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Energy Efficiency of Access Control With Rate Constraints in Cognitive Radio Networks

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ABSTRACT In the next-generation cognitive radio networks, numerous secondary users will share the spectrum resource with the primary users. As it may not be possible to support all the communication rate requirements, there are many supporting sets for the secondary users as long as the communication rates of the primary users are guaranteed. In this paper, we study the maximum feasible set problem to access as many secondary users as possible, under the constraints of power budgets and communication rates in cognitive radio networks. In this interesting issue, the existing literature generally removes a subset of the secondary users so that the remaining users achieve the thresholds with communication rates and power budgets. However, the removal algorithms cause more interference when there are plenty of unsupported secondary users. We leverage the spectral radius of the network characteristic matrix as the admission price to access the new secondary user. Then, we design a hybrid access control algorithm to reduce the interference time and approximate the maximum network capacity. Moreover, different supported sets produce the different energy efficiency, even having the same network capacity, while all users require the high communication rates. Numerical results demonstrate that our algorithms provide the decent energy efficiency under the communication rate constraints.

INDEX TERMS Cognitive radio networks, admission control, network capacity, energy efficiency, spectral radius.

I. INTRODUCTION

Energy efficiency in the next-generation cognitive radio networks turns into a major issue, because most of the wireless terminals are power limited and the global environmental concern attracts more attention [1]–[3]. The interference becomes more severe because the intelligent equipments are exponentially growing to access the wireless networks, while the useful spectrum is limited. In recent years, cognitive radio is developed as a novel technology to tackle this problem. There are two kinds of users in the cognitive radio networks, i.e., the primary users that have the higher priority to occupy the spectrum resource and the secondary users that are able to actively sense the radio environments for dynamic spectrum access.

The existing spectrum access strategies for cognitive radio networks mainly include two manners. One is the overlay spectrum sharing that the secondary users access the network by using part of the spectrum that has not been used by licensed primary users [4], [5]. The other is the underlay spectrum sharing that the secondary users share the band with primary users under acceptable interference [6], [7]. We focus on the underlay spectrum sharing that the secondary users simultaneously communicate with the primary users, while the quality of service of the primary users is guaranteed [8], [9], as shown in Figure 1.

In general, power control is leveraged to satisfy the requirements of the communication rates and to provide proper energy efficiency for the cognitive radio networks [10]. The traditional power control algorithms work well in the feasible wireless networks. However, it may not be possible to simultaneously achieve the communication requirements of all users, due to the exponentially increasing wireless terminals. In this scenario, the cognitive radio network is infeasible, meaning that some secondary users transmit at their max-

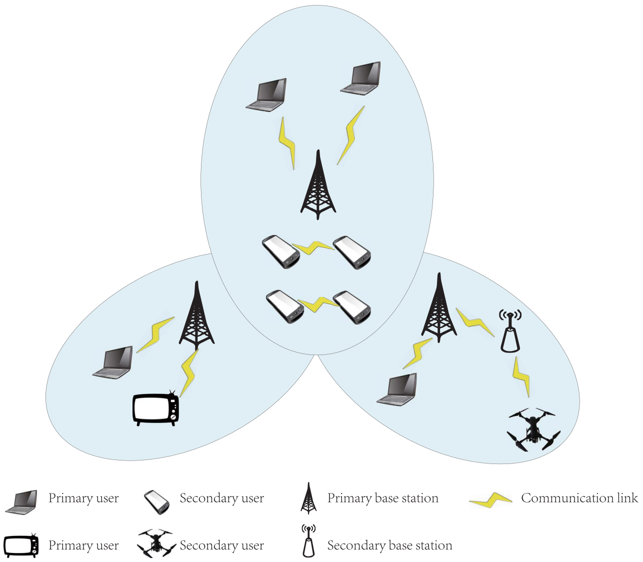

FIGURE 1. An illustration of the cognitive radio network where the secondary users share with the primary users in the underlay manner.

imum possible power but still cannot satisfy their communicate rate requirements due to the exorbitant interference. Existing power control algorithms, e.g., in [11] and [12], may be unstable or diverge when the cognitive radio network is infeasible. In particular, in order to guarantee the communication quality of the primary users, we should properly deal with this interference in cognitive radio networks.

The network capacity is the main concern if it is not possible to achieve the communication rate requirements of all users at the same time. As the interference of the dynamic secondary users may overwhelm the primary users, this maximum feasible set problem is more important in a cognitive radio network [13]–[17]. Moreover, this maximum feasible set problem is NP-hard in general [18], as it is equivalent to the optimization problem given a set of infeasible constraints in [19]. Therefore, admission control is necessary to tackle this infeasibility issue in order to maximize the network capacity. In practice, it is interesting to note that the network capacity is related to the amount of energy consumption. Different supported sets produce the different energy efficiency, even having the same network capacity. The challenge of access control is to support the secondary users as many as possible, and to simultaneously produce high energy efficiency. In the literature, many studies have been done to guarantee the feasible wireless networks under various quality of service constraints based on the power control technique. Mahdavi-Doost *et al.* [20] designed a centralized algorithm by gradually removing the users whose required SINR is out of the feasible SINR region. Rasti *et al.* [21] designed a distributed algorithm by using the removing strategy to avoid the transmit power of the secondary users exceed the given threshold. Liu *et al.* [22] made use of linear programming relaxation to get the approximate network capacity. The network capacity was enhanced via the convex approximation approach in [23]. Zhai *et al.* [24] proposed a joint power and admission control to obtain a close maximum network capacity with low energy consumption. It is also helpful for the green communications in multi-access Internet of Things [25]. In order to avoid the outage for the robustness, Bambos *et al.* [26] designed a joint channel access and power control algorithm. Tan *et al.* [27], [28] analyzed the power-robustness tradeoff to balance the power consumption and robustness. Reference [29] increased the transmission rates of the primary users further and guarantee their priorities. Besides, the point selection algorithm in [30] could be referenced to solve the secondary users selection problem. Interference alignment reduced the interference among users to improve energy efficiency in cognitive radio networks [31], [32].

