Fair Power Control Using Game Theory with Pricing Scheme in Cognitive Radio Networks

Xianzhong Xie, Helin Yang, Athanasios V. Vasilakos, and Lu He

Abstract: **This paper proposes a payment-based power control scheme using non-cooperative game with a novel pricing function in cognitive radio networks (CRNs). The proposed algorithm considers the fairness of power control among second users (SUs) where the value of per SU' signal to noise ratio (SINR) or distance between SU and SU station is used as reference for punishment price setting. Due to the effect of uncertainty fading environment, the system is unable to get the link gain coefficient to control SUs' transmission power accurately, so the quality of service (QoS) requirements of SUs may not be guaranteed, and the existence of Nash equilibrium (NE) is not ensured. Therefore, an alternative iterative scheme with sliding model is presented for the non-cooperative power control game algorithm. Simulation results show that the pricing policy using SUs' SINR as price punishment reference can improve total throughput, ensure fairness and reduce total transmission power in CRNs.**

Index Terms: **Cognitive radio networks (CRN), fairness, game theory, power control, price.**

I. INTRODUCTION

Cognitive radio (CR) is an enabling technique that promises to overcome the problem of spectrum scarcity caused by the current way of fixed spectrum allocation. The Federal Communications Commission (FCC) found the utilization of the spectrum is low most of the time [1]. Thus, the technology of cognitive radio networks (CRNs) [2] is proposed to solve the problem of spectrum scarcity and improve spectrum efficiency.

In CRNs, power control deals with the selection of proper transmission power for second users (SUs) that achieves high spectrum efficiency by enabling SUs to reuse the primary users (PUs) spectrum bands under the interference constraints imposed by PUs. In the next generation wireless communications, SUs are expected to be uncoordinated opportunistic users, whereas there are conflicting interests among the SUs [3]. This motivates the use of non-cooperative game theory to perform researches on CRNs (see a survey paper [4]).

Non-cooperative power control game (NPG) was developed in [5], in which the existence and uniqueness of 'Nash equilibrium (NE)' were verified, based on NPG with pricing (NPGP) achieved Pareto improvement by introducing a linear-pricing into the utility function [6]. Considering the fluctuation of radio resource in CRNs, it is desirable to investigate more effective game algorithms. A linear pricing function based on throughput has been proposed under single-user and multi-users scenario in [7], [8]. Different game theories were applied to form power control algorithms in [9], [10], where effective receiver and strategy attempted to maximize global utility were developed. The finitely repeated game and discounted repeated game have been proposed to achieve Pareto improvement in the energy-efficient power control game [11]. In order to improve convergence speed, a modified shuffled frog leaping algorithm (NPG-MSFLA) for solving NE was proposed in [12]. For power control in the underlay scenario, a new iterative algorithm using game theory has been proposed in [13]. In [14], a realistic primary-secondary game theoretic scheme was proposed, in which Rician and Rayleigh fast flat fading channels were analyzed, but energy efficiency was not taken into account. Moreover, an efficient swarm intelligent algorithm based on power control game (NPGP-ESIA) with underlay spectrum access to attain NE was proposed in [15]. Also, a better global utility is achieved and the transmission quality of PUs and SUs is guaranteed by NPGP-ESIA.

In addition, the issue about pricing in power control game CRNs was important for NPGP. In [16], the authors investigated the pricing issue for the power control problem in CRNs. In [17], the optimal investment and pricing decisions in CRNs under spectrum supply uncertainty were addressed. In [18], the authors proposed a joint pricing and power control scheme for CRNs. Another important issue of power control is to reduce power consumption to extend terminal's life-time [19]. Considering the utility of the base station (BS) is non-convex function, it is difficult to find the optimal pricing scheme, so the literature [20] presented a novel price-based power control algorithm to find the optimal price for each SU. However, those papers ignored the minimum signal to interference plus noise ratio (SINR) requirement among SUs and fairness issue in the CRNs. Therefore, several payment schemes [16], [21], [22] under a game theoretic framework termed non-cooperative game with pricing, as an attempt to provide throughput fairness among SUs. The paper [16] proposed a novel non-cooperative game power control model to verify the sub-optimality, fairness, and efficiency of the proposed pricing scheme. A double-threshold adaptive algorithm [21] based on game theory was proposed to optimize the power control as well as maintain the fairness

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among SUs in CRNs. In [22], a cost function based on fairness is designed, a power control algorithm based on SINR cost function was presented, and a non-cooperative power control game via fairness pricing (NPGFP) algorithm was developed. However, those research studies didn't take the energy efficiency into account, and the minimum SINR requirement among each SU was also ignored, too.

In this paper, inspired by the game theory used in networks, we propose a dynamic power control scheme based on non-cooperative game theory for power control in CRNs. In this power control game algorithm (NPGP), where the value of each SU's SINR or position distance is used as the punishment pricing setting reference in CRNs, as an attempt to provide throughput fairness among SUs. In addition, due to the effect of uncertainty fading environment, the system disables to get the link gain coefficient to control SUs' transmission power accurately, the minimum quality of service (QoS) requirements of SUs may not be guaranteed, and the existence of NE is not ensured. Therefore, an alternative iterative algorithm with the sliding model called (R-NPGP) is presented based on the NPGP algorithm in order to guarantee user's QoS requirement and ensure fairness among SUs.

The rest of the paper is organized as follows. Section II describes the system model. In Section III, we study the conventional non-cooperative power control game algorithms, and propose our non-cooperative power control game model with four pricing punishment parameter setting strategies. This section also investigates the existence of NE in the proposed scheme. An available iterative algorithm with sliding model is presented to guarantee SUs' QoS requirement and ensure the existence of NE in Section IV. Simulation results and analysis are illustrated in Section V. Finally, Section VI concludes this paper.

II. SYSTEM MODEL

In this paper, we set a CNR shown in Fig. 1 and focus on uplink power control game. For simplicity, it is assumed that one PU link which consists of a primary transmitter and an access point (AP) and SUs are collocated in the CRN. The secondary base station (SBS) is located at the centre of the network. Several SUs near the primary transmitter will interfere with the primary transmitter to a certain degree. Therefore, SUs should limit their transmission power to avoid extreme interference.

