Mixed Power Control Strategies for Cognitive Radio Networks under SINR and Interference Temperature Constraints

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Abstract. *Without consideration of the minimum signal-to-interference-plus-noise ratio (SINR) and frequent information exchange, traditional power control algorithms can not always satisfy SINR requirements of secondary users (SUs) and primary users (PUs) in cognitive radio networks. In this paper, a distributed power control problem for maximizing total throughput of SUs is studied subject to the SINR constraints of SUs and the interference constraints of PUs. To reduce message exchange among SUs, two improved methods are obtained by dual decomposition approaches. For a large-scale network, an average interference constraint is presented at the cost of performance degradation. For a small-scale network, a weighted interference constraint with fairness consideration is proposed to obtain good performance. Simulation results demonstrate that the proposed algorithm is superior to ADCPC and TPCG algorithms.*

Keywords

Cognitive radio networks, SINR requirement, distributed power control, interference temperature.

1. Introduction

At present, radio spectrum is a scarce resource which should be efficiently used to accommodate the development of wireless communication technology. Traditional fixed spectrum allocation mechanism leads to spectrum underutilization, since in recent reports by Federal Communications Commission, it is demonstrated that there are vast temporal and spatial variations in the usage of allocated spectrum as low as 15 percent [1]. Cognitive radio (CR) [2]-[3] has been considered as a promising technology that can improve spectrum utilization by allowing secondary users (SUs) to use the spectral bands unoccupied by primary users (PUs). As a result, the unused parts of spectrum resource become temporarily reused.

Power control (i.e., resource allocation) in cognitive radio networks (CRNs) is an effective way for achieving spectrum sharing between licensed users (i.e., PUs) and unlicensed users (i.e, SUs). It can guarantee quality-of-service (QoS) of SUs and simultaneously avoid harmful interference to PUs through adjusting transmit power of SU-transmitters (SU-Txs). Different from traditional cellular networks, the transmit power of SU-Txs in CRNs is limited by interference temperature (IT) level [1] and battery capacity. In other words, the interference to PU-receivers (PU-Rxs) needs to be strictly controlled from the perspective of SUs. For SUs, the actual signal-to-interference-plus-noise ratios (SINRs) of SUs is not only related with the interference from other SUs but also affected by PUs.

In general, power control can be classified into two categories: centralized framework and distributed framework [4]. In the centralized framework, there is a central processing unit (e.g., base station or central control node) to manage transmission message for users. For instance, secondary base station collects global information of SUs and adjusts power update command to achieve an optimization objective. However, there are several disadvantages: 1) It has a high cost of configuring and managing large-scale networks in practice. 2) Date information (e.g., target SINR, channel gain) needs to be repeatedly exchanged between secondary base station and SUs. Therefore, it increases the computational complexity. The convergence properties of power control algorithms are very sensitive to the number of SUs and link delays. 3) It serves a limited geographical region, which can not be scalable to large number of SUs. Moreover, when there are some malfunctions in the central controllers, the whole communication system will interupt. On contrary, in distributed framework, spectrum allocation and access method are based on local messages distributively achieved by each node. There is no central controller to collect related system information (e.g., channel gain, interference power) so that no above disadvantages exist. Therefore, distributed algorithm is more suitable in practical CR systems.

In this paper, we study the power control problem for underlay CRNs with multiuser scenario in the distributed way. Taking both SINR and transmit power constraint of each SU into account, distributed power control algorithms without user cooperation are proposed to maximize total throughput of SUs with average/weighted IT constraints. The proposed algorithms can ensure QoS requirements of SUs and PUs. The major contributions of this paper can be summarized as follows:

- Different from capacity maximization of each SU under interference constraint, the total throughput maximization of SUs in a multiuser CRN is considered subject to the SINR constraint of each SU, transmit power constraint of SUs and IT constraints of PUs.
- Since interference channel gain of SUs is coupled in the IT constraint, which increases the information exchange between SUs, two distributed power control algorithms with decoupled interference constraints (i.e., the average/weighted IT constraints) are proposed. A mixed power control strategy is designed based on the number of active SUs.

The rest of this paper is organized as follows. Section 2 reviews related works. In Section 3, a system model for multiuser underlay spectrum sharing is addressed. Section 4 formulates power allocation problem and traditional optimal algorithm without QoS constraints. In Section 5, a mixed distributed power control algorithm is presented. In Section 6, simulation results are provided to demonstrate the performance of the proposed algorithm. Section 7 concludes the paper.

