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Spectrum pricing for cognitive radio networks with user's stochastic distribution

Li Wang^{1,3} · Kwok-Yan Lam³ · Mudi Xiong² · Feng Li^{1,3}  · Xin Liu⁴ · Jian Wang⁵

Abstract

Amid the dynamic spectrum access in cognitive radio networks, when complex spectrum conditions should be taken into account, how to price the spectrum in order to benefit primary systems in maximization is still under-investigated. In this paper, we devise a spectrum pricing method to address this issue in cognitive networks. In our proposed mechanism, leasing spectrum is collected for uniform selling and classified into three kinds of channels—high-quality channel, midquality channel and low-quality channel, respectively. They will be priced variously according to different interference characteristics caused by versatile path fading and user positions. In respond to heterogeneous channel qualities, secondary users also have own selection preferences. They can purchase one kind of channel for usage in based of channel quality and available budget. Then, we obtain the final pricing solution which is an iterative algorithm converging to a fixed point. Also, the existence of a pure Nash equilibrium is discussed to ensure the rationality of the method. In numerical results, we evaluate the effects of this proposal in spectrum pricing and primary systems' profits.

Keywords Cognitive radio (CR) Spectrum allocation Hotelling Normal distribution

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1 Introduction

With the bloom of various wireless applications especially of the Internet of Things and near-future 5G services, the huge demand for high-quality wireless spectrum can be envisioned [1–3]. In this regard, many

techniques focusing on different networks such as vehicular networks, wireless sensor networks, Internet of Things, cloud access networks and satellite networks, have been deeply investigated by research community recent years [4–8]. Cognitive radio, which is conducted in basis of dynamic spectrum access, consistently attracting attentions from academic and engineering areas, has been seen as a promising and practical solution to enhance spectrum efficiency and upgrade transmission capacity [9].

To realize effective and smooth dynamic spectrum access in cognitive networks, how to manage the wireless resources between plenty of terminals and primary systems plays a key role [10, 11]. During the course, market-based method for spectrum resource allocation for secondary users can improve spectrum utilization and benefit primary systems in monetary incomes. In general, to attain a spectrum allocation balance for different participants in this spectrum trading, game theory is often applied [12–14]. In [12], the authors investigated the dispersed spectrum cognitive radio systems over independent and nonidentically distributed generalized fading channels. The proposed solution was performed in terms of the high-order statistics of the channel capacity over the specific fading channels. In [13], the proposed centralized algorithm ensures some minimum throughput for all flows in the cognitive radio networks using fairness ratio and maximizes this ratio to increase the overall network capacity. In [14], the authors proposed a cross-layer approach to maximize the multicast throughput in multi-hop cognitive radio networks. They introduced a new service provider, named secondary service provider, to

harvest the available spectrum and allocate the collected bands among secondary users.

The main contribution of this paper lies in that we devise a differential spectrum pricing algorithm which is more practical and suitable for real spectrum trading circumstance wherein heterogeneous spectrum and secondary user's preference need to be taken into account. In fact, many technical schemes with respect to heterogeneous spectrum and participants in dynamic spectrum access have been proposed recent years [15–19]. To be specific, Ref. [15] and [18] focused on spectrum auction mechanism in cognitive networks with heterogeneous secondary users' QoS requirements. In contrast, our paper pays attention to spectrum pricing with relatively low overhead cost. Besides, in [16], heterogeneous fading channels were investigated when seeking a tradeoff between decreasing the interference to primary users and increasing secondary users. In [17], a subchannel allocation scheme was designed to satisfy heterogeneous users' rate requirements. In [19], a five-stage Stackelberg game model was adopted to address users' heterogeneous valuations and spectrum demands. The above-mentioned methods' main research points are diverse to our proposal which involves differential user spectrum preferences and adopts corresponding Hotelling game model.

In this paper, we investigate how to price the spectrum especially when heterogeneous spectrum and stochastic secondary user's preference are under consideration. A concept of spectrum pool constituted by the idle bands to be leased is introduced to facilitate the following spectrum deal. Suffering from different levels of interference, these channels have various qualities. In this case, secondary users are supposed to select channels for usage based on their preference. It can be envisioned that a secondary buyer with sufficient capital or urgent demand for ideal QoS can pick a high-quality channel. A secondary spectrum customer will pick a high-quality channel for usage when its capital is ample or broadband is required to support essential service. We adopt Hotelling model which is proper to describe the product pricing issue in heterogeneous market. By analyzing the secondary user's preference parameter, an iterative algorithm for spectrum pricing is obtained after fixing the Nash equilibrium. Numerical results are further provided to evaluate how the pricing parameters affect the primary system's profits.