One of the designing goals of power control in a CRN is to ensure that no SU's SINR γ_k falls below its threshold $\gamma_k^{\min}$ to ensure minimum transmission QoS requirement. Thus, there is

$$\gamma_k \geq \gamma_k^{\min}, \quad \forall k. \tag{1}$$

For individual mobiles, this threshold can be calculated to maintain a satisfactory frame error rate. The SINR of the kth SU can be defined as

$$\gamma_k(p_k) = \frac{G h_k p_k}{\sum_{i=1, i\neq k}^{K} h_i p_i + \sigma^2}, \quad k = 1, 2, \cdots, K \tag{2}$$

where p_k denotes the kth SU's transmission power, is the processing gain respectively, h_k denotes the channel link gain of the communication link between the kth SU and the SBS, σ^2 is the power of the Gaussian noise.

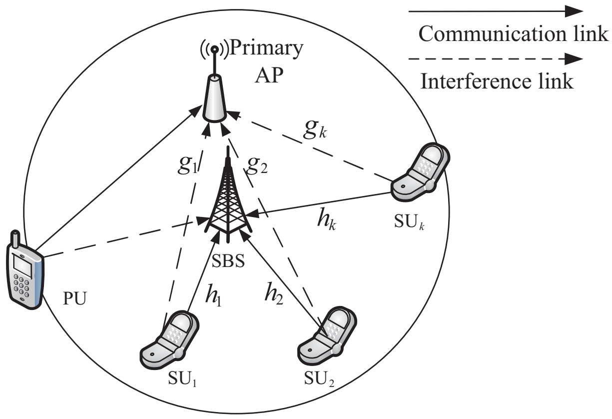

Fig. 1. Illustration of system model.

In this model, the total interference power made by SUs should be below a given threshold T to ensure the SUs' transmission would not cause unendurable interference to the PU

$$\sum_{k=1}^{K} g_k p_k \leq T, \quad k = 1, 2, \cdots, K \tag{3}$$

where g_k denotes the link gain from the kth SU to AP. Meanwhile, the power of the kth SU satisfies $0 \leq p_k \leq p_{k,\max}$.

III. NON-COOPERATIVE GAME ALGORITHM FOR POWER CONTROL

Non-cooperative game theory plays an important role in the complicated and competitive schemes in CRNs. In this section, motivated by conventional classic non-cooperative game algorithms, we investigate the design guideline of pricing function in the NPGP. It is challenging to find an optimal power control strategy with fairness among all SUs. Therefore, a novel pricing function of each SU is developed, and we prove that the proposed game model has a NE by supermodular game theory.

A. Conventional Classic Non-Cooperative Game Algorithm

Game theory represents a set of mathematical tools developed for the purpose of analyzing player interactions in decision processes. This paper proposes a game model to control transmission power among SUs in CRNs, and uses the SINR value as the punishment price reference. We define the power control problem as a non-cooperative game to get the solution for the power control problem

$$\Theta = \{K, \{P_k\}, \{U_k(\cdot)\}\} \tag{4}$$

where $k = [1, 2, \cdots, K]$ is the index of the participating SUs, who are decision makers that select a particular power level to transmit; P_k denotes the set of transmission power strategies of the kth SU,and $U_k(\cdot)$ is the utility functions of the kth SU.

The profit in the power control game is usually determined by a given utility function. The utility function in [6] can be written as

$$\text{NPGP} : U_k(p_k, \mathbf{P}_{-k}) = \frac{LR}{M p_k}(1 - e^{-\gamma_k/2})^M - c_1 p_k \tag{5}$$

where M is the length of the packet and every SU transmits L information bits in every packet ($L < M$), $c_1$is predefined positive cost factor, $\mathbf{P}_{-k}$ is all SUs power vector sets except for the kth SU: $\mathbf{P}_{-k} = [p_1, p_2, \cdots, p_{k-1}, p_{k+1}, \cdots, p_K]$, and R is the transmission rate. Based on the utility function above, a more effective one has been proposed in [12] as follows

$$\begin{aligned}\mathrm{NPG-MSFLA}: U_k(p_k, \mathbf{P}_{-k}) &= \frac{LR}{Mp_k}(1 - e^{-\gamma_k/2})^M \\ &\quad - c_2 e^{p_k} - c_3(\gamma_k - \gamma_k^{\min})\end{aligned} \tag{6}$$

where c_2 and c_3 are predefined positive cost factors. In (5) and (6), the same efficiency function $f(\gamma_k)$ related to non-coherent frequency shift keying (FSK) modulation scheme defined to match with the frame success ratio (FSR), which the efficiency function can be described as follows

$$f_1(\gamma_k) = (1 - e^{-\gamma_k/2})^M. \tag{7}$$

A novel utility function based on a new-designed pricing function was proposed in [15], which is defined as follows

$$\begin{aligned}\mathrm{NPGP-ESIA}: U_k(p_k, \mathbf{P}_{-k}) &= \frac{LR}{Mp_k}\frac{1 - e^{-\gamma_k}}{1 + e^{\gamma_k - \gamma_k^{\min}}} \\ &\quad - \alpha e^{\beta((\gamma_k/\gamma_k^{\min})-1)}\frac{p_k}{p^{\mathrm{th}}}\end{aligned} \tag{8}$$

where α and β are positive constants. The unit of α is bits/Joule and α is used to adjust the order of punishment. In the paper, the authors set the parameters: $\alpha = 2$ and $\beta = 1$. Moreover, $f_2(\gamma_k) = (1 - e^{-\gamma_k})/(1 + e^{\gamma_k - \gamma_k^{\min}})$ represents the efficiency function based on the sigmoid function [23]. p^{th} denotes the available interference power of the SU maximum signal leakage power interference from other SUs. The average interference power threshold can be obtained by the mean value of p_k^{th} : $p^{\mathrm{th}} = (p_1^{\mathrm{th}} + p_2^{\mathrm{th}} + \cdots + p_K^{\mathrm{th}})/K$.

