Spectrum allocation strategy for heterogeneous wireless service based on bidding game

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Abstract

The spectrum scarcity crisis has resulted in a shortage of resources for many emerging wireless services, and research on dynamic spectrum management has been used to solve this problem. Game theory can allocate resources to users in an economic way through market competition. In this paper, we propose a bidding game-based spectrum allocation mechanism in cognitive radio network. In our framework, primary networks provide heterogeneous wireless service and different numbers of channels, while secondary users have diverse bandwidth demands for transmission. Considering the features of traffic and QoS demands, we design a weighted interference graph-based grouping algorithm to divide users into several groups and construct the non-interference user-set in the first step. In the second step, we propose the dynamic bidding game-based spectrum allocation strategy; we analyze both buyer's and seller's revenue and determine the best allocation strategy. We also prove that our mechanism can achieve balanced pricing schema in competition. Theoretical and simulation results show that our strategy provides a feasible solution to improve spectrum utilization, can maximize overall utility and guarantee users' individual rationality.

Keywords: cognitive radio network, dynamic game, heterogeneous service, Nash Equilibrium, weighted interference graph

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1. introduction

With the appearance of emerging wireless technology (such as wireless sensor networks, software-defined networks and ubiquitous networks) and the popularization of mobile multimedia devices, wireless communication traffic has increased dramatically. In the last few decades, spectrums on the authorized frequency band have already been totally distributed by radio management agencies and are nearly exhausted. As a consequence, emerging services do not have enough spectrum for transmission, and their application has been restricted severely. According to a survey by the CISCO corporation, by 2017, spectrum demand for mobile communication will exceed available capacity; by 2025, the global spectrum shortage will reach 900MHZ[1]-[3]. To overcome these challenges and improve transmission quality, many researchers have begun exploring fifth generation (5G) networks. 5G networks provide extraordinarily high data rates and guaranteed Quality-of-Service (QoS) for mobile multimedia content. Key technologies for 5G networks include massive MIMO, energy efficient communications, OFDM, cognitive radio networks (CRN), and visible light communication [4].

As spectrum demand will increase significantly with 5G networks, cognitive radio technology and white space utilization have become effective tools in wireless systems. Many scholars have investigated the convergence of heterogeneous networks into a single wireless network in order to increase the utilization of available spectrum resources. MinHo Jo etc. provided an overview of heterogeneous mobile networks' convergence; they investigated different types of network convergence, categorized network heterogeneity into four types, noted current problems and provided solutions[5]. Given that heterogeneous networks usually consist of network densification, N. UL Hasan etc. proposed a network selection and spectrum selection mechanism to increase system revenue; they formulated a particle swarm-based optimization problem and found a near-optimal solution[6].

In CRN, spectrum management strategy is one of the most popular research topics; questions that have been addressed include how to select proper service providers among different spectrums and how to achieve guaranteed QoS on the basis of rational price and cost. To solve these problems, we should design efficient mechanisms to encourage authorized users to provide idle or less utilized spectrums to secondary users (SUs) and charge some payment thus maximizing social welfare. Market competition mechanisms can achieve optimal resource allocation; many scholars have applied economic models to spectrum allocation and modified unit-price and supply-demand situations to improve heterogeneous wireless service QoS[7]-[11].

Game theory is one of the most effective methods for spectrum allocation in CRN, and multi-user game models for wireless markets have been widely studied. Game theory has been used for resource management, routing protocol modeling, dynamic spectrum sharing in CRN. In addition, there are studies that apply non-cooperative game theory to cognitive ad

hoc networks, and game theory has been shown to be a very powerful basis for distributed power allocation schemes. Earlier studies are mainly concerned with government dominated auctions and focus on exploiting unallocated idle spectrums[12]. With resources becoming increasingly scarce, the secondary market auction has become a hot issue. Baochun Li etc. proposed a Bi-Direction auction mechanism based on a spectrum-market local feature and designed the local-market auction strategy separately based on uniform pricing and discriminatory pricing [13]. He Huang proposed a completely competitive equilibrium based double auction mechanism; they converted a multi-participant game into a two-players game and transformed the problem into a complete information game through the Harsanyi Transformation[14]. Although this mechanism can effectively solve problems such as small market scale, it lacks the evaluation of players' overall revenue. Fangwei Li proposed a spectrum leasing trade algorithm based on the dynamic Cournot game; they modeled the spectrum trading between users and modified user's payment dynamically. Their method ensures user revenue maximization and higher spectrum utilization but fails to consider user special service demands and individual rationality[15]. Yanjiao Chen proposed a spectrum allocation scheme that takes into account both income and user utility. They modeled wireless market interactions as a 3-stage game and derived the unique sub-game perfect equilibrium; their scheme can improve users' aggregate utility with limited spectrum income loss [16]. However, the above methods are limited when the service type in wireless networks is heterogeneous and the competitive SUs dynamically lease spectrums to obtain maximum profits.

In this paper, we propose a dynamic bidding game-based spectrum allocation model for heterogeneous wireless service in CRNs. We analyze a network model with multiple diversified spectrum owners and SUs, primary users (PU) that have spectrums to lease in certain areas, and SUs that have heterogeneous QoS requirements. We divide the resource allocation optimization problem into two steps: First, we divide the SU nodes into several groups and construct the non-interference user-set. In the second step, we formulate the allocation decision-making process as a dynamic bidding game, analyze both buyers' and sellers' revenue and determine the best strategy.

