constraint is to ensure the quality of the received signal, and the transmission of the signal to meet the minimum acceptable bit error rate of the small user.

(3) Total transmission power limitation.

The limitation is to reduce the same frequency interference between the cells, and also to minimize the differentiation performance of the user terminals.

(4) The specificity of subcarriers is that each sub carrier can only be allocated to one user in each allocation.

Through the above analysis, the adaptive resource allocation problem can be abstracted as the following mathematical model.

$$\begin{aligned} &\max\left(\sum_{k=1}^{K}\sum_{n=1}^{N} R_k(n)\right) \\ subject\ \ to: C1 &: \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le P_{total} \\ C2 &: p_{k,n} \ge 0 \quad for \quad all \quad k,n \\ C3 &: \rho_{k,n} = \{0,1\} \quad for \quad all \quad k,n \\ C4 &: \sum_{k=1}^{K} \rho_{k,n} = 1 \quad for \quad all \quad n \\ C5 &: BER_k <= BER_k^{\lim} \quad for \quad all \quad k \\ C6 &: \Phi = 1 \end{aligned} \tag{2-3}$$

Where six constraints C1-C6 denotes as followed:

C1: The total transmission power of each user in the system can’t exceed the total transmission power limit required by the system.

C2: The transmission power of each sub carrier in the system is positive.

C3 and C4: Each subcarrier of a communication system in a primary allocation can only be allocated to a single user, and there is no subcarrier which can be allocated to two users simultaneously.

C5: The error rate of each user in the system can’t exceed the minimum BER requirement of the business.

C6: The fairness restriction between users in a communication system.

2.2 Simplified processing of adaptive resource allocation model

In the mathematical model of adaptive resource allocation for the communication system based on orthogonal frequency division multiplexing, the allocation of subcarriers belongs to the discrete integer allocation problem. The allocation of transmission power belongs to the continuous allocation problem. Therefore, the adaptive resource allocation problem composed of two parties belongs to the non-linear two layers mixed integer programming problem. The optimal allocation of subcarriers and transmission power to each user at the same time can be considered as a NP-hard problem, and the optimal permutation and combination can't be solved in polynomial time. Therefore, in order to simplify the model, the resource allocation problem is divided into two parts: subcarrier allocation and transmission power allocation in this paper. In the two parts, the transmission power is suboptimal for the first step carrier allocation, and the second step power allocation will be based on the results of the first step carrier distribution as the basis for the distribution of the transmission power. Dividing this resource allocation process into two parts will bring at least two advantages:

(1) Control variable method. Reducing the scope of the optimal solution space can make the algorithm easier to find a feasible solution.

(2) Step-by-step optimization can help to control the algorithm in different stages and improve the flexibility of the whole resource allocation algorithm. According to the requirements of communication system and the characteristics of the algorithm (such as convergence rate and accuracy), the algorithm's parameters and objective functions can be adjusted at different stages, so that the algorithm can be adjusted more flexibly.

However, the two step resource allocation scheme is still very difficult to find a feasible allocation scheme because of the existence of the nonlinear constraint condition C6. Therefore, we seek a reasonable relaxation of constraints and the design of a unique objective function, and then the mathematical model of adaptive resource allocation can be further simplified.

1. Relaxing restrictions

The limiting condition C6 in formula 3-2 requires absolute fairness between users in the system. This restriction is too strict for the actual communication system. It can be appropriately relaxed to $\Phi \in (\varepsilon, 1)$, which ε is a positive constant less than 1. Through the relaxation process here, the mathematical model of adaptive resource allocation can be simplified to:

$$\begin{aligned}
&\max\left(\sum_{k=1}^{K}\sum_{n=1}^{N} R_k(n)\right) \& \max(\Phi) \\
&subject \quad to: C1: \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le P_{total} \\
&\qquad C2: p_{k,n} \ge 0 \quad for \quad all \quad k,n \\
&\qquad C3: \rho_{k,n} = \{0,1\} \quad for \quad all \quad k,n \\
&\qquad C4: \sum_{k=1}^{K} \rho_{k,n} = 1 \quad for \quad all \quad n \\
&\qquad C5: BER_k <= BER_k^{\lim} \quad for \quad all \quad k \\
&\qquad C6: 1 \ge \Phi > \varepsilon
\end{aligned} \tag{2-4}$$

2. Objective function design

Through the analysis of (3-3) the simplified adaptive resource allocation mathematical model, it is found that the total throughput of the system and the fairness between the users have the same independent variables and there are tradeoffs between them. Therefore, we consider the design of penalty function and intuitively reflect the tradeoffs relationship. The fitness function is designed as followed:

$$\sum_{k=1}^{K} R_k - c \times \left|\max(0, 1-\Phi)\right| \tag{2-5}$$

Where c is the penalty factor and R_k denotes the capacity of user k. The penalty factor should not be too large or too small. According to the tolerance of the system, a penalty factor can be set accordingly. In general, the penalty factor should be set at least to keep the constraints and the restricted conditions at the same order of magnitude.

After introducing the concept of penalty function, the simplified mathematical model of adaptive resource allocation can be expressed as:

1. Subcarrier allocation stage

$$\begin{aligned} &\arg\max\left(\sum_{k=1}^{K} R_k - c\times\left|\max\left(0,1-\Phi\right)\right|\right) \\ &subject\quad to: C1:\rho_{k,n} = \{0,1\}\quad for\quad all\quad k,n \\ &C2:\sum_{k=1}^{K}\rho_{k,n} = 1\quad for\quad all\quad n \\ &C3: BER_k <= BER_k^{\lim}\quad for\quad all\quad k \end{aligned} \tag{2-6}$$

2. Power allocation stage:

$$\begin{aligned} &\arg\max\left(\sum_{k=1}^{K} R_k - c_1\times\left|\max\left(0,1-\Phi\right)\right| - c_2\times\left|\min\left(0, P_{total} - \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n}\right)\right|\right) \\ &subject\quad to: BER_k <= BER_k^{\lim}\quad for\quad all\quad k \end{aligned} \tag{2-7}$$

To sum up, the general adaptive resource allocation problem has been abstracted into two continuous optimization problems. The problem of solving adaptive resource allocation has become the problem of solving the optimal value. Considering the quality and optimization time of the optimal value, as well as providing sufficient flexibility for the cognitive radio system in decision making, this paper focuses on the particle swarm optimization algorithm in the evolutionary algorithm.

2.3 Particle Swarm Optimization

At present, the mainstream heuristic algorithm is genetic algorithm and particle swarm optimization. Genetic algorithm is inspired by the natural law of survival of the fittest for many years in the biological world [29].Its characteristic is that it has excellent global search ability, but its convergence speed is slow, especially in multi parameter and large search space, its convergence speed can't get satisfactory results. In the process of resource allocation in communication systems, every OFDM symbol is usually μ second level, even in a relatively stable indoor environment, the change of communication channel is usually at the m second level. Therefore, the resource allocation problem has higher requirements for the convergence rate of the algorithm. Genetic algorithm is obviously not the best choice under the requirement of high convergence speed.

Particle swarm optimization is a new optimization algorithm in recent years [30].

There are many similarities between particle swarm optimization (PSO) and genetic algorithm (GA). They are both based on swarm intelligence optimization method. The algorithm has strong parallelism, and the two algorithms do not need gradient information. It only needs to use the information of the target value. It has very strong usability and guarantees the flexibility of the algorithm in the application. Unlike the genetic algorithm (GA), the power of the particle swarm optimization (PSO) convergence is to use the information interaction between each particle, to transmit the global optimal information at the present time in the entire search population network, and to guide the search behavior of the particles in the population. The convergence power of genetic algorithm (GA) is mainly derived from the variations, crossover and heredity of chromosomes. Each of the chromosomes is a relatively independent individual, which is not affected by the optimal solution at present. Therefore, particle swarm optimization algorithm has faster convergence speed, but at the same time, particle swarm optimization algorithm is more likely to fall into local extremum and the global search ability is weak. In recent years, scholars have great interest in particle swarm optimization, and are committed to using particle swarm algorithm instead of genetic algorithm as the mainstream algorithm of biological heuristic algorithm [30-35].

Since particle swarm optimization (PSO) has the characteristics of fast convergence, it is more suitable for fast changing wireless channels as an evolutionary algorithm. Therefore, the particle swarm optimization (PSO) algorithm is used as the core algorithm to solve the adaptive resource allocation problem. Based on the standard particle swarm optimization (PSO) algorithm, a reasonable improvement is made on the basis of the characteristics of the application scene, in order to improve the ability of the global search and the fast search for the optimal solution.

2.3.1 Original particle swarm optimization

Particle swarm optimization (PSO) was first proposed by Kennedy and Eberhart in 1995 [30]. By simulating the phenomenon of birds gathering and foraging, it realized the optimization of multidimensional space. They were originally designed to simulate the biological phenomenon of bird foraging, and the experimental results reveal that the simulation model has strong optimization ability, especially in solving the problem of multi-dimensional space optimization. Particles in particle swarm optimization

(PSO) are regarded as massless and volume - Free entities in space. They fly in the solution space by changing direction and size. The whole particle swarm is composed of individual particles, each particle has memory function, and particles in the population can share information with each other.

In real space R^n, the feasible solution of the optimization problem can be represented as the location of particles moving in space. The particle's present position $x_i(t)$ is determined by the position $x_i(t-1)$ of the previous time and the present speed $v_i(t)$, where i represents the i th particle:

$$x_i(t) = x_i(t-1) + v_i(t) \tag{2-8}$$

The location of each particle can be regarded as a set of feasible solutions to the optimization problem. Since each particle has the ability to remember, it is able to remember the best point $pbest_i$ record that has been flying over and share it with other particles. In contrast to all $pbest_i$, it will find the best point, which is the best of all particle flying points. That is, the global optimal location found at present is recorded as $gbest$. The velocity of particles will be affected by two directions of $pbest_i$ and $gbest$, and the trend of continuous flight to these two points can be calculated in the following way:

$$\begin{aligned} v_i(t) = {} & w \times v_i(t-1) + \\ & c_1 \times rand_1 \times \left(pbest_i - x_i(t-1)\right) + \\ & c_2 \times rand_2 \times \left(gbest - x_i(t-1)\right) \end{aligned} \tag{2-9}$$

Where w denotes Inertia factor; c_1 and c_2 are two positive real numbers, called acceleration factors, which are used to adjust the weights of local information $pbest_i$ and global information $gbest$. $rand_1$ and $rand_2$ are random numbers in two [0,1], which increase diversity in two directions. The position and speed are limited by the range of change, which are $[-x_{\max}, x_{\max}]$ and $[-v_{\max}, v_{\max}]$. If the position or speed exceeds the limit after the update, the new position and speed are randomly generated within the limits. $v_{\max}$ is particularly important in the setting of these two limitations. Because too large $v_{\max}$ may be a particle in a finer fly over the optimal solution position, too small $v_{\max}$ may cause particles to jump out of the local optimum. Therefore, in general particle swarm optimization, $v_{\max} = x_{\max}$ is usually used as the maximum constraint of speed.

According to the update formula (2-8) and formula (2-9) of particle position and velocity in particle swarm optimization, the basic algorithm flow of standard particle swarm in real space A is as follows:

1) Initialization. It includes initializing the random position and initial velocity of individuals, initializing the optimal location of individuals and the optimal location of population.