The remainder of this paper is organized as follows. We introduce the system model for dynamic spectrum pricing in Sect. 2. Section 3 gives the utility function and

finds the Nash equilibrium. Furthermore, numerical results are supplied to analyze the performance of the pricing algorithm in Sect. 3. Finally, we conclude this paper in Sect. 5.

2 System model

In this paper, we suppose the spectrum trading is performed in centralized mode. The primary center acting as a virtual operator will collect all the user and spectrum information. Then, all the idle spectrum can form a spectrum pool for centralized selling as shown in Fig. 1. Centralized spectrum trading mode can decrease dealing overhead and spectrum sensing cost. Otherwise, if every single cognitive terminal communicates with licensed users one by one to seek proper spectrum dealing, it will be more inefficient for both participants.

Furthermore, we suppose the spectrum can be divided into many uniform channels for facilitating the selling operation. We also consider the channels with same bandwidth in the whole pool are not homogenous due to complex electromagnetic environment and user's diverse position. It is well known that various spectrum bands have different fading characteristics, and secondary users migrating to cell edges will suffer heavy interferences from adjacent cells. Hence, we take the spectrum quality diversity into account in this paper to attain a more practical spectrum trading scheme.

We cast the spectrum pricing issue into Hotelling model which is usually adopted to depict the product price

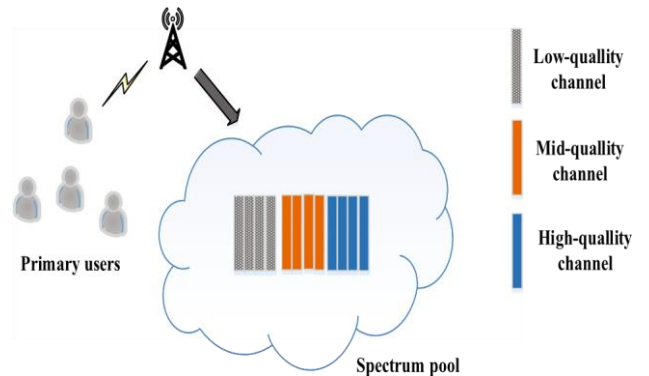


Fig. 1 Spectrum pool competition when product diversity and user selection are both required to be considered in a monopoly market. Wherein, in the market, only very few commodity manufacturers can render the product or service. The Hotelling model which can describe this trading situation well was first formulated by scholar Hotelling and became well known as it specializes the pricing rule when product

differentiation is obvious leading to price insensitivity [20]. The model has two essential preconditions: product diversity and monopolistic product makers. Hotelling generalized and developed Bertrand's pricing model by further taking into account different manufacturers' location diversity in geographic space, thus this model could be used to solve the pricing problem involving in quality diversity. Actually, in a sufficient competitive and mature modern society, one product market is always controlled by few huge firms. They compete for not only product price, but also product diversity.

During the spectrum trading, we assume the primary center do not have prior knowledge of secondary users' purchasing intention on different kinds of spectrum. They need to predict users' preference characteristics and design a rational channel price to maximize profits. To describe secondary user's preference, we define h as preference parameter. As shown from Figs. 1, 2 and 3, we give the presentation of preference parameter's normal distribution when there are two or three types of spectrum to be chosen. In condition of only two kinds of spectrum to be selected, there is $h \sim \frac{1}{2}h_1;h_2 \sim \delta h_1|h_2 \mathcal{P}$, where h_1 and h_2 correspond to the low and high quality spectrum, respectively. Then, after purchasing a licensed channel j , the profit or utility function reaped by secondary user i can be expressed as

$$U_i \approx x h_i C_j p_j - t P_i g_i; \quad \delta \mathcal{P}$$

where x and t denote monetary coefficients transferring various pricing parameters into uniform price unit. h_i denotes the spectrum preference of user i , C_j denotes the capacity received by user i on channel j . We have