2. Related Work

In a dynamic channel environment of CRNs, the main challenge is to achieve some objectives with specific constraints. For instance, the authors developed power control algorithms for achieving energy efficiency problems (i.e., transmit power minimization) [5]-[7]. However, they cannot improve spectrum efficiency (i.e, increase transmission rate and system throughput). In addition, in [8], the authors proposed a power allocation scheme to maximize the performance of CRNs. But all the above-mentioned works focused on the centralized algorithms [5]-[8] which need global information about channel gains and transmit power of SUs.

To improve the flexibility and reliability of CRNs, several distributed power control approaches have been proposed. An initial distributed power control (DPC) algorithm known as Foschini and Miljanic algorithm was given in [9]. Then distributed constrained power control (DCPC) was proposed in [10]. Research on the distributed algorithms for different objective functions and constraints in CRNs had been concerned in [11]-[19]. Optimal resource allocation algorithms for a single-user CRN was studied in [11]-[12]. For instance, an optimal scheme derived through Lagrangian formulation was proposed to maximize downlink capacity of SU while guaranteeing the interference to PU below a predefined IT threshold [12]. Extend to multiple SUs and one PU scenario, DPC algorithms based on different utility functions and constraints were given in [13]-[16]. For an overlay spectrum sharing CRN, a distributed power allocation scheme based on game theory was proposed to maximize throughput of each SU under transmit power and IT constraints [13]. However, mutual interferences between SUs was not considered. In [14], an autonomous DCPC (ADCPC) algorithm was proposed to satisfy QoS requirements of SUs. In [15], a DPC strategy based on geometric programming (GP) was presented to maximize the total capacity of secondary network. In [16], an optimal power allocation method based on GP was obtained to maximize sum rate of SUs under minimum signal-to-interference ratio (SIR) and IT constraints. Although GP method has been shown as an effective way in practical applications, it is a centralized one. In addition, introducing new variables in optimization formula may result in a non-convex optimization problem requiring excessive calculations to solve it. In [17], based on non-cooperative game theory, a tax-based power control game (TPCG) algorithm was proposed to solve distributed multichannel power allocation problem for CRNs under the IT restrictions imposed by primary system. But the interference from PUs was ignored. In addition, the authors of [18]-[19] discussed optimal power control problems for dynamic spectrum sharing with multiple SUs and PUs. In [18], a simple distributed algorithm derived through repeated game theory was proposed to solve resource allocation problem in CRNs. However, the transmit power constraint of each SU was not considered. Considering both network efficiency and user fairness, a cooperative Nash bargaining power game model was formulated under coupled interference power constraints [19]. Most of previous works neglect the SINR requirement of each SU and the interference power from PUs or SUs, which may not always ensure QoS of SUs. Furthermore, these works assume that each SU could obtain global information and deal with channel information and complex computation, which is sometimes impractical for practical communication networks. Moreover, the algorithms with auxiliary variables and coupled IT constraint will increase burden of information exchange and complexity of algorithm.

3. System Model

We consider a cognitive ad-hoc network with underlay spectrum sharing and no central control node. Under this network, each SU only knows its own channel information without exchanging information with others. Each SU and PU is equipped with a single antenna. There are M SUs and N PUs in the network as illustrated in Fig. 1. Under the underlay mode, SUs access licensed frequency bands without affecting normal communication of PUs. let $\mathrm{A} = \{1,2,\cdots,M\}$ and $\mathrm{B} = \{1,2,\cdots,N\}$ denote the sets of links of SUs and PUs, respectively, and $\forall i, j \in \mathrm{A}, \forall k \in \mathrm{B}$.

In order to guarantee QoS of PUs, the most important constraint is that the interference power from SUs to each PU should be under the prescribed IT level [2]

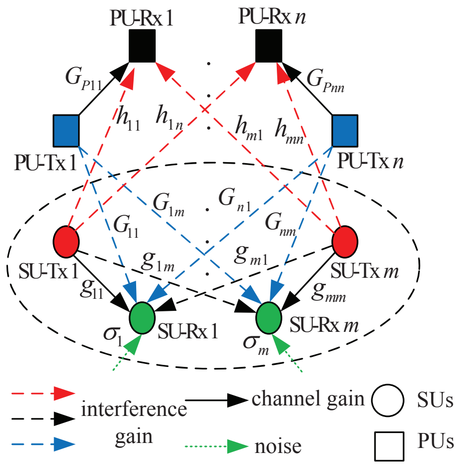

Fig. 1. System model.

$$\sum_i p_i h_{ik} \leq IT_k \tag{1}$$

where p_i is the transmit power at the ith SU-Tx. h_{ik} denotes the channel gain from the ith SU-Tx to the kth PU-Rx. IT_k is a predefined threshold for the tolerable power at the kth PU-Rx.

Since transmit power of each SU is limited by battery capacity, the transmit power at the ith SU-Tx is limited by

$$p_i \leq p_i^{\max} \tag{2}$$

where $p_i^{\max}$ represents the maximum allowable transmit power at the ith SU-Tx.

