Adaptive Power Allocation Schemes for Spectrum Sharing in Interference Alignment (IA)-Based Cognitive Radio Networks

Nan Zhao, *Member, IEEE,* F. Richard Yu, *Senior Member, IEEE,* Hongjian Sun, *Senior Member, IEEE,* and Ming Li, *Member, IEEE*

***Abstract*—Interference alignment (IA) is a promising technique for interference management, and can be applied to spectrum sharing in cognitive radio (CR) networks. However, the sum rate may fall short of the theoretical maximum especially at low signal-to-noise ratio (SNR), and the quality of service (QoS) of the primary user (PU) may not be guaranteed. Besides, power allocation (PA) in IA-based CR networks is largely ignored, which can further improves its performance. Thus in this paper, PA in IA-based CR networks is studied. To guarantee the QoS requirement of the PU, its minimal transmitted power is derived. Then, we propose three PA algorithms to maximize the throughput of secondary users (SUs), the energy efficiency of the network, and the requirements of SUs, respectively, while guaranteeing the QoS of the PU. To reduce the complexity, the closed-form solutions of these algorithms are further studied in detail. The outage probability of the PU according to its rate threshold is also derived to analyze the performance of these algorithms. Moreover, we propose a transmission-mode adaptation scheme to further improve the PU's performance when its QoS requirement cannot be guaranteed at low SNR, and it can be easily combined with the proposed PA algorithms. Simulation results are presented to show the effectiveness of the proposed adaptive PA algorithms for IA-based CR networks.**

***Index Terms*—Cognitive radio, energy efficiency, interference alignment, power allocation, spectrum efficiency, transmission-mode adaptation.**

I. Introduction

COGNITIVE radio (CR) has attracted significant attention as a technology to overcome the problem of spectrum scarcity [1], [2]. In CR networks, spectrum sharing is a key technique allowing secondary users (SUs) to share the licensed spectrum of primary users (PUs), on the condition that the interference from SUs is not deemed harmful by the PUs [3]. Generally, there are two types of spectrum sharing schemes, i.e., overlay and underlay spectrum sharing [4]. In the underlay spectrum sharing, SUs can share the licensed spectrum with PUs, and the power of interference and noise at the primary receiver is constrained by interference temperature limit (ITL) [5]–[7]. In [6], Clancy showed that the resulting performance of SUs from the interference temperature model is low, compared to the performance degradation of PUs due to the interference from SUs. Thus it is still a key challenge in the underlay spectrum sharing to enhance SUs' rate while guaranteeing the quality of service (QoS) of PUs [7], [8].

Interference alignment (IA) is a promising technique for interference management [9], [10]. Nevertheless, there are still some challenges when IA is utilized in practical systems, and one problem is the imperfect channel state information (CSI). Accurate global CSI should be available at all the transceivers to calculate the solutions of IA, which is difficult to achieve in practical systems, and there are several works that focus on solving this problem [11]–[16]. On the other hand, the sum rate by IA can approach the capacity of interference channel at very high signal-to-noise ratio (SNR). However, it may decrease at moderate or low SNRs [15], since IA mainly focuses on eliminating interference, without involving the quality of desired signal [17]. Some research works have focused on improving the performance of IA networks when SNR is low [15], [18]. Gomadam *et al.* proposed a Max-SINR algorithm for IA in [18] to optimize the signal-to-interference-plus-noise ratio (SINR) of the desired signal, and it was verified that the sum rate of interference networks can be improved obviously when SNR is low. However, its advantage tends to be lost when SNR becomes larger. An antenna-switching IA scheme was proposed to improve its sum rate in [15], and the performance degradation of IA at low SNR was also analyzed. In most of the early research works, only the equal power allocation scheme was adopted. Recently, power allocation (PA) and control were adopted to IA to further improve its performance [19], [20]. Farhadi *et al*. proposed a distributed power control algorithm for IA networks in [19], to ensure the data transmission at a fixed rate for each user. PA was introduced to IA by Shu *et al.*, to optimize the throughput of IA networks in [20].