2) Calculating the fitness of each particle in the current position according to the fitness function.

3) Comparing and select the best location of the best individuals.

4) Comparing all the fitness values after this update to the group best position $gbest$, and if it is better, then update the value of $gbest$, if not $gbest$ will remain unchanged.

5) Updating the speed and location of each particle in the population (updated according to formula (2-8) and formula (2-9)).

6) If it does not reach the termination condition (usually to achieve the default fitness threshold or to achieve the largest iteration), it returns 2). When the end condition is reached, the output is recorded and the result is recorded.

2.3.2 Modified Particle Swarm Optimization

The modified particle swarm optimization algorithm is mainly based on the complementarity between the advantages and disadvantages of particle swarm optimization (PSO) and genetic algorithm (GA). The advantage of genetic algorithm is that it has strong ability of global optimization, but the rate of convergence is not good. The advantage of particle swarm optimization algorithm is that it has high convergence speed, but it is easy to fall into local extremum and the global search ability is not very good. Original particle swarm optimization (PSO) is mainly due to its own update formula, which makes it easy to jump into local extremum: The update of position depends on the update of speed, and the update of speed is determined only by the three aspects of the current speed, the optimal position of the individual particle and the optimal position of the population, and the lack of a mechanism to effectively improve the diversity of the population so that the population's lack of vitality can't effectively jump out of the regional extreme value. Genetic algorithm has strong global search ability, mainly because it includes two points: 1. Each chromosome in genetic algorithm is relatively independent, and has no interaction at the same time. The update process of genetic algorithm includes crossover and mutation, all of which come from the birth and death process of the organism itself. Crossover and mutation substantially increase the diversity of the population, thus providing sufficient diversity guarantee for global search ability. Therefore, we consider adding the unique crossover and mutation process of genetic algorithm to the updating process of particle swarm optimization, which can increase the diversity of particle swarm optimization and improve the global optimization ability while maintaining the convergence speed of the particle swarm optimization.

The basic process of the modified PSO algorithm is as follows:

1) Initialize the population. This includes initialization of the random position and initial velocity of particles, initialization of the global best position and personal best position of each particle.

2) Calculating the fitness of each particle according to the fitness function.

3) Comparing and selecting the best location of the best individuals.

4) Comparing all the fitness values after this update to the group best position $gbest$, and if it is better, then update the value of $gbest$, if not $gbest$ will remain unchanged.

In this part, we add the restart mechanism. When the whole population has not updated the historical optimal value of the population over N generation, it shows that the particle in the population has lost the vitality to continue to find the better quality of the solution, that is, the population lack of population diversity, which leads to the whole algorithm falling into the local extreme value. In this resource allocation scheme, the method of reinitializing the population under the premise of preserving the historical optimal location of the original population is used to greatly improve the diversity of the population so as to jump out of the local extremum and continue to seek the global optimal solution.

5) Crossover and mutation: two particles are randomly selected for crossover and probabilistic variation in all particles.

6) Then the other particles update their speed and position according to the speed and position update formula (2-8) and (2-9).

7) If a termination condition is not reached (usually reaching the default fitness threshold or reaching the maximum iterated algebra), it returns 2). When the end condition is reached, the output is recorded and the result is recorded.

The specific crossover and mutation processes in step 5) are shown in Figure 2-1:

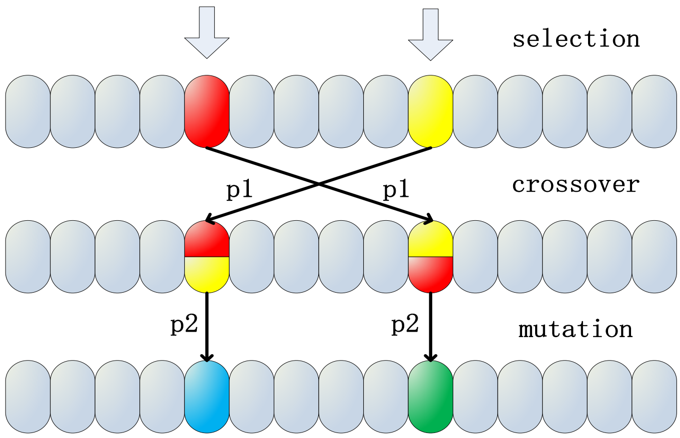

Fig.2-1 crossover and mutation

The whole process of crossover and mutation involves three steps: 1. choosing particles; 2. crossover; 3. mutation. The first line in the graph represents all the particles in the particle swarm. Before the updating process of original particle swarm algorithm, a crossover and mutation process similar to the genetic algorithm is added to the algorithm. Considering the complexity of the algorithm, in the crossover process, we consider the two particles will exchange half of the address information. Every bit of data in the particle after crossover is mutated with probability $p2$. Since the particle content designed in the system's resource allocation process is decimal, we first convert decimal number to binary number in the process of mutation, and then change each bit in the binary number with $p2$ as a probability, of which the variation of binary number is considered to be from 0 to 1 or from 1 to 0, and then the conversion of binary numbers to the decimal numbers will eventually produce two new particles. The two new particles are completely separated from the constraints of the original particle swarm optimization, which improves the particle diversity of the whole population and provides a basic guarantee for the search for the global optimal value.

2.4 Conclusion

The general problem of resource allocation in communication system is modeled. Through the combination of the proper relaxation of the restrictive conditions and the design of the penalty function, the constraints of the communication system and the requirements of the system are designed in the adaptive function value, and the relationship between the two is intuitively reflected by the size of the adaptive value. In order to provide effective algorithm flexibility guarantee for decision adaptation of cognitive radio systems, we introduce an evolutionary algorithm based on particle swarm optimization (PSO), which has very strong generality and can provide sufficient algorithm flexibility to support the adaptation needs of cognitive radio systems. When analyzing the advantages and disadvantages of common evolutionary algorithms, we start with the complementarity of particle swarm optimization and genetic algorithm on the advantages and disadvantages, and propose an improved particle swarm optimization algorithm, which inherits the fast convergence characteristics of the particle swarm optimization and has a higher global search ability in the genetic algorithm. In addition, the restart mechanism is introduced on the basis of improved particle swarm optimization (PSO). When the system has not updated the global optimal solution and the global optimal position for the continuous N generation, it is considered that the whole population has lost its vitality and falls into the local extremum. At this point, the method of reboot is used to maintain the diversity of the system.

Chapter 3 Cognitive Engine Design for Centralized Cognitive Radio Networks

Cognitive radio is viewed as the most promising communication technology in years. Because of that there is a need to improve the utilization of the precious radio frequency electromagnetic spectrum. And cognitive engine is the core of cognitive radio system as the brain of human. In this paper, we design a cognitive engine basing on modified particle swarm optimization to deal with the LTE-advanced (long term evolution-advanced) communication system's adaptive resource allocation problem. To design that, we divide the allocation process into three continuous parts and each part has its only goal and fitness function of particle swarm optimization. By comparison of simulations under Matlab 2011b, our proposed particle swarm optimization for cognitive engine can conclude a better performance with acceptable computing time.

3.1 Introduction

Nowadays, lots of wireless communication standards are using in the same time, especially in developing country, GSM and WCDMA and LTE are in the market at the same time for different kind of users' need. LTE-advanced viewed as the LTE standard's final evolution version should be used in future [6]. Cognitive radio is needed to solve such kind of coexistence problem of heterogeneous networks and make full using of the precious frequency resources

Adaptive resource allocation is an important part in cognitive engine design. Transmit-power control and dynamic spectrum management is one of the three fundamental cognitive tasks of cognitive radio [10].

To satisfy the great transmit capacity need, latest communication standard are all OFDM based communication system. In my last research, I already discussed the OFDM based communication standard's resources allocation [36]. But as the most promising 4G candidate LTE-advanced has its own characteristics. It uses not only OFDM technology but also an unique technology called carrier aggregation [37]. Carrier aggregation or channel aggregation enables multiple LTE carriers to be used together as a continuous frequency spectrum to provide the high data rates required for 4G LTE-advanced [38]. This makes the adaptive resources allocation problem more complicated.

With CA, a user equipment (UE) is supposed to be equipped with multiple independent RFCs and can be simultaneously scheduled on multiple CCs. CC allocation determines which CC can be used by each RFC of users. On the base of CC allocation, RB and power allocation can be implemented with less computational complexity. In this article, we design a cognitive engine for LTE-advanced adaptive resources allocation based on modified particle swarm optimization.

3.2 System Model

CA is introduced by Rel-10 as a main feature of LTE-A systems for meeting the peak data rate requirements (1 Gbps and 500 Mbps for downlink and uplink, respectively) for 4G mobile communication systems [39]. CA combines spectrum component in continuous or non-continuous frequency bands to realize broadband transmission. Each individual frequency band used by CA is referred to as a Component Carrier (CC). The bandwidth of each CC could be 1.4, 3, 5, 10, 15 and 20 MHz, following the bandwidth configuration in LTE system. As specified in Rel-10, CA technically allows at most 5 CCs to be simultaneously used for a capable User Terminal (UE). This means that a bandwidth of up to 100 MHz can be achieved by aggregating 5 20MHz-CCs. In this way, peak data rates can be significantly improved.

To deal with different requirements and conditions of venders, the following three categories of CA techniques are defined by 3GPP [40]:

1) Intraband contiguous CA supports aggregation of adjacent CC in the same bandwidth. Intraband contiguous CA is easy to be deployed in the practical system. However, it is difficult to have several contiguous CCs in a signal frequency band due to the limitation of each band.
2) Intraband non-contiguous CA supports the aggregation of non-adjacent CCs in the same bandwidth. Frequency resource of most mobile communication operators has been severely fragmented. To deal with it, 3GPP also proposes non-contiguous CA in LTE-A system to improve spectrum efficiency. CCs in intraband non-contiguous CA are in the same frequency band, but frequency intervals exist between them.

Interband non-contiguous CA supports the aggregation of non-adjacent CCs in the different bandwidth. It is obvious that interband non-contiguous CA takes the best use of frequency fragments in the overall system, and can theoretically achieve a favorable performance. However, the implementation of the physical layer of interband CA is much more complex than intraband CA.

Application of the CA technique brings new challenges, especially in terms of RRM of LTE-A systems. The first concern is the computation complexity of resource allocation. Apart from the RB allocation and power allocation involved in LTE system, scheduling CC resources for multiple UEs is also necessary, which brings serious difficulties for RRM. In LTE-A system, a UE is supposed to be equipped with multiple independent radio frequency chains (RFCs) to support CA. Consider a general LTE-A system consisting of M CCs and K UEs, and each UE is equipped with S RFCs. In this system, there are at most $\prod_{K=1}^{K}\binom{S}{M}$ possible results of CC allocation. The computation cost and allocation delay would exert heavy burden on the eNB, which in turn deteriorates the system performance, if an efficient allocation approach is absent. Second, unlike conventional resource allocation, CC allocation is generally performed before RB allocation and power allocation, which gives rise to great difficulties in evaluation on the quality of solution of CC allocation itself at the system level. Last but not least, with the limitation of available contiguous spectrum resources, interband non-contiguous CA scheme is more realistic to wireless operators. However, using non-contiguous CCs may introduce new constraints for resource allocation. For example, the limitation of UEs' capability of transmitting data on multiple CCs in the same time restricts the achievable performance of CA.