B. The Proposed Game Model

In this section, we propose a novel pricing algorithm to maximize its revenue according to the property of the transmission power of SUs under the optimal price. Moreover, in order to reduce the computational complexity, a new efficiency function is presented in this section.

Inspired by the sigmoid function [24], we define the "efficiency function" in order to reduce the complex to implement in practice as follows

$$f_3(\gamma_k) = \frac{1}{1 + e^{\gamma_k^{\min} - \gamma_k}}. \tag{9}$$

This sigmoid efficiency function $f_3(\gamma_k)$ is related with user's SINR and can be used regardless of the modulation of radio access technology. The presented efficiency function is the S-shaped (sigmoidal) with $f(\infty) = 1$, and $f(0) = 0$ to ensure $U_k = 0$ when $p_k = 0$.

The comparison among these efficiency functions is shown in Fig. 2.

Pricing issue is a tool that improves performance by encouraging the users to use system resources more efficiently in an efficient pricing mechanism, where decentralized decisions are compatible with the overall system performance. So, non-cooperative power control game pricing model provides a better power control solution as follows

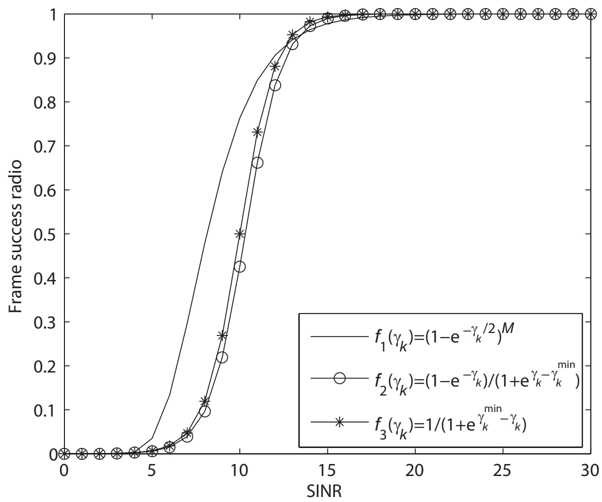

Fig. 2. Different efficiency functions comparison.

$$\mathrm{NPGP}: \max U_k^*(p_k, \mathbf{P}_{-k}) = U_k(p_k, \mathbf{P}_{-k}) - c_k(p_k, \mathbf{P}_{-k}) \tag{10}$$

where $c_k : \mathbf{P} \longrightarrow R^+$ is the pricing function of the SU. In this paper, we have $c_k(p_k, \mathbf{P}_{-k}) = \mu\lambda_k(p_k/p^{\mathrm{th}})$, where λ_k denotes the punishment parameter of the SU, μ is positive cost factor. The pricing punishment parameter setting among all SUs are different according to their general situation.

Therefore, our proposed NPGP pricing model is expressed as

$$\mathrm{NPGP}: \max U_k^*(p_k, \mathbf{P}_{-k}) = \frac{LR}{Mp_k}\frac{1}{1 + e^{\gamma_k - \gamma_k^{\min}}} - \mu\lambda_k\frac{p_k}{p^{\mathrm{th}}}. \tag{11}$$

The pricing function is a nonlinear function of the received power to indicate interference to other SUs achieving better throughput performance. So, we adopt an adaptive pricing scheme in which λ_k varies for different SUs based on their generated conditions. Therefore, we propose four following adaptive pricing punishment parameter setting policies.

Before the discussion of the policies, a performance metric is needed to assess the fairness incurred in the system as a result of competition in our metric. The throughput fairness factor is adopted here [25] and defined as

$$\xi = 1 - \left(\frac{1}{\overline{T}}\right)\sqrt{\frac{1}{N-1}\sum_{k=1}^{K}\left(\frac{T_k}{T_k^{\max}} - \overline{T}\right)^2} \tag{12}$$

where $T_k^{\max}$ is the maximal throughput if transmitters only distribute power to the user k ; and $\overline{T} = 1/K\sum_{k=1}^{K} T_k/T_k^{\max}$, is the normalized throughput per communication pair. The physical meaning of ξ is the normalized variance of SUs throughput compared with that of the single-user case. So, ξ provides a possible definition to measure the fairness in CRNs. Therefore, if

ξ is higher, then the throughput sharing among the SUs will be more fair.

B.1 Policy 1

In the policy, we present a pricing punishment parameter setting based on their generated interference (SINR), λ_k can be denoted as

$$\lambda_k = \frac{\gamma_k}{\sum_{k=1}^{K} \gamma_k}. \tag{13}$$

From (13), we can see that the SU who with higher SINR (better channel condition) after each one receives their maximized utility should be distributed with lower transmission power by setting higher pricing punishment. In contrast, the SU with lower SINR (worse channel condition) is encouraged to transmit with higher power by setting lower pricing punishment. The punishment parameter should be strictly charged according to the SINR value to discourage SUs who have high SINR and interference. So the effective pricing punishment parameter setting can confine selfish behaviors who want to increase their transmission power level. The SUs who are charged high prices will rationally reduce their transmission power in order to maximize their utility. Hence, all SUs have fair opportunities to transmit with similar throughput level and the throughput fairness can implicitly be achieved in this context.

B.2 Policy 2

In this policy, the adaptive pricing punishment parameter λ_k as follows

$$\lambda_k = \frac{1/\gamma_k}{\sum_{k=1}^{K} (1/\gamma_k)}. \tag{14}$$

The pricing policy presented in this system is similar to the one presented in [5], where the pricing function encourages users transmitting at high power to increase their power levels continuously until NE is reached when all SUs ensure the minimum QoS requirement (minimum SINR requirement). In other words, the SU with higher SINR (good channel condition) is encouraged to transmit with more power by setting lower pricing punishment. In contract, the SU with lower SINR (bad channel condition) is forced to transmit with lower power, so they will be set higher pricing punishment.

