An Efficient and Unbiased Power Control Algorithm Based on Game Theory in Cognitive Radio

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***Abstract*—Based on the non-cooperative power control game theory, we propose an efficient and unbiased power control algorithm in cognitive radio network (CRN) by improving the utility function. Without causing interference to the primary users (PUs), this effective utility function balances the fairness and system throughput of secondary users (SUs) via a fair pricing function. The pricing punishment parameter setting depends on the quality of received signal to guarantee the quality of service (QoS) requirement of the SUs. In addition, we prove that the proposed game model has 'Nash equilibrium point (NE)' by supermodular game theory and we give the iterative algorithm for the proposed game to attain the optimal power for all SUs. Simulation results show that the proposed game not only enhances the system throughput, reduces transmission power of SUs, and maximizes the global utility, but also takes the system fairness into account to some extent, which differs from other previous schemes.**

***Index Terms*—Cognitive radio networks; power control; game theory; efficiency function; pricing function; fairness**

I. INTRODUCTION

With the rapid development of wireless communication technology, more and more access demands of communication terminals lead to increasingly scarce spectrum resources. Federal Communications Commission (FCC) indicates that under the fixed spectrum allocation, the utilization of licensed spectrum is 15%-85%. To deal with the dilemma between spectrum congestion and spectrum underutilization, Cognitive radio (CR) technology has been proposed and advocated [1]. CR is an enabling technique that allows SUs to make full use of spectrum holes to improve the efficiency of the spectrum by spectrum sensing and spectrum sharing, without causing interference to PUs [2].

In CRNs, power control is an efficient way to select proper transmission power for SUs that achieves high spectrum efficiency by enabling SUs to reuse PUs spectrum bands under the interference constraints imposed by PUs. Game theory is used as an efficient mathematical tool for resource allocation in [3-4]. Moreover, power control using game theory has been attracted considerable attention recently [5-6]. Excellent literatures for power control using game theory can be found in [7]-[12]. Non-cooperative power control game (NPG) was first developed in [7], in which the existence and uniqueness of NE were proved, which is an equilibrium point where each player has no chance to increase its utility by unilaterally deviating from this equilibrium. Unfortunately, this NE point could not achieve Pareto-optimality which shows the achievable network-wide sum utility can be low compared with centralized optimization. In these games, rational but selfish users maximize their individual utilities in a self-interested manner without considering the impact of their strategies on other users.

There has been recent work that aims to improve the network-wide utility by introducing some pricing schemes [13]-[21]. Some forms of user cooperation are enforced in these pricing schemes to improve network utility. The improvement of Pareto-optimality was first achieved by NPG with pricing (NPGP) which introduced a linear-pricing function into the utility function in [13]. The combination pricing function (NPGP-CP) which was improved via non-linear function was proposed in [14]. In order to improve convergence speed, a modified shuffled frog leaping algorithm (NPGP-MSFLA) for solving NE was proposed in [15]. Moreover, an efficient swarm intelligent algorithm based on power control game (NPGP-ESIA) with underlay spectrum access to attain

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NE was proposed in [16]. the problem of efficient distributed power control in the uplink of CDMA wireless networks supporting multiple services was addressed in [17] , via the introduction of a game theoretic framework adopting convex pricing of users' transmission power. However, those papers ignored the minimum SINR requirement among SUs and fairness issue in the CRNs.

Because the utility of the base station (BS) is a non-convex function, it is difficult to find the optimal pricing scheme. Therefore, a novel price-based power control algorithm was presented in [18] to find the optimal price for each SU. In [19], a novel non-cooperative game power control model was given to verify the sub-optimality, fairness, and efficiency of the proposed pricing scheme. Joint pricing and power allocation for Dynamic Spectrum Access (DSA) networks with Stackelberg game was developed in [20]. In [21], the authors considered a wireless amplify-and-forward relay network with one relay node and multiple source-destination pairs and proposed a pricing framework that enabled the relay to set prices to maximize either its revenue or any desirable system utility. However, those research studies didn't take the energy-efficiency into account, and the minimum SINR requirement among each SU was ignored either. While these schemes offer some remedies to the non-cooperative game approach, they still leave room for improvement toward the global optimum.

In this paper, motivated by the game theory in wireless system, we improve the sigmoid efficiency function and pricing function to propose an efficient and unbiased non-cooperative power control game with pricing algorithm (S-NPGP). This pricing punishment parameter setting depends on the quality of received signal to guarantee the QoS requirement of the SUs, which is suitable for CRNs to balance the fairness and system throughput of SUs. Simulation results show that the S-NPGP enhances the network throughput, reduces transmission power of SUs, improves the utility, and considers system fairness to some extent.