The main contributions of this paper are summarized as follows:

- A CRN with multiple heterogeneous wireless services is studied, and the unified resource allocation model for diversified QoS demands is proposed;
- A weighted interference graph-based grouping algorithm is proposed to solve the problem of traffic-type distinction.
- The resource allocation process is formulated as a dynamic bidding game, the existence of Nash Equilibrium is proved, and the equilibrium pricing strategy is deduced.
- Theoretical analysis is provided to prove the economic properties of our strategy: individual rationality and trustfulness.

The rest of the paper is organized as follows: Section 2 describes the details of the

system model; section 3 presents the two processes of the system design: non-interference user-set construction, constrained optimization problem formulation and the solution; section 4 presents the analysis of our strategy's important economic properties; simulation results are illustrated in section 5; finally, we provide a brief conclusion in section 6.

2. System Model

Cognitive radio technology allocates and manages spectrums in a dynamic way; it not only uses authorized frequency bands (5G Cellular Network) but also unauthorized spectrums (such as super wi-fi) for data transmission, this provides ample development space for different types of multimedia traffic, such as real-time audio, online video and interactive games. We analyze a heterogeneous network that incorporates multiple primary networks at any given time slot; each primary network has a different number of channels available for the SUs, and each channel has different capacity. Although multiple protocols (LTE, wifi, Bluetooth, Zigbee, etc.) are available, we use equivalent bandwidth to express the resource demands of all users. The whole system is composed of two covered networks: the PU network and SU network (in **Fig. 1**). The primary network is a centralized network; it contains several primary users that communicate with each other through PBS. The SU network is a distributed network; it has several SUs randomly scattered in the region.

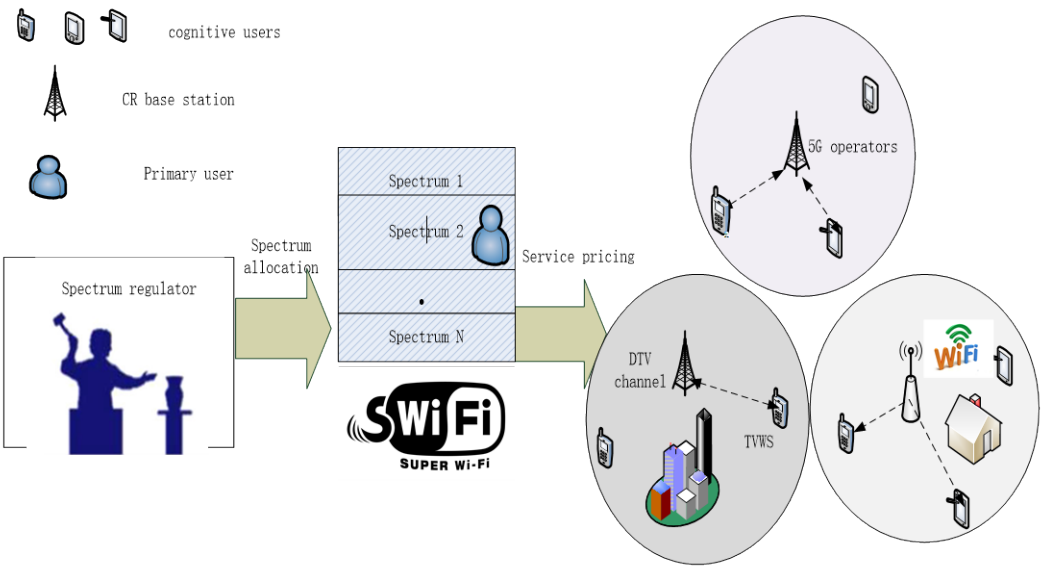

Fig. 1. Spectrum allocation model

In **Fig. 1,** several heterogeneous service providers coexist: 5G Cellular Network can realize large-scale and ubiquitous network coverage, and users can use the channel resource

whenever and wherever possible. High spectrum utilization and communication quality are possible through detailed design and deployment, but the service price is rather expensive for multimedia service with high bandwidth and throughput demand. Super wi-fi can be deployed both indoors and outdoors, has fewer access points and a lower price, and is suitable for multimedia traffic. However, super wi-fi has lower coverage and transmission power, and it works in unauthorized frequency bands and therefore must face problems of interference constraints, heterogeneous network convergence, and so on. In addition, TVWS (TV white space) also provides widespread coverage and low-cost high-efficiency solutions. Using TVWS in CRNs can provide satisfying real-time transmission quality, and solve network congestion at low cost. TVWS also faces problems, such as sensing available spectrums and interference avoidance [17] [18].

Because of resource limitations and uncertainty regarding PU behavior, SUs have to obtain the utilization of spectrum through competition. Meanwhile, users have different priorities and QoS demands; resource managers must ensure that users with higher priority have resource preference, and SUs with higher QoS demands should be allocated to spectrums with better channel conditions. In addition we should ensure that spectrums are not monopolized by high-priority users, and PBS manages resources in a fair and rational way. Therefore, we should design an allocation strategy that can maximize system utility and improve SU social welfare without causing QoS degradation for PUs.

3. Game Theoretical Based Spectrum Allocation Model

3.1 Non-interference User-set Construction

When N SU nodes locate randomly in a certain area, the network topology and channel selection problem is always modeled as an interference graph. This method constructs network topology as an undirected connected graph; the vertex represents SU nodes that participate in spectrum allocation, and every vertex has a set of channels to select. The edge represents the interference relation between users; if there are direct connections between two vertexes, there is interference between them, and they cannot transmit in the same channel simultaneously.