B.3 Policy 3

In this policy, we propose a new pricing scheme, which depends on the distances from the SUs to the SBS. The pricing punishment parameter λ_k can be defined as

$$\lambda_k = \frac{1/d_k}{\sum_{k=1}^{K} (1/d_k)} \tag{15}$$

where d_k denotes the distance between the kth SU and the SBS. In the CRN, the SU whose node locates further away from the SBS than other SUs may suffer more environmental effect, such as fading, so the SU is encouraged to be more transmission power to satisfy their minimum SINR requirement by setting lower pricing punishment. In contract, the SU who places closer to the SBS is forced to distribute with less transmission power level by setting higher pricing punishment.

B.4 Policy 4

According to the relevant discussion of the *Policy* 3, in this policy, we set the pricing punishment parameter as follows

$$\lambda_k = \frac{d_k}{\sum_{k=1}^{K} d_k}. \tag{16}$$

From (16), we observes that the SU who places closer to the SBS is encouraged to distribute with more transmission power by setting lower pricing punishment. In contrast, the SU who locates further away from the SBS than other SUs is forced to transmit with lower power, so the SU will be set higher pricing punishment. From the above discussion of the pricing punishment setting policies, it is obvious that the *Policy* 1 considers the fairness among SUs more than others', and the performance comparison certification will be presented in Section V-B. Because the SU with higher SINR situation is forced to reduce their transmission power level by setting higher pricing punishment, so it can reduce the interference to other SUs. At the same, the SU who with lower SINR is engorged to be higher transmission power level by setting lower pricing punishment, so it can increase the SU' SINR after the process. In contract, the *Policy* 2 and *Policy* 4 reveal that the SU who with good transmission environment (high SINR or close distance) is encouraged to transmit higher power to improve their throughput by ignoring casing high interference to other SUs who have bad transmission environment (low SINR or far distance). So, those two policies may improve the total throughput, but throughput fairness is ignored among SUs.

C. Existence of NE

According to [26], all of the participants in the utility function should satisfy the following two conditions can be a supermodular game.

1) All the game players' strategy space is tight sets.
2) $\partial^2 U^*_{k(\mathrm{SINR})}/\partial p_k \partial p_i \geq 0,\ \forall k \neq i \in K.$

According to the theory of the Topkis fixed point theorem [26], all supermodular games have at least a NE point. It is obvious that our proposed NPGP algorithm satisfies the first condition of a supermodular game because of each SU's strategy space $P_k \in [p_{\min}, p_{\max}]$. In addition, the scheme is similar to a study [26], where the authors proved the advanced method could improve the Pareto dominance. So, our scheme is a supermodular game if we prove the scheme satisfies the second condition. And we take the *Policy* 1 as an example to prove our scheme is a supermodular game.

The mixed second-order partial derivatives of the utility function can be written as

$$\frac{\partial^2 U^*_k}{\partial p_k \partial p_i} = \frac{\gamma_k LR}{M p_k^2} \frac{\partial^2 f_3(\gamma_k)}{\partial \gamma_k^2} \frac{\partial \gamma_k}{\partial p_i} + \frac{2\mu \gamma_k h_i}{p_k^{\mathrm{th}} \left(\sum_{i=1, i\neq k}^{K} h_i p_i + \sigma^2 \right)^2} - \frac{\partial \gamma_k}{\partial p_i} \frac{2\mu}{p_k^{\mathrm{th}} \left(\sum_{i=1, i\neq k}^{K} h_i p_i + \sigma^2 \right)^2}. \tag{17}$$

The first-order derivative of γ_k with respect to p_i can be written as

$$\frac{\partial \gamma_k}{\partial p_i} = -G\frac{h_k p_k h_i}{(\sum_{i=1,i\neq k}^{K} h_i p_i + \sigma^2)^2} < 0 \tag{18}$$

The second-order derivative of the efficiency function $f_3(\gamma_k)$ with respect to γ_k has the form

$$\frac{\partial^2 f_3(\gamma_k)}{\partial \gamma_k^2} = \frac{e^{\gamma_k^{\min}-\gamma_k}(e^{\gamma_k^{\min}-\gamma_k}-1)}{(1+e^{\gamma_k^{\min}-\gamma_k})^3} < 0. \tag{19}$$

Substituting (1), (18), and (19) into (17), we can get the inequality $\partial^2 U^*_{k(\mathrm{SINR})}/\partial p_k \partial p_i \geq 0$. Hence, based on the aforementioned definition, the proposed power control game is a supermodular game. So the NPGP model at least has a reasonable NE point.

IV. ROBUST POWER CONTROL FOR THE PROPOSED MODEL

In practical implementations, the important concern in wireless systems is the estimation of the time-varying channel conditions which occur due to mobility and/or changing environment, so channel information can hardly be known precisely a priori. In the paper, all SUs have the ability to estimate the environmental shadow fading situation to a certain extent, the link gain of kth SU is modified as [27]

$$h'_k = w_k d_k^{-4} \tag{20}$$

where w_k means the shadow fading factor of kth SU. Then, the SINR for kth SU is modified as

$$\gamma'_k(p_k) = \frac{G h'_k p_k}{\sum_{i=1,i\neq k}^{K} h'_i p_i + \sigma^2}, \quad k = 1, 2, \cdots, K. \tag{21}$$

Due to the estimation error of the shadow fading effect, the design of an optimal power control scheme is challenging but is definitely required for commercial implementation requiring SINR information as well as being robust to uncertainty when partial SINR information is available to the transmitter. In addition, the NE point is hard to achieve when the accuracy of SINR value can't be ensured.

In this section, we take the novel pricing punishment setting strategy *Policy* 1 as an example into the analysis (The performance certification why *Policy* 1 is the best strategy shown in Section V). Motivated by the sliding mode theory [28], the sliding model controller makes the transmission power controller robust to modeling errors and unknown disturbances and guarantees the desired QoS of SUs through the power control process. Therefore, this section presents an iteration algorithm for NPGP scheme to control the total transmission power with the sliding model help, in order to guarantee the minimum SINR requirements among all SUs and ensure NE point in opportunistic available SINR information.