The rest of the paper is organized as follows. Section II describes the system model. In Section III, we not only introduce the classic NPG models, but also propose our NPG model with pricing punishment parameter setting and sigmoid efficiency function. This section also proves the existence of NE in the proposed game and gives the iteration algorithm. Simulation results and analysis are illustrated in Section IV. Finally, Section V concludes this paper.

II. SYSTEM MODEL

In this paper, we consider a spectrum-sharing scenario in a heterogeneous network in which a primary network coexists with a secondary cognitive network in a spectrum underlay manner shown in Fig. 1. SUs and PU can transmit data simultaneously, but SUs have to strictly control their transmit power to avoid harmful interference to PUs.

We focus on the uplink of power control. For simplicity, it is assumed that one PU link consists of a primary BS, denoted as BS_p and a PU, denoted as U_p, which uses a licensed spectrum to communicate with the BS_p . A single-cell cognitive communication system without the spectrum license lies in the range of the PU networks. There are N SUs transmitting data to the secondary base station, denoted as BS_s . Assuming that the PU and SUs employ code division multiple access (CDMA) technique to utilize common spectrum for their own communications, the PU sends data to BS_p with a constant power. The received SINR of the kth SU can be written as follows

$$\gamma_k(p_k) = \frac{Gh_k p_k}{\sum_{i=1, i\neq k}^{N} h_i p_i + \delta_k{}^2}, \quad k = 1,2,...,K \tag{1}$$

where p_k is the transmission power of the kth SU and G is the processing gain. h_k denotes the path gain between the kth SU and the BS_s , g_k denotes the channel gain of the kth SU to the BS_p , and δ_k^2 is the power spectral density of the additive white Gaussian noise (AWGN) which causes degradation of the received signal at the BS. For practical consideration, the received SINR of the kth SU is no less than its threshold $\gamma_k^{\min}$ which is defined as minimum requirement of SINR for kth SU that is, $\gamma_k \geq \gamma_k^{\min}$.

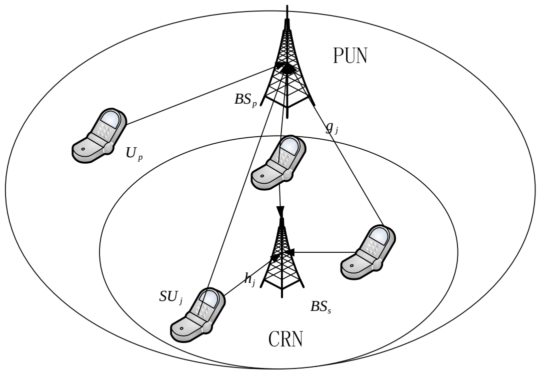


Figure 1. Illustration of system model

In this scenario, the power of the kth SU satisfies $0 \leq p_k \leq p_{k,\max}$. Meanwhile, all the SUs must restrain their transmission power in order not to cause interference to the PUs. The interference power received by the PU is $\sum_{k=1}^{N} g_k p_k$ which is no greater than the interference power threshold tolerable for U_p denoted as T . So the interference power constraint of the SUs system is given as

$$\sum_{k=1}^{N} g_k p_k \leq T \tag{2}$$

III. NON-COOPERATIVE GAME MODLE FOR POWER CONTROL

In the next generation wireless communications, SUs are expected to be uncoordinated opportunistic users. Therefore, there are conflicting interests among the SUs. This motivates the NPG theory play an important role in the complicated and competitive schemes in CRNs.

In this section, first, we introduce the classic NPG model and investigate the design guideline of pricing function in the NPGP. Second, we present our proposed S-NPGP model by introducing a new efficiency function and a fair pricing function. Third, we prove the existence of the NE for S-NPGP by supermodular game theory. In addition, we give the iteration algorithm to achieve the optimal transmission power of each SU.