The traditional power control algorithms (including centralized and distributed manner) work well by gradually removing the unsupported secondary users whose number is small. In the practical scenario, the removal methods cost more time due to the redundant reference if there are numerous secondary users waiting to access the spectrum, especially for the distributed manner. In addition, the aggressive admission control may under-utilize the cognitive radio network due to the unduly removing the secondary users, albeit with the less power consumption. In this paper, we leverage the well known distributed power control framework to get the optimal power allocation and to check the feasibility. Note that the spectral radius of network characteristic matrix is a necessary but not sufficient criterion for the network feasibility. The cognitive radio network can not support all users if this spectral radius is larger than one. Therefore, we design a hybrid access control algorithm in both centralized and distributed manner to control the access of the secondary users, while the communication rate requirements of the primary users is guaranteed. We first iteratively access the secondary user that causes the minimal impact on spectral radius based on the centralized information, and then allocate the transmit power to guarantee the feasible cognitive radio networks based on the decentralized method in [24]. Moreover, we introduce the criteria of the energy efficiency for comparison, as we aim to provide higer communication rates even with the same network capacity and/or the same transmit power. Finally, experimental results reveal that our hybrid access control methods get higher energy efficiency than the traditional single power control algorithms.

In sum, the contributions in this paper are as follows:

1) we design a decentralized power control algorithm with new admission price under rate constraints to check the network feasibility and to approximate the maximum network capacity with low power consumption,

2) we propose a hybrid access control algorithm that makes use of the spectral radius of network characteristic matrix and Lagrange duality as the admission prices for the secondary user,

3) we do the comparison between various power control methods in terms of energy efficiency.

The rest of paper is organized as follows: We introduce the system model and the used important criteria in Section II. In Section III, we analyze the the spectral radius of network characteristic matrix in cognitive radio networks. Then, we propose a decentralized power control algorithm to satisfy the communication rate requirements of all users, and a hybrid access strategy to admit the secondary users in Section IV. We evaluate the performance of our algorithms numerically and compare them to the other removal algorithms in Section V. Finally, we conclude the paper in Section VI.

The following notations are adopted in this paper: Boldface uppercase and lowercase letters are used as matrices and column vectors, respectively. Italics is used as scalars. $\rho(\cdot)$ is used as the spectral radius of a nonnegative matrix. The superscript $(\cdot)^\top$ is used as the transpose of a matrix or a vector. $\mathbf{I}$ is used as the identity matrix with the entries of ones on the diagonal. $\|\cdot\|_0$ is used as the cardinality of a vector, i.e., ℓ_0 norm. diag($\mathbf{x}$) is used as the diagonal matrix with the entries of $\mathbf{x}$ on the diagonal. $[\mathbf{x};\mathbf{y}]$ is used to stack the entries of vector $\mathbf{y}$ after the column vector $\mathbf{x}$.

II. SYSTEM MODEL

In this section, we focus on a cognitive radio network with a finite number of L_m primary users with higher priority and L_s secondary users with lower priority, having $L_s \gg L_m$. Each user denotes a transmitter-receiver pair, transmitting on a common flat spectrum at the same time. Let the superscript m denote the primary users and the super-script s denote the secondary users, respectively. The transmit power vectors of the primary and secondary users are written as $\mathbf{p}^m = (p_1^m, \cdots, p_{L_m}^m)^\top$ and $\mathbf{p}^s = (p_1^s, \cdots, p_{L_s}^s)^\top$. Then, we denote the received SINR of the i-th primary user and the j-th secondary user in terms of the transmit power $\mathbf{p} = [\mathbf{p}^m; \mathbf{p}^s]$ as follows [33]:

$$\mathsf{SINR}_i^m(\mathbf{p}) = \frac{G_{ii}^{mm} p_i^m}{\sum_{\substack{l=1\\ l\neq i}}^{L_m} G_{il}^{mm} p_l^m + \sum_{j=l}^{L_s} G_{ij}^{ms} p_j^s + \sigma_i^m}, \tag{1}$$

and:

$$\mathsf{SINR}_j^s(\mathbf{p}) = \frac{G_{jj}^{ss} p_j^s}{\sum_{i=1}^{L_m} G_{il}^{mm} p_l^m + \sum_{\substack{l=j\\ l\neq i}}^{L_s} G_{jl}^{ss} p_j^s + \sigma_j^s}. \tag{2}$$

G_{ij}^{ms} is the path loss at the i-th primary receiver from the j-th secondary transmitter, and σ_i is the additive white Gaussian noise (AWGN) at the i-th receiver.