According research [36], because of the computing complexity, we divided the whole resource allocation process into two continuous parts: subcarrier allocation and transmit power allocation. Subcarrier allocation works with the transmit power average pre-allocation, and the transmit power allocation allocates by the results of the subcarrier allocation. By dividing the allocation into parts can successfully reduce the complexity of the calculation. So by the same point and the carrier aggregation technology in LTE-advanced, we could divide the whole allocation process into three parts: component carrier allocation, subcarrier allocation and transmit power allocation as Fig 3-1.

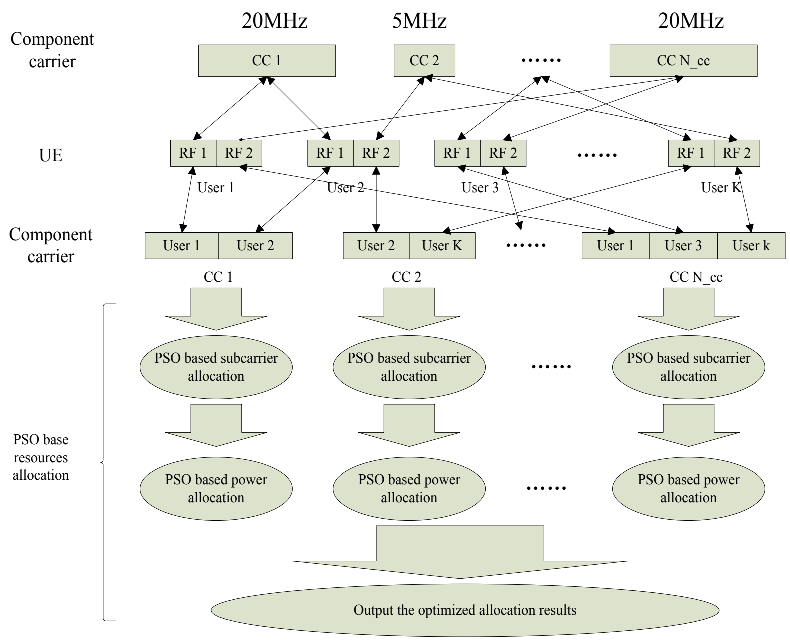

Fig 3-1 resources allocation in LTE-advanced system

Because of considering the computing time of the whole algorithm, we instead the transmit power allocation with the average power allocation. And the in my last article we concluded that: 1.When the fitness function is to maximize the fairness of users' transmit capacities, the algorithm has the best computing time. 2. When the fitness function is to maximize the lowest user's transmit capacity, the algorithm has a better whole transmit capacity with a acceptable user's fairness. So basing on these above, the cognitive engine for LTE-advanced system's resources allocation turn into following three parts:

1. First component carrier allocation with maximize the user's fairness as the fitness function
2. Second component carrier allocation with maximize the lowest user's capacity.
3. Subcarrier allocation.
4. In this article, we use the spatial channel model as follows:

$$PL_i^k = 58.83 + 37.6 \times \log_{10}(d_i) + 21 \times \log_{10}(f_k) \tag{3-1}$$

In this equation, a is the transmit loss when user i transmit by subcarrier k, d_i is the distance between user i and base station, f_k is the subcarrier k's central frequency. And we assume that every user have two RF modules, and each of them can transform their receive/transmit frequency. User's fairness is an important index to judge a communication system good or not, because this make the users who is the farther away from base station has the same QoS as another user has. Fairness function is defined as follows:

$$\Phi = \left(\sum_{k=1}^{K} C_k / \gamma_k \right)^2 \bigg/ K \sum_{k=1}^{K} \left(C_k / \gamma_k \right)^2 \tag{3-2}$$

$C_k = \sum_{n \in \Omega_k} C_k(n)$ is the user k 's transmit capacity. γ_k is the allocation weight which is the service requirement rate, which means this weight is higher the service requires more transmit capacity.

Component carrier allocation can be formulated as follows:

$$\begin{gathered}
[RF_{1,1},...,RF_{1,\alpha},RF_{2,1},...,RF_{2,\alpha},...,RF_{N,1},...RF_{N,\alpha}] = \arg\max(\Phi) \\
[RF_{1,1},...,RF_{1,\alpha},RF_{2,1},...,RF_{2,\alpha},...,RF_{N,1},...RF_{N,\alpha}] = \arg\max(\min(R_i))\ for\ all\ i \\
subject\ \ to: C1: p_{n,l} = P_n / |\Psi_n|, l \in \Psi_n \\
C2: \sum_{n=1}^{N_{cc}} \sum_{i \in \Lambda_n} |\Omega_i^n| = \sum_{n=1}^{N_{cc}} |\Psi_n| \\
C3: BER_i <= BER_i^{\lim}\ \ for\ \ all\ \ i
\end{gathered} \tag{3-3}$$

N_{cc} is the number of the component carrier, $RF_{i,j}$ is the user i's number j RF module, Ψ_n is the subcarriers in component carrier n, $|\Psi_n|$ is the number of the subcarriers in component carrier n. Λ_n is the users using component carrier n, $|\Lambda_n|$ is the number of users using component carrier n, $|\Omega_i^n|$ is the number of the subcarrier which is using by user I, $p_{n,l}$ is the transmit power of subcarrier l in component carrier n.

C1 represents that in component carrier n, each subcarrier has the same transmit power.

C2 represents each subcarrier can only be used by one user at the same time.

C3 represents the BER restriction.

And in component carrier allocation, subcarrier pre-allocation is based on following equations:

$$\Omega_{k_1}^n \log_2\left(1 + PH_{k_1,n}\right) = \Omega_{k_2}^n \log_2\left(1 + PH_{k_2,n}\right) = ... = \Omega_{|\Lambda_n|}^n \log_2\left(1 + PH_{|\Lambda_n|,n}\right)$$

$$
\begin{aligned}
&\left|\Omega_{k_2}^n\right| = \left|\Omega_{k_1}^n\right| \frac{\log_2\left(1+PH_{k_1,n}\right)}{\log_2\left(1+PH_{k_2,n}\right)} \\
&\left|\Omega_{k_3}^n\right| = \left|\Omega_{k_1}^n\right| \frac{\log_2\left(1+PH_{k_1,n}\right)}{\log_2\left(1+PH_{k_3,n}\right)} \\
&\mathrm{M} \\
&\left|\Omega_{|\Lambda_n|}^n\right| = \left|\Omega_{k_1}^n\right| \frac{\log_2\left(1+PH_{k_1,n}\right)}{\log_2\left(1+PH_{|\Lambda_n|,n}\right)}
\end{aligned}
\tag{3-4}
$$

$$
\left|\Psi_n\right| = \left|\Omega_{k_1}^n\right| + \left|\Omega_{k_2}^n\right| + \ldots + \left|\Omega_{|\Lambda_n|}^n\right| = \left|\Omega_{k_1}^n\right| \log_2\left(1+PH_{1,n}\right)\left(\sum_{l=k_1}^{|\Lambda_n|} \frac{1}{\log_2\left(1+PH_{l,n}\right)}\right)
$$

$$
\left|\Omega_{k_1}^n\right| = \left|\Psi_n\right| \Big/ \log_2\left(1+PH_{1,n}\right)\left(\sum_{l=k_1}^{|\Lambda_n|} \frac{1}{\log_2\left(1+PH_{l,n}\right)}\right)
$$

Where $k_1, k_2, ..., k_{|\Lambda_n|}$ is the user index in component carrier n, $\left|\Lambda_n\right|$ is the number of users in component carrier n. $H_{k_1,n} = \dfrac{\sum_{l\in|\Psi_n|} h_{k_1,l}^2 / \Gamma N_0 B/N}{\left|\Psi_n\right|}$ represents the average transmission gain when user i transmit in component carrier n. P_n is the whole transmit power in component carrier n, $h_{m,n}$ is the transmission gain when user m transmit in subcarrier n.

3.3 Modified particle swarm optimization based cognitive engine's design for LTE-advanced

1. Component carrier allocation

1.1 First component carrier allocation with maximizing the user's fairness as the fitness function.

1.1.1 Initialization of LTE-advanced communication system

1.1.2 Construct the particle frame as follows:

1.1.3 Initialization of particles

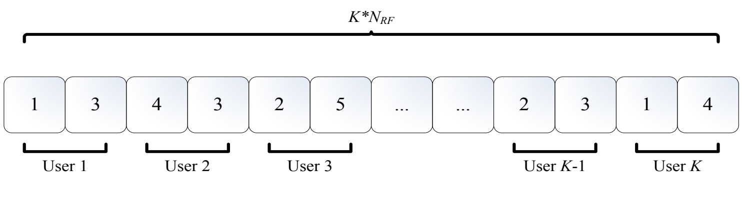

Fig 3-2 particle structure in component carrier allocation

Particle frame in this allocation is viewed as a vector. The vector represents this particle's position, and fitness function is calculated by this position. In communication system, this vector's dimension the number of radiofrequency module of all users. Vector's content is the index of component carrier.

1.1.4 Calculate the fitness value of each particle.

1.1.5 Update particle velocity and position, global best position and fitness value.

1.2 Second component carrier allocation with maximizing the lowest user's capacity.

1.2.1 Calculate the fitness value of each particle.

1.2.2 Update global best position and fitness value.

1.2.3 Update the particles' velocity and position

1.2.4 Calculate the user's fairness.

1.2.5 If the fairness is satisfied the system requirement, then end the algorithm.

1.2.6 If the iteration runs out, then end the algorithm.

1.2.7 Save the component allocation results.

2. Subcarrier allocation.

2.1 Load the component allocation results.

2.2 Transform the particles' structures form component carrier allocation to subcarrier allocation.

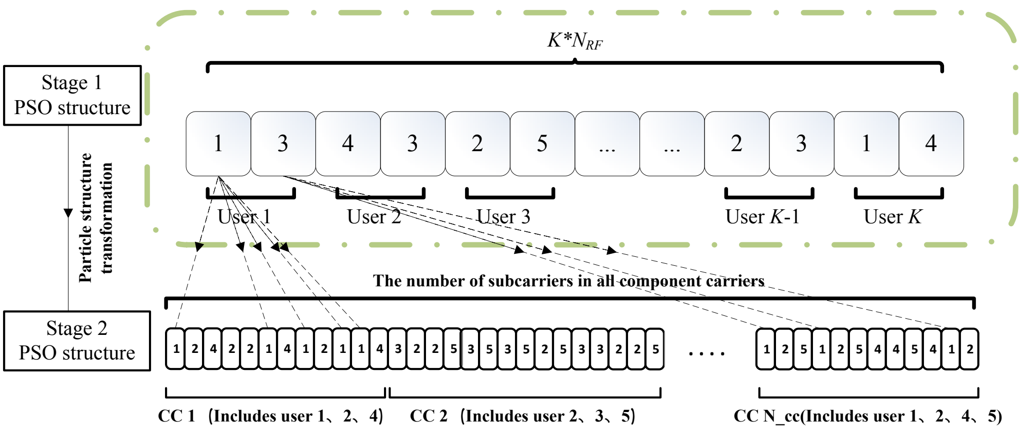

Fig 3-3 particle structure in subcarrier allocation

Fig 3-3 shows the particle structure's transformation process, the circled one is the particle structure in component carrier allocation, the other one is the particle structure in subcarrier allocation. In stage 1, the dimension of the particle structure is the number of radiofrequency module. In stage 2, the dimension of the particle structure is the number of subcarriers in all component carriers. In stage 1, the vector's content is the component carrier index which using by the user's certain RF module. In stage 2, the vector's content is the user's index which is transmitting in component carrier's certain subcarrier.