A. Classic Non-cooperative Game Model

Game theory represents a kind of mathematical tool which is proposed for the purpose of analyzing interactions among players in decision processes. In [13], the authors define the power control as a non-cooperative game as follows

$$G=\left\{\mathcal{N},\left\{P_k\right\}\left\{U_k\left(\cdot\right)\right\}\right\} \tag{3}$$

where $\mathcal{N}=\left\{1,2,...,N\right\}$ is the index set for the participating SUs currently in the cell, P_k is the strategy spaces of transmission power, $U_k(\cdot)$ is the payoff function of SU k which measures the number of bits that can be successfully transmitted per joule of energy consumed. Each SU selects a power level p_k such that $p_k \in P_k$. Let the power vector $\mathbf{p}=(p_1,...,p_N)$ denote the outcome of the game in terms of the selected power levels of all the SUs. The resulting utility level for the kth SU is $U_k\left(\mathbf{p}\right)$. The objective of each SU in the system is to adapt its transmit power to maximize the utility under the power threshold tolerable of PU.

Based on the classic NPG model, a more effective utility function has been proposed in [14] can be expressed as follows

$$\text{NPGP-CP}: U_k(p_k,\mathbf{p}_{-k})=\frac{LR}{Mp_k}(1-0.5*e^{(-\gamma_k/2)})^M-Ah_k\left(1-e^{-Bp_kh_k}\right) \tag{4}$$

Where M is the length of the packet and every SU transmits L bits in every packet ($L<M$), R is the transmission rate of the kth SU. For simple consideration, the transmission rate of all the SUs are the same. c is predefined positive cost factor , $\mathbf{p}_{-k}$ is the power vector sets of SUs other than the kth SU denoted as $\mathbf{P}_{-k}=[p_1,p_2,\cdots,p_{k-1},p_{k-2},\cdots,p_K]$. In this utility function, the efficiency function related to non-coherent frequency shift keying (FSK) modulation scheme defined to match with the frame success ratio (FSR) which can be described as follows

$$f_1(\gamma_k)=(1-0.5*e^{(-\gamma_k/2)})^M \tag{5}$$

Based on the utility function above，a novel one with a new designed pricing function is proposed in [16] which is defined as

$$\text{NPGP-ESIA}: U_k\left(p_k\right)=\frac{LR}{Mp_k}\frac{1-e^{-\gamma}{}_k}{1+e^{\gamma_k^{tar}-\gamma_k}}-\eta e^{\mu((\gamma_k/\gamma_k^{tar})-1)}\frac{p_k}{p^{\mathrm{th}}} \tag{6}$$

where η and μ are positive constants. The unit of η is bit/Joule and μ is used to adjust the order of punishment. Moreover, the efficiency function based on [16] can be described as follows which is different from $f_1\left(\gamma_k\right)$

$$f_2(\gamma_k)=(1-e^{-\gamma_k})\Big/(1+e^{\gamma_k^{tar}-\gamma_k}) \tag{7}$$

Which is regardless of the modulation schemes, is only relevant to the γ_k of the kth SU and its threshold γ_k^{tar}.

In that paper, the authors set the parameters $\eta=2$ μ=1 . The available interference power of the kth SU under maximum interference is denoted by p_k^{th}. Assuming that all the SUs have the same priority to use the licensed spectrum, the PU treats all the SUs equally. Therefore the average interference power threshold can be obtained by the mean value of $p_k^{th}: p^{th}=(p_1^{th}+p_2^{th}+\cdots+p_k^{th})/K$.

For a reasonable pricing function, the link quality and the fairness of punishment should be concerned. The utility function of NPGP-CP is unfair for which it is only related to the SINR of SU. But the link quality is not taken into account. The pricing function of NPGP-ESIA is unreasonable either, for which it fails to guarantee the minimum QoS requirement of SUs.

B. The Proposed Game Model

In this section, focusing on the problem in paper [14] and [16], we propose a proper pricing function to maximize its revenue according to the optimal transmission power of SUs. Moreover, in order to reduce the computational complex, a new efficiency function based on the sigmoid function [22] is presented as follows

$$f_3\left(\gamma_k\right)=\left(1-e^{-\gamma_k}\right)\Big/\left(1+e^{x-\gamma_k}\right) \tag{8}$$

This sigmoid efficiency function is related to the SINR of SU and the value of x which is superior to others for which our efficiency function can reduce the computational complexity under the similar frame success ratio. This efficiency function is the S-shaped with $f(\infty)=1$, and $f(0)=0$ to ensure $u_k=0$ when $p_k=0$. In addition, the value of x is related to M defined in (4) and we can get the optimal x by using the least square method.

Fig. 2 illustrates the flowchart of calculation x and error compensation. When $M=80$, we get the optimal value of x that is, $x=8$ and error compensation according to the flowchart.