Due to its promising performance, IA has also been applied to CR networks [14], [17], [21]–[24]. Yi *et al.* [21] identified the opportunity of using IA to exploit frequency domain diversity from the available spectrum in CR networks to support transmission and improve the throughput of SUs. In [22], an MIMO CR network with relay was designed by Tang

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The corresponding author is Ming Li.

N. Zhao and M. Li are with the School of Inform. and Commun. Eng., Dalian University of Technology, Dalian, Liaoning, P. R. China (email: {zhaonan,mli}@dlut.edu.cn).

F. R. Yu is with the Depart. of Systems and Computer Eng., Carleton University, Ottawa, ON, Canada (email: richard.yu@carleton.ca).

H. Sun is with the School of Engn. and Comp. Sci., Durham University, Durham, DH1 3LE, UK (email: Hongjian@ieee.org).

et al., and IA was used to enhance the achievable degrees of freedom (DoFs) for the network. Xu *et al.* [23] proposed a practical interference alignment and cancellation algorithm for CR networks that can avoid the interference at the PU and optimize SUs' DoFs. In [14], [17], [24], resources allocation was studied in CR networks to optimize the performance of the network.

In underlay spectrum sharing CR networks, ITL is usually adopted to guarantee the QoS of PUs [5]–[7]. When IA is applied, ITL does not need to be considered, because the interferences among PUs and SUs can be eliminated perfectly [9]. Thus IA provides a convenient framework for spectrum sharing in CR networks free of interference. On the other hand, the received SINR of PUs in an IA-base CR network may decrease, compared to the scenario without IA and SUs. This may reduce PUs' QoS, even though the residual interference is trivial [14], [17], [24]. Therefore, the QoS of PUs in IA-based CR networks should be further improved and guaranteed. To this end, power allocation can be a potential candidate [25].

Although there exist some research works about PA in underlay spectrum sharing CR networks [26], [27], PA in IA-based CR networks is quite different due to the characteristics of IA. To the best of our knowledge, the PA problem in IA-based CR networks has not been studied systematically. The distinct features of this paper are as follows.

- PA is always an important issue in wireless communications [28]. However, the PA problem in IA-based CR networks is largely ignored in the existing works. In this paper, we study the fundamental issues about PA in IA-based CR networks.
- The PA problem in IA-based CR networks is quite different from the PA problem in traditional IA wireless networks, because the QoS of PUs must be guaranteed. Thus we derive the minimal transmitted power of the PU to guarantee its rate threshold in IA-based CR networks. This is an important metric for designing PA algorithms.
- We propose three PA algorithms to maximize the sum rate of SUs, the energy efficiency (EE) of the network, and the satisfaction of SUs, respectively, in IA-based CR networks. To reduce the complexity of these algorithms, the closed-form solutions are studied in detail. The outage probability of PU and SUs in the proposed algorithms is also derived according to its rate threshold with specific transmitted power.
- When SNR is low, all the transmitted power may be allocated to the PU to guarantee its rate threshold. In this case, it does not make sense to still adopt the IA scheme. We propose a transmission-mode adaption scheme to further improve the PU's rate at low SNR, and it can be easily combined with the proposed PA algorithms.

The rest of the paper is organized as follows. In Section II, the system model is presented, and the QoS requirement of the PU is analyzed. In Section III, the minimal transmitted power of the PU to guarantee its rate threshold is derived, three adaptive PA algorithms for IA-based CR networks are proposed, and the outage probability of the PU is derived according to its rate threshold. In Section IV, a transmission-

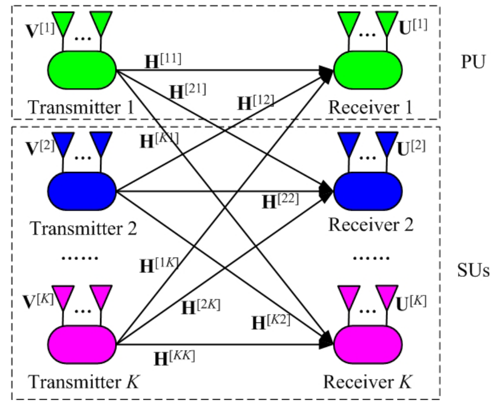

Fig. 1. A K-user IA-based CR network with 1 PU and $K-1$ SUs sharing the spectrum in the same frequency band simultaneously.

mode adaptation scheme is proposed to further improve the QoS of the PU. Simulation results are discussed in Section V, and finally, conclusions and future work are presented in Section VI.