2.3 Initial particles

2.4 Calculate the fitness function of each particle

2.5 Update global best position and fitness.

2.6 Update particles' velocity and position

The whole allocation's flow chart is as follows:

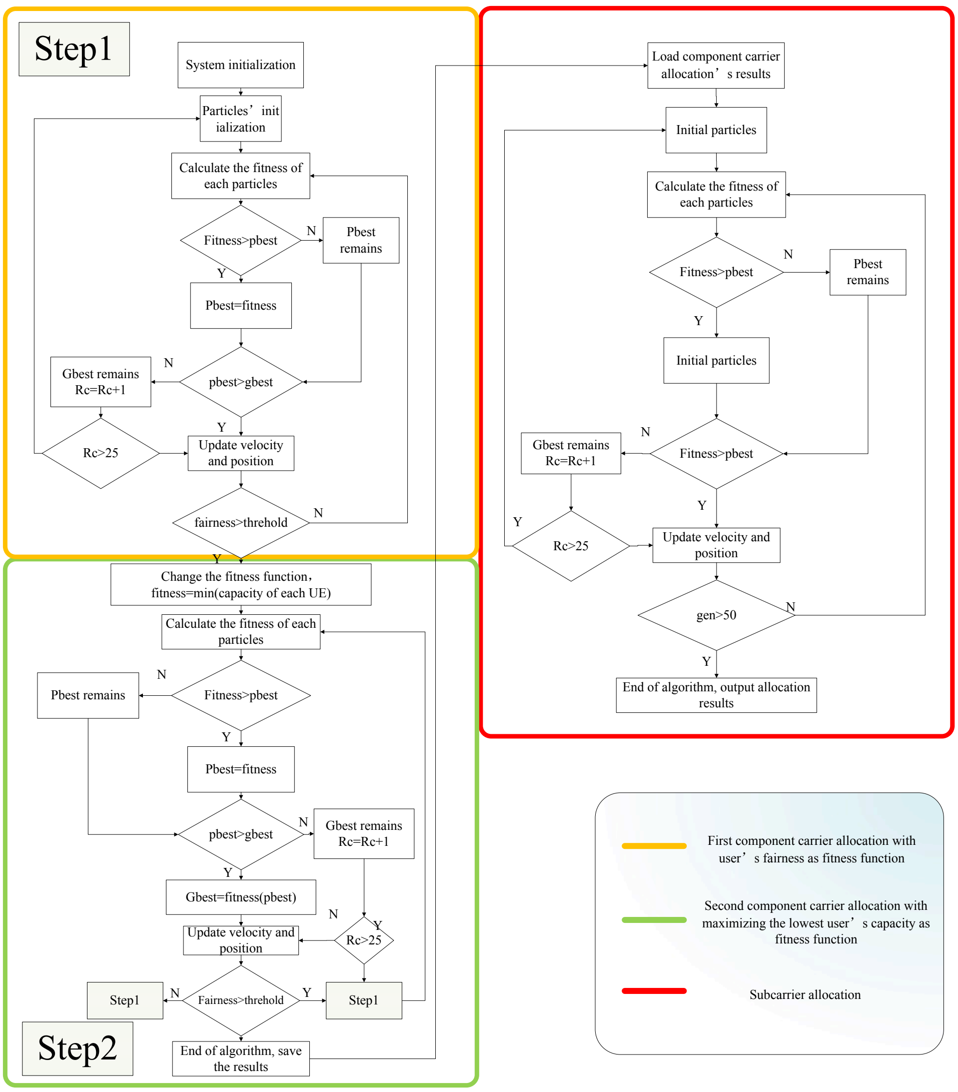

Fig 3-4 allocation algorithm's flow chart

3.4 Simulation results

Simulation is worked by following conditions: there are 8 users in use, every user has two independent RF modules, there are four component carriers with bandwidth as [20MHz, 5MHz, 10MHz, 20MHz], and have the number of subcarrier as [64, 16, 32, 64].

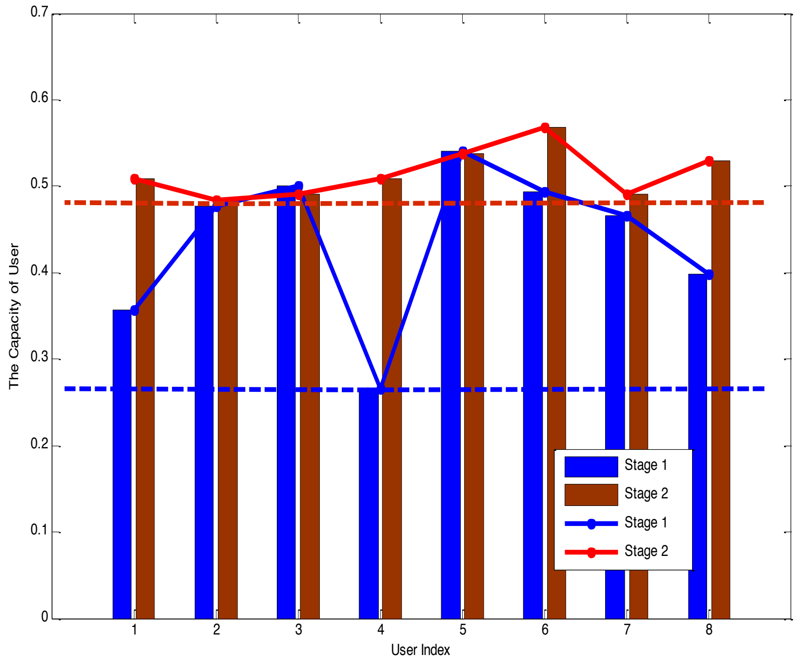

Fig 3-5 transmit capacity of each user's

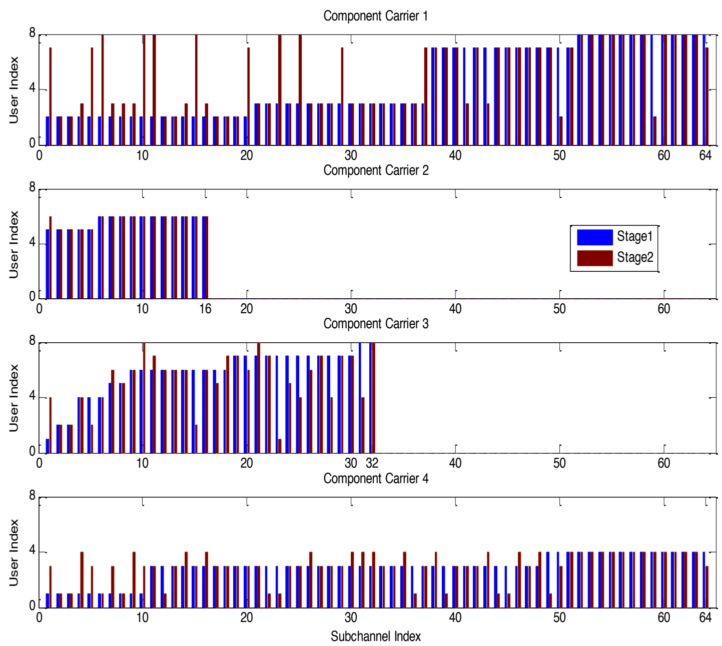

Fig 3-6 Subcarrier allocation results.

In Fig 3-5 and Fig 3-6, stage 1 means the component carrier allocation and stage 2 means the subcarrier allocation. In Fig 5, we can see in stage 2 the whole transmit capacity and user's fairness are all better than the stage 1, that because stage 2 allocates the subcarrier based on the stage 1's allocation results to get a better system performance. And Fig 6 shows the final subcarrier allocation results.

We also do some comparison simulations between PSO based algorithm and a fixed algorithm which can only be used for LTE-advanced system called carrier exchange algorithm. There three comparison simulations down there: (1) comparison of the operating time. (2) comparison of the lowest user’s capacity. (3) comparison of the whole transmit capacity

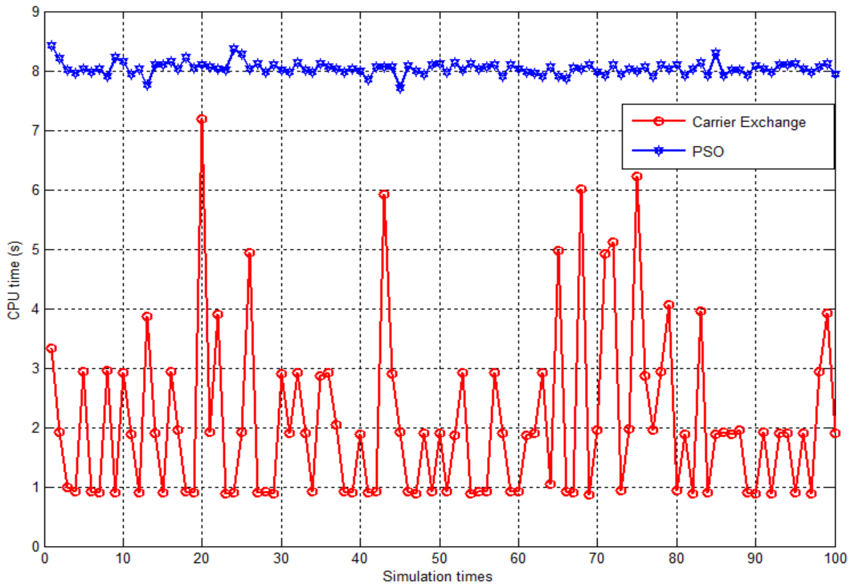

Fig 3-7 comparison of the operating time

Fig 3-7 shows the operating time comparison, which simulated by matlab on the same computer 100 times. And we can carrier exchange based algorithm has a faster operation time, and PSO based algorithm get almost the same time.