We assume the set of power control strategies of the kth SU: $p_k = [p_{k,\min}, p_{k,\max}]$, and set an infinitely small quantity $\varepsilon(\varepsilon > 0)$. So the power control algorithm based on iteration algorithm with the sliding model as follows.

- Step 1. Set $n = 0$, and input the initial transmission power array $\mathbf{P}(n) = [p_1(n), p_2(n), \cdots, p_K(n)]$.
- Step 2. Then $n = n + 1$, update the value of γ'_k according to (21) and set the punishment price for the kth SU based on (13).
- Step 3. Use the sliding model to make the transmission power controller robust to the uncertainty SINR information and guarantee all SUs' minimum QoS requirement.
- Step 3.1. Calculate the sliding surface S_k and the Lyapunov function V_k [29] for kth SU as follows

$$S_k(n) = \gamma'_k - \gamma_k^{\min}, \quad V_k(n) = \frac{1}{2}S_k^2(n), \quad k \in K. \tag{22}$$

- Step 3.2. Calculate the following equation

$$\overline{V_k(n)} = \overline{\gamma'_k(n)}(\gamma'_k(n) - \gamma_k), \quad k \in K. \tag{23}$$

where $\overline{\gamma'_k(n)}$ and $\overline{V_k(n)}$ denote the time derivative of $\gamma'_k(n)$ and k. If $\overline{V_k(n)} < 0$, then the sliding surface $S_k(n)$ is globally asymptotically stable (see, for example, [29]) meaning the system guarantees QoS requirement for kth SU.
- Step3.3. Ensure $\overline{V_k(n)} < 0$ using the sliding model [29], obtaining the suitable power interval of kth SU: $p'_k(n) = [p'_{k,\min}, p'_{k,\max}]$.
- Step 4. According to each SU suitable power interval power based on the step 3, obtain the transmission power array $\mathbf{P}'(n)$ for all SUs through NPGP scheme.
- Step 5. If all SUs satisfy with the following condition: $|\gamma'_k(n) - \gamma'_k(n-1)| < \varepsilon$, then stop the algorithm, the obtained transmission power array $\mathbf{P}'(n)$ is the optimal power control array for SUs. Else, go back to step 2.

In addition, the convergence and computational simulation time will be discussed in subsection V-B. The flow chart illustrating the proposed scheme (called R-NPGP) is shown in Fig. 3. According to the forward proved progress of the above description, the algorithm can get the final NE point, and obtain the final optimal power control array $\mathbf{P}'(n)$ with the uncertainty SINR information. Also, the system guarantees SUs' QoS requirement and ensures fairness among all SUs.

V. SIMULATION RESULTS

We consider a CRN with the cell radius of 1 km. The SBS is placed at the centre of the cell where SUs are uniformly distributed around the SBS. The distance between the SUs and the SBS is chosen arbitrarily within $(0, 1)$ km. The parameters $\mu = 50,000$, processing gain $G = 100$, bit rate $R = 10,000$ bit/s, total number of bits $M = 80$ bits, number of information bits $L = 64$ bit, each SU deploys an isotropic transmitter with the same maximum power of $p_{\max} = 20$ mW, and $\varepsilon = 10^{-2}$.is assumed to be unity for all users. The background noise is assumed to be white Gaussian noise of $\delta^2 \sim N(0, 10^{-12})$.

A. The Enhancement of Proposed Iteration Algorithm Based Policy 1

We take the *Policy* 1 as an example to prove the effectiveness and superiority of the proposed iteration algorithm with sliding model for power control game when we set the number of SUs $K = 3$ in this chapter. Fig. 4(a), (b), and (c) depict the transmission power level updating, SINR variety among three SUs,

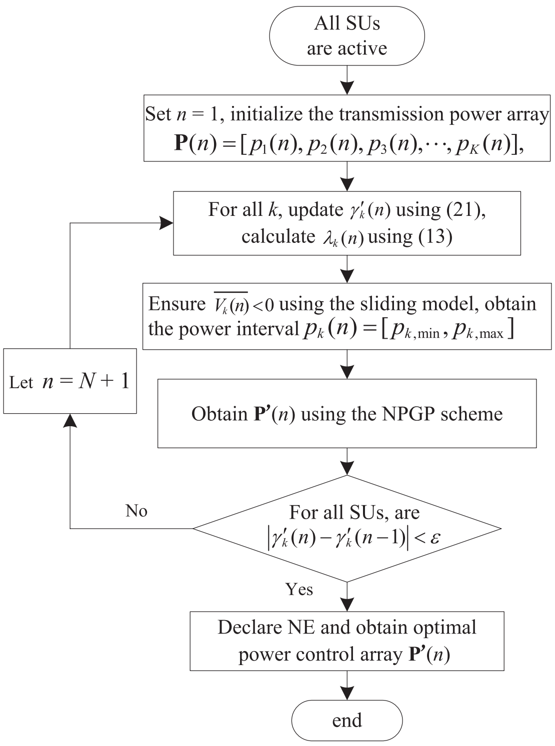

Fig. 3. Flowchart illustrating the R-NPGP scheme.

and fairness increase versus the numbers of iterations curves for the proposed algorithm. In more simulations, we find that after four to five iterations, the algorithm can converge. This means the convergence rate of our algorithm is fast and suitable for the real-time power control in CRNs.

Fig. 4(a) and (b) illustrate that updating the punishment price weights (see (13)) subsidizes the SU who generates bad channel condition (lower SINR) with higher transmission power level by setting lower pricing punishment. For example, the SU3 with lower SINR is encouraged to transmit with higher power by setting lower pricing punishment, SU1 and SU2 with higher SINR are forced to transmit with lower power. Five iterative processes are experienced to approximately reach the SINR at the same level. In addition, we observe that the fairness is enhanced in the system with more iteration (less than five iterations), shown in the Fig. 4(c), it indicates that the iteration algorithm with sliding model can guarantee all SUs' minimum QoS requirement and increase the throughput fairness among SUs.