Notation: $\mathbf{I}_d$ represents the $d\times d$ identity matrix. $\mathbf{A}^\dagger$ and $|\mathbf{A}|$ are the Hermitian transpose and the determinant of matrix $\mathbf{A}$, respectively. $\|\mathbf{a}\|$ is the ℓ^2-norm of vector $\mathbf{a}$. $|a|$ is the absolute value of complex number a. $\mathbb{C}^{M\times N}$ is the space of complex $M\times N$ matrices. $\mathbb{R}^N$ is the space of real $N\times 1$ vectors. $\mathcal{CN}(\mathbf{a},\mathbf{A})$ is the complex Gaussian distribution with mean $\mathbf{a}$ and covariance matrix $\mathbf{A}$. $\mathbb{E}(\cdot)$ stands for expectation.

II. System Description

In this section, we first introduce the model for IA-based CR networks. Then, the QoS requirement of the PU is analyzed.

A. IA-based CR Networks

Consider a K-user interference channel in a CR network as shown in Fig. 1, including one PU and $K-1$ SUs sharing the spectrum in the same frequency band simultaneously. The PU can be seen as user 1, and users 2 to K are SUs. $M^{[k]}$ and $N^{[k]}$ antennas are equipped at the kth transmitter and receiver, respectively. Perfect CSI of the network is assumed to be available at each node, and linear IA is harnessed to avoid interferences among the PU and SUs in the CR network [9], [18]. The received signal with $d^{[k]}$ data streams at the kth receiver can be expressed as

$$\mathbf{y}^{[k]}(n)=\mathbf{U}^{[k]\dagger}(n)\mathbf{H}^{[kk]}(n)\mathbf{V}^{[k]}(n)\mathbf{x}^{[k]}(n) \\ +\sum_{j=1,j\neq k}^{K}\mathbf{U}^{[k]\dagger}(n)\mathbf{H}^{[kj]}(n)\mathbf{V}^{[j]}(n)\mathbf{x}^{[j]}(n)+\mathbf{U}^{[k]\dagger}(n)\mathbf{z}^{[k]}(n),\quad(1)$$

where $\mathbf{H}^{[kj]}(n)\in\mathbb{C}^{N^{[k]}\times M^{[j]}}$ is the channel coefficient matrix from the jth transmitter to the kth receiver in the time slot n, with each of its entities independent and identically distributed (i.i.d.) and following $\mathcal{CN}(0,1)$. We assume that the channels follow block fading [29]. For clarity, the time slot number n is henceforth omitted. $\mathbf{V}^{[k]}$ and $\mathbf{U}^{[k]}$ are the unitary $M^{[k]}\times d^{[k]}$ precoding matrix and $N^{[k]}\times d^{[k]}$ interference suppression matrix of the kth user, respectively. $\mathbf{x}^{[k]}$ consists of $d^{[k]}$ data streams of user k with power constraint $P_t^{[k]}$, i.e., $\mathbb{E}\left[\left\|\mathbf{x}^{[k]}\right\|^2\right] = P_t^{[k]}$. $\mathbf{z}^{[k]} \in \mathbb{C}^{N^{[k]}\times 1}$ is the additive white Gaussian noise (AWGN) vector with distribution $\mathcal{CN}(\mathbf{0}, \sigma^2\mathbf{I}_{N^{[k]}})$ at the receiver k, where σ^2 is the noise power at each antenna of the receiver.