Although graph theory could allocate spectrum to different users considering mutual interference, it lacks an efficient mechanism to comprehend the different requirements of users, and thus has low allocation utility and fairness. In addition, there are numerous heterogeneous services in wireless networks; their demands for spectrum quality are diversified. For example, video service has high throughput and bandwidth requirements (online video requires data rates greater than 500kbps, while audio requires between 100 and 200 kbps; non-real-time service requires less than 100kbps), audio streaming requires high real-time performance and low delay, image transmission requires low distortion, and so on.

Therefore, we use a weighted interference graph to divide SU nodes into several non-interference groups, and use the weight of the node to represent the QoS-demand level of heterogeneous service.

To express the relations of users, we first build a weighted-interference graph G=(V,E,W). The vertex set in graph $V=\{n_1,n_2\ldots,n_i\}$ signifies all the buyers in the game, and edge set E signifies whether two users have interference with each other. Weight set W of all nodes $W=\{w_1,w_2\ldots,w_i\}$ shows users' special QoS-demands level, and w_i represents user n_i's service demands in its current transmission. For example, as shown in **Fig. 2**, node set $V=\{n_1,n_2\ldots,n_8\}$, and weight set W={6，3，7，5，5，3，8，6}.

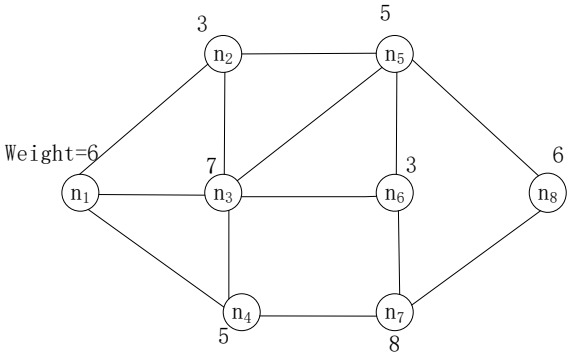

Fig. 2. weighted interference graph

After constructing the interference-graph shown in **Fig. 2**, we transform the problem into constructing max-weighted independent sets, and IS_i represents the node set i that contains several independent nodes. If buyers could join the maximum weight set available to them, they will get the desired benefit; however, the overall resource is limited, and there will be conflict if everyone requires its maximum weight. To ensure fairness of competition, we define that every user submits the appropriate requirement according to the traffic feature, and the agreed weight is the maximal weight of all participants. In addition, the weight of the group is the summation of all nodes' weight, so the weight of set IS_i is :

$$Weight\_IS_i = \max\{\min\{Weight_l\} | l \in IS_i\} \times |Is| \tag{1}$$

Then we design the buyer group constructing algorithm as Algorithm 1. On the condition that buyer i joins the same group with nodes having approximate QoS demands, we can maximize the spectrum utilization and user's satisfaction concurrently. Therefore, we use Weight_diff to express the acceptable differences between users in the same group, which is dynamic depending on the diversity of service type. In the grouping process, we first construct the non-interference neighbor set of buyer i, which is expressed as T, then choose its partners with similar transmission demands in set T and form the sub-group.

Algorithm 1 Non-interference Secondary-user node set construct

```
Input: Weighted Interference Graph of buyers G=(V,E,W)
Output: Non-interference buyer set IS1, IS2…ISn and Weight {Weight_ ISi}
id=1;
While(G ≠ ∅)    do
    Weight_ ISid=0;
    Add Node_id to set ISid;
      For(i=Node_id+1 to    |V|) do
            If there are no direct connections between Node_id and i
                Add Node_id to set T;
            Endif
      Endfor
    Construct the non-interference neighbor set of Node_id T;
    Current_weight=Weight(Node_id);
      For (j=1 to |T|) do
            If | Current_weight-Tj_weight|<Weight_diff;
                Add node Tj to set ISid;
                Delete Tj from G=(V,E,W);
            Endif
      Endfor
      Update Weight_ ISid  according to formula (1);
       Delete Node_id from G=(V,E,W);
      id=id+1;
Endwhile
```

In algorithm 1, every sub-group constructed in iteration is the weighted independent set that could minimize the divergence of QoS demands in the same group; it can ensure that every buyer chooses suitable spectrum resource according to current service type. This could maximize every user's profit, and ensure fair competition between buyers. When the input of algorithm1 is the interference graph shown in **Fig. 2**, the buyer group and group bid in iteration is as shown in **Table 1**:

Table 1. buyer groups and group bid

Iteration	Buyer group IS_i	Group bid
1	{n1,n8}	12
2	{n2,n6}	6
3	{n3,n7}	16
4	{n4,n6}	10

3.2 Resource Allocation Game Model

The goal of our research is to maximize system utility, including PU (seller) and SU (buyer) revenue, and to ensure that the allocation has fairness and user satisfaction to a certain degree. In the game process, PBS is the owner and dominant over the spectrum, and can be considered the leader, while SUs can be viewed as a followers[19]. The sequence of every player's strategy is: step 1, PBS obtains the current idle spectrums, forms an available spectrum matrix, and informs all buyer groups; step 2, SUs decide the spectrum purchase quantity and bidding price P_s rationally according to traffic demand; step 3, PBS computes the optimum solution that can maximize overall utility and decides the spectrum allocation strategy.