Considering the interference power from SUs and PUs along with background noise, the actual SINR at the ith SU-receiver (SU-Rx) is

$$\gamma_i = \frac{p_i g_{ii}}{\sum_{j \neq i} p_j g_{ji} + \sum_k p_{ki} g_{ki} + \sigma_i} \tag{3}$$

where γ_i is the received SINR at the ith SU-Rx. g_{ii} is the direct channel gain of the link i. g_{ji} is the interference gain from the jth SU-Tx to the ith SU-Rx. g_{ki} is the interference gain between the kth PU-transmitter (PU-Tx) and the ith SU-Rx. p_{ki} is the interference power from the kth PU-Tx to the ith SU-Rx. σ_i is the background noise at the ith SU-Rx. (3) describes the relationship between transmit power and interference plus noise. It can be rewritten as

$$\gamma_i = p_i g_{ii} / z_i \tag{4}$$

where the sum interference plus noise received at the ith SU-Rx (i.e., z_i) is defined as

$$z_i = \sum_{j \neq i} p_j g_{ji} + \eta_i \tag{5}$$

where $\eta_i = \sum_k p_{ki} g_{ki} + \sigma_i$ denotes the sum of background noise and the interference from PUs.

To keep QoS of SUs, the received SINR at SU-Rx should exceed the minimum SINR (i.e., target SINR), namely,

$$\gamma_i \geq \gamma_i^{\min} \tag{6}$$

where $\gamma_i^{\min}$ is a target SINR which may be different for different SUs. According to (3) and (6), the SINR constraint satisfies following matrix form

$$(\mathbf{I} - \mathbf{F})\mathbf{p} \geq \mathbf{Q} \tag{7}$$

where $\mathbf{p} = [p_1, \cdots, p_M]^T$ is a $M \times 1$ transmit power vector. $\mathbf{I}$ is a $M \times M$ identity matrix. $\mathbf{Q} = [\frac{\gamma_1^{\min}\eta_1}{g_{11}}, \cdots, \frac{\gamma_M^{\min}\eta_M}{g_{MM}}]^T$ is a $M \times 1$ column vector. $[\cdot]^T$ denotes transpose operator. $\mathbf{F} = [F_{ji}]$ is a $M \times M$ matrix with the elements as follows,

$$F_{ji} = \begin{cases} \frac{\gamma_i^{\min} g_{ji}}{g_{ii}}, & \text{if } i \neq j, \\ 0, & \text{if } i = j. \end{cases} \tag{8}$$

Let $\rho_{\mathbf{F}}$ denote the maximum modulus eigenvalue of $\mathbf{F}$.

For traditional cellular communication system, DPC algorithms are proposed in [9]-[10] which only consider (2) and (6). If $\rho_{\mathbf{F}} < 1$ satisfies, the analytical solution of optimal power is $\mathbf{p}^* = (\mathbf{I} - \mathbf{F})^{-1}\mathbf{Q}$. The convergence of the algorithm is proved in [9]. Since it is unnecessary to make separate local measurements of interference and noise, a simplified form of DPC algorithm [9] is $p_i(t+1) = \frac{\gamma_i^{\min}}{\gamma_i(t)} p_i(t)$ where t denotes time instant. Obviously, each link independently increases its power to meet its required SIR threshold when the current SIR is below the target $\gamma_i^{\min}$, and vice versa. Since the maximum transmit power constraint was not ignored in DPC algorithm [9], DCPC algorithm is proposed in [10], i.e., $p_i(t+1) = \max(\frac{\gamma_i^{\min}}{\gamma_i(t)} p_i(t), p_i^{\max})$ to make the received SIR converge to the target SIR $\gamma_i^{\min}$ distributively except for the case when the maximum transmission power $p_i^{\max}$ is reached. All the above-mentioned DPC algorithms are not easily extended to CR scenario.

4. Problem Description

Due to lack of a centralized control or cooperation among SUs, DPC algorithm for CRNs should be an asynchronous way where IT and SINR constraints are considered. In this section, DPC problem is described in such way that the following goals are simultaneously satisfied: (i) total throughput of SUs is maximized while the SINR of each SU maintains the above target SINR $\gamma_i^{\min}$; (ii) total interference power from SU-Txs to the kth PU-Rx is kept below the threshold IT_k; and (iii) transmit power of each SU is upper bounded by maximum transmit power $p_i^{\max}$. Hence, the power allocation problem becomes

$$\begin{aligned} &\max \sum_i \log(1+\gamma_i), \\ &\text{subject to} \begin{cases} C_1 : p_i \leq p_i^{\max}, \\ C_2 : \sum_i p_i h_{ik} \leq IT_k, \\ C_3 : \gamma_i \geq \gamma_i^{\min}. \end{cases} \end{aligned} \tag{9}$$

Since transmit power p_i is coupled in C_2, problem (9) is not in a separable form. Each SU needs to exchange channel gain with others for the performance of system.