B. The Performance Comparison of Our Four Proposed Policies

We now investigate the corresponding total throughput and the fairness issue among SUs for different number of SUs for the four proposed policies. The results are presented in Fig. 5, where the figures show that when the SU with better transmission environment (higher SINR, see the *Policy* 2) is encouraged to set higher transmission power level, a higher total throughput is attained but the throughput unfairness becomes more severe when the network grows larger. On the other hand, although

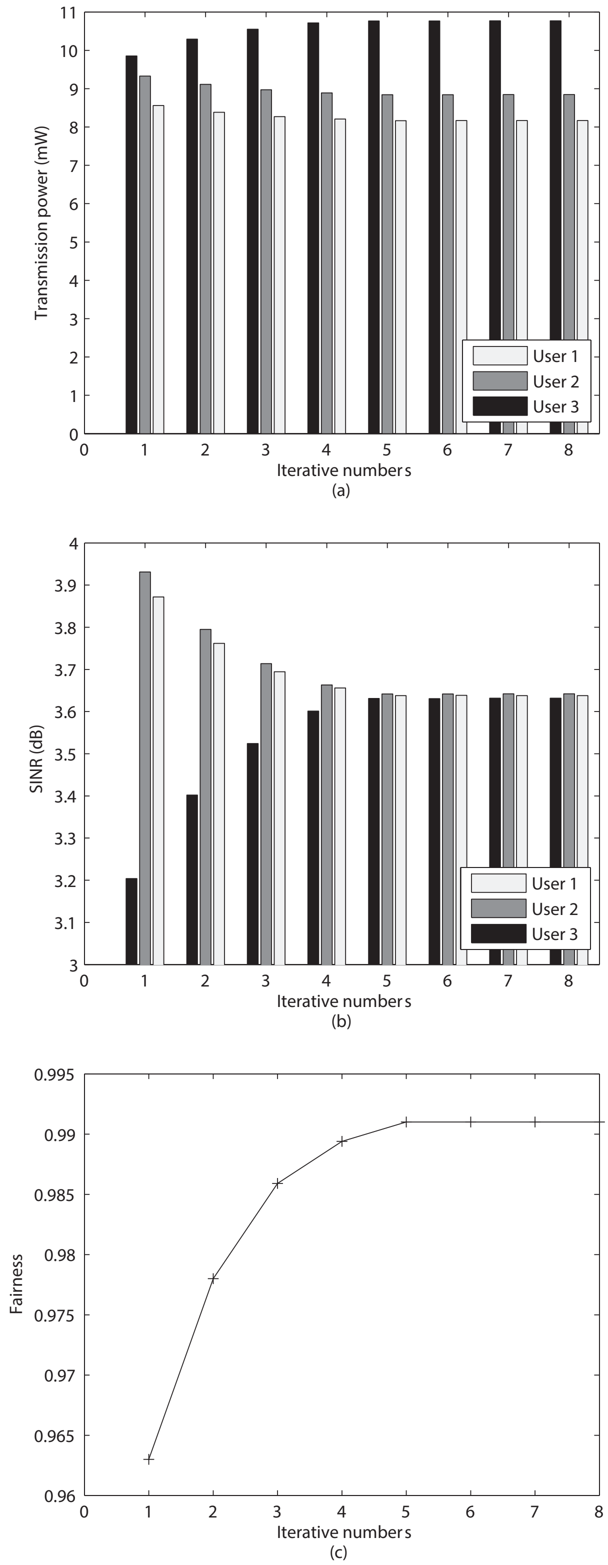

Fig. 4. Convergence of: (a) Transmission power levels, (b) SINR updating, and (c) fairness increase for three SUs.

fairness can always be ensured in the range of the number of SUs, however, this scheme (*Policy* 3) achieves the worst total throughput as compared with the *Policy* 1 and *Policy* 2. Com-

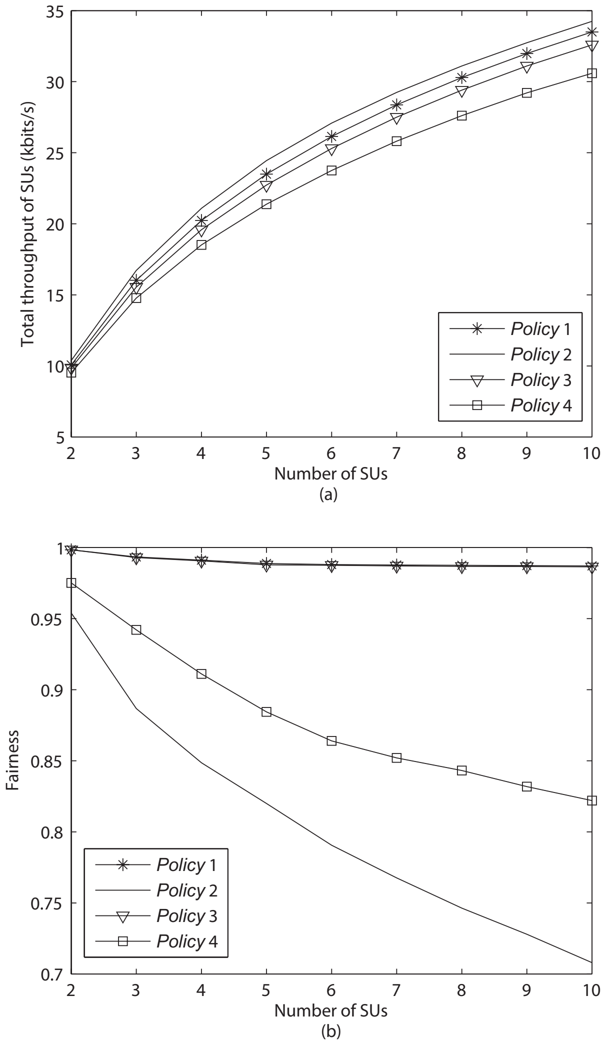

Fig. 5. Total throughput and fairness comparison with respect to different number of SUs.