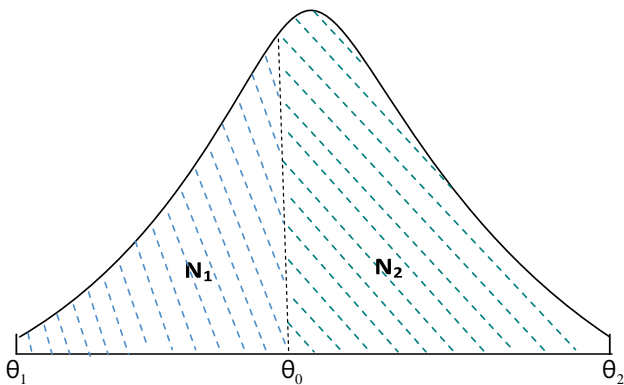


Fig. 2 User preference in condition of two kinds of spectrum

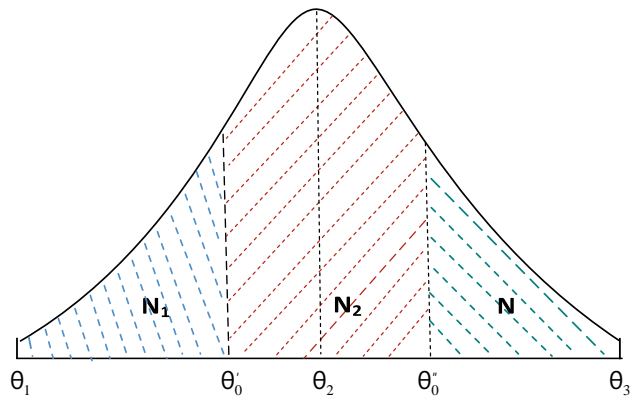


Fig. 3 User preference in condition of three kinds of spectrum

$C_j \approx B \log_2 \delta \mathcal{P} \approx \text{snr}_j \mathcal{P}$, where snr_j denotes the signal-noise ratio closely related to channel quality. p_j denotes the price of spectrum j . P_i is the transmit power of user i , and g_i is the corresponding channel fading from user i to its closest primary base station. Thus, $P_i g_i \approx I$ means the interference caused by user i to the primary networks. We suppose the primary networks will charge secondary users for the additional interference.

Then, we define a non-preference parameter h_0 which means that in condition of $h \approx h_0$, the secondary user does not have any preference on any kinds of spectrum. In another word, it can reap identical benefit from different spectrum. When two kinds of spectrum exists, the non-preference parameter can be given as

$$h_0 \approx \frac{x h_0 C_1 p_1 - t P_i g_i \approx x h_0 C_2 p_2 - t P_i g_i}{x \delta C_1 C_2 \mathcal{P}} \quad \delta \mathcal{P}$$

In this paper, we consider the secondary user's spectrum preference is stochastic in given region. Thus, a normal distribution model can be used in this case, as shown in Figs. 2 and 3. In the figures, N_i denotes the user number. In addition, in Fig. 3, h_0' is the non-preference parameter between $\frac{1}{2}h_1;h_2$. h_0'' is the non-preference parameter between $\frac{1}{2}h_2;h_3$, where $h_0'' \approx \frac{x \delta C_2 p_2 - C_3 \mathcal{P}}{x \delta C_2 p_2 - C_3 \mathcal{P}}$.

For the case of three kinds of spectrum, the demand functions for the corresponding three kinds of secondary users can be given as

$$D_1 \approx \frac{1}{N_1} \int_{h_1}^{h_0'} g \delta h \mathcal{P} dh \quad \delta \mathcal{P}$$

$$\int_{h_0''}^{h_0} g \delta h \mathcal{P} dh \quad \delta \mathcal{P}$$

$\delta \mathcal{P}$

$$D_2 \sim N_2 \quad g_{\delta h} p_{dh}$$

$$\begin{matrix} h_{00} \\ Z_{h_3} \end{matrix}$$

$$D_3 \sim N_3 \quad g_{\delta h} p_{dh} \quad \delta 5 p$$

Then, the profits function for the primary system is as follows

$$p \sim \frac{X_3}{i \sim 1} \quad \delta p_i \quad M_i \quad p \quad t P_j g_j p D_i \quad \delta 6 p$$

3 Spectrum pricing

Secondary user's preference parameter is considered to be subject to the normal distribution for practical application. The probability density of a standard normal distribution can be expressed as

$$u_{\delta x} p \sim \frac{1}{\sqrt{2\pi} e^{\frac{x^2}{2}}} \quad \delta 7 p$$

Then, the distribution function is

$$f_{\delta x} p \sim \int_{-\infty}^x u_{\delta x} p \sim \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt \quad \delta 8 p$$

According to [20], f(a) can be simplified as

$$f_{\delta a} p \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{a^2}{2}} \quad \delta 9 p$$

Thus, the probability can be approximately calculated in given region $\frac{1}{2}a; a$. Besides, according to [21], the conclusion obtained from (9) can also be applied to the case of general normal distribution.