When IA is feasible [30], the interferences in the CR network can be assumed to be completely eliminated if the following conditions are met [18]:

$$\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{V}^{[j]} = 0, \ \forall j \neq k, \tag{2}$$

$$\mathrm{rank}\left(\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}\right) = d^{[k]}. \tag{3}$$

Thus the desired signals of user k can be assumed to be received through a $d^{[k]} \times d^{[k]}$ full rank channel matrix $\overline{\mathbf{H}}^{[kk]} \triangleq \mathbf{U}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}$, and thus (1) can be rewritten as

$$\mathbf{y}^{[k]} = \overline{\mathbf{H}}^{[kk]}\mathbf{x}^{[k]} + \overline{\mathbf{z}}^{[k]}, \tag{4}$$

where $\overline{\mathbf{z}}^{[k]} = \mathbf{U}^{[k]\dagger}\mathbf{z}^{[k]}$, also follows $\mathcal{CN}(\mathbf{0}, \sigma^2\mathbf{I}_{d^{[k]}})$.

Since this paper mainly concentrates on the adaptive PA of CR networks among different users instead of DoFs, it is assumed that there is only one data stream for each user in the rest of this paper. Besides, symmetric networks are considered, and all the users are assumed to have the same parameters, i.e., $M^{[k]} = M$, $N^{[k]} = N$ and $d^{[k]} = 1$ for all k. Thus the largest number of users that can be accommodated in the IA-based CR network should follow [30]

$$K \leq M + N - 1. \tag{5}$$

The transmission rate of user k in the IA-based CR network when interferences are perfectly eliminated can be denoted as

$$R^{[k]} = \log_2\left(1 + \frac{\left|h^{[k]}\right|^2}{\sigma^2}P_t^{[k]}\right), \tag{6}$$

where $h^{[k]} \triangleq \mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}$. $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are the unitary precoding and decoding vectors for the kth user, respectively.

B. QoS Requirement of the PU in the IA-based CR network

In the underlay spectrum sharing CR networks, SUs can coexist with the PU on the condition that the interference from SUs will not be deemed harmful by the PU. The power of interference and noise at the primary receiver is usually constrained by the ITL, which can be used to guarantee the QoS requirement of the PU.

When IA is leveraged in the CR network, the interferences among the PU and SUs can be eliminated perfectly, and the ITL can be always satisfied with reasonable power of the background noise because there is no residual interference at the primary receiver. Therefore, IA can provide a convenient framework for the spectrum sharing, in which the interference among the PU and SUs need not be considered any longer.

Nevertheless, the SINR of the received signal at the primary receiver will decrease [15], [18], compared to the scenario with one MIMO PU and no SUs. Thus the problem of QoS requirement of PU should also be considered in the IA-based CR network. Transmission rate can reflect the variability of PU's QoS directly, and it is leveraged to measure the QoS of received signal in this paper. We define a rate threshold $R_{th}^{[1]}$ according to the QoS requirement of the PU, and the following constraint should be satisfied based on the principle of CR.

$$R^{[1]} \geq R_{th}^{[1]}. \tag{7}$$

In the IA-based CR network, the SUs should try to satisfy the QoS requirement of the PU defined in (7), otherwise they will not be allowed to access the licensed spectrum.

III. Adaptive Power Allocation Algorithms in IA-Based CR Networks

In most previous works of IA, equal transmitted power P_t is allocated to each user as usually assumed. However, this may hinder the improvement of IA's performance. In this section, PA among users in IA-based CR networks is studied, under the condition that the sum transmitted power of all the users is constrained to be lower than a constant, i.e., $\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}$. The minimal transmitted power of the PU to guarantee its rate threshold is first presented. Then three adaptive PA algorithms with different objectives are proposed for IA-based CR networks. Finally, the outage probability of PU and SUs is analyzed.

A. Minimal Power of PU to Guarantee its QoS Requirement

In the IA-based CR network, when the PA among users is considered, the threshold of the PU's transmission rate should be satisfied. Proposition 1 is presented to define the minimal transmitted power of the PU that can guarantee its transmission threshold $R_{th}^{[1]}$.