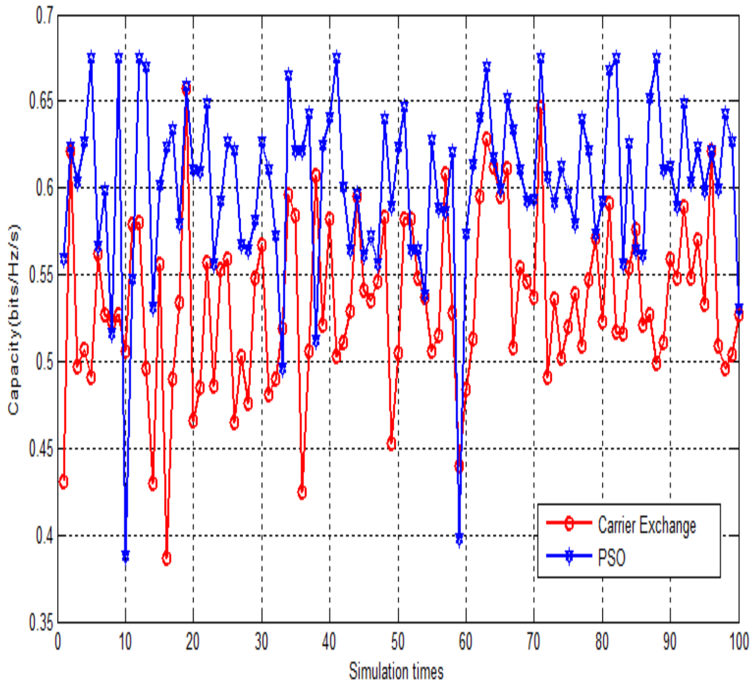

Fig 3-8 comparison of system performance in step 1

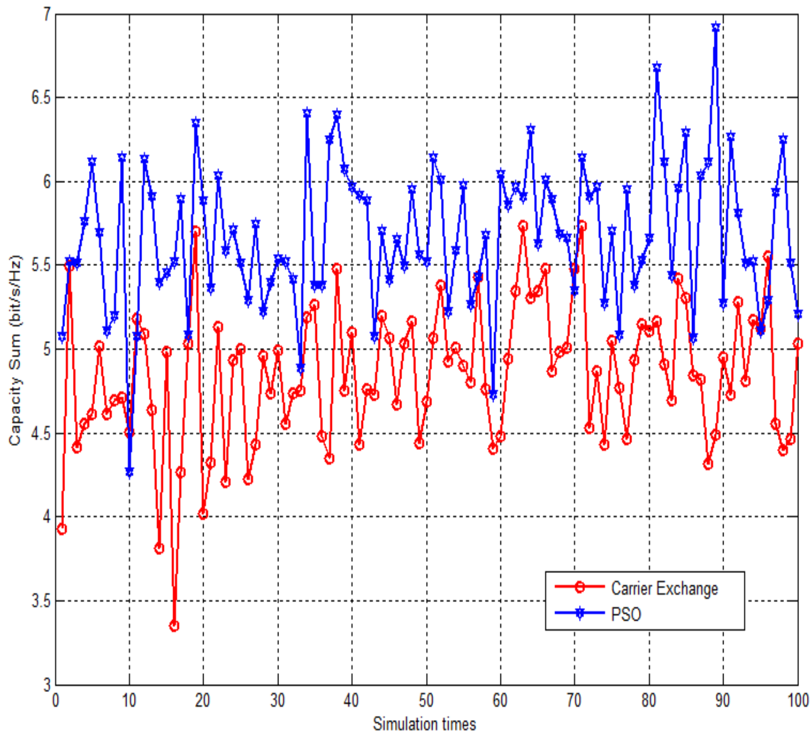

Fig 3-9 comparison in step 2

Fig 3-8 and Fig 3-9 shows us, both in lowest user's transmit capacity and the whole transmit capacity, PSO based algorithm always get a better system performance.

3.5 Conclusion

In this paper, we proposed a modified particle swarm optimization based cognitive engine design for LTE-advanced system. Because there is a unique technology called carrier aggregation which could improve the usage rate of frequency spectrum, we divide the resources allocation calculated by cognitive engine into two main parts: component carrier allocation and subcarrier allocation. And in component carrier allocation there are two steps in it, each step has a different fitness function which make the algorithm as faster and better allocation than only use one fitness function. By comparison with the carrier exchange allocation algorithm for LTE-advanced, modified PSO based algorithm can get a better allocation results with an acceptable computing time. And considering the cognitive engine is not just for LTE-advanced only at the same time, particle swarm optimization as a heuristic algorithm has a flexibility of fitness function which is the key point in cognitive engine design under the heterogeneous networks' background.

Chapter 4 A Spectrum Sensing and Learning Strategy for Distributed Cognitive Radio Networks

Cooperative spectrum sensing is one of the widely used spectrum sensing methods in cognitive radio systems, which can increase the spectrum sensing quality by leveraging the diversity of multiple secondary users. However, in distributed communication system there are no effective central controller and cooperative strategy, most secondary users are likely to overhearing others' sensing results other than contributing to spectrum sensing. This is also called the free-riding attack in distributed cognitive radio system, which will not only make the cooperative spectrum sensing unstable but also causes even more problem in the congestion communication systems. To address the free-riding attack especially in the congested cognitive radio systems, we proposed a cooperative sensing and congestion control strategy with replicator dynamics in evolutionary game theory and a priority system. By using this proposed strategy, rational secondary users have an effective incentive to participate in cooperative sensing, and the associated priority system can elimate the free-riding attack and congestion problems in communication system, making the cognitive radio system effective and fair.Simulation results show that the average throughput achieved in the proposed cooperative sensing game is higher than the case where secondary users sense the primary user individually without cooperation. And the proposed strategy can also achieve a higher system throughput than the fully cooperative scenario.

4.1 Introduction

The frequency spectrum is a kind of natural resources and it is usually licensed by governments and provided for primary users. With the high development of telecommunication industry, multiple communication standards are applied simultaneously, so frequency spectrum has become a kind of precious resource [10]. Cognitive radio is known as the most promising technique to improve the utilization of frequency spectrum resources [9]. The method to increase the spectrum utilization in cognitive radio networks is that it's allowed the secondary users use the licensed spectrum when the primary user is absent [41].

In order to minimize the primary users' transmission interference caused by secondary users, spectrum sensing is one of essential functions of cognitive radio [42]. Cooperative spectrum sensing is known as a promising method which can greatly improve the spectrum sensing performance. In [43], in order to deal with shadow-fading effects a collaborative spectrum sensing is proposed. A secondary user selection strategy for cooperation is proposed in [44]. The work in [45] proposed light-weighted cooperation in spectrum sensing based on hard decisions in order to reduce the sensitivity requirements. In [46], the authors proved cooperative sensing can both reduce the detection time and increase the overall performance simultaneously. The authors in [47] proposed a design of sensing slot duration which can maximize the secondary users' throughput. A cooperative detection methods based on two energy is proposed in [48]. How to increase the spectrum sensing performance of centralized cognitive radio networks is exploited in [49]. The motivation of selfish secondary users' cooperation in spectrum sensing is analyzed in [50].

The works in [43]-[49] are focusing on a fully cooperative scenario in the centralized cognitive radio networks which is assumed: all secondary users are willing to contribute. In every time slot, they voluntarily contribute to sensing and fuse their spectrum detection results to make a final decision in a central controller. In these works, they all focused on the centralized cognitive radios networks system that there is a central controller to make a final decision for all the secondary users, and this decision is made to achieve a common goal. All the secondary users participate in spectrum sensing in these sensing schemes, but all secondary users participate in sensing in every time slot may not be optimal. Secondary users could individually make their own decisions for themselves to their own goals under certain constraints which aren't under consideration in these works. In works [50] focused on distributed cognitive radio networks and proposed a cooperative spectrum sensing scheme with selfish secondary users, an evolutionary game is proposed by the authors to model the cooperative spectrum sensing progress, but there is no consideration of secondary users' fairness, the effect of free-riding and all the secondary users can access the licensed spectrum band without congestion problems.

In this paper, we focus on a multiuser distributed cognitive radio system. Multiple secondary users use different sub-bands of one primary user's licensed spectrum frequency and can overhear the others' sensing results, they are willing to take advantage of the others which means they wait for the others to sense so as to get the access to the spectrum band because of their own selfishness. This kind of free-riding effect will break the fairness balance among secondary users, further more there will be no one willing to sense, the whole cognitive system will shut down because of it. In order to deal with secondary users'strategy selection, free-riding and congestion problems, we add a priority system into evolutionary game spectrum sensing strategy. The replicator dynamics in evolutionary game theory will address the strategic uncertainty by exploring different actions, adaptively learning during the strategic interactions, and approaching the best response strategy under changing conditions and environments. The priority system will deal with the congestion and free-riding problems in order to keep a considerable high fairness among secondary users. The proposed spectrum sensing and congestion control strategy could achieve a more steady system than the cognitive radio with only greedy selfish secondary users and a higher average throughput in spectrum sensing than full cooperative spectrum sensing scheme and a better congestion control.

4.2 System Model

In this paper, we focus on the distributed cognitive radio system. Comparing with centralized communication system, distributed system is more suitable for the conception of cognitive radio. Distributed communication system is more and more important in our lives, because of applications of mobile and ad-hoc networks. It's different with centralized cognitive radio systems. There are no center controllers for all the secondary users' strategy selection in distributed systems. All the secondary users make their own decision without any global consideration. These decisions are made for their own purpose and may not benefit the whole cognitive radio system in the whole picture. Congestion control is also a common problem when the number of secondary users is bigger than the number of available sub-carriers. In this distributed cognitive radio systems, we assume all the secondary users are rational and selfish, secondary users don't serve a common goal of the whole system such as the best detection accuracy and transmission protection for primary user or the biggest throughput of all secondary users. Rational and selfish secondary users in this system only focus on maximizing their own payoff function under certain constraints. These selfish secondary users always take advantage of others by overhearing others spectrum sensing results if there is any chance. In this paper's cognitive radio communication system, we assume that multiple secondary users will occupy different sub-bands of one primary user when it is absent, and the number of secondary users is more than the number of the sub-carriers of this licensed spectrum as Fig.1. So there are two groups of these secondary users, the first one the accessible ones and the other one the congested ones.