Fig. 3 shows the comparison of $f_1\left(\gamma_k\right)$ with M =80 and $f_3\left(\gamma_k\right)$ with the optimal x and other x. When

$x = 8$, our proposed efficiency function $f_3(\gamma_k)$ is the most closest to the efficiency function $f_1(\gamma_k)$ proposed in [14].

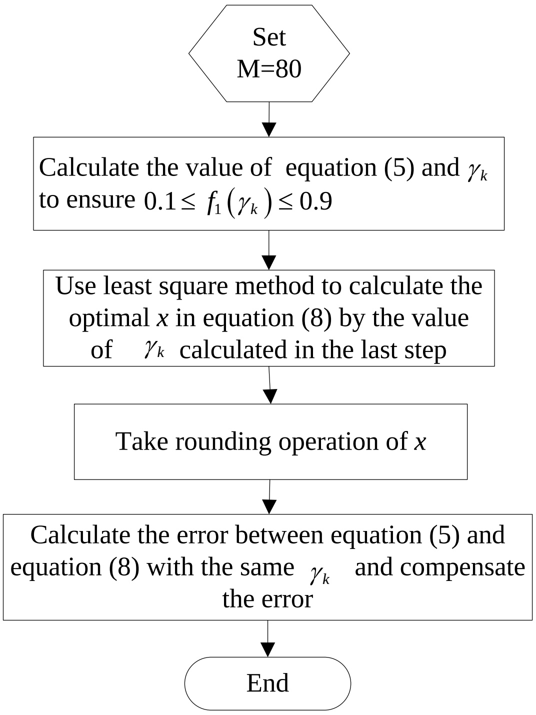


Figure 2. Flowchart illustrating of calculation x and error compensation

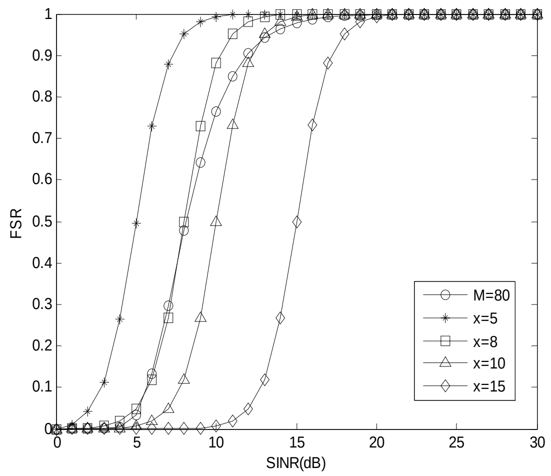


Figure 3. Comparison of the optimal x and other x

Table 1 shows the error compensation compared to the efficiency function $f_1(\gamma_k)$ when $x = 8$, from which we can see that the frame success ratio of our efficiency function is similar to $f_1(\gamma_k)$. The comparison among these efficiency function is shown in Fig.4, which shows that the performance of the three efficiency functions are analogous. However, our efficiency is superior to $f_1(\gamma_k)$ for which ours can reduce the computational complexity compared to $f_1(\gamma_k)$. Moreover, $f_2(\gamma_k)$ is not as flexible as ours for which the FSR of $f_2(\gamma_k)$ is related to γ_k^{tar}.

TABLE I.
ERROR COMPENSATION

SINR	7	8	9	10	11	12
Error compensation	0.027	0.021	0.091	0.117	0.103	0.077

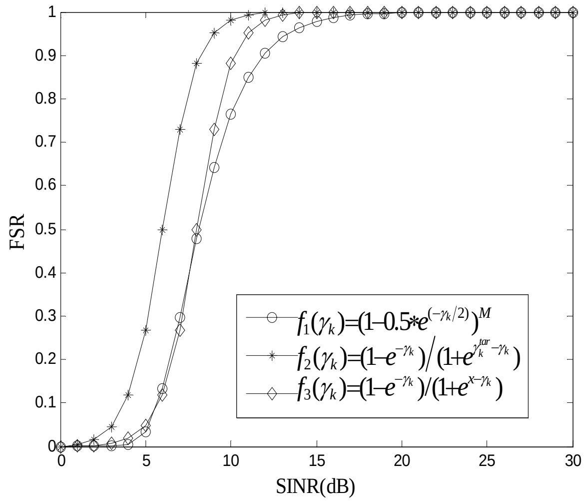


Figure 4. Different efficiency functions comparison

Before the discussion of the pricing function, a performance metric is needed to assess the fairness incurred in the system as a result of competition. We adopt the throughput fairness defined in [23] which can be described as

$$\xi = 1 - \left(\frac{1}{\overline{T}}\right)\sqrt{\frac{1}{N-1}\sum_{k=1}^{K}\left(\frac{T_k}{T_k^{\max}} - \overline{T}\right)^2} \tag{9}$$

Where $T_k^{\max}$ is the maximal throughout if transmitters only distribute power to the user k, and $\overline{T} = (1/K)\sum_k^K (T_k / T_k^{\max})$ is the normalized throughput per communication pair, ξ is the normalized variance of SUs throughput compared with the single-user case. So ξ provides a possible definition to measure the fairness in CRNs, that means ξ is higher, the throughput among the SUs will be more unbiased.