However, the existing works (e.g., [12]-[13]) for DPC problems are without constraint C_3, namely,

$$\begin{aligned} & \max \ \sum_i u_i(\gamma_i). \\ & \text{subject to} \begin{cases} C_1 \ : \ p_i \le p_i^{\max}, \\ C_2 \ : \ \sum_i p_i h_{ik} \le IT_k. \end{cases} \end{aligned} \tag{10}$$

From (10), utility function $u_i(\gamma_i) = \log(1+\gamma_i)$ can be approximated by $u_i(\gamma_i) = w_i \log \gamma_i$ [16], which can maximize the throughput of system and maintain the fairness for secondary links. In addition, the resource allocation problem without SINR constraint becomes a convex one with linear constraints [20] and concave objective function evaluated by Hessian matrix [21].

If h_{ik} and g_{ji} are available for SUs, the optimal solution is obtained by Lagrange function [22] as

$$p_i = \left[\frac{1}{\alpha_i + \sum_k \beta_k h_{ik}} - \frac{z_i}{g_{ii}} \right]^+ \tag{11}$$

where α_i and β_k are nonnegative Lagrange multipliers associated with C_1 and C_2 in (10), and $[x]^+ = \max\{0, x\}$. According to Karush-Kuhn-Tucher (KKT) conditions [22], the optimal power and Lagrange multipliers should satisfy

$$\alpha_i(p_i - p_i^{\max}) = 0 \text{ ,} and \ \ \beta_k(\textstyle\sum_i p_i h_{ik} - IT_k) = 0. \tag{12}$$

From (11), the optimal power resembles a modified water-filling solution with the variable water levels that depends on α_i and β_k. If $p_i^{\max} \gg IT_k$ holds, the IT constraint is severely restricted. As a result, C_2 must be satisfied while C_1 can be ignored, i.e., $\alpha_i^* = 0$ and $\beta_k^* > 0$. If the IT level is moderate (e.g., $p_i^{\max} \approx IT_k$), both C_1 and C_2 should be considered. If the IT level is bigger than the maximum transmit power, i.e., $p_i^{\max} \ll IT_k$, C_2 can be ignored while C_1 should be considered, namely, $\alpha_i^* > 0$ and $\beta_k^* = 0$. In other words, the optimal solution is equivalent to the classic iterative water filling algorithm. Therefore, the power allocation problem becomes a traditional optimization one without IT constraints.

However, (11) may not keep QoS of each SU if there is no consideration of SINR constraints of SUs. In addition, (11) is not suitable for distributed applications in practice, since some SUs can not achieve target SINR under bad channel environment. For example, a selfish SU continuously increases its transmit power for a higher rate and brings more harmful interference to other SUs in the network. In addition, channel gain h_{ik} requires to be frequently exchanged between SUs from (11).

5. Distributed Power Control Algorithms

In this section, two DPC algorithms are proposed under the geographic distribution of SUs as shown in Fig. 2.

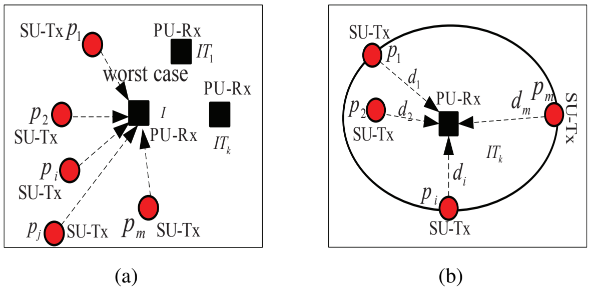

Fig. 2. Geographic distribution information of users.

5.1 Proposed Scheme A

In this subsection, we study DPC algorithm under average interference constraint. From Fig. 2(a), the distance between SU-Tx and PU-Rx is equal. Since channel gain is mainly determined by the distance [23], constraint (1) can be formulated as

$$p_i h_{i0} \le \frac{I}{M} \tag{13}$$

where I is the worst IT level of $\mathbf{IT}$, namely, $I = \min_{\forall k} IT_k$ and $\mathbf{IT} = \{IT_1, \cdots, IT_N\}$. h_{i0} denotes the channel gain between the ith SU-Tx and the nearest PU-Rx. We assume that each SU knows the channel gain between its transmitter and the PU-Rx as well as the number of users M by sensing method [24]. Although the method is a little conservative in some degree (e.g., some SUs are far from the PU-Rx), it can protect PUs in the network without interference and be applied to the large-scale network (i.e., M is big).