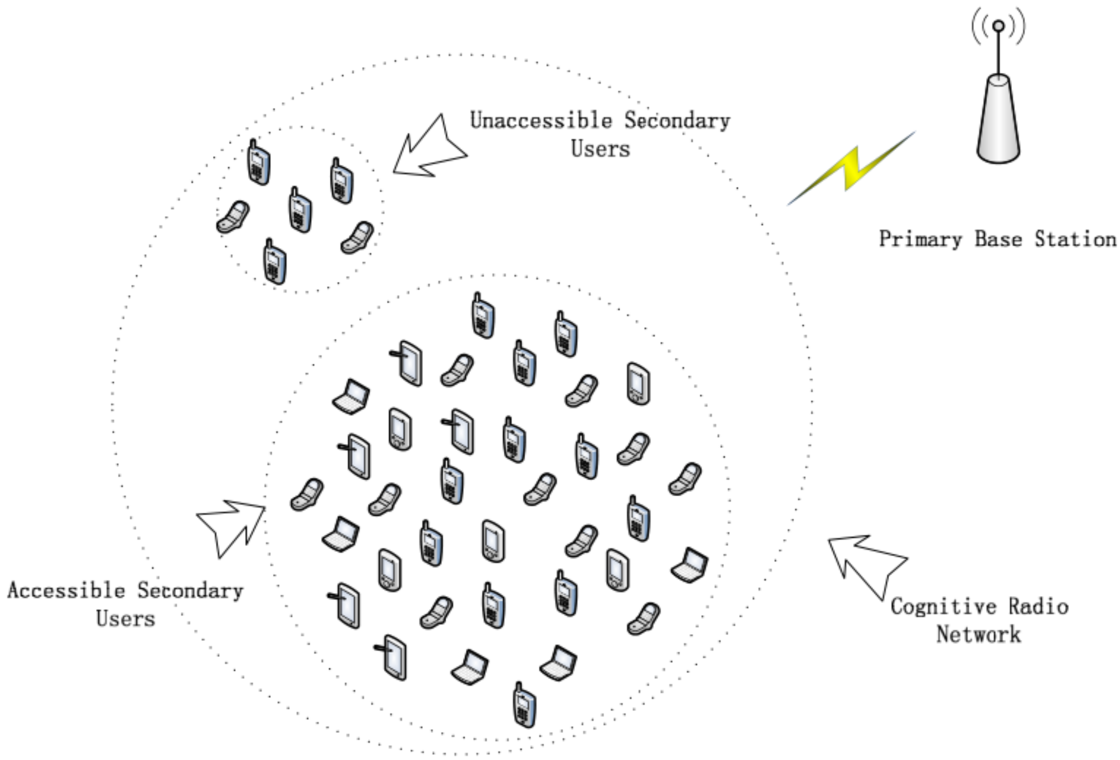

Fig. 4-1 System Model

In this system, multiple secondary users are intending to use the same licensed spectrum of one primary user and all of them have the spectrum sensing ability which could sense the primary user's presence status. Secondary users can share its own spectrum sensing outcome and overhear others spectrum sensing results among secondary users in signal exchange channel in order to improve the accuracy of spectrum sensing. In this study, all the secondary users are assumed as rational and selfish users, they want benefit their throughput other than spectrum sensing performance.This nature of selfish secondary users makes no one willing to spectrum sense which makes the probability of detection is very low and interferences with primary user are not negligible. As the primary user in this communication system, interferences aren't allowed in its transmission time or they aren't out of primary user's receiver's correcting capability. So in order to maintain primary user's quality of service in transmission, a threshold value for secondary users' smallest probability of detection must be set by primary user. As these selfish secondary users, they must consider with two basic things : 1. Because of their selfish nature, they want to maximize their own throughput by spending less time in spectrum sensing and saving more time for transmission. 2. In order to access sub-bands in this licensed spectrum band, secondary users' probability of detection must be higher than the threshold value which is set by primary user. For each secondary users, these two things above become a tradeoff in spectrum sensing strategy, and make each secondary user's fitness function change from purely maximizing its own throughput into maximizing its transmission time with a consideration of probability of whole secondary users. In another words, in order to guarantee the access to licensed spectrum band for secondary users, there must be some of these secondary users participate in spectrum sensing. Free-riding is a situation that secondary users occupy sub-band in sensed licensed spectrum band without spending time on sensing only by overhear others spectrum sensing results. Free-riding will decrease the secondary users' fairness in one communication system. By decreasing the fairness, secondary users are willing to find another licensed spectrum band to restate a system other than keep contributing in former unfairness system and then this unfairness lead the cognitive radio system breakdown. So a proper system strategy is necessary to maintain this de-centralized cognitive radio system working with 2 goals in mind: 1. primary user's interference caused by secondary users' access is under a certain threshold value. 2. Maximize secondary users' throughput under certain constraints. In next part of this paper, we will analyze the rational and selfish secondary users' behavior dynamics and propose a spectrum sensing strategy to achieve the 2 goals mentioned above.

4.3 Spectrum Sensing and Congestion Control Strategy

4.3.1 Hypothesis of Spectrum Sensing

As we known, the conception of cognitive radio is to allow the secondary users occupy the licensed spectrum which allocated for primary user. If a secondary user wants to use this licensed spectrum, he must know if the primary user is presence or not. Spectrum sensing is designed for this purpose. The primary user is presence status is denoted by hypothesis H_1 and H_0. The received signal is denoted as $r(t)$, then $r(t)$ can be written as follow:

$$r(t) = \begin{cases} hs(t) + w(t), & \text{if } H_1 \\ w(t), & \text{if } H_0 \end{cases} \tag{4-1}$$

In this equation, h is the channel gain between primary user and secondary user, $s(t)$ is the primary user's transmission signal which is assumed to be an $i.i.d$ random process with mean 0 and variance σ_s^2. $s(t)$ and $w(t)$ are assumed to be mutually independent.

In this paper, the spectrum sensing method we used is energy detection which is considered as a commonly effective method. Test statistics $T(r)$ is defined as

$$T(r) = \frac{1}{N}\sum_{t=1}^{N}|r(t)|^2 \tag{4-2}$$

where the number of collected samples is denoted as N . To evaluate the performance of the energy detection for licensed spectrum sensing, two probabilities P_D and P_F are shown as follow. P_D is the probability of detection which denotes the probability of detecting the presence status of primary user under hypothesis H_1. P_F is the probability of false alarm which denotes the probability of detecting the presence of primary user under hypothesis H_0. The higher P_D, the better transmission protection of primary user; Also the lower P_F , the more spectrum access of secondary user.

If the noise $w(t)$ is assumed to be CSCG (circularly symmetric complex Gaussian), using central limit theorem the PDF (probability density function) of the test statistics $T(r)$ under H_0 can be approximated by a Gaussian distribution $N(\sigma_w^2, \frac{1}{N}\sigma_w^2)$ [10][47]. Then, the probability of false alarm P_F is given by [51]

$$P_F = \frac{1}{2} erfc\left(\left(\frac{\lambda}{\sigma_w^2} - 1\right)\sqrt{\frac{N}{2}}\right) \tag{4-3}$$

Where λ is the threshold of the energy detector, and $erfc(\cdot)$ denotes the complementary error function, i.e.,

$$erfc(x) = \frac{2}{\sqrt{\pi}}\int_x^\infty e^{-t^2} dt \tag{4-4}$$

We assume the primary signal is a complex PSK signal, then under hypothesis H_1, the PDF (probability density function) of $T(r)$ can be approximated by Gaussian distribution $N\left(\left(\gamma+1\right)\sigma_w^2, \frac{1}{N}\left(2\gamma+1\right)\sigma_w^4\right)$ [10], where $\gamma = \frac{|h|^2 \sigma_s^2}{\sigma_w^2}$ denotes the received SNR (signal-to-noise ratio) of the primary user under H_1. Then, the probability of detection P_D can be approximated by [47][51] :

$$P_D = \frac{1}{2} erfc\left(\left(\frac{\lambda}{\sigma_w^2} - \gamma - 1\right)\sqrt{\frac{N}{2\left(2\gamma+1\right)}}\right) \tag{4-5}$$

If The detection probability threshold is set as $\overline{P_D}$, and the probability of false alarm P_F can be further rewritten as

$$P_F\left(\overline{P_D}, N, \gamma\right) @ \frac{1}{2} erfc\left(\sqrt{2\gamma+1} erf^{-1}\left(1-2\overline{P_D}\right) + \sqrt{\frac{N}{2}}\gamma\right) \tag{4-6}$$

Where $erfc(x) = \frac{2}{\sqrt{\pi}}\int_x^\infty e^{-t^2} dt$ and $erf^{-1}(\cdot)$ is the inverse function of the error function $erf(\cdot)$.

4.3.2 Throughput of Secondary User

Under the hypothesis, the throughput of a secondary user is determined by two factors: 1. Transmission time. 2. Transmission rate. The transmission time for a sensing user is denoted as $T-\delta(N)$, where T is the frame duration, $\delta(N)=\frac{N}{f_s}$ denotes the time spent in sensing and N is the collected samples for energy detection, f_s is the sampling frequency. So there are two situations here:

1. The primary user is absent.

In these time slots where no false alarm is generated, the average throughput of a secondary user is

$$R_{H_0}(N)=\frac{T-\delta(N)}{T}(1-P_F)C_{H_0} \tag{4-7}$$

where C_{H_0} is the data transmission rate of the secondary user under H_0.

2. The primary user is present.

In these time slots, the primary user's presence is not detected by the sensing secondary user, the average throughput of a secondary user is

$$R_{H_1}(N)=\frac{T-\delta(N)}{T}(1-P_D)C_{H_1} \tag{4-8}$$

where C_{H_1} is the data transmission rate of the secondary user under H_1.

If P_{H_0} represents the probability that the primary user is absent, then the total throughput of a secondary user is

$$R(N)=P_{H_0}R_{H_0}(N)+(1-P_{H_0})R_{H_1}(N) \tag{4-9}$$

In cognitive radio system, secondary user shouldn't interfere with the primary user when the primary user is present, so P_D should equal to 1 in this ideal situation. According to the formula (4-6), P_F will also equal to 1 and the throughput of secondary user turn to 0 as well, which is impractical. So a primary user who allows secondary users to access usually set a target detection probability threshold $\overline{P_D}$ very close to one [47], under which the secondary user's spectrum access will be prohibited as a punishment. Rational and selfish secondary user always tries to maximize his own total throughput, subjects to $P_D > \overline{P_D}$. $\overline{P_D}$ is predetermined very close to 1, and we usually have $C_{H_1} < C_{H_0}$ due to the interference by the primary user, so the second term in equation (9) is much smaller than the first term and can be omitted. Therefore, (4-9) can be approximated by

$$\overline{R}(N) \approx P_{H_0} R_{H_0}(N) = P_{H_0} \frac{T - \delta(N)}{T}(1 - P_F)C_{H_0} \tag{4-10}$$

P_F is a decreasing function of N, and as a secondary user tries to reduce $\delta(N)$ in order to have more time to transmit, but P_F also will increase as the same time. So there is a trade-off here, secondary users want to reduce both P_F and N, i.e., keep low false alarm P_F with a smaller N, for this reason a secondary user intend to cooperate with other secondary users for spectrum sensing in the same licensed spectrum band.

4.3.3 Spectrum Sensing and Congestion Control Strategy

In this paper, secondary users' spectrum sensing is modeled as a non-cooperative game. There are two kinds of strategies $\{C, D\}$ for each secondary user to choose, where strategy C represents contributing to spectrum sensing, strategy D represents free-riding other secondary users' sensing results. According to equation (4-10), the throughput of a contributed secondary user can be approximated by

$$\overline{U}_{C,s_j} = P_{H_0}\left(1 - \frac{\delta(N)}{|S_C|T}\right)\left(1 - P_F^{S_C}\right)C_{s_j}, \qquad \text{if } |S_C| \in [1, K] \tag{4-11}$$

where j is the number $j\text{th}$ secondary user chose strategy C, $|S_C|$ is the number of secondary user chose strategy C, $P_F^{S_C}$ is the false alarm probability calculated by the set of spectrum sensing secondary users S_C.

Then the throughput of a denied secondary user can be approximated by

$$\overline{U}_{D,s_i} = P_{H_0}\left(1-P_F^{S_c}\right)C_{s_i}, \qquad \text{if } |S_C| \in [1, K-1] \tag{4-12}$$

where i is the number i th secondary user chose strategy D.