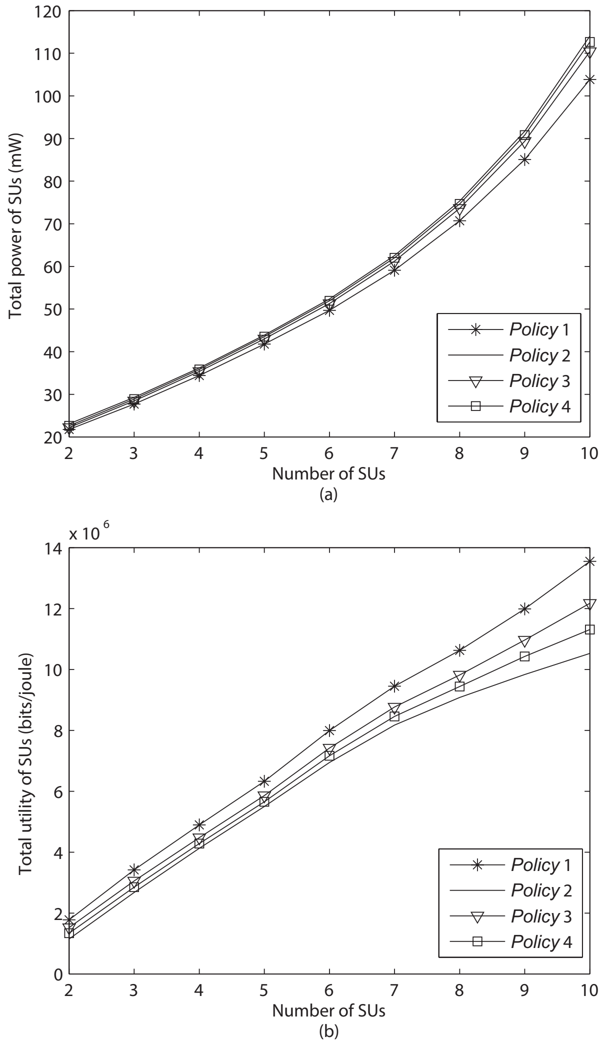

Fig. 6. Total power and utility comparison of different number SUs.

paring the *Policy* 1 with *Policy* 2, the fairness can be guaranteed in larger networks with a slight reduction in the throughput of the *Policy* 1, and the throughput fairness the *Policy* 2 suffers more serious with the increase of SUs, so we select the *Policy* 1 as the novel pricing scheme. In sort, it observes that the *Policy* 1 is novel scheme for the power control game algorithm in term of total throughput and throughput fairness among SUs.

In order to prove that the *Policy* 1 is a novel scheme further, the total power and secondary utility against the number of SUs are illustrated in Fig. 6. It can be seen that the total transmission power rises with the increasing of the number of SUs for all the algorithms. However, it observes from Fig. 6(a) that the performance gap between the *Policy* 1 and other policies is expanded with the rise of the number of SUs. Because we design an effective pricing function to confine the pricing punishment parameter, the SU with higher SINR is forced to reduce the transmission power, and the SU who needs more transmission power to guarantee the minimum QoS requirement is encouraged to set more transmission power level, so SUs can reasonably assign their own power (see *Policy* 1).

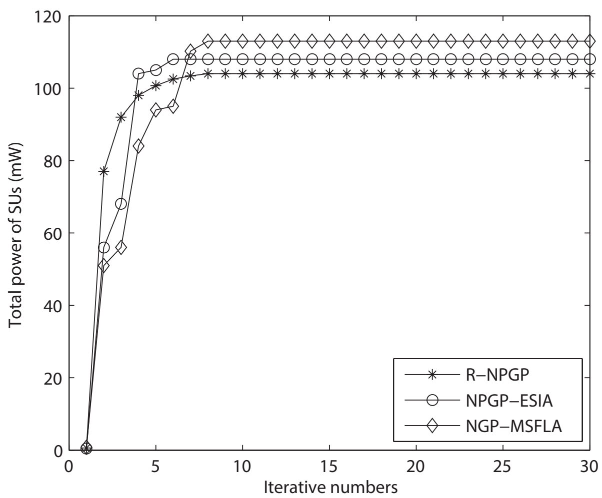

Fig. 7. Comparison of convergence speed.

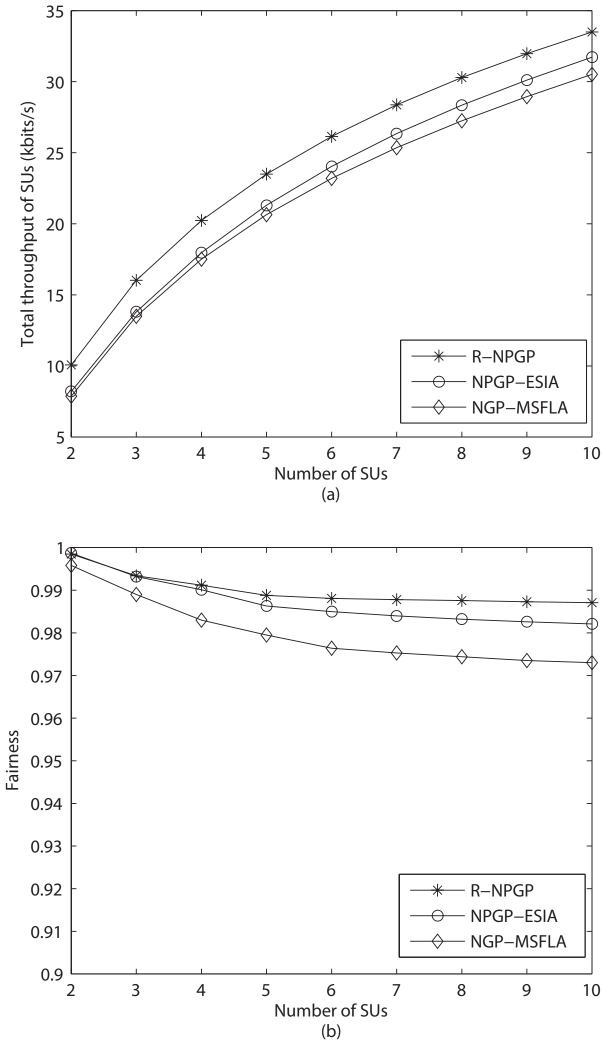

Fig. 8. Total power and secondary utility comparison for the three schemes.