The resource allocation process is a dynamic game with N SUs as players and PBS as game manager. This game is played over a sequence of time slots $t \in \{0,1,2,...\}$. At every slot t there is an event vector $w^t = (w_0^t, w_1^t, ..., w_N^t)$ representing the current spectrum condition, and the random w^t is independent of the process w^{t-1}. PBS observes the full vector w^t, while SUi only knows component w_i^t. At every time slot, SUs observe their available spectrums and take a control action, and their actions affect the individual utilities. Mixed pure strategies with different probabilities for every slot could adapt to resource variation at different times, and optimality can be achieved with an algorithm that chooses actions according to the probability function [21]. In our model, SUs make an effort to maximize their time average utility, and PBS is interested in providing allocation schemes that lead to fair allocation utilities among SUs. Our goal is to maximize a concave utility function subject to resource constraints.

3.2.1 Primary User's Spectrum Sharing Model

Primary users have strict transmission requirements, and in order to avoid QoS degradation caused by spectrum leasing, PBS must reserve at least B_s bandwidth for PUs. Suppose that PBS has M available spectrums, defined as (s_1 , s_2…s_M), and the corresponding bandwidth is (B_1,B_2….B_M). PBS leases some idle spectrums to SUs according to users' demands and receives profit from them. We consider CRN as a spectrum leasing market, and the market capacity is quantity of spectrums' SU demands; the change in market capacity in different time slots can be viewed as a dynamic Markov process. The dynamic market capacity in time slot t is expressed as $v^{(t)}$, the idle spectrum's increment is expressed as e_t ,

and all SUs start rent for $\sum_{i=1}^{n} s_t^i$ spectrums in total in current time slot, so the relation between $v^{(t)}$ and $v^{(t+1)}$ is:

$$v^{(t+1)} = v^{(t)} + e_t - \sum_{i=1}^{n} s_t^i \tag{2}$$

The overall revenue of PBS contains three parts: First, PU transmission revenue when they have transmission traffic and occupy some spectrums; second, the reward received from SUs for leasing idle spectrums; third, the management cost during the lease process.

We discuss the first part considering the traffic's elastic feature; the revenue from using spectrums is not simply in line with spectrum demands but in logarithmic relation. Users have a higher unit profit when they demand a small amount of spectrum, and with the increase in demand quantity, the unit profit per one spectrum decreases. The function relation of profit and spectrum quality is:

$$F(x_s) = k_s \ln(1 + x_s l_s B_s) \tag{3}$$

In formula (3), $F(x_s)$ is PU's profit in transmission and x_s denotes the amount of spectrum PU occupies in the current time slot. B_s denotes the bandwidth PU demands to sustain its service transmission; k_s denotes the spectrum efficiency of the PU system, depending on factors such as modulation technique, distribution and location of base station; $l_s \in [1,5]$ denotes the QoS demand level of current traffic.

We analyze overall utility considering profit as in linear with SU demands and spectrum unit price, and the management cost is linear with the amount of rented spectrums; the overall utility function can be expressed as:

$$U = \alpha \sum_{s=1}^{m} k_s \ln(1 + x_s l_s B_s) + (1-\alpha) \sum_{i=1}^{n} P_s^i \times x_i - \beta \sum_{i=1}^{G} s_t^i \tag{4}$$

We use x_i to express the number of spectrums that PBS lease to SU_i, and the market capacity is limited, which is expressed as $\sum_{i=1}^{n} x_i \le v^{(t)}$. P_s^i denotes the unit price SU_i pays for the needed spectrum, and the pricing strategy is submitted by users and then decided by PBS through a bidding game. $\alpha \in (0,1)$ is PBS's weight of system utility function; a higher α indicates that PU's percentage of spectrum use is larger. β is the system cost coefficient and is used to compute the management cost for spectrum leasing.

3.2.2 Secondary User's Cost and Utility Function

Suppose there are N SUs in a wireless network, and their strategy can be defined as (st_1 , st_2…st_N). Every user leases some spectrums for its traffic transmission; meanwhile, it pays rent to PBS. SUs compete for the service and adapt the spectrum selection strategies dynamically according to their time-varying performance. According to users' service demand, SUs lease spectrums to obtain the maximum profits. We define the SU revenue function in the game process as:

$$F(x_i, P_s, B_i) = k_i \ln(1 + x_i d_i B_i + P_s^2) \tag{5}$$

In this formula, d_i denotes SU_i's spectrum demand factor in time slot t, B_i denotes the bandwidth that SU_i needs in transmission, and P_s is the unit price submitted to PBS. Users' overall utility should be the revenue from traffic transmission minus the rent from resources. From this point of view, we build the SU's utility function as:

$$U_{buyer} = F(x_i, P_S, B_i) - P_s \times x_i = k_i \ln(1 + x_i d_i B_i + P_s^2) - P_s \times x_i \tag{6}$$

The bidding game modulates spectrum demand and pricing through market discipline and prompts users to realize a stable agreed pricing after several rounds of competition. When SU informs PBS of its bid, it should consider factors such as: traffic features, QoS demands, spectrum amount, channel quality, urgency, and so on. We formulate the pricing strategy as:

$$P_s = (d_i + l_i) \ln B_i - \frac{x_i}{M} \qquad \forall i \in \{1,2...N\} \tag{7}$$

In this equation, l_i denotes the QoS demand level of current traffic. Users with different requirements and price expectations have different QoS demands; x_i is the amount of spectrum SU demand, and M denotes the total amount of available spectrums. We consider SU's transmission requirement to be elastic, and this can provide a guarantee for different types of traffic. For multimedia users with strict performance requirements, admission control mechanisms and a withdrawal strategy can be used to guarantee QoS.