In order to improve the fairness of the pricing function, we define the pricing function according to the link quality, transmission power, and the received SINR which can be denoted as

$$c_k(p_k, \mathbf{P}_{-k}) = \alpha e^{I_k/I^{\mathrm{th}}} + \beta e^{\gamma_k/\left(\sum_{k=1}^{N}\gamma_k^{\min}\right)} \frac{p_k}{p^{\mathrm{th}}} \tag{10}$$

where α and β are the price weight of the punishment parameter, $I_k(\mathbf{p}_{-k})=\sum_{i=1,i\neq k}^{N} h_i p_i$ means that the interference of the i th SU except the interference itself and the average interference can be obtained follow as: $I^{\text{th}}=(I_1+I_2+\cdots+I_N)/N$ .Moreover, $\gamma_k/\left(\sum_{k=1}^{N}\gamma_k^{\min}\right)$ means 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 and vice versa. p_k/p^{th} is combined with p_k and the average interference power threshold p^{th} means that the punishment is light when p^k is less than p^{th} , otherwise, the punishment is serious. Therefore the punishment parameter should be strictly charged according to the SINR value and the interference from other SUs to discourage SUs who have high SINR and interference. So our proposed utility function is denoted as follows

$$\text{S-NPGP}: U_k(p_k)=\frac{LR}{Mp_k}\frac{1-e^{-\gamma_k}}{1+e^{x-\gamma_k}}-\alpha e^{I_k/I^{\text{th}}}-\beta e^{\gamma_k/\left(\sum_{k=1}^{N}\gamma_k^{\min}\right)}\frac{p_k}{p^{\text{th}}} \quad (11)$$

In this utility function, the punishment should be strictly charged by the interference, the SINR, and transmission power. So the effective pricing punishment parameter setting can avoid the selfish SUs who want to increase power level to reach the QoS requirement irrationally. Therefore, the throughout fairness can be achieved in this context implicitly as SUs who are interfered severely can improve their SINR by increasing their transmission power level fairly.

C. Existence of NE

According to [12], if all of the participants in the utility function satisfy the following two conditions, the schema will be a supermodular game.

(1) All of the strategy spaces is tight sets.

(2) $\dfrac{\partial^2 U^*_{k(SINR)}}{\partial p_k \partial p_i}\geq 0, \forall k\neq i\in K$

Based on Topkis fixed point theorem, all supermodular games have at least a NE point. Therefore, as long as our proposed game $G=\{\mathcal{N},\{P_k\}\{U_k(\cdot)\}\}$ is proved as a supermodular game, it has at least a NE point. Since the strategy space of the kth SU satisfies $0\leq p_k\leq p_{k,\max}$, it is obvious that it satisfies the first condition of supermodual game. We only need to verify whether the scheme satisfy the second condition or not.

The first-order derivative of the S-NPGP utility function with respect to p_k has the form

$$\frac{\partial U_k^*}{\partial p_k}=\frac{LR}{Mp_k^2}\left(\frac{\partial f_3(\gamma_k)\gamma_k}{\partial\gamma_k}-f_3(\gamma_k)\right)-\frac{\beta e^{\gamma_k/\left(\sum_{k=1}^{N}\gamma_k^{\min}\right)}}{p^{th}}\left(\frac{\gamma_k}{\sum_{k=1}^{N}\gamma_k^{\min}}+1\right) \quad (12)$$

And then, the second-order derivative of (12) with respect to p_i can be written as

$$\frac{\partial^2 U_k^*}{\partial p_k \partial p_i}=\frac{\gamma_k LR}{Mp_k^2}\frac{\partial^2 f_3(\gamma_k)}{\partial\gamma_k^{\,2}}\frac{\partial\gamma_k}{\partial p_i}-\frac{\beta e^{\gamma_k/\left(\sum_{k=1}^{N}\gamma_k^{\min}\right)}}{p^{th}\sum_{k=1}^{N}\gamma_k^{\min}}\frac{\partial\gamma_k}{\partial p_i}\left(\frac{\gamma_k}{\sum_{k=1}^{N}\gamma_k^{\min}}+2\right) \quad (13)$$