Combining (9) and (13), the power allocation problem becomes

$$\begin{aligned} & \max \ \sum_i \log(1+\gamma_i), \\ & \text{subject to} \begin{cases} C_1 : p_i - p_i^{\max} \le 0, \\ C_2 : p_i h_{i0} - I/M \le 0, \\ C_3 : \gamma_i^{\min} z_i - p_i g_{ii} \le 0. \end{cases} \end{aligned} \tag{14}$$

From (14), when a SU is far from the worst PU-Rx, e.g. the jth SU in Fig. 2(a), link gain h_{j0} is very small. As a result, the range of transmit power p_j becomes bigger, which helps to improve system performance. When the SU satisfies $p_i^{\max} h_{i0} < \frac{I}{M}$, the optimal power allocation in CRNs becomes an optimization problem in non-cognitive system. Therefore, it does not require to consider the IT constraints. When the ith SU-Tx under good channel state (i.e., g_{ii} is big.) is nearer to the worst PU, h_{i0} becomes bigger. Therefore, the feasible region of transmit power p_i becomes small to protect QoS of PU. Since C_3 can be converted into a linear combination with transmit power variables, it can be treated as convex constraint [20]. According to Lagrange dual method [3]-[5], Lagrangian dual function of problem (14) is

$$\begin{aligned} L(\{p_i\},\{\lambda_i\},\{\upsilon_i\},\{\mu_i\}) = & \textstyle\sum_i \log(1 + p_i g_{ii}/z_i) \\ & + \textstyle\sum_i \lambda_i \left(p_i^{\max} - p_i\right) \\ & + \textstyle\sum_i \mu_i \left(I/M - p_i h_{i0}\right) \\ & + \textstyle\sum_i \upsilon_i \left(\gamma_i^{\min} z_i - p_i g_{ii}\right) \end{aligned} \tag{15}$$

where λ_i ,υ_i and μ_i are the nonnegative Lagrange multipliers (i.e., dual variables) in problem (14). Define dual objective $D(\{\lambda_i\},\{\upsilon_i\},\{\mu_i\})$ as an unconstrained maximization problem

$$\begin{aligned} D(\{\lambda_i\},\{\upsilon_i\},\{\mu_i\}) &= \max_{\{p_i\}} L(\{p_i\},\{\lambda_i\},\{\upsilon_i\},\{\mu_i\}) \\ &= \textstyle\sum_i \max L_i(p_i,\lambda_i,\upsilon_i,\mu_i) \\ &\quad + \textstyle\sum_i (\lambda_i p_i^{\max} + \upsilon_i \gamma_i^{\min} z_i + \mu_i I/M) \end{aligned} \tag{16}$$

where $L_i(p_i,\lambda_i,\upsilon_i,\mu) = \log(1+p_i g_{ii}/z_i) - \upsilon_i p_i g_{ii} - \lambda_i p_i - \mu_i p_i h_{i0}$, and the dual optimization problem is

$$\begin{aligned} &\min\ D(\{\lambda_i\},\{\upsilon_i\},\{\mu_i\}), \\ &\text{subject to } \lambda_i \geq 0, \upsilon_i \geq 0, \mu_i \geq 0. \end{aligned} \tag{17}$$

According to KKT conditions [22], the optimal power can be obtained as

$$p_i^{\text{ave}} = \left[\frac{1}{\lambda_i + \mu_i h_{i0} + \upsilon_i g_{ii}} - \frac{z_i}{g_{ii}}\right]^+. \tag{18}$$

We define this algorithm as scheme A. The Lagrange multipliers can be updated by sub-gradient search method in a parallel way as follows

$$\lambda_i(t+1) = \left[\lambda_i(t) - s_{\lambda_i}(p_i^{\max} - p_i)\right]^+, \tag{19}$$

$$\mu_i(t+1) = \left[\mu_i(t) - s_{\mu_i}(I/M - p_i h_{i0})\right]^+, \tag{20}$$

$$\upsilon_i(t+1) = \left[\upsilon_i(t) - s_{\upsilon_i}\left(\gamma_i^{\min} z_i - p_i g_{ii}\right)\right]^+ \tag{21}$$

where s_{λ_i}, s_{μ_i} and s_{υ_i} are small step sizes properly selected to guarantee convergence of the algorithm. t denotes number of iterations. The step sizes are chosen by the methods in [25]. From (19)-(21), dual variables are updated by local information. In addition, Lagrange multiplier increases when the corresponding constraint is out of range, and decreases otherwise. If transmit power of the ith SU-Tx p_i exceeds the maximum transmit power $p_i^{\max}$, the corresponding component s_{λ_i} will increase from (19). And the optimal power will decrease from (18). In other words, component s_{λ_i} represents a price for the transmit power. Similar conclusions about other Lagrange multipliers can be obtained.