3.2.3 Utility Optimization Model

In our game model, PBS is responsible for managing all resources uniformly; it leases part of the idle spectrum to SUs and receives revenue. When the absent PU returns and has to reoccupy a channel for transmission, PBS must recall some of the rented spectrums and return to the authorized user. In this situation, the stochastic feature of the PU's behavior leads to resource allocation being highly dynamic, and we should design the allocation mechanism according to the users' property. In order to maximize overall social welfare, we build the optimization objective as:

$$\max \quad \alpha\sum_{s=1}^{m} k_s \ln(1+x_s l_s B_s) + (1-\alpha)\sum_{i=1}^{n} P_s^i \times x_i - \beta\sum_{i=1}^{G} s_t^i \tag{8}$$

Subject to:

$$\sum_{s=1}^{m} x_s + \sum_{i=1}^{n} x_i = M \tag{9}$$

$$\sum_{i=1}^{n} x_i \le v^{(t)} \tag{10}$$

$$\sum_{s=1}^{m} B_S + \sum_{i=1}^{n} B_i \le \sum_{i=1}^{M} B_M \tag{11}$$

The objective of the problem is to find the optimal allocation strategy and make the decision for (x_1,x_2,x_3….x_n) as the spectrum allocation vector for every SU. Constraint 9 means that the sum of PU occupied spectrums and the spectrums rented to SUs should be the total amount of spectrum the system can provide. Constraint 10 means that the sum of spectrum rented to the SUs should not exceed the current market capacity. Constraint 11 means that all users' total transmission bandwidth should not exceed the bandwidth upper bound of the wireless service system.

According to the definition of Nash Equilibrium[21], if none of the players can increase revenue by changing his strategy, the strategy profile containing all players' behavior could be a Nash Equilibrium solution. The bidding game strategy we proposed has a Nash Equilibrium solution if the following three conditions are satisfied [22]:

1) The player set has limited elements;
2) The players' strategy set is a bounded, closed convex set;
3) The utility function is a continuous concave function in action space;

Theorem 1 In the dynamic bidding game strategy, there are a finite number of players, the player's action space is a bounded convex set, and the utility function is a continuous concave function, so there is a Nash Equilibrium in the strategy profile.

Proof: 1) Suppose there are N (N is an integer and N>1) users in the network topology, every user can be viewed as a player and the player set has a limited number of elements. Meanwhile, there are M (M is an integer and M>1) spectrums available to SUs, and $l_{st(i)}$ defines the number of channels allocated to user $st(i)$. Assuming that all users participate in the spectrum allocation game, the system strategy profile can be defined as $(l_{st(1)}, l_{st(2)} \ldots\ldots l_{st(N)})$, $l_{st(i)} \in \{1, 2 \ldots\ldots M\}$. Owing to the time-varying feature of the

spectrum resource, users take dynamic actions to achieve optimal utility; this induces a probability distribution on the user's strategy. To every user, the strategy in the current time slot is an integer in the range of [1, M] indicating the spectrum opportunity provided by PBS. In a mixed strategy game, the strategy profile is a probabilistic mixture of users' pure strategy, which is expressed as $\sum_{i=1}^{s} Pr^i \times l_{st(i)}$ with the condition $l_{st(i)} \in \{1,2.....M\}$ and $\sum_{i=1}^{s} Pr^i = 1$; Pr^i defines the user's probability of obtaining $l_{st(i)}$ channels in a game. Therefore, the strategy profile of the bidding game is a closed convex set.

2) To judge whether the problem can find a global optimum solution, we first compute the system utility function's first order derivation of spectrum unit price P_s:

$$\frac{\partial U(P_S)}{\partial P_S} = (1-\alpha)\sum_{i=1}^{n}[(d_i + l_i)\ln B_i] - 2(1-\alpha)M \times P_s \tag{12}$$

Then we deduce $U(P_S)$'s second-order derivation of variable P_s, and we get:

$$\nabla_{P_s}^2 U(P_s, B, k) = -2(1-\alpha)M \tag{13}$$

Because we have $\alpha \in (0,1), M > 0,$ we can easily get $\nabla_{P_s}^2 U(P_s, B, k) < 0$.

Therefore, we can see the utility function is a concave function in the definition domain, the bidding game has a Nash Equilibrium, and the system has a global optimization solution that can maximize system revenue. We can find the optimum unit price P_s^* and resource allocation scheme by solving the condition $\frac{\partial U(P_s)}{\partial P_s} = 0$ and we get:

$$P_s^* = \frac{(1-\alpha)\sum_{i=1}^{n}(d_i + l_i)\ln B_i}{2(1-\alpha)M} \tag{14}$$

Then we can obtain solution P_S^*, which is a Nash equilibrium. Owing to the fact that sellers want to maximize revenue and buyers desire to maximize their utility in terms of QoS performance, pricing and spectrum allocation are closely related in CRNs. The spectrum allocation strategy can be obtained from the utility function.

To realize competitive equilibrium, we design an algorithm for spectrum allocation. We assume that the payment of the SU in a group is independent of other SUs, and the algorithm

can be described as follows:

Algorithm 2 Compute the equilibrium price P_s^* and allocation strategy x;

Input: a set of buyers N, a vector of spectrum demands v, a vector of bid price st;

Output: equilibrium price P_s^* and spectrum allocation vector x;

```
v=∅ ;
For (i=1 to N) do
    SU_i attains the bandwidth demand v_i;
    SU_i computes the bid price st_i according to formula (7);
Endfor
PBS receives the vectors and computes the equilibrium price P_s^* according to formula (14);
PBS announces the equilibrium price to all SUs;
Compute the allocation vector x by solving the optimization problem (8);
Return P_s^* and x;
```

4. Economic Property Analysis of Bidding Game

Definition 1 Trustfulness[24] A game is trustful if neither the seller nor the buyer can improve their utility by bidding untruthfully.