Then, we compute the achievable communication data rate of the i-th primary user based on the Shannon capacity formula [34]:

$$r_i^m(\mathbf{p}) = \log(1 + \mathsf{SINR}_i^m(\mathbf{p})), \tag{3}$$

and the one of the j-th secondary user:

$$r_j^s(\mathbf{p}) = \log(1 + \mathsf{SINR}_j^m(\mathbf{p})). \tag{4}$$

In order to guarantee the quality of service of all users, the achievable communication rates of all the users should be larger than a given minimum communication rate threshold, denoted as the vector $\bar{\mathbf{r}} = [\bar{\mathbf{r}}^m; \bar{\mathbf{r}}^s]$. In addition, each user has its own limited power. We use $\bar{\mathbf{p}} = [\bar{\mathbf{p}}^\mathbf{m}; \bar{\mathbf{p}}^\mathbf{s}]$ to denote the power budgets of all users. As we aim to cost the least power to satisfy all the communication rate requirements of all users under the limited individual power budgets, the optimization problem is similarly formulated as [10], [11]:

$$\begin{aligned}
&\text{minimize} \ \sum_{i=1}^{L_m} p_i^m + \sum_{j=1}^{L_s} p_j^s \\
&\text{subject to} \ r_i^m(\mathbf{p}) \geq \bar{r}_i^m, \quad \forall i \\
&\qquad\qquad r_j^s(\mathbf{p}) \geq \bar{r}_j^s, \quad \forall j \\
&\qquad\qquad \mathbf{0} \leq \mathbf{p}^m \leq \bar{\mathbf{p}}^m, \\
&\qquad\qquad \mathbf{0} \leq \mathbf{p}^s \leq \bar{\mathbf{p}}^s, \\
&\text{variables:} \ \mathbf{r}^m, \mathbf{r}^s, \mathbf{p}^m, \mathbf{p}^s.
\end{aligned} \tag{5}$$

In general, (5) could be infeasible, which represents that there may be a secondary user j whose achievable rate can not achieve $\bar{r}_j$ even transmitting at its maximum power. For the convenient of looking into (5), we introduce the new nonnegative vector:

$$\mathbf{v} = \left(\frac{\sigma_1^m}{G_{11}^{mm}}, \cdots, \frac{\sigma_{l_m}^m}{G_{l_m L_m}^{mm}}, \frac{\sigma_1^s}{G_{11}^{ss}}, \cdots, \frac{\sigma_{l_s}^m}{G_{l_s L_s}^{mm}}\right)^\top, \tag{6}$$

and the nonnegative matrix $\mathbf{F}$:

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}^{mm} & \mathbf{F}^{ms} \\ \mathbf{F}^{sm} & \mathbf{F}^{ss} \end{bmatrix}, \tag{7}$$

with the sub-matrix being $F^{ms} \in \mathbb{R}^{L_m \times L_s}$ and $F^{sm} \in \mathbb{R}^{L_s \times L_m}$, where the entries is given as $F_{ij}^{ms} = G_{ij}^{ms}/G_{ii}^{mm}$, and $F_{ji}^{sm} = G_{ji}^{sm}/G_{jj}^{ss}$. The diagonal sub-matrices are $F^{mm} \in \mathbb{R}^{L_m \times L_m}$ and $F^{ss} \in \mathbb{R}^{L_s \times L_s}$, where the entries is given as follows:

$$F_{li}^{mm} = \begin{cases} 0, & l = i \\ \dfrac{G_{li}^{mm}}{G_{ll}^{mm}}, & l \neq i, \end{cases} \tag{8}$$

and:

$$F_{lj}^{ss} = \begin{cases} 0, & l = j \\ \dfrac{G_{lj}^{ss}}{G_{ll}^{ss}}, & l \neq j. \end{cases} \tag{9}$$

In addition, we assume that the matrix $\mathbf{F}$ is irreducible, which means that each primary or secondary users must have no less than an interferer. Then, we rewrite (5) to the linear programming in terms of $\mathbf{p}$ which is in matrix form [10] as follow:

$$\begin{aligned}
&\text{minimize} \ \mathbf{1}^\top \mathbf{p} \\
&\text{subject to} \ (\mathbf{I} - \mathsf{diag}(e^{\bar{\mathbf{r}}} - 1)\mathbf{F})\mathbf{p} \geq \mathsf{diag}(e^{\bar{\mathbf{r}}} - 1)\mathbf{v} \\
&\qquad\qquad \mathbf{0} \leq \mathbf{p} \leq \bar{\mathbf{p}}, \\
&\text{variables:} \ \mathbf{p}.
\end{aligned} \tag{10}$$

Note that (10) is convex, many existing algorithms could be applied. When (10) is feasible, there are efficient distributed power control algorithms to tackle (10) as follows:

$$p_l(t+1) = \min\left\{\frac{e^{\bar{r}_l}-1}{\mathsf{SINR}_l(\mathbf{p}(t))}p_l(t), \bar{p}_l\right\}, \quad (11)$$

or:

$$p_l(t+1) = \min\left\{\frac{\bar{r}_l}{\log(1+\mathsf{SINR}_l(\mathbf{p}(t)))}p_l(t), \bar{p}_l\right\}, \quad (12)$$

for all $l = 1, \cdots, L_m + L_s$ with $\mathsf{SINR}(\mathbf{p}) = [\mathsf{SINR}^m(\mathbf{p}); \mathsf{SINR}^s(\mathbf{p})]$. Intuitively, the l-th user reduces its transmit power if $r_l(\mathbf{p})$ is beyond $\bar{r}_l$, otherwise it increases its transmit power. These constrained iterative algorithms have been provided in [12] and [35]. They are proved to converge to the optimal solution as long as (5) is feasible. But both (11) and (12) converge to a solution that only the part of secondary users could achieve their communication rate requirements, if (5) is infeasible. It is possible that there is no feasible solution to (5), due to the high interference from the numerous secondary users. In this scenario, it is valuable to get the maximum network capacity with low energy consumption.