Furthermore, when the distribution mean is 1, the probability calculated approximately in $\frac{1}{2}a; 2l$ a is obtained as

$$f_{\delta a} p \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{a^2}{2}} \quad \delta 10 p$$

As shown in Fig. 4, in case of two kinds of spectrum available, the secondary customer whose preference parameter h locates in $\frac{1}{2}h_L; h_0$, will purchase low-quality channels. The user with preference parameter locating in $h \geq \frac{1}{2}h_0; h_H$ chooses a high-quality channel.

Then, we figure out the distribution probabilities for the two cases. Divide the red shadow part in Fig. 4 into two parts. Wherein, there are $h_0 \sim \frac{1}{2} h_0$ and $h_H \sim \frac{1}{2} h_H$, as shown in Fig. 5.

According to the corresponding regions of high-quality and low-quality channels, we have the probability densities as follows

$$q_{ff} \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_L p^2}{2}} \quad \delta 11 p$$

$$q_{ff} \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_H p^2}{2}} \quad \delta 12 p$$

$$u_{\delta H} p \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_L p^2}{2}} \quad \delta 13 p$$

$$q_{ff} \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_L p^2}{2}} \quad \delta 14 p$$

$$q_{ff} \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_H p^2}{2}} \quad \delta 15 p$$

$$u_{\delta L} p \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{\delta h_L p^2}{2}} \quad \delta 16 p$$

Generally, it is essential to take the the opportunity cost of the primary system into account which means the primary system abandons the potential benefits in future to seek current spectrum trading. Thus, assume the marginal cost of the primary user is related to the quality of the channel which can be expressed as $c_i \sim \frac{1}{2} a_i$, where a is the marginal factor. Formulating the problem by Berland game model, the profit functions of system H and L can be given as

$$p_H \delta p_1; p_2 p \sim N \delta p_1 \quad M_1 \quad p \quad t P_j g_j p \quad \frac{1}{2} \quad \delta 17 p$$

$$1 \quad e^{-\frac{\delta h_L p^2}{2}} \quad 1 \quad e^{-\frac{\delta h_H p^2}{2}} \quad ; \quad \delta 18 p$$

$$p_L \delta p_1; p_2 \delta p_2 \approx \frac{1}{2} N \delta p_2 M_2 \delta p_1 \delta p_2$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

where N is the number of secondary users. The non-preference parameter h_0 is not fixed and changing in $h_L; h_H$. Besides, whether $h_0 \leq 1$ holds will affect the deductions. The profits obtained above are subject to the situation when h_0 locates at the left side of 1. Similarly, when h_0 locates at the right side of 1, the corresponding profit functions can be deduced as

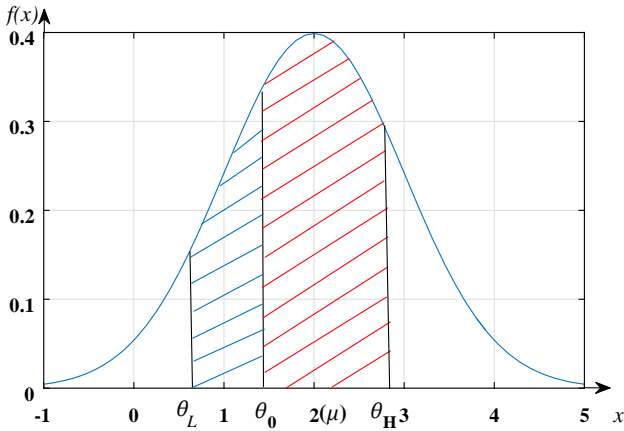


Fig. 4 Divide the channels into two kinds of qualities

$$p_H \delta p_1; p_2 \delta p_2 \approx \frac{1}{2} N \delta p_1 M_1 \delta p_2 \delta p_1$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

$$p_L \delta p_1; p_2 \delta p_2 \approx \frac{1}{2} N \delta p_2 M_2 \delta p_1 \delta p_2$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