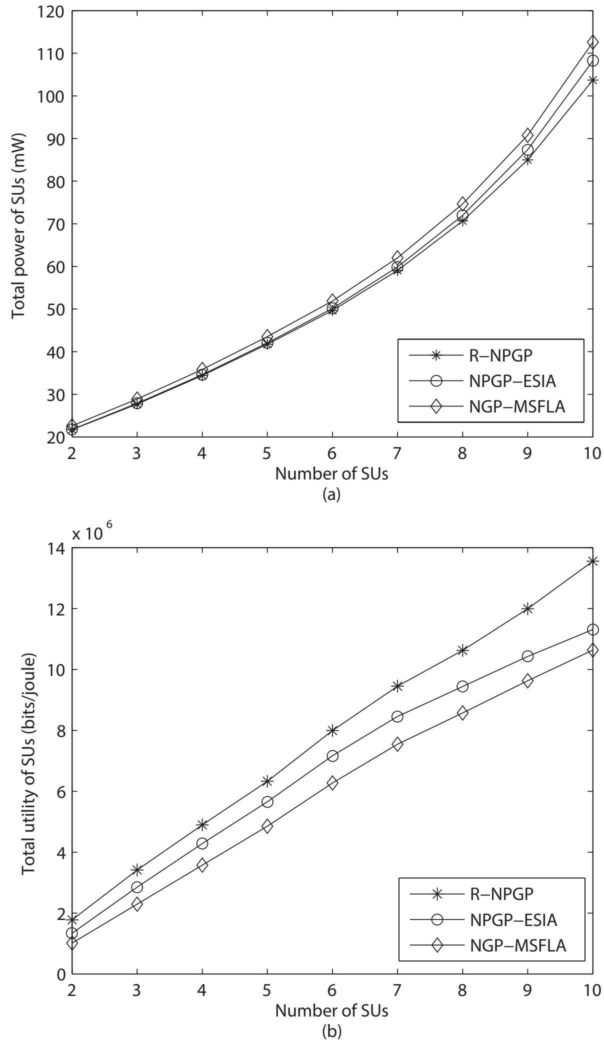

Fig. 9. Total power and secondary utility comparison for the three schemes.

Table 1. Comparison of simulation time.

Algorithms	R-NPGP	NPGP-ESIA	NGP-MSFLA
Simulation time (s)	2.26	7.37	5.18

From the previous analysis, the utility represents the number of information bits by successful SUs transmissions per Joule of energy expended. It can be seen from Fig. 6(b) that, with the increase of the number of SUs, the total utility is increased for all the algorithms. The secondary total utility of the *Policy* 1 is larger than other policies. Since the energy of mobile terminal is finite in practice, it is of great importance to enhance the energy-efficiency. Based on the observation from Fig. 6(b), it can be concluded that the *Policy* 1 improves the energy-efficiency substantially.

C. The Performance Comparison of the Three Game Algorithms

Fig. 7 describes the convergence performance and simulation time comparison of simulation time the three algorithms when $K = 10$. Without loss of generality, we suppose that all the SUs solve the optimal power with the same process. It can be seen from Fig. 7 that ESIA takes less than 6 iterations to converge to the steady state, and other two algorithms need 8 iterations which is minor more iterations process than ESIA performance. However, in Table 1, it is quite obvious that R-NPGP saves much simulation time than other two algorithms, which means that our proposed scheme reduces the computational complexity. This is because other two algorithms used artificial algorithms to search for the optimal power control strategies without considering the algorithm complexity. In addition, R-NPGP reduces total SUs transmission power compared with other methods.

In this section, we will compare the performance of the proposed R-NPGP scheme based on the *Policy* 1 with NPG-MSFLA [12] and NPGP-ESIA [15].

Fig. 8 shows the total throughput performance and fairness comparison with respect to different number of SUs for different algorithms. It can be seen that the performance of R-NPGP is better than NPGP-ESLA and NPG-MSFLA. In addition, the performance gap between R-NPGP and the other algorithms increase when the network grows larger, by which it can be concluded that R-NPGP is more suitable for applying in larger networks. Because R-NPGP scheme sets the adaptive punishment parameter among all served SUs based on the SINR information, and using a sliding model to guarantee the minimum QoS requirement among SUs and takes an available iteration algorithm to achieve NE. Therefore, our proposed scheme can improve the total throughput and guarantee fairness among SUs.

Fig. 9 shows the total power and secondary utility comparison with the increase of the number of SUs for the three schemes. In this paper, we design an adaptive effective pricing function to confine selfish behaviors, where the SUs need to pay the price for transmission power based on their SINR value. Therefore, the pricing strategy prevents the blind increase power from making serious interference to other SUs, and the total transmission power is naturally reduced. In addition, the total utility of R-NPGP is also larger than other two algorithms with the increase of the number of SUs. It can be concluded from Fig. 9 that compared with NPGP-ESLA and NPG-MSFLA, R-NPGP can obtain a significant improvement on secondary utility and reduces the total transmission power.

VI. CONCLUSION

In this paper, we propose a novel price-based power control algorithm in a CRN. This effective utility function considers the throughput fairness among SUs, where the SUs' SINR information is used as reference for the pricing punishment parameter setting. Moreover, due to the effect of uncertainty fading environment, the system is unable to get the link gain coefficient to control SUs' transmission power accurately. Therefore, we presented an alternative robust power control scheme with sliding model to guarantee SUs' QoS requirement and ensure the existence of NE. Simulation results show that R-NPGP based on SUs' SINR as price punishment reference can improve total throughput, ensure fairness and reduce total transmission power in CRNs.

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