Theorem 2 The mechanism for diverse users we proposed in a cognitive environment has the property of trustfulness.

Proof: Suppose that buyers are untruthful in their bidding price; we then deduce their social wealth.

Case 1 We supposed that the buyer group's bidding price was lower than their actual price:

$$0 < P_S^{'} < P_s$$

$P_S^{'}$ denotes buyer group's bidding price, while P_s denotes actual unit price.

SU i can obtain the social welfare by computing function $F(x_i, P_S, B_i)^{'}$ through the use of spectrum in transmission.

Then $$U = F(x_i, P_S, B_i) - P_s \times x_i \tag{15}$$

$$U^{'} = F(x_i, P_S^{'}, B_i)^{'} - P_S^{'} \times x_i \tag{16}$$

U represents the utility buyer i can obtain when bidding truthfully, and $U^{'}$ represents the utility when bidding untruthfully.

$$\because \text{When } P_S^{'} < P_s,\ \frac{\partial U}{\partial P_S} = \frac{\partial \mathrm{F}(\mathrm{x}, \mathrm{P_s}, B_x) - P_S \times x_i}{\partial P_S} = \frac{\partial F(x, P_S, B_x)}{\partial P_S} - x_i \geq 0 \tag{17}$$

$$\therefore\ U^{'} \leq U$$

Thus, when the bid of the buyer group is lower than the actual price, the revenue they can obtain is not higher than that they can obtain by bidding truthfully.

Case 2 When the buyer's bidding price is higher than the actual unit price of spectrum, their revenue is expressed as:

$$U^{'} = F(x, P_S^{'}, B_x)^{'} - P_S^{'} \times x_i$$

Because the group's bid is P_s =max{ $P_{s1}, P_{s2} ... P_{sn}$ }, when $P_S^{'} > P_S$, $F(x_i, P_S^{'}, B_i)$ could not increase monotonically with the increase in price, and in this situation, $U^{'} < U$,buyer's utility is lower than bidding truthfully when the bid price is higher than the actual spectrum price.

Definition 2 Individual Rationality[24] A game has an individual rational characteristic if neither the seller nor the buyer will receive negative utility.

Theorem 3 In the spectrum allocation mechanism that we proposed, both the buyers and the sellers participating in the bidding game are individual rational.

Proof: We analyze both seller's and buyer's revenue as follows:

Case 1 For sellers such as PBS, their revenue is expressed as:

$$U_{seller} = \alpha F(x_s) + (1-\alpha)\sum_{i=1}^{|G|}(P_s^i \times x_i - \beta v^{(t)}) \tag{18}$$

It is obvious that sellers' social welfare is positive because both their utility in using spectrum for service transmission and the revenue from leasing idle spectrums minus the management cost are positive.

Case 2 For buyers, we divide all buyers into several no-interference groups in algorithm 1; suppose one buyer group has two users $\{i_1,i_2\}$, and their bid is p_1 and p_2, respectively. Then, their group bid is max{ p_1,p_2} and we can deduce that when $p_1>p_2$, $P_s=p_1$.

We express the actual utility user i_1 can get through the grouping and bidding game as U_1, and the revenue it can get without grouping from theoretical analysis is expressed as $U_1^{'}$; we can get:

$$U_1 = F(x_1, P_S, B_1) - P_S \times x_1 = F(x_1, p_1, B_1) - p_1 \times x_1 = U_1^{'} > 0$$

Then, we deduce user i_2's utility; we express the actual utility user i_2 can get as U_2, and the revenue from theoretical analysis is expressed as $U^{'}_2$; we derive:

$$U_2 = F(x_2, P_S, B_2) - P_S \times x_2 = F(x_2, p_1, B_2) - p_1 \times x_2 \tag{19}$$

$$U_2^{'} = F(x_2, p_2, B_2) - p_2 \times x_2 \tag{20}$$

$$U_2 - U_2^{'} = F(x_2, p_1, B_2) - F(x_2, p_2, B_2) - (p_1 - p_2) \times x_2$$

According to algorithm 1,

$$|p_1 - p_2| \le \frac{\Delta F(x_2, B_2, l_2)}{x_2} \tag{21}$$

$$\therefore U_2 \ge U_2^{'} > 0$$

This deduction can also be applied in multi-user situations, and all the buyers participating in the game can have positive utility. Therefore, our mechanism is individual rational both to sellers and buyers.

5. Simulation and Analysis

5.1 Simulation Settings

In this section, we use MATLAB R2012a to simulate and evaluate the performance of the dynamic bidding game strategy that we proposed. We suppose PBS has spectrums with a total of 1000KHZ of bandwidth, and every PU has spectrum with a bandwidth of B_i(B_i is an integer value between 10KHZ and 30KHZ). When the amount of SUs changes within the scope of [10,80], we set the range of available spectrum quantity from 30 to 50 and execute the allocation process more than 1000 times. The interference distance between two SUs is 25; i.e., if the geometric distance between two buyers is less than 25m, they create interference for each other and cannot participate in the same spectrum bidding. In addition, we generate an integer randomly in the range of [1, 5], representing the user's QoS-level as the weight of nodes, and the weight is related to the service type parameters. We set the bidding rule as follows: The buyer's price obeys a uniform distribution in [10, 15], and every buyer can purchase at most 5 spectrums simultaneously (according to the radio constraint in an actual situation). Selling price distributes uniformly in [13, 18] and when the buyer's offer price is not lower than the selling price, the transaction can be achieved.