The secondary user s_i is a denier when it selected the strategy D which means this user will not spend time for sensing. If no secondary user contributes to sensing and waits for the others to sense, i.e., $|S_C| = 0$, from equation (6), $\lim_{N\to 0} P_F = 1$, in this case, the payoff for a denier becomes

$$\overline{U}_{D,s_i} = 0, \qquad \text{if } |S_C| = 0 \tag{4-13}$$

In this paper, we chose the majority rule as the decision fusion rules. Then, under the majority rule we have:

$$P_D = \Pr[\text{at least half users in } S_C \text{ report } H_1|H_1] \tag{4-14}$$

$$P_F = \Pr[\text{at least half users in } S_C \text{ report } H_1|H_0] \tag{4-15}$$

If the detection probability's threshold given by the primary user is $\overline{P_D}$ for the whole users in the contribution set S_C, then each individual user's target detection probability $\overline{P}_{D,s_j}$ can be calculated by following equation:

$$\overline{P}_D = \sum_{k=\left\lceil \frac{1+|S_C|}{2} \right\rceil}^{S_C} \binom{|S_C|}{k} \overline{P}_{D,s_j}^{k} \left(1-\overline{P}_{D,s_j}\right)^{|S_C|-k} \tag{4-16}$$

and in this contribution set we assumed that each user takes equal responsibility and has the same ability in making the final decision because of fairness concern. Then,

$$P_{F,s_j} = \frac{1}{2}\operatorname{erfc}\left(\sqrt{2\gamma_{s_j}+1}\operatorname{erf}^{-1}\left(1-2\overline{P}_{D,s_j}\right) + \sqrt{\frac{N}{2|S_C|}}\gamma_{s_j}\right) \tag{4-17}$$

These throughput we discussed above is in the scenario when all the secondary users can access the sub-band at the same time. But if there are congestion problems, the accessibility is the number one thing to be considered with for a secondary user, in another word no accessibility no throughput for the secondary user. And there are two congestion scenarios here: 1. The number of secondary users are bigger than the sub-bands' number and the number of cooperative sensing secondary users is smaller than the sub-bands' number; 2. The number of secondary users are bigger than the sub-bands' number and the number of cooperative sensing secondary users is also bigger than the sub-bands' number. The proposed priority system for congestion control works in both scenarios. In scenario number 1, cooperative sensing secondary users have the priority of access and because this kind of users are less than the sub-bands, so all the cooperative secondary users can access the sub-bands. The rest of sub-bands will distribute to the uncooperative sensing secondary users depending on their credits order. In scenario number 2, only the cooperative secondary user are out number the sub-bands, so all the non-cooperative secondary users are congested for transmission and cooperative secondary user will access the sub-band depending on the credits order. So the flowchart of this proposed spectrum sensing strategy is shown in Fig.4-2, and specific flowcharts of scenario 1 and scenario 2 are shown in Fig.4-3 and Fig.4-4.

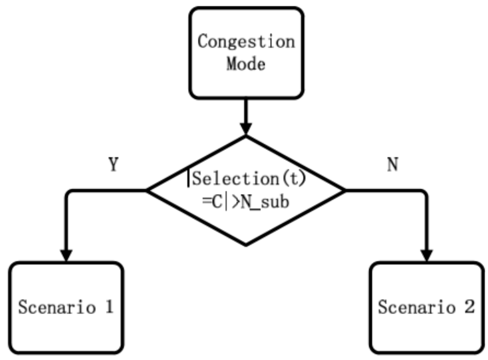

Fig 4-2 Flow Chart of Proposed Strategy

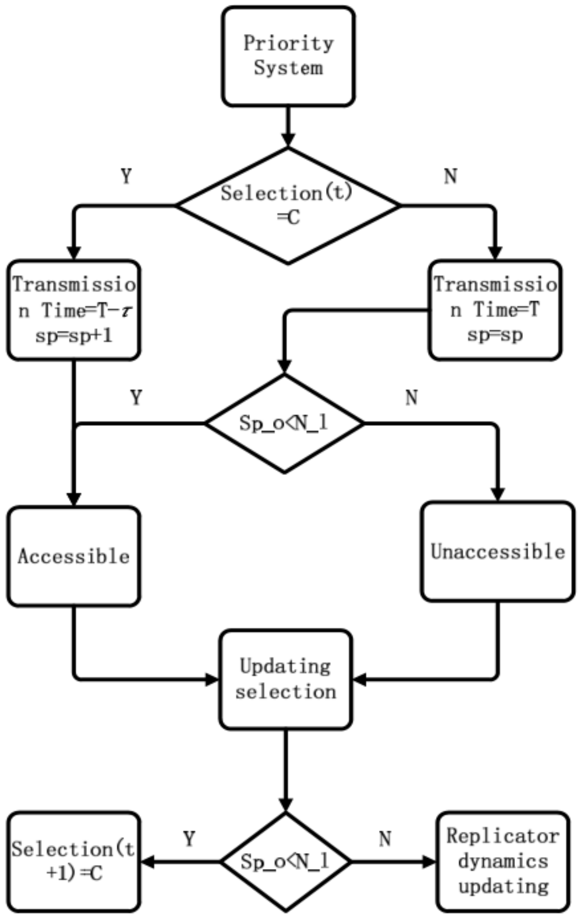

Fig 4-3 Flow Chart of Scenario 1

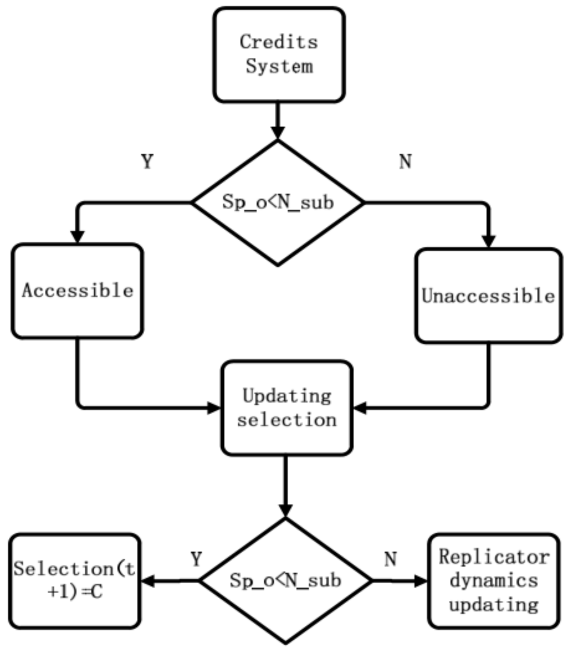

Fig 4-4 Flow Chart of Scenario 2

Fig. 4-5 shows an example of the initial time slot of secondary users' transmission. The blue bar represents the time spent on spectrum sensing, the green bar represents the time spent on low rate transmission, the red bar represents the time spent on high rate transmission. In our proposed spectrum sensing strategy, we combined a priority system into replicator dynamics, so in the initial time slot of secondary users' transmission there are no credits without contribute to sensing. In other words, if you want to transmit by high transmission rate you must contribute on sensing in order to consume the permission with the credits earned by sensing.

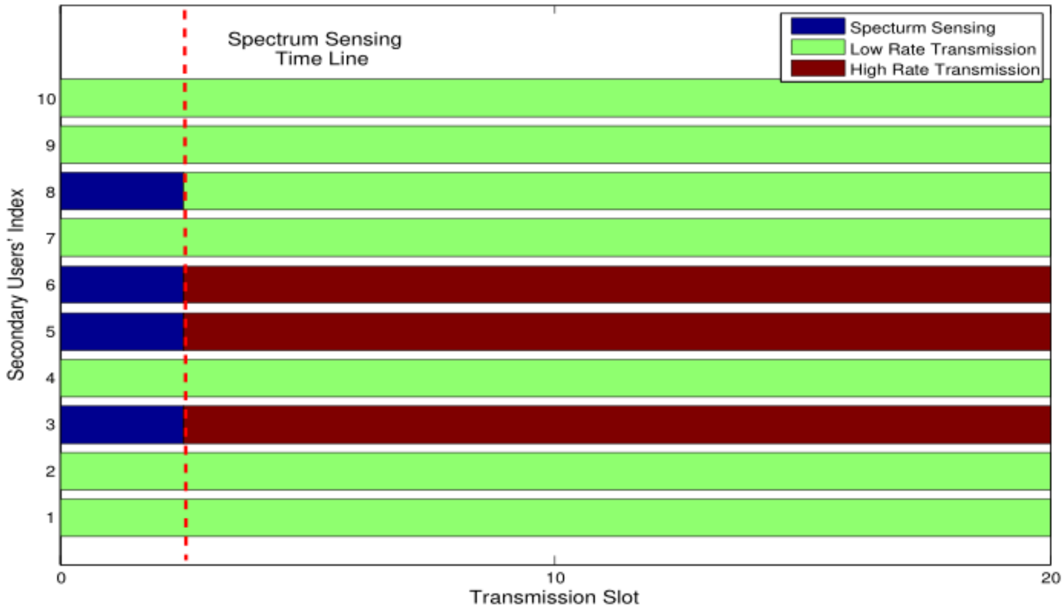

Fig 4-5 Secondary Users’ Transmission Initial Status

Fig.4-6 shows an example of the middle stage time slot of secondary users' transmission status, and these three bars present the same content as Fig.5. In this figure, there are several situations are shown: 1. Secondary users transmit at high transmission rate after contributing on spectrum sensing. 2. Secondary users transmit at high transmission rate without contributing on spectrum sensing. 3. Secondary users transmit at low transmission rate without contributing on spectrum sensing. 4. Secondary users transmit at low transmission rate after contributing on spectrum sensing. Situation NO.1 and Situation NO.3 are easy to understand which can be explained as no pay no gain in single time slot of credits system. Situation NO.2 means these secondary users have enough credits before this time slot and they choose to purchase the high transmission rate permission this time slot according to their service category at this time. Situation NO.4 means these secondary want to get some credits without purchasing which will make sure they have enough credits for the coming service no matter they contribute or not at that time slot. Comparing Fig.3 and Fig.4, we can see the spectrum sensing time are different depending how many secondary users are contributing on spectrum sensing. The more users contribute, the less spectrum sensing spend for each user.

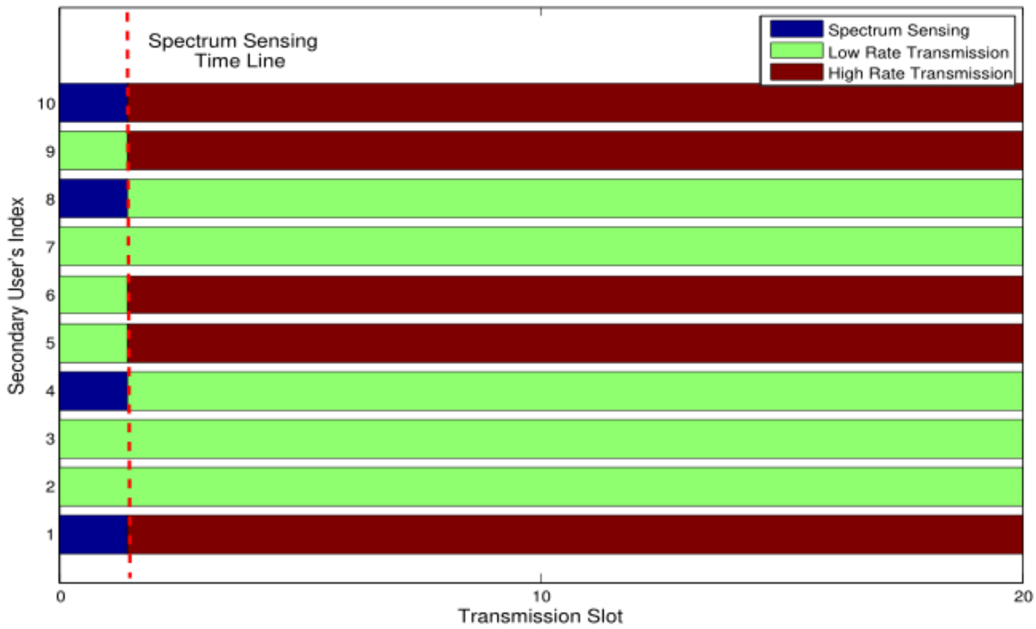

Fig 4-6 Secondary Users' Transmission Status

4.4 Distributed Learning Algorithm

We can deduce the decision making method of secondary users as follows: Let $A_{s_j}(t)$ denotes the pure strategy user s_j selected at time t. Then the indicator function $1_{s_j}^h(t)$ is defined as followed:

$$1_{s_j}^h(t) = \begin{cases} 1, & \text{if} \quad A_{s_j}(t) = h; \\ 0, & \text{if} \quad A_{s_j}(t) \neq h \end{cases} \tag{4-18}$$

In the time interval mT, $\overline{U}_{s_j}(h, x_{-s_j})$ can be approximately represented as followed:

$$\overline{U}_{s_j}(h, x_{-s_j}) \approx \frac{\sum_{0 \le t \le mT} \tilde{U}_{s_j}(A_{s_j}(t), A_{-s_j}(t)) 1_{s_j}^h(t)}{\sum_{0 \le t \le mT} 1_{s_j}^h(t)} \tag{4-19}$$

Where $\tilde{U}_{s_j}(A_{s_j}(t), A_{-s_j}(t))$ represents the payoffs of user s_j. Then $\overline{U}_{s_j}(x)$ represents the average payoffs of user s_j from 0 to mT as followed:

$$\overline{U}_{s_j}(x) \triangleq \frac{1}{m}\sum_{0 \le t \le mT} \tilde{U}_{s_j}(A_{s_j}(t), A_{-s_j}(t)) \tag{4-20}$$

Then the probability of this strategy that user s_j will select for next time interval can be calculated as followed:

$$x_{h,s_j}((m+1)T) = x_{h,s_j}(mT) + \eta_{s_j}[\overline{U}_{s_j}(h, x_{-s_j}) - \overline{U}_{s_j}(x)]x_{h,s_j}(mT) \tag{4-21}$$

Where η_{s_j} is the step length adjustment coefficient for the user s_j selection strategy.