Definition 1: The network capacity is the number of maximum feasible set including primary users and the most supported secondary users under the constraints in (5) being all feasible.

Note that we should assume that the cognitive radio network is feasible when there are only the primary users. Thus, the focus lies on finding out the additional secondary users which are accessed to the network. However, it is difficult to obtain the maximum network capacity when (10) is infeasible, as it is a flagrant combinatorial optimization problem [18]. Moreover, different strategies produce different energy efficiency, even having the same network capacity. Therefore, we would like to provide high energy efficiency by consume the power as few as possible, after the secondary users access the channel in the cognitive radio network. There is a necessary but not sufficient criterion about the feasibility of (10), which is called as the spectral radius of network characteristic matrix [36]:

$$\rho\left(\mathrm{diag}\left(e^{\bar{\mathbf{r}}}-1\right)\mathbf{F}\right) < 1. \quad (13)$$

Remark 1: The spectral radius of network characteristic matrix is still the same if we disorder the rows.

Next, we introduce two criteria for the energy efficiency. One is the weighted total energy efficiency as follow:

$$\frac{\sum_{i=1}^{L_m}\omega_i^m r_i^m + \sum_{j=1}^{L_s}\omega_j^s r_j^s}{\sum_{i=1}^{L_m}\omega_i^m p_i^m + \sum_{j=1}^{L_s}\omega_j^s p_j^s}. \quad (14)$$

The other is the weighted individual energy efficiency as follow:

$$\sum_{i=1}^{L_m}\omega_i^m \frac{r_i^m}{p_i^m} + \sum_{j=1}^{L_s}\omega_j^s \frac{r_j^s}{p_j^s}. \quad (15)$$

The vector $\boldsymbol{\omega}$ is regarded as the weights that satisfy:

$$\sum_{i=1}^{L_m}\omega_i^m + \sum_{j=1}^{L_s}\omega_j^s = 1, \quad (16)$$

on both primary and secondary users. It denotes the same weight when the weights are all the same, i.e.:

$$\omega_1^m = \cdots = \omega_{L_m}^m = \omega_1^s = \cdots = \omega_{L_s}^s. \quad (17)$$

Then, the energy efficiency in (14) is equivalent with the one in [37].

Remark 2: Usually, the communicate rate requirements for the primary users are guaranteed, i.e., $r_i^m = \bar{r}_i^m$. As long as the cognitive radio network is feasible, the communicate rate requirements for the secondary users are also tight, i.e., $r_j^s = \bar{r}_j^s$.

III. CHARACTERIZATION OF SPECTRAL RADIUS

In this section, we analyze the relationship between the spectral radius and the power consumption. Different from [20], the secondary user is removed based on the price of the spectral radius. Instead, we add the new secondary user into the already feasible cognitive radio network based on the spectral radius, because there are numerous waiting secondary users. Intuitively, we admit the secondary user who leads to the smallest spectral radius, i.e., $\rho(\mathrm{diag}(e^{\bar{\mathbf{r}}_j}-1)\mathbf{F})$ after adding j-th user.

Note that $\rho(\mathbf{A}) \leq \rho(\mathbf{B})$ for nonnegative matrices $\mathbf{A} \leq \mathbf{B}$ based on the nonnegative matrix theory [38]. Thus, the selected secondary user depends on the corresponding transmitting distance and the communication rate requirement. Firstly, we show the characterization of spectral radius for homogeneous networks that the path losses are identical, i.e., $G_{ij} = G_{jj}$. There are five users sharing the same channel in a cognitive radio network with the distance vector $d = [300, 530, 740, 860, 910]^\top$m. Each entry denotes the distance between the receiver and corresponding transmitter. The communication rate requirement vector is $\bar{r} = [0.2, 0.1, 0.2, 0.1, 0.1]^\top$. The noises $\boldsymbol{\sigma}$ at all receivers are assumed to be the same 1×10^{-15}W. The path loss uses the model $G_{jj} = kd_j^{-4}$ in [39], where d_j represents the distance from the j-th transmitter to its receiver, and $k = 0.08$ denotes the factor of power variations. The power budgets for all users are regarded as the same $\bar{p}_l = 1$W.

We check whether the network is feasible by tackling (10). Then, we calculate the spectral radius by successively trying to add one more secondary user. Figure 2 demonstrates the almost exponential trend about the total energy consumption with the increases spectral radius $\rho(\mathrm{diag}(e^{\bar{\mathbf{r}}_l}-1)\mathbf{F})$. This means that we should select the secondary user who has

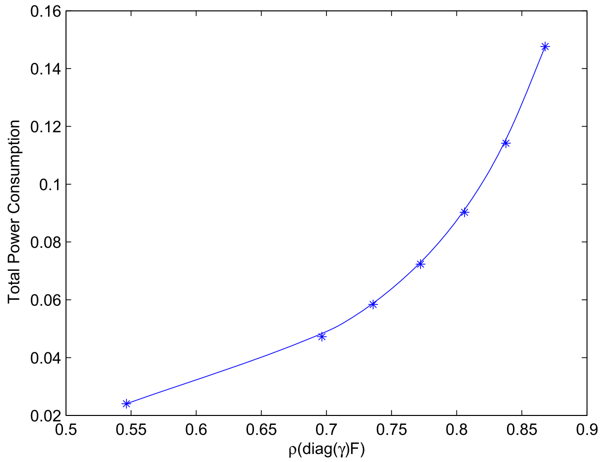

FIGURE 2. An illustration of the impact of different spectral radius if the channel access a new secondary user in a homogeneous cognitive radio network.