Currently, there are N SUs distributed randomly in a 100m×100m geographic area. Since a CRN is a stochastic system, we adopt a Markov process to model the dynamics of

nodes in the network. Markov processes not only consider changes to states but also the actual time spent during that process. The operation of a CRN is similar to a Markov process. It takes a random amount of time for the network traffic to stay in a source node before it moves to a destination node. The PU's traffic follows a semi-Markov process with ON/OFF periods following an exponential distribution, and we apply a Monte Carlo simulation on channel probabilities.

5.2 PBS's System Utility

In our bidding-game spectrum allocation model, we first divide all SUs into several non-interference weighted sets, then formulate the bidding game and choose the optimal allocation strategy according to the equilibrium. We simulate and analyze PU system profit by setting the PU's cost weight parameter α to be 0.3 and 0.7. In addition, we set PBS's management cost coefficient as β=2 and the spectrum efficiency factor as k_s=2.5 and increase the amount of SU from 10 to 80 progressively; the experiment result is shown in **Fig. 3.**

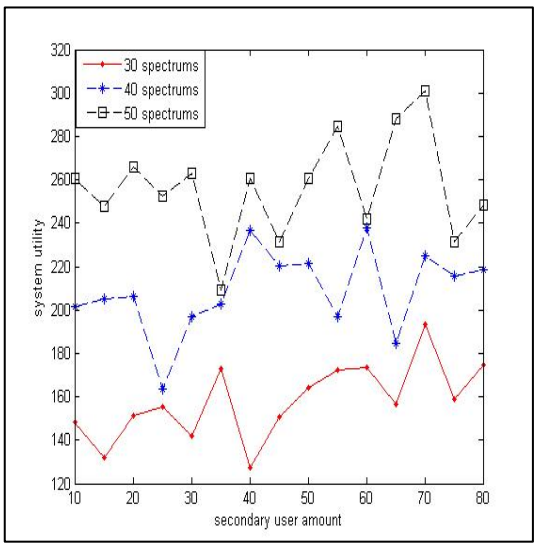

Fig. 3.a. System utility (α=0.3)

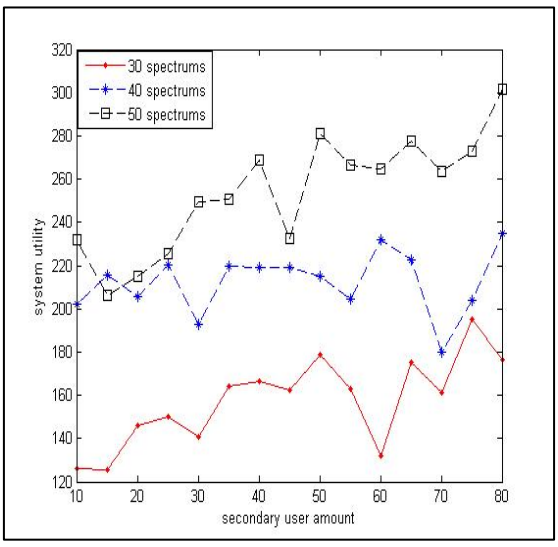

Fig. 3.b. System utility (α=0.7)

From the revenue shown above, we can observe that the PU system's social welfare increases gradually with the available spectrum amount and total bandwidth. When there are 30 spectrums in total, overall revenue is lower; when the amount increases to 40 and 50, revenue is increasing correspondingly. Sufficient resource could provide more access and transmission opportunities to SUs and increase system social welfare by receiving more payments from buyers. We can also observe from **Fig. 3** that PBS's system revenue does not increase monotonically as the SU amount augments; in some points, it appears to have a decreasing tendency. Because SU location and service type are generated randomly, in

situations where the interference between adjacent nodes is substantial or the distinction between different nodes' weight is obvious, grouping efficiency is influenced and the management cost will rise, so system revenue decreases. When α=0.7, system profit increases continuously with more SUs joinning the game; however, when α=0.3, sytem profit decreases after SU amount exceeds 60; when the spectrum resource becomes insufficient and more and more SUs need idle spectrums for transmission, which could probably lead to lower overall revenue, PBS will begin to set restrictions on SU spectrum occupancy in order to guarantee PU's prority and avoid causing PU's QoS degradation.

5.3 SU's Social Welfare

Suppose in a cognitive radio network there are three types of buyers {SU_1 , SU_2 , SU_3} with hetegeneous traffic service. SU_1 represents users with high QoS parameter demands, such as real-time video with higher bandwidth demands and delay sensitive features; SU_2 represents services such as audio and online conference with medium QoS requirements; and SU_3 represents users with non-real-time traffic. SU's revenue from participating in the bidding game could be calculated according to formula 5 to formula 7. We set up the simulation and get SU utility in different situations, and the result is shown in **Fig. 4.**