The formula (4-21) can be regarded as a discrete replicator dynamics. It has been proved in literature [52] that if a stable state is asymptotically stable under the dynamic imitators of continuous time, it is also asymptotically stable for a sufficient time interval in the corresponding discrete time imitator dynamics. Since the evolutionary stability strategy is a stable stable point [53] that is asymptotically stable in a continuous time imitator dynamic. If a user knows the historical information of $\dot{x}_{h,s_j}$, then this user can converge to an evolutionary stable strategy according to the formula (4-20). Through this learning algorithm, users will try different strategies in each time slot, accumulate relevant information about average income through formula (4-18) and formula (4-19), and calculate the probability changes of the use of strategy according to the formula (4-19), and adjust their behavior to a state of balance. This learning algorithm can be expressed as follows:

1. Initialization

(1) For every s_j select a proper step length adjustment coefficient η_{s_j}.

(2) For every s_j, $h \in A$, let $x(h, s_j) \leftarrow \frac{1}{|A|}$

2. In every time interval of m time intervals, for every s_j:

(1) Select a strategy h with the probability $x(h, s_j)$.

(2) According formula (4-18), (4-19) and (4-20), users' payoff can be calculated.

(3) Save the value of indicator function.

3. Every s_j's $\overline{U}_{s_j}(h, x_{-s_j})$ and $\overline{U}_{s_j}(x)$ can be calculated.

4. Update every strategy's probability.

5. Return to step 2 until convergence to a stable equilibrium state.

4.5 Simulation Results

In the simulation the parameters we used are as follows: We assume that the primary signal is a baseband QPSK modulated signal with the sampling frequency is $f_s = 1$ MHz, and the frame duration is $T = 20$ ms. The probability that the primary user is absent is set as $P_{H_0} = 0.9$, and the required target detection probability $\overline{P_D}$ is 0.95. The noise is assumed to be a zero-mean CSCG process.

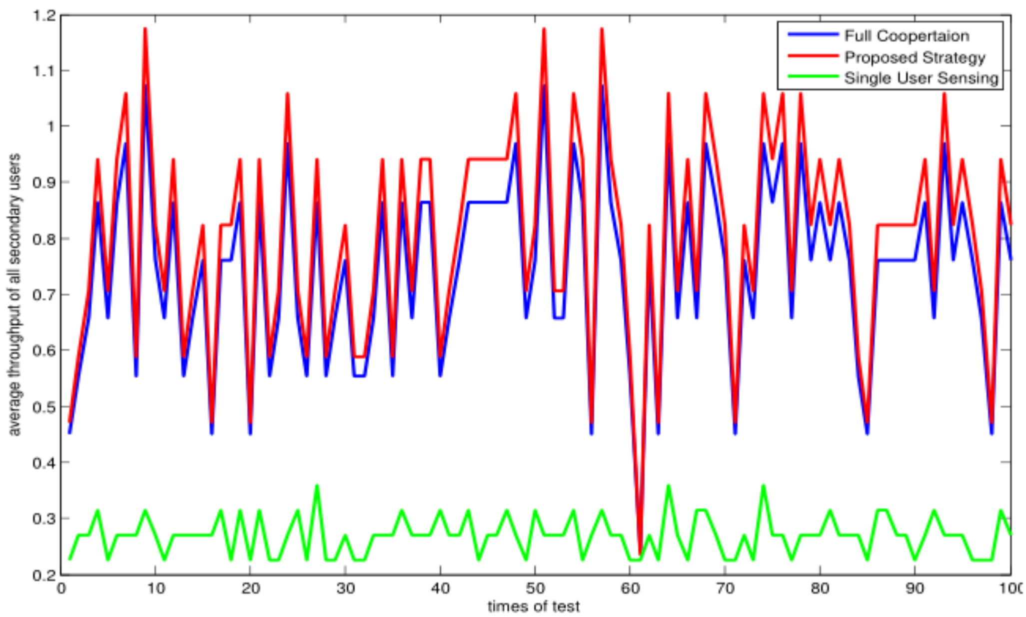

Fig 4-7 Average Throughput of 100 Times Trials

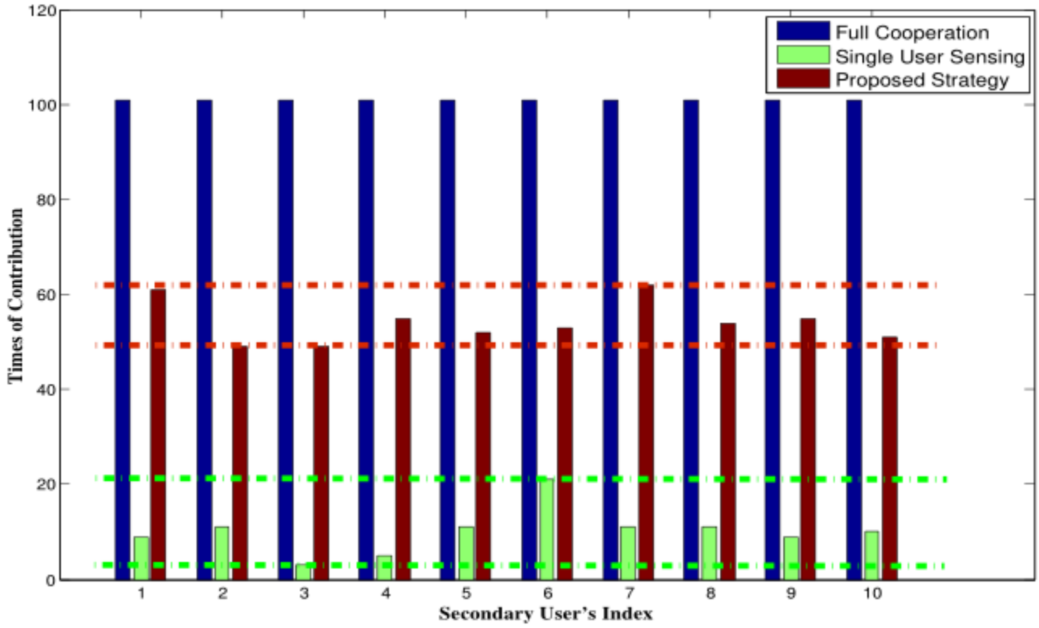

Fig 4-8 Contribution Times of Each Secondary Users

In Fig.4-7, it's the simulation results after 100 times test in different service categories. The blue line represents the average throughput of secondary users using the full cooperation spectrum sensing strategy, the green line represents the average throughput of secondary users using single user sensing strategy, and the red line represents the average throughput of secondary users using the proposed spectrum sensing and congestion control strategy. In these simulation results of each time of trial are under the same service category assumption and service category is randomly different from each time of trials without loss of generality. From Fig.4-7 we can see the average secondary users' throughput of the proposed spectrum sensing strategy is mostly bigger than the full cooperation strategy's and they are equal at a certain trial which the proposed the spectrum sensing strategy makes the same decision as the full cooperation sensing strategy. And both proposed spectrum sensing strategy and full cooperation strategy's performance is better than the single user sensing strategy .

Fig.4-8 shows secondary users' contribution times of in 100 times trial by using these three different spectrum sensing strategies. The blue one is simulation results using the full cooperation strategy, all of secondary users have the equal contribution times, which means it's a complete fair with all secondary users. The green one represents the single user sensing strategy and the red one represents the proposed spectrum sensing strategy. Contribution times are different between each secondary users in these two strategies, they aren't complete fair here. The bigger the difference between the most contribution times to the lowest contribution times the more unfair with each secondary users. In simulations, the proposed spectrum sensing strategy have a better fairness performance than the one using the single user sensing strategy which means cognitive radio network is harder to break down by using the proposed spectrum sensing strategy.

4.6 Conclusion

Cooperative spectrum sensing with secondary users can achieve a better performance than individually sensing without cooperation in centralized cognitive radio networks both in speed and accuracy are proved by lots of work. However, in distributed cognitive radio system how to collaborate in cooperative spectrum sensing is still an open problem, because selfish secondary users don't want to contribute their energy and time on sensing instead of transmitting. In this paper, we proposed a spectrum sensing and congestion control strategy of distributed cognitive radio networks. As the secondary users are selfish and they overhear other's spectrum sensing results, we add a priority system into replicator dynamics which makes secondary users can try different strategies and learn a better strategy through strategy interactions and ensure secondary users' relative fairness to make the whole system work properly and deal with congestion problem effectively. From the simulation results, the proposed spectrum sensing and congestion control strategy has a better performance of total throughput than fully cooperative strategy which have all secondary users sense at every time slot. Moreover, the proposed spectrum sensing strategy also has a better fairness performance than single user sensing strategy in order to reduce the effect of free-riding and congestion problems.

Chapter 5 Conclusions

Cognitive radio technology is the key technology to solve the current shortage of spectrum resources and low spectrum utilization. Cognitive engine is regarded as the

brain of a cognitive radio system. Cognitive engine always include decision making mechanism and learning algorithm. In this dissertation we studied centralized cognitive communication system and distributed cognitive radio system respectively. For centralized system, we proposed a modified PSO based adaptive resource allocation algorithm for cognitive radio in LTE-A frame. And this proposed algorithm designed by combining PSO and GA's advantages. Simulation results proved our proposed algorithm can get a better performance than original PSO and perfectly fit for a centralized cognitive radio system. For distributed cognitive radio system, because there is no central controller, it's hard to globally control these secondary users' strategy. So we proposed an evolutionary game based cooperative sensing strategy for distributed cognitive radio. In this strategy, we can clearly study secondary users' strategy interaction process and through this process we can get an evolutionary stable strategy (ESS). All the secondary users in this game intend to choose ESS and get their best interest out of the game. And based on this evolutionary stable strategy, we proposed a distributed learning scheme. This leaning scheme can make sure a secondary user achieve ESS without knowing other user's strategy.

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