Based on the marginal utility functions, by taking derivatives of (13) and (14), we can achieve the iterative optimal channel pricing to be

$$p_1 \approx \frac{1}{2} p_1 \delta p_2 N$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

$$2 \delta p_1 \delta p_2 \approx 2 \delta p_2 \delta p_1$$

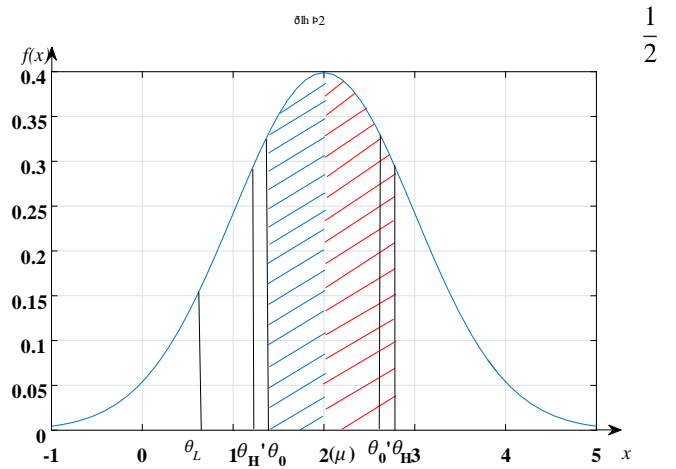


Fig. 5 Divide the high-quality channels into two parts

$$p_2 \approx \frac{1}{2} p_2 \delta p_1 N$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

$$2 \delta p_2 \delta p_1 \approx 2 \delta p_1 \delta p_2$$

$$1 - e^{-\frac{\delta}{1.6058} p} \approx 1 - e^{-\frac{\delta}{1.6058} p}$$

To be similar, we can achieve the optimal channel pricing when $h_0 \geq 1$. Then, we discuss the pure Nash equilibrium of this game model.

Remark 1 In order to ascertain the proposed iterative solution can be convergent, we provide the following discussion for essential supplement. In fact, the pricing algorithm can be rewritten as follows

$$p_i^{k+1} = \frac{1}{\sum_{j=1}^n w_j} \sum_{j=1}^n w_j p_j^k$$

Then, based on Reference [25], if $q \in \mathbb{R}^n$ can be satisfied, the proposed algorithm p_i^k will converge to a fixed point. In basis of the solution above-mentioned, we can easily obtain the Jacobi matrix and identify the maximal eigenvalue. After selecting proper algorithm's parameter, it can be ensured $q \in \mathbb{R}^n$. Besides, the oscillating point of the iterative curves occurs only when $q \in \mathbb{R}^n$.

Theorem 1 For given utility function $f_i \in \mathbb{R}^n$ and strategy function $s_i \in \mathbb{R}^n$, a pure Nash equilibrium for the proposed pricing game algorithm exists.

Proof In this paper, we prove the existence of a pure Nash equilibrium is positive by using Debreu's equilibrium model [22]. Debreu model provides the proof for a common existence of Nash equilibrium. It originated from Wairas's equilibrium theory, and extended the theory with an original intention to solve social welfare allocation problem. Debreu gave detailed mathematical proof for a common equilibrium in Ref. [22]. Based on the theorem of Debreu's equilibrium existence, for the functions s_i and f_i given above, a pure ategy Nash equilibrium exists once the following sufficient nditions can be satisfied: (1) in limited Euclidean space, strategy function s_i is a nonempty and compact subset. (2) For a strategy combination S , f_i is continuous and concave.

For strategy combination S , defining $S : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is the Cartesian direct product of s_i , since R_i is a simplex with dimension $|s_i| - 1$, s_i is a compact subset in limited Euclidean space. When the payoff function is concave with its strategy which ensures the reaction convex, the maximal u_i is continuous with s_i and its reaction function has compact subset. Thus, we can get that strategy s_i is a nonempty and compact subset in distance space. Second, since u_i is a concave function and has maximum in its compact space, it can be concluded that u_i is nonempty and continuous.