The DPC algorithm under the average IT constraint (i.e., scheme A) is summarized as

(i) Initialization: initialize parameters $\gamma_i^{\min}$, $p_i^{\max}$; Set $t = 0, \lambda_i(0) > 0, \mu_i(0) > 0, \upsilon_i(0) > 0, 0 < p_i(0) < p_i^{\max}$;

(ii) Iteration:
(a) For slow-varying channels, measure $\gamma_i(t)$; for static channels, $\gamma_i(t)/p_i(t) = g_{ii}/z_i$.
(b) Update transmit power p_i based on (18).
(c) Update multipliers λ_i, μ_i and υ_i by (19)-(21).

(iii) Decision: after (ii) if $\|\mathbf{p}(t+1) - \mathbf{p}(t)\|_2 \leq \varepsilon$ satisfies, the algorithm converges and the power control decisions p_i reaches the optimal solution. ε is the error tolerance for exit condition. $\|\cdot\|_2$ denotes 2-norm.

5.2 Proposed Scheme B

Although the proposed scheme A can reduce communication overhead, it is conservative for the user who is near the PU-Rx. In addition, the performance of the system (e.g., throughput) degrades with the increasing SUs. Therefore, the distributed power control algorithm with user fairness (i.e., scheme B) is studied in this subsection. From Fig. 2(b), we design a weighted IT constraint as follows

$$p_i h_{ik} \leq \omega_{ik} I T_k \tag{22}$$

where ω_{ik} denotes the weighted factor, namely, $\omega_{ik} = d_i/\sum_i d_{ik}$, and $\sum_i \omega_{ik} = 1$. We assume that SUs know the position information of the users obtained by global positioning system (GPS) or localization technology [26]. (22) can be rewritten as $p_i h_{ik}/\omega_{ik} \leq IT_k$. When the ith SU-Tx is close to the kth PU-Rx (i.e., d_i is small), the range of transmit power decreases to protect QoS of PUs and increases to improve system throughput otherwise. Under this mode, this scheme guarantees the fairness of SUs and allows more SUs to access the network meanwhile prevents energy waste of SUs by endlessly increasing their transmit power. Similar to Subsection 5.1, the optimal power is

$$p_i^{\text{wei}} = \left[\frac{1}{\lambda_i + \mu_{ik} h_{ik} + \upsilon_i g_{ii}} - \frac{z_i}{g_{ii}}\right]^+ \tag{23}$$

where the dual variable is updated by $\mu_{ik}(t+1) = \left[\mu_{ik}(t) - s_{\mu_{ik}}(\omega_{ik} I T_k - p_i h_{ik})\right]^+$. To balance time overhead and performance of the system, we obtain mixed power control strategies as

$$p_i^* = \begin{cases} p_i^{ave} & if\ M \geq \bar{M} \\ p_i^{wei} & if\ M < \bar{M} \end{cases} \tag{24}$$

where $\bar{M}$ denote decision variable of the network size predefined in procedure. In CRNs, when a new user accesses the network, $\bar{M}$ represents the current number of users when transmission delay happens. $\bar{M}$ is also determined by communication state. Moreover, if the number of active users is below the critical value, there are not so many users in the network. The time of obtaining the distance message can be ignored. In order to improve the performance of the system, power control command switches to scheme B. Otherwise, scheme A is used. The problem about adaptive selection of the size of $\bar{M}$ is another difficult research issue which will be discussed in the future.

6. Simulation Results

In this section, we present some numerical results to illustrate the performance of the proposed algorithms by comparing with the existing ADCPC algorithm [14] and TPCG algorithm [17]. The proposed algorithms are implemented and simulated by MATLAB R2010b, 3.2 GHz CPU and 1.96 GB of RAM. During the simulation process, the convergence threshold of the algorithm is $\varepsilon = 10^{-6}$. The