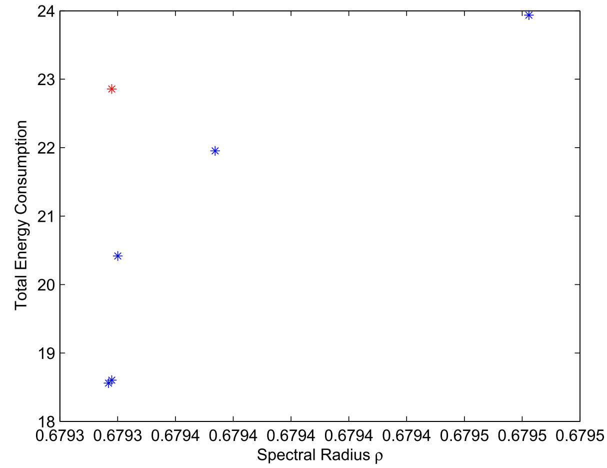

FIGURE 4. An illustration of the disorder impact of the spectral radius in a heterogeneous cognitive radio network. The red point denotes the disorder impact of the secondary user.

the short transmitting distance and small communication rate requirement.

Next, we study a feasible heterogeneous cognitive radio network with four users. $G_{ji} = kd_{ji}^{-4}$ where d_{ji} represents the distance from the i-th transmitter to the j-th receiver. We randomly produce six secondary users attempting to access the channel. Figure 3 demonstrates that the energy consumption is still the same increasing trend with the spectral radius $\rho(\mathrm{diag}(e^{\bar{\mathbf{r}}_l} - 1)\mathbf{F})$ in the heterogeneous cognitive radio network. Figure 4 demonstrates that the selected user for smaller energy consumption may be not the secondary user who leads to the smallest spectral radius, e.g., the red case. But the heterogenous cognitive radio networks have the same trend between the energy consumption and the spectral radius in high probability as the homogenous networks.

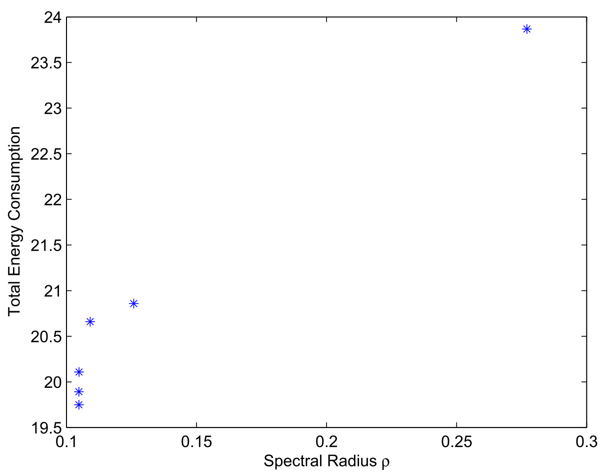

FIGURE 3. An illustration of the normal impact of the spectral radius in general case of heterogeneous cognitive radio network.

IV. HYBRID ACCESS CONTROL ALGORITHM

Generally, selecting the largest set of secondary users whose communication rate requirements can all be achieved in (5) is a NP-hard combinatorial problem [21], if the network is infeasible. Especially for the huge number of secondary users, it takes too many computation to get the feasible set having the maximum cardinality. We introduce an auxiliary variable q_s^j for each secondary user to the right side of the rate constraint:

$$\begin{aligned}
&\text{minimize } \|\mathbf{q}^s\|_0\\
&\text{subject to } \frac{e^{\bar{r}_i^m}-1}{\mathsf{SINR}_i^m(\mathbf{p})} \le 1, \quad i=1,\ldots,L_m\\
&\qquad\qquad \frac{e^{\bar{r}_j^s}-1}{\mathsf{SINR}_j^s(\mathbf{p})} \le 1+q_j^s, \quad j=1,\ldots,L_s\\
&\qquad\qquad \mathbf{0} \le \mathbf{p} \le \bar{\mathbf{p}},\\
&\text{variables}: \ \mathbf{p}, \mathbf{q}^s.
\end{aligned} \tag{18}$$

q_j^s is regarded as an indicator of infeasibility that has also a practical meaning of rate margins. The objective $\|\mathbf{q}^s\|_0$ is the ℓ_0 norm that denotes the cardinality of $\mathbf{q}^s$. It is interesting to note that (18) is always feasible.

A. FEASIBILITY CHECK

For the convenient of demonstration, we have $\mathbf{q} = [\mathbf{q}^m; \mathbf{q}^s]$ that $\mathbf{q}^m$ denotes the zero vector with L_m zeros.

Remark 3: When $\mathbf{q}$ is a feasible solution of (18), we get:

$$\rho\left(\mathsf{diag}\left(\frac{e^{\bar{\mathbf{r}}}-1}{\mathbf{1}+\mathbf{q}}\right)\left(\mathbf{F}+\frac{1}{\bar{p}_l}\mathsf{v}\mathsf{e}_l^\top\right)\right) \le 1, \quad l=1,\ldots,L_m+L_s. \tag{19}$$

Based on Remark 3, (5) is feasible if and only if the optimal value of (18) is zero. The introduced variable q_j^s will be positive when the communication rate requirement of the j-th secondary user cannot be satisfied. Then, we propose the following distributed feasibilities power control algorithm to approximate (18) based on the method in [24].