Since the subset $e_1 = 3$ is finite $N \in \mathbb{R}^n$ $\frac{1}{\sum_{i=1}^n w_i} \sum_{i=1}^n w_i p_i$, then based on the characteristic of continuity, we have $q \in \mathbb{R}^n$. Besides, due to $\sum_{j=1}^n w_j p_j \in \mathbb{R}^n$, in condition of $q \in \mathbb{R}^n$, we achieve the following inequality

$$\sum_{j=1}^n w_j p_j \in \mathbb{R}^n \quad \delta_i \in [1; 2; \dots; n] \quad \delta \in \mathbb{R}^n$$

As $\sum_{j=1}^n w_j p_j \in \mathbb{R}^n$ enables $\sum_{j=1}^n w_j p_j \in \mathbb{R}^n$, we can obtain

$$\sum_{j=1}^n w_j p_j \in \mathbb{R}^n$$

$$\sum_{j=1}^n w_j p_j \in \mathbb{R}^n \quad \sum_{j=1}^n w_j p_j \in \mathbb{R}^n \quad \sum_{j=1}^n w_j p_j \in \mathbb{R}^n$$

$$\sum_{j=1}^n w_j p_j \in \mathbb{R}^n \quad \text{when } q \in \mathbb{R}^n \quad \delta \in \mathbb{R}^n$$

where $\delta \in \mathbb{R}^n$ $\frac{1}{\sum_{j=1}^n w_j} \sum_{j=1}^n w_j p_j$. Besides, it is apparent that s_i should be continuous and differentiable, thus we can concluded s_i is a nonempty and compact subset in limited Euclidean space. Furthermore, we can take derivation of the objective function of primary system profits, thus it can be concluded that the strategy is continuous and concave. Apparently, proper parameter settings can satisfy this condition. Hence, we can conclude the existence of an unique Nash equilibrium for our proposed algorithm is satisfied [23]. \square

4 Numerical results

In this section, numerical results are provided to testify the effects of the proposed pricing method. In dynamic access networks, we suppose the idle spectrum is controlled by the licensed users. The secondary users who aim to access the spectrum must participant in the spectrum trading and pay for the cost to the primary systems. As the proposed pricing solution is an iterative algorithm, we thus give the initial spectrum pricing for two kinds of channels to be $s_1 \in [2, 1]$, $N \in [100, 1]$, $a \in [1, 2]$, $b \in [0.028, 0.028]$. The cognitive user's preference locates in $[1, 3]$ which means $h_L \in [1, 1]$, $h_H \in [3, 3]$. Furthermore, since the proposed pricing method is an iterative algorithm, we set the initial spectrum pricing for two kinds qualities of channels as $p_i^{0p} \in [0.01, 0.01]$. In simulation tests, the channel pricing parameters, such as monetary parameters, channel qualities and preference coefficients, are subject to corresponding physical meaning. For example, $h_L \setminus h_H$ and $C_L \setminus C_H$ should conform to the definition of secondary users utility function. Besides, due to the convergence characteristic of the proposed algorithm, the initial values of channel pricing p_i^{0p} can be random and will converge to a fixed point eventually. The variance and mean value of the normal distribution depends on user preference's region $\frac{1}{2} h_1; h_2$.

In Fig. 6, we give the performances of the channel prices obtained in this paper with different marginal factors a . We can achieve from the figure that the optimal price of high-quality channel is much higher than that of lowquality

channel. Furthermore, the channel pricing rises with increasing marginal factor α since higher marginal cost needs to be compensated for the primary system. We further obtain that the iterative algorithm converges very fast which will attain a stable value within 15 iterations.