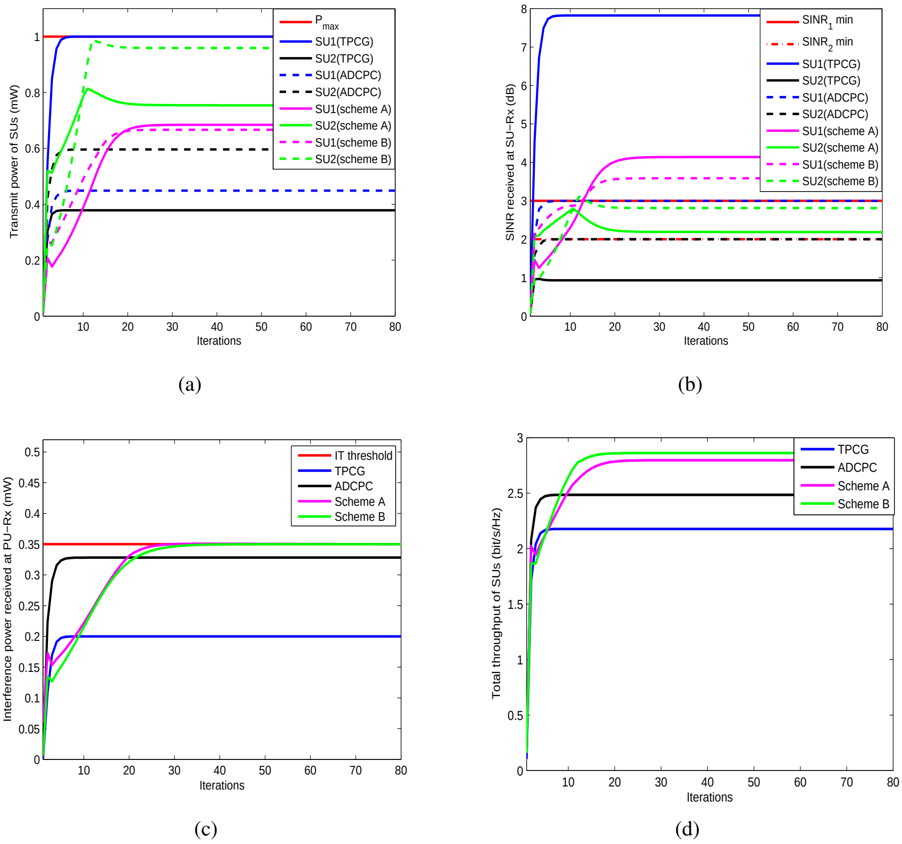

Fig. 3. Performance comparisons between the proposed algorithms and the existing algorithms; (a) Transmit power of SUs. (b) Received SINRs of SUs. (c) Aggregated interference power at PU-Rx. (d) Total throughput of system.

background noise σ_i and normalized channel gain g_{ji} or h_{jk} are chosen randomly from the interval $(0, 0.1/(M-1))$ and $(0, 1/(M-1))$ [23].

Fig. 3 shows the convergence of the algorithms. We assume there are two SUs and one PU in the network. Each SU has same maximum transmit power and background noise, and $p_i^{\max} = 1$ mW and $\sigma_i = 0.05$ mW. The minimum SINR of SUs is $\gamma^{\min} = [3,2]^T$ dB. The interference weighted factor is $\omega = [0.4; 0.6]$. The IT level is $IT = 0.35$ mW. In Fig. 3, the performance of the system can converge to the equilibrium point in a finite number of iterations. Specifically, the transmit power of SUs is shown in Fig. 3(a). The actual received SINR at SU-Rxs is given in Fig. 3(b). The interference at PU-Rx is shown in Fig. 3(c). And the total throughput of SUs is presented in Fig. 3(d).

From Fig. 3(d), the total throughput of the proposed algorithms is higher than that of TPCG algorithm and ADCPC algorithm. Since both scheme A and scheme B consider the QoS constraint of each SU. Under TPCG algorithm, the SU under the bad channel state (e.g., SU2) can not reach its own target SINR due to the interference from other SUs (e.g., SU1) in Fig. 3(a). The selfish SU endlessly increases its transmit power to obtain higher SINR in Fig. 3(b). In consequence, the transmit power of SU1 can reach maximum transmit power from Fig. 3(a). However, under TPCG algorithm, the communication outage of SU2 happens according to the black solid line as shown in Fig. 3(b). Therefore, the performance of TPCG algorithm is the worst one from Fig. 3(d). The interference power is limited by the IT constraint from Fig. 3(c).

Moreover, ADCPC algorithm considers the SINR of each SU, it can reach the target SINR as shown in Fig. 3(b), but it can not reach a better performance (i.e., higher throughout). The performance of ADCPC algorithm is moderate from Fig. 3(d). The throughput of SUs in ADCPC algorithm is better than that of TPCG algorithm, but is worse than that of the proposed algorithms.

Furthermore, both scheme A and scheme B can satisfy communication requirement of SUs from Fig. 3(b). Since scheme B considers the fairness between SUs, the performance of scheme B is better than that of scheme A. In particular, scheme B provides a big feasible region for SU2 who is far away from the PU-Tx and has a bad channel case. The average IT constraint can make the transmit power range of SU1 tight, the SU under a good channel state can not reach higher SINR. As a result, scheme A brings less interference to other SUs in the network. When the actual SINR of SU is below the target SINR, the price factor υ_i decreases to allow more transmit power at SU-Tx from (22). And total throughput of SUs is restricted by the IT level from Fig. 3(c).