Algorithm 1 Distributed Feasibilities Power Control

1) **Update the transmitter power of each primary user** $i \in \{1, \ldots, L_m\}$**:**

$$p_i(k+1) = \min\left\{\frac{e^{\bar{r}_i}-1}{\mathsf{SINR}_i(\mathbf{p}(k))}p_i(k), \bar{p}_i\right\}. \quad (20)$$

2) **Update the transmitter power of each secondary user** $j \in \mathcal{A}(k)$**:**

$$p_j(k+1) = \min\left\{\frac{(e^{\bar{r}_j}-1)p_j(k)}{\max\{\nu_j(k), 1\}\mathsf{SINR}_j(\mathbf{p}(k))}, \bar{p}_j\right\}. \quad (21)$$

3) **Update all users** $l \in \{1, \ldots, L_m\} \bigcup \mathcal{A}(k)$**:**
If $p_l(k+1) < \bar{p}_l$
- Update $x_l(k+1)$:

$$x_l(k+1) = \sum_{i=1}^{L_m} F_{il}(e^{\bar{r}_i}-1)x_i(k) + \sum_{j\in\mathcal{A}(k)} \frac{F_{jl}(e^{\bar{r}_j}-1)x_j(k)}{\max\{\nu_j(k), 1\}}. \quad (22)$$

- Update the dual variable $\nu_l(k+1)$:

$$\nu_l(k+1) = x_l(k+1)p_l(k+1). \quad (23)$$

else
- Update the dual variable $\nu_l(k+1)$:

$$\nu_l(k+1) = \frac{e^{\bar{r}_l}-1}{\mathsf{SINR}_l(\mathbf{p}(k+1))}. \quad (24)$$

- Update $\mathbf{x}(k+1)$:

$$x_l(k+1) = \nu_l(k+1)/p_l(k+1). \quad (25)$$

end

4) **Inner loop condition:**
If $\|\mathbf{p}(k+1) - \mathbf{p}(k)\|_2 < \epsilon$
- Go to Step 5.

else
- Go to Step 1.

end

5) **Secondary user admission control:**
- Let $q_j(k+1) = \max\{\nu_j(k+1) - 1, 0\}$ for all secondary users $j \in \mathcal{A}(k)$. If $\mathbf{1}^\top \mathbf{q}(k+1) > 0$, then eliminate the worst secondary user z, i.e.:

$$z = \arg\min_{j\in\mathcal{A}(k)} \omega_j^s \frac{\log(1+\mathsf{SINR}_j(p_j(k+1)))}{p_j(k+1)}, \quad (26)$$

- Update the supported set $\mathcal{A}(k+1) \leftarrow \mathcal{A}(k) - z$ and go to Step 1.

B. ACCESS CONTROL

In this section, we design the following algorithm to iteratively access the secondary user until that the spectral radius of $\rho(\mathrm{diag}(e^{\bar{r}_l}-1)\mathbf{F})$ is less than one. As this is not the sufficient criterion of feasibility for the cognitive radio network, the system may stay in the infeasible state. Thus, we make use of Algorithm 1 to eliminate the potential unsupported secondary users. Let $\mathcal{B}$ be the set of the unsupported secondary users.

Algorithm 2 Hybrid Access Control

1) **Initialization:**
- Initialize the set of potential secondary users $\mathcal{B}(0) = \{1, \ldots, L_s\}$.

2) **Select the supported secondary user:**
- Calculate each spectral radius:

$$\begin{aligned} j &= \arg\min_{l\in\mathcal{B}(k)} \rho_l(k+1) \\ &= \rho(\mathrm{diag}(e^{\bar{\mathbf{r}}_l}-1)\mathbf{F}_l). \end{aligned} \quad (27)$$

3) **Access the supported secondary user:**
If $\rho_j < 1$
- Access the j-th secondary user into the cognitive radio network.
- Update the potential set $\mathcal{B}(k+1) \leftarrow \mathcal{B}(k) - j$.
- Go to Step 2.

else
- Go to Step 4.

end

4) Run Algorithm 1 to check whether the cognitive radio network is feasible and obtain the optimal transmitting power allocation.

Remark 4: The approximated potential set of secondary users, i.e., $\mathcal{B}*$, contains the remaining unsupported secondary users in $\mathcal{B}(k)$ and the eliminated secondary users in Step 4. We design a mixed access strategy to choose the supported secondary users.

V. NUMERICAL EXAMPLES

In this section, we numerically evaluate our algorithm in terms of both network capacity and energy efficiency.

Example 1: We initialize the same network parameters as the scenario in [24]. There is a user indexed by 1 and four secondary users with the distance vector $\mathbf{d} = [310, 540, 640, 880, 950]^\top$m in a single-cell channel. The communicate rate requirements vector for these five users is $\bar{\mathbf{r}} = [0.3364, 0.2623, 0.3001, 0.2231, 0.2231]^\top$. Algorithm 2 gets the same supported secondary users with the distributed removal algorithm in [24], that eliminates User 3 such that the rest of users satisfy their communication rate requirements.