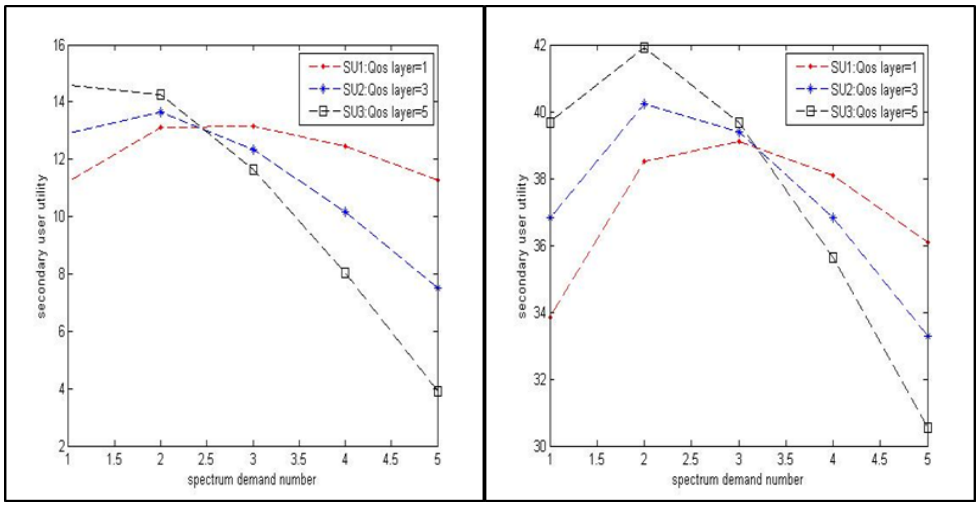

Fig. 4.a. SU's utility (d_i=0.3,k_i=5) **Fig. 4.b.** SU's utility (d_i=0.6,k_i=10)

From the above figures, all SU's utility in different parameter settings is positive; this verifies the individual rationality property of our strategy. In **Fig. 4.a,** when the spectrum amount allocated to three users is (3, 2, 1) , their utility could maximize simultaneously, and this allocation schema is the Nash Equilibrium. In addition, when SU's spectrum demands increase from 1 to 5, SU_3's utility reduction is the sharpest, and when the number

reaches 5, the utility decreases to nearly zero; SU_1's utility variance is not obvious. Because mobile multimedia users have higher bandwidth demands; only when they are allocated more spectrums can their QoS be sustained. In our allocation mechanism, the high-quality channels are allocated preferentially to real-time and delay-sensitive traffic; meanwhile PBS restricts low-QoS-demand users from occupying too many spectrums unnecessarily. SU's utility in **Fig. 4.b** is higher than in **Fig. 4.a** because if there are emergent requirements and the spectrum efficiency is satisfying, the SUs could obtain greater revenue.

In the bidding process, if buyers have a higher estimation of a spectrum's value, the actual transaction value may be higher; this will bring an economic loss to buyers. To avoid this, buyers usually report a lower unit price to probe the market and moderate the price with the demand-and-supply relation in the market. From **Fig. 5** we can observe that three users achieve an equilibrium spectrum unit price within 10 iterations.

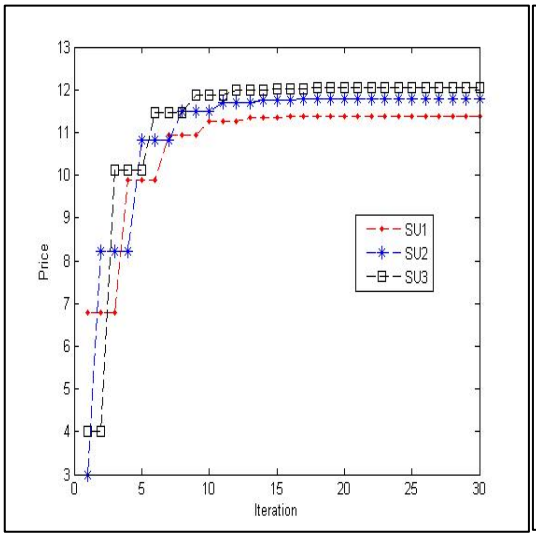

Fig. 5.a. Equilibrium Unit Price
Market capacity=50

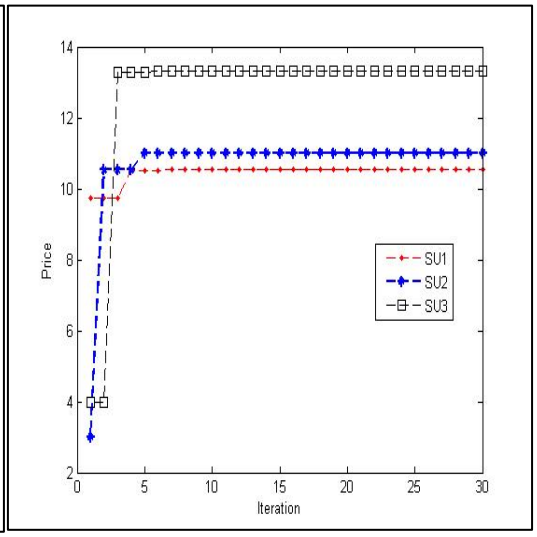

Fig. 5.b. Equilibrium Unit Price
Market capacity=30

6. Conclusion

In this paper, we propose a dynamic bidding game-based spectrum allocation model for heterogeneous wireless service in cognitive radio networks. We study a CRN with multiple service types and propose the unified resource allocation model for different QoS demands. First we propose a weighted interference graph-based grouping algorithm to solve the problem and divide SU nodes into several independent groups. Second, we formulate the allocation decision-making process as a dynamic bidding game, analyze both buyer and seller utility functions, prove the existence of a Nash Equilibrium and deduce the equilibrium allocation strategy. Theoretical and simulation results illustrate that our proposed strategy

can optimize both seller's and buyer's utility and can guarantee user's individual rationality. In future work, we will study the detailed characteristics of heterogeneous wireless service and formulate the optimization objective of QoS parameters such as data rate, delay, and packet delivery rate in transmission. In addition, we could build our framework from the perspective of cross-layer design and achieve route-channel joint optimization to improve end-to-end performance.

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