From (13), we get the first-order derivative of γ_k with respect to p_i can be written as

$$\frac{\partial\gamma_k}{\partial p_i}=-G_k\frac{h_k p_k h_i}{(\delta_k^2+\sum_{i=1,i\neq k}^{K}h_i p_i)^2}<0 \quad (14)$$

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

$$\frac{\partial f_3(\gamma_k)}{\partial\gamma_k}=\frac{e^{-\gamma_k}+e^{x-\gamma_k}}{(1+e^{x-\gamma_k})^2} \quad (15)$$

$$\frac{\partial^2 f_3(\gamma_k)}{\partial\gamma_k^{\,2}}=\frac{(e^{-\gamma_k}+e^{x-\gamma_k})(e^{x-\gamma_k}-1)}{(1+e^{x-\gamma_k})^3} \quad (16)$$

From (16), when $x\leq\gamma_k$, we can get $\partial^2 f_3(\gamma_k)/\partial\gamma_k^2\leq 0$. Substituting (16) and (14) into (12), we can get inequality $\partial^2 U_k^*/(\partial p_k\partial p_i)\geq 0$. Hence, based on the aforementioned definition, the S-NPGP model is a supermodular game. So it has a reasonable NE point at least. Moreover, we introduce the iteration algorithm to attain the optimal power of each SU as follows.

Algorithm :S-NPGP

The efficient and unbiased non-cooperative power control game with pricing algorithm (S-NPGP) given in (11) is described as follows.

1) Set $k=0$, and input the initial transmission power vector $\mathbf{P}(k)=[p_1(k),p_2(k),\cdots,p_K(k)]$ and set an infinitely small quantity ε ($\varepsilon>0$).

2) $k=k+1$, update the value of γ_i by the follow equation

$$\gamma_i=\frac{Gh_i p_i(k)}{\sum_{j\neq i}h_j p_j(k-1)+\delta_i^2} \qquad i=1,2,...,n \quad (17)$$

And then compute the value of $p_i(k)$ by $\partial u_i/\partial p_i(k)=0 \quad i=1,2,...,n$

3) for each SU i , if $|p_i(k)-p_i(k-1)|>\varepsilon$ go back to step (2), otherwise stop the algorithm, $\mathbf{p}(k)=\{p_1(k),p_2(k),...,p_n(k)\}$ is the optimal power control vector for all the SUs.

The flow chart illustrating the S-NPGP scheme is shown in Fig. 5. 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 $\mathbf{P}(k)$. Also, the system guarantees the QoS requirement of SUs and ensures fairness among all SUs.