In another scenario, we compare our algorithm with the centralized removal algorithm in [20] for general networks with heterogenous path loss. There are four primary users communicating in a feasible cognitive radio network. Their transmit power thresholds and communication rate requirements are set as the same. Meanwhile, there are six secondary

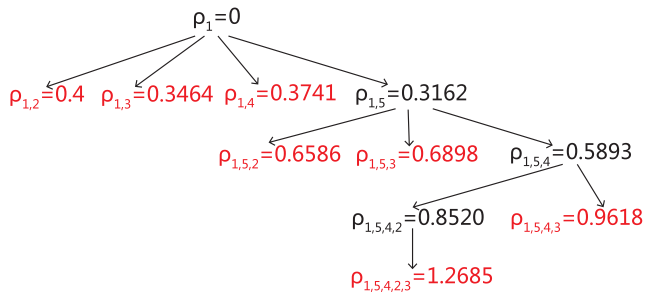

FIGURE 5. **The evolution of the spectral radius ρ in our algorithms. The red elements denote the leaves of the selecting tree.**

users trying to access the channel. When the cognitive radio network serves all these ten users with $\mathcal{A} = \{5, 6, \ldots, 10\}$, the maximum spectral radius is $\rho = 0.4956 < 1$. We use Algorithm 1 to find that the network is infeasible, i.e., all ten users can not be satisfied at the same time. In the contrary, the network becomes feasible after eliminating three secondary users $\mathcal{B}^* = \{8, 10, 5\}$, according to the centralized removal algorithm in [20]. Table 1 verifies the necessary of Step 4 in Algorithm 2 by listing the corresponding spectral radius for these three secondary users. It is interesting that the descending order of the spectral radius is identical with the eliminating order of the removal algorithm in [23]. Our hybrid algorithm gets the same set of unsupported secondary users $\mathcal{B}^* = \{5, 8, 10\}$.

TABLE 1. **Spectral radius of eliminated secondary users.**

	Min	User 5	User 8	User 10	Max
ρ	0.3202	0.3774	0.3884	0.3793	0.4956

Example 2: We compare our hybrid algorithm with the constrained DPC algorithm for networks that have more general channel gains $G_{lj} \neq G_{jj}$ for all $l \neq j$. We consider a network with 2 primary users (cannot be removed) and 8 secondary users. The channel gains are generated randomly to make (5) infeasible. The transmit power upper bounds and the rate thresholds for all the users are the same, i.e., $\bar{p}_l = 1$ W and $\bar{r}_l = 0.1761$, respectively.

Figure 6 shows the evolution of the DPC algorithm where the eight secondary users are transmitting at their maximum power and cannot achieve the rate thresholds yet. Once these secondary users are all removed, the remaining two primary users can achieve their rate thresholds. Figure 7 shows the evolution of our hybrid algorithm where there are altogether seven users that can achieve their rate thresholds after the {3,5,10}-th users (which are the secondary users) are iteratively removed. As compared to the DPC algorithm, our algorithm increases the system capacity from 20% to 70%. At the same time, the average energy efficiency of DPC algorithm is 0.4176 and the one of our algorithm is 0.4668, using the criteria (15).

In conclusion, in the case of the same energy, Algorithm 2 has a greater data transfer rate than DPC algorithm. In other

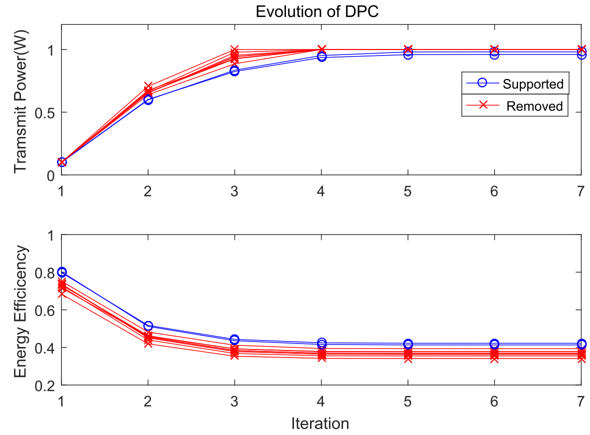

FIGURE 6. **The evolution of transmit power and individual energy efficiency for the DPC algorithm. The blue lines are the two supported users. The red lines are the eliminated secondary user.**

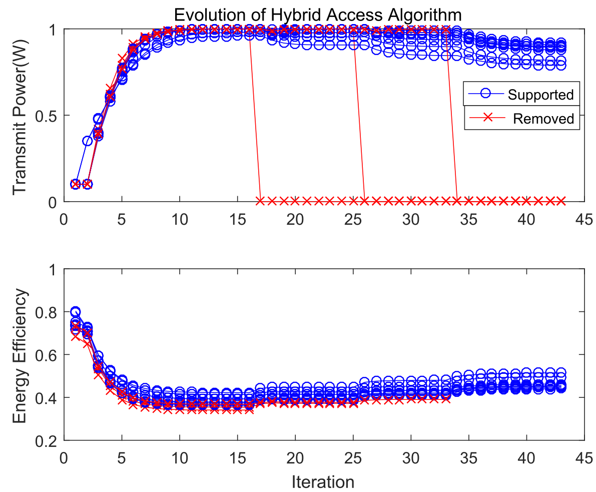

FIGURE 7. **The evolution of transmit power and individual energy efficiency for our algorithm. The blue lines are the seven supported users. The red lines are the eliminated secondary user.**

words, if Algorithm 2 and DPC algorithm have the same constrain of data transfer rate, Algorithm 2 can save more energy than DPC algorithm. The main reason is that the DPC algorithm excessively eliminates secondary user depending on the transmit power, however Algorithm 2 makes use of the access price to decide which secondary user is the worst. We also compare our solution with that obtained by Algorithm 1, which removes the user to maximize the minimum achievable data transfer rate, and both obtain the same solution.

The previous experiment is conducted with the same weights, i.e., $\boldsymbol{\omega}$=[0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1]. The total energy consumption is 6.1042W and the average energy efficiency in (15) is 0.4668. When we change the weights to be $\boldsymbol{\omega}$=[0.2,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0], the total energy consumption becomes 6.1005W which gives an additional energy saving of 0.06% and the average energy efficiency in (15) becomes 0.4669. From this we can find that different weights have a certain effect on our experimental results.