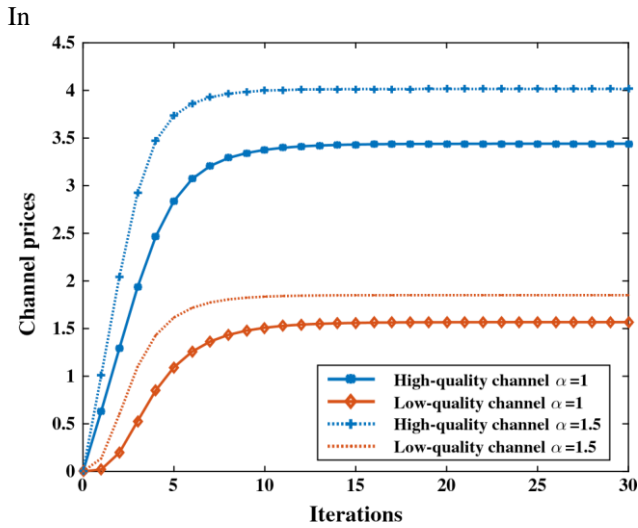


Fig. 6 Channel prices with different marginal factors

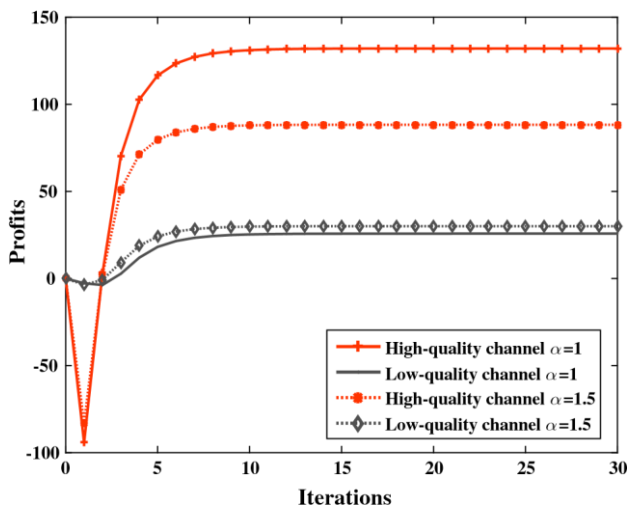


Fig. 7 System profits with different marginal factors

the counterpart, Fig. 7 gives the performances of the system profits under the optimal pricing with different marginal factors α . It is apparent in Fig. 7 that the system profits decrease with increasing marginal factor α which means the close relation between spectrum cost and system profit. Besides, it should be noted that the profit received on the high-quality channel overcomes that on the low-quality channel which is understandable since the primary system in nature expects to reap more profits through more excellent products.

Besides, Fig. 8 gives the performance of low-quality channel's pricing in various distribution types including linear, uniformed and normal distributions. When spectrum preference is subject to linear distribution, secondary users prefer to the high-quality channel which leads to a price increase as a result. In this case, spectrum customers have more cost endurance to pursue higher transmission

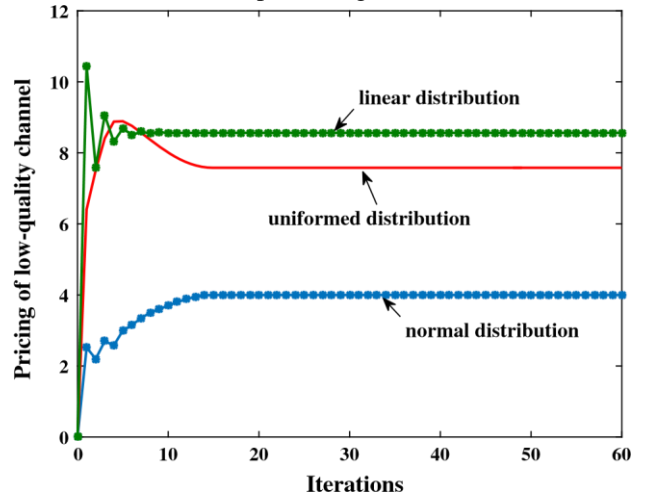


Fig. 8 Channel pricing in various distribution types

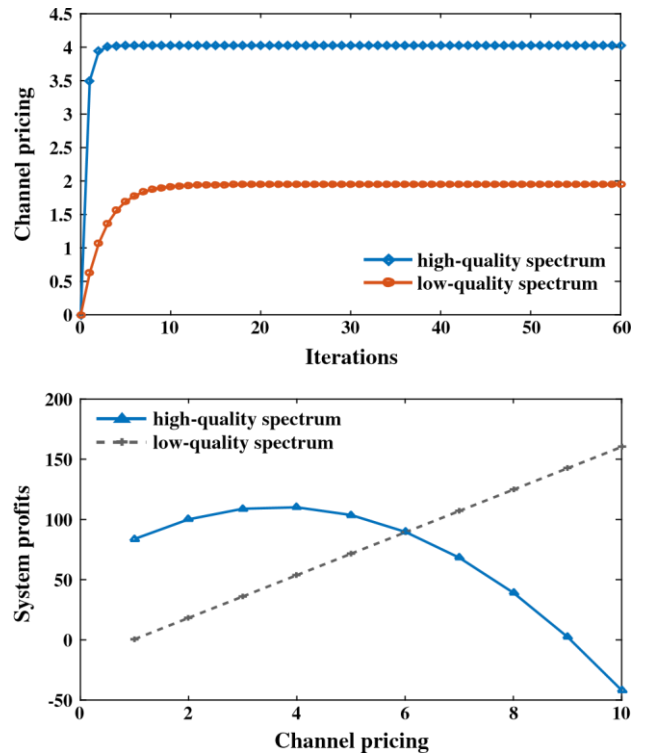


Fig. 9 Channel pricing and system profits of IPA method

capacity. For the case of normal distribution, the spectrum pricing is affected by the position of preference parameter's mean value and variance.