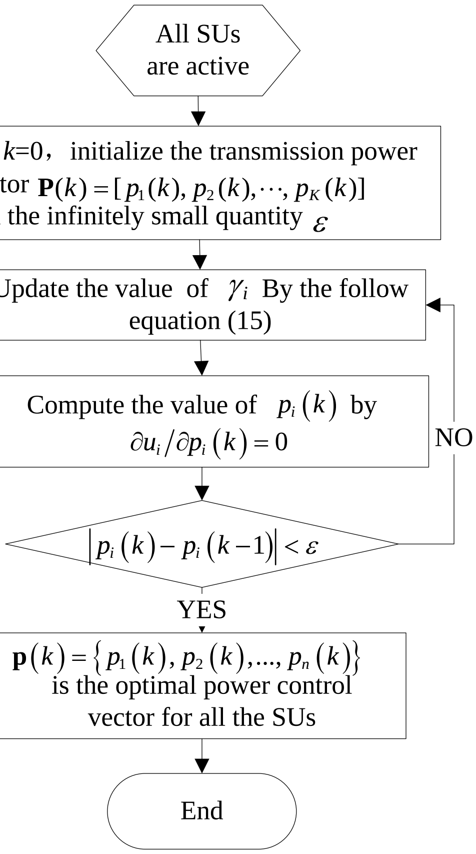


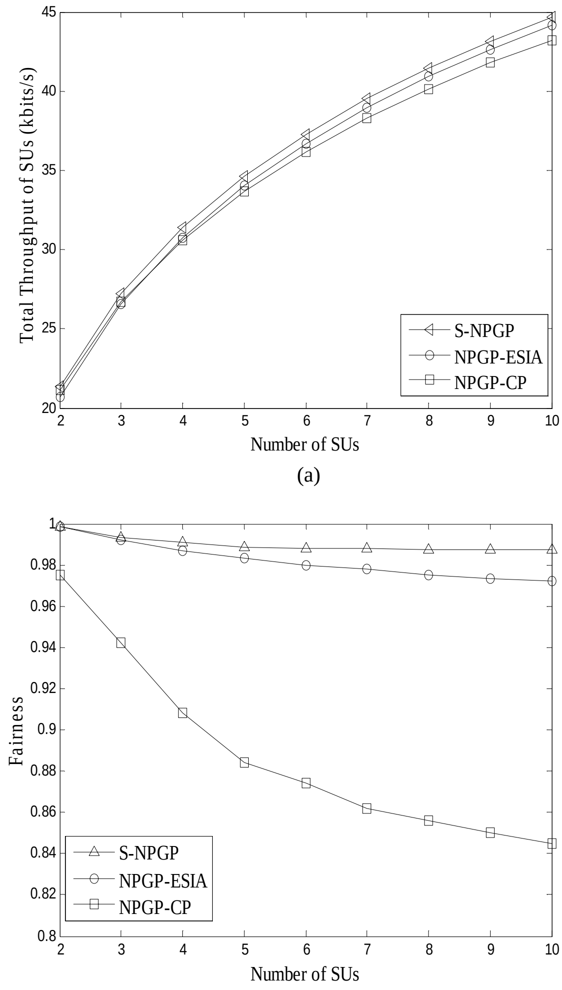
Figure 5. Flowchart illustrating the S-NPGP scheme

IV. SIMULATION RESULTS

In this context, we compare the efficient and unbiased power control algorithm (S-NPGP) with the power control algorithm based on nonlinear pricing (NPGP-CP) algorithm described in [14] and efficient swarm intelligent algorithm for power control (NPGP-ESIA) described in [16].

As shown in Fig.1, we consider a heterogeneous CRN with radius of 3km with primary BS BS_p in the center of the cell. The CRN with radius 1km, lies $500m$ south to BS_p where SUs are uniformly distributed around the secondary BS BS_s. The distance between the SUs and the BS_s is chosen randomly within (0,1) km. The processing gain $G=100$, bit rate $R=10^4$bit/s, total number of bits $M=80$bits, number of information bits $L=64$bits, and minimum requirement of SINR for kth SU $\gamma_k^{\min}=8$. Each SU deploys an isotropic transmitter with the same maximum power of $p_{\max}=20$ mW, channel path gain $h_k=0.097/d^{-4}$, d is the distance between the SU and BS_s, and the background noise is assumed to be additive white Gaussian noise of $\delta_k \sim \mathcal{N}(0,\ 10^{-12})$ which is assumed to be uniform for all users.

Moreover, we set the punishment parameters $\alpha=30000$, $\beta=50000$ and $\varepsilon=10^{-2}$. It is assumed that all SUs cannot cause the interference to PUs beyond the maximum interference threshold of the PUs. Simulation results are shown in Fig.6 and Fig.7, which illustrates the system performance of the three algorithms.

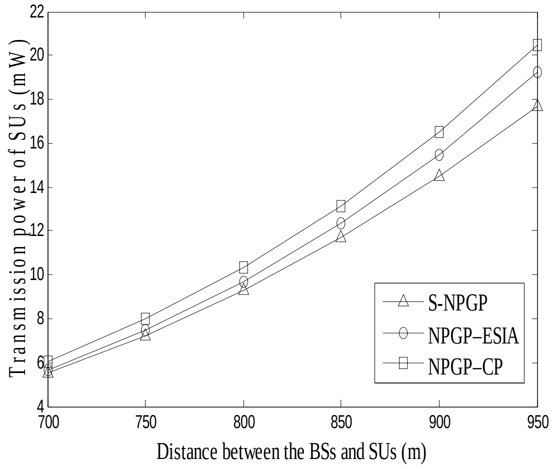


(b)