Different weights may make our algorithm more outstanding in some cases. The influence of weights on the algorithm will be our future work.

Example 3: Note that different algorithms may get different sets of supported secondary users, because the maximum feasible set is not unique in high probability. Now, we compare different algorithms in terms of the outage probability and the energy efficiency based on Monte-Carlo (MC) methods with at least 200 MC runs. For each MC run, the transmitters randomly locate on a 2 Km $\times$2 Km square. The primary users are randomly chosen 10% from all the users. The rest of users are regarded as the secondary users. All the power budgets are set the same as $\bar{p}_l = 1$W. The noises at all receivers are set as -60 dBm. The required communication rates are the same $\bar{r}_l = 0.2231$ for all l.

We compare hybrid Algorithm 2 with Algorithm 1 and the approaches in [23] and [24], in the same setup of network parameters for both capacity and energy efficiency. In terms of selecting the maximal possible feasible set, Figure 8 shows that our algorithms outperform the removal heuristic method in [23] but it is not better than Alg. [24]. In the aspect of energy efficiency, it can be seen from Figure 9 that our hybrid Algorithm 2 performs better than Algorithm 1, Alg. [23] and Alg. [24], using the criteria (14). From Figure 10 we can find that the energy efficiency of our hybrid algorithm is still efficient using another criteria (15). Our algorithms have a greater data transfer rate than other algorithms with the same energy, especially when the number of users is not very large.

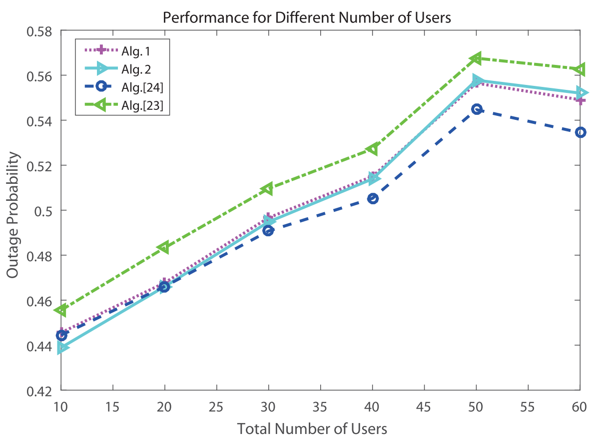

FIGURE 8. Average outage probability versus the total number of users. The lower bounds of all the communication rate requirements are set to be the same.

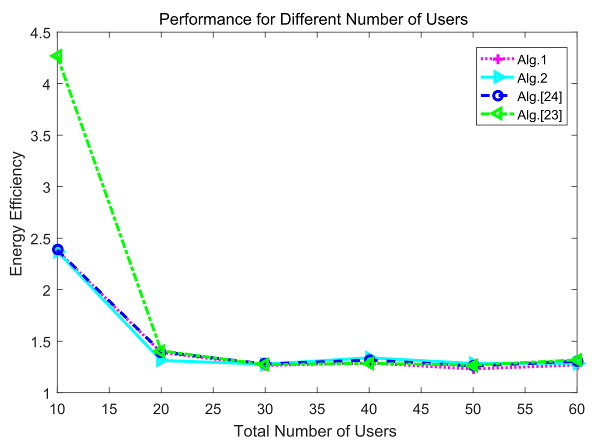

FIGURE 9. Energy efficiency in (14) versus the total number of users.

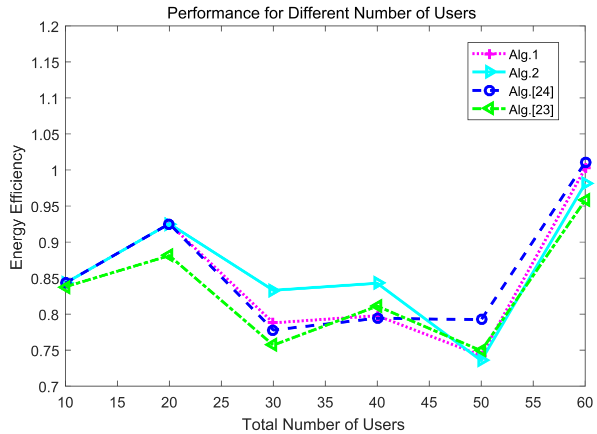

FIGURE 10. Energy efficiency in (15) versus the total number of users.

VI. CONCLUSION

We studied the network capacity for the next-generation cognitive radio networks with numerous secondary users under the constraints of power budgets and communication rate requirements. We showed that we should iteratively access the secondary user who has the short transmitting distance and small communication rate requirement based on the characterization of spectral radius. Then, we propose a decentralized power control algorithm to check the feasible state, and design a hybrid access control algorithm to reduce time of suffering interference. Numerical evaluations verified that our algorithm is well combined with existing removal algorithm and fast enough to converge to a near-optimal solution in terms of maximum supporting set of secondary users and high energy efficiency. It approves that the hybrid access strategy is better than the arbitrary access strategy. As future work, we will extend these price-driven algorithms to the joint spectrum access of both the primary and the secondary users and we will consider the influence of different weights on the performance of our algorithm.

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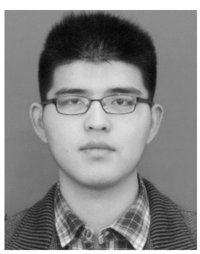

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