Fig. 4 depicts the total throughput versus the IT threshold. The target SINR is $\gamma^{\min} = [2,2]^T$ dB. Other parameters are the same as those for Fig. 3. From Fig. 4, it is shown that both scheme A and scheme B can achieve better throughput than ADCPC algorithm and TPCG algorithm. The total throughput increases rapidly with the increasing IT threshold, since the range of transmit power monotonically increases with the increasing IT level. In addition, scheme B has better throughput than scheme A. On the one hand, the throughput of ADCPC algorithm does not change as the increasing IT threshold. But the throughput of TPCG algorithm is better than that of ADCPC algorithm. For higher IT region, the throughput of the system is limited by the maximum transmit power of SUs.

Fig. 5 presents throughput performance versus the target SINR. The maximum transmit power and IT level are 1 mW. Other parameters are the same as those for Fig. 3. From Fig. 5, the total throughput of system increases with the increasing SINR, since there is needed more transmit power to satisfy QoS requirement from (6). In high SINR region, the throughput of the algorithms does not change and it is limited by the maximum transmit power of SU-Tx. But, under low SINR region, the throughput difference of TPCG algorithm and the proposed algorithms is bigger than that in the high SINR region. Meanwhile the performance of ADCPC algorithm is the worst one, since ADCPC algorithm only maintains basic requirement instead of obtaining the optimal performance.

Fig. 6 shows the average transmit power versus the number of PUs. There are two SUs in the network, and the minimum SINR of each SU is 2 dB. The maximum IT threshold and transmit power are 0.4 mW and 1 mW, respectively. The background noise of each SU-Rx is 0.1 mW.

From Fig. 6, the average transmit power of all algorithms except of TPCG algorithm improves with the increasing numbers of PUs in the network, since the interference power from PUs is not considered in TPCG algorithm and the minimum transmit power does not increase with the increasing interference. In addition, since ADCPC algorithm only reaches basic SINR requirement, the SU-Tx does not transmit more power for higher data rate of SUs. And small transmit power causes less mutual interference power in the CRN. Therefore, the average transmit power of ADPC algorithm is lower than that of scheme A and scheme B. Moreover, the transmit power of SUs under scheme B is lower than that of scheme A, since scheme B needs less transmit power to satisfy the target SINR requirement.

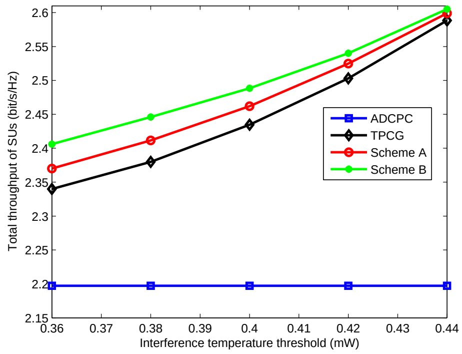

Fig. 4. Total throughput versus the IT threshold.

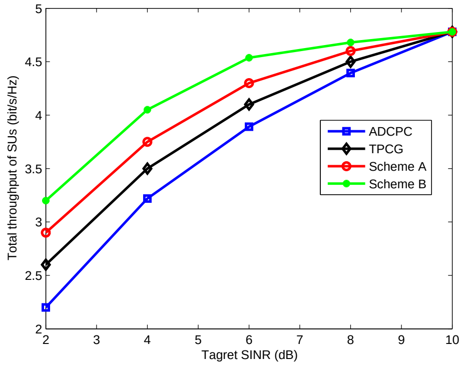

Fig. 5. Total throughput versus the target SINR.

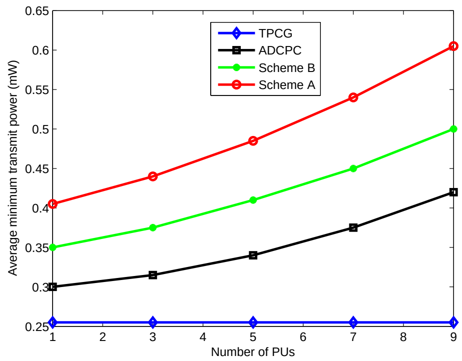

Fig. 6. Average transmit power versus the number of PUs.

7. Conclusions

In this paper, we have studied the resource allocation problem for underlay spectrum sharing in multiuser cognitive radio networks under the SINR and the interference temperature constraints. To reduce burden of information exchange and achieve distributed control, two different distributed power control algorithms based on dual optimization are proposed to maximize total throughput of the system. Simulations demonstrate the efficiency and the performance of the proposed algorithms.

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