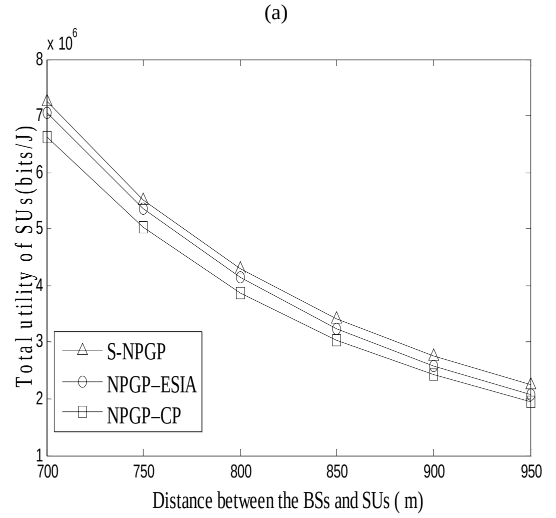
Figure 6. Total throughput and fairness comparison for the three schemes

Fig. 6 shows the comparison of total throughput performance and fairness with respect to different number of SU of different algorithms. From Fig. 6 (a), it can be seen that the total throughput of S-NPGP is always larger than that of NPGP-CP and NPGP-ESLA with different number of SU.

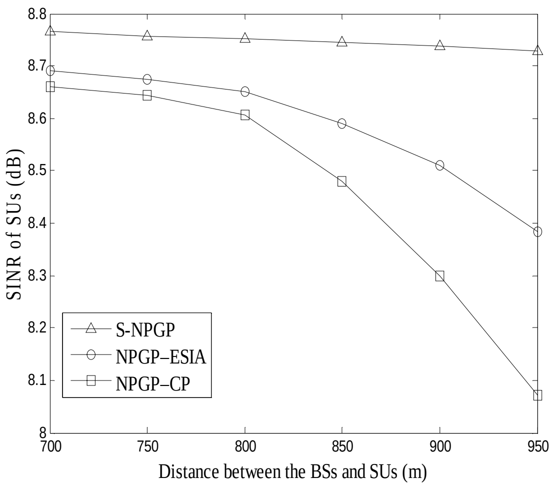
In addition, Fig. 6 (b) shows that the fairness is also larger and more stable than the other two algorithms. With the increase of the number of SU, the fairness of NPGP-CP reduces fast and so does NPGP-ESLA. Moreover, the fairness gap between S-NPGP and the other algorithms is increased with the increase of the number of SU, by which it can be concluded that S-NPGP is more suitable for being applied in larger networks. Because S-NPGP scheme not only sets the adaptive punishment parameter among all served SUs based on the SINR information, but also set other punishment parameter like interference from other SUs to guarantee the minimum QoS requirement of SUs and takes an available iteration algorithm to achieve NE. Therefore, our proposed scheme can improve the total throughput and guarantee fairness among SUs.



(a)



(b)



(c)

Figure 7. The transmission power, total utility, and SINR comparison for the three schemes.

From Fig. 7 (a) and (b) here, we can easily get the conclusion that S-NPGP with sigmoid efficiency function and new pricing function has obvious improvement. Not only because the transmit power of the SUs are lower than the other two, but also the utilities of the SUs are also larger with the rise of distance between the BS_s and SUs.

Due to the adaptive price mechanism presented in S-NPGP, the SUs need to pay the price to prevent selfish SUs increase power blindly, which can affect other SUs, so the total transmit power naturally reduce compared with other schemes. In addition, although the utilities of all the three algorithms reduce as link quality become worse with the rise of distance between the SU BS and SUs, the total utility of S-NPGP is always larger than the other algorithms. Moreover, the sigmoid efficiency function is used to approximately match with the success probability of data transmission to reduce the system error.

The comparison of SINR of SUs for the three schemes are shown in Fig.7 (c), which shows when the SUs are far away from the SBs, the SINR reduce fast in NPGP-CP. Because the author ignores the minimum requirement of SINR, it cannot ensure fairness among all the SUs. In addition, the same does NPGP-ESLA, for which the path gains cannot be taken into account. However, the SINR of S-NPGP keep stable with the rise of distance between the BS_s and SUs, thanks to the pricing function which can ensure the fairness and the minimum requirement of SINR among all the SUs with different distance by using the quality of received signal as punishment.

V. Conclusion

In this paper, we propose an efficient and unbiased power control algorithm based on game theory in a heterogeneous CRN by improving the sigmoid efficiency function and pricing function to balance the fairness and system throughput of SUs. This effective utility function considers the throughput and fairness among SUs, where the pricing punishment parameter setting depends on the quality of received signal to guarantee the QoS requirement of the SUs. Simulation results show that the proposed power control game not only enhances the network throughput, reduces emission power of SUs, and improves the utility, but also takes the system fairness into account to some extent, which differs from other previous schemes.

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