Furthermore, as shown in Fig. 9, we give the channel pricing and system profits of another spectrum pricing algorithm for heterogeneous secondary users defined as iterative pricing algorithm (IPA) [24]. The primary system profits and channel pricing in the IPA method are as follows

$$p_i = \frac{N \delta p_i a s_i p_i \delta h_i}{h_i} \quad \delta 22p$$

$$N \delta p_i a s_i p_i \delta h_i \quad \delta 23p$$

$$p_i = \frac{N \delta p_i a s_i p_i \delta h_i}{h_i} \quad \delta 24p$$

where p_i denotes the channel pricing, s_i denotes the channel quality, N denotes the total number of the leased channels.

h_i are the preference thresholds. a, b are the monetary coefficients. The system model and utility function of IPA method are more simple than ours. As the secondary user's preference in IPA method is assumed to be complied with ideal uniform distribution, the system profits and channel pricing are quite different to our method.

At last, we testify the performances of system profits with different channel prices as shown in Fig. 10. We can obtain from the figure that the system profits of the highquality channels do not grow continually with the increasing price of high-quality channel. Similar to the conclusions we deduced before, the utility functions of the system profits are convex with respect to corresponding channel pricing. Thus, the system profits of the highquality channels can attain a maximum. Besides, the performances of low-quality channel's profits differ from that of the high-quality channel as the argument in x-axis is the pricing of high-quality channel. On the other hand, the increase of the high-quality channel's pricing will lead to the loss of potential costumers to the high-quality channel which in turn improves the low-quality channel's profits.

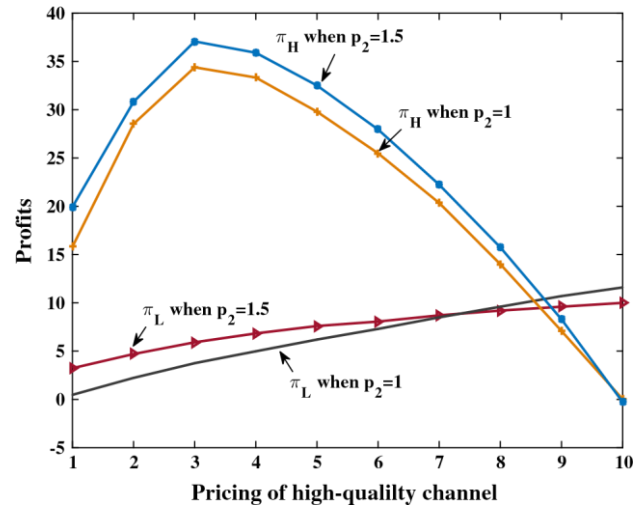


Fig. 10 System profits with changing channel pricing

5 Conclusions

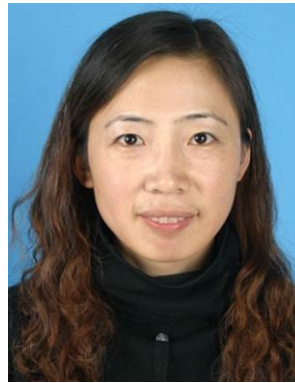
In this paper, we investigate how to price the heterogeneous spectrum in condition of secondary users' stochastic selection preferences. The main contribution of this paper lies in that we introduce a Hotelling game model to formulate and address the differential spectrum pricing. In the proposed model, we assume the idle spectrum is collected and leased to potential secondary users centrally so that a centralized spectrum pricing can be carried out by the primary system. Various qualities of idle spectrum constitutes a spectrum pool in which the bands are divided into numbers of uniform channels for leasing. It is foreseen the high-quality channels can incur more profits for the primary system by offering a high price. On the other hand, a

preference factor is introduced to describe the secondary user's selection tendency on the channels. We analyze the impact of secondary users' preference on spectrum trading, and propose an iterative algorithm for pricing. Proofs of the integrability of the utility function and existence of Nash equilibrium used in the proposal are also given. Numerical results are provided to testify the performances of the proposed optimal spectrum pricing and the corresponding system profits as a result.

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