Proposition 1: To satisfy the threshold of the PU's rate in the IA-based CR network, $R_{th}^{[1]}$, the transmitted power of the PU should follow

$$P_t^{[1]} \geq \frac{\left(2^{R_{th}^{[1]}} - 1\right)\sigma^2}{\left|h^{[1]}\right|^2} \triangleq P_{t-min}^{[1]}. \tag{8}$$

Proof: See Appendix A. ∎

When IA is adopted in CR networks, the residual interference at the primary receiver is trivial, and can be assumed to be perfectly eliminated. Thus we can deem $P_{t-min}^{[1]}$ as the minimal transmitted power of PU to satisfy $R_{th}^{[1]}$ requirement.

Remark 1: To guarantee the QoS requirement of the PU in the IA-based CR network, $P_t^{[1]}$ should satisfy

$$\begin{cases} P_{t-min}^{[1]} \leq P_t^{[1]} \leq P_t^{max}, & \text{if } P_{t-min}^{[1]} \leq P_t^{max}, \\ P_t^{[1]} = P_t^{max}, & \text{if } P_{t-min}^{[1]} > P_t^{max}. \end{cases} \tag{9}$$

Thus we can discuss the PA problem in the IA-based CR network as follows.

- $P_{t-min}^{[1]} > P_t^{max}$: This means when the constraint of the sum transmitted power of the network, P_t^{max}, is all allocated to the PU (corresponding to its rate of $R_{max}^{[1]}$), its rate threshold $R_{th}^{[1]}$ still cannot be satisfied, as shown in Fig. 2. Thus we should assign all the power P_t^{max} to

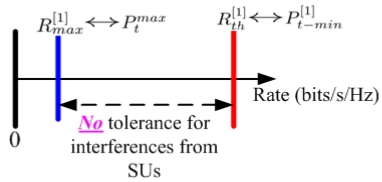

Fig. 2. Demonstration of the case when the PU's QoS requirement still cannot be met with P_t^{max} all allocated to it in the IA-based CR network.

the PU to maximize its rate, and the SUs cannot access the licensed spectrum.

- $P_{t-min}^{[1]} \le P_t^{max}$: If we want to optimize the performance of the network, $P_t^{[1]} \in [P_{t-min}^{[1]}, P_t^{max}]$ can be determined by the specific optimization problem. For example, when we want to optimize the performance of SUs, only $P_{t-min}^{[1]}$ should be assigned to the PU to guarantee its rate threshold while maximizing SUs' performance.

B. PA Algorithm for Maximizing the Sum Rate of SUs

In the spectrum trading based CR network [31], the income of PUs is proportional to the sum rate of SUs they provided. Besides, when there are multiple PUs selling spectrum to multiple SUs [31], the SUs can adapt their behavior by observing the variations in price and quality of spectrum offered by these PUs. Thus the sum rate of SUs should be maximized by means of PU with its $R_{th}^{[1]}$ constraint, to maximize its utility and maintain trading with SUs, and a PA algorithm for Maximizing the Rate of SUs (PAMRSU) is proposed in this subsection. SUs' sum rate can also be called the spectrum efficiency if we consider unit bandwidth.

In the PAMRSU algorithm, when $R_{th}^{[1]}$ constraint to the PU can be satisfied, i.e., $P_{t-min}^{[1]} < P_t^{max}$, allocate minimal power that can satisfy the $R_{th}^{[1]}$ constraint to the PU, i.e., $P_t^{[1]} = P_{t-min}^{[1]}$. All the remaining power $P_t^{max} - P_{t-min}^{[1]}$ is allocated to SUs to maximize their throughput. In this case, the PA optimization problem of the $K-1$ SUs can be represented as

$$\begin{aligned} \text{(P1)} \quad & \max_{P_t^{[2]}, P_t^{[3]}, \ldots, P_t^{[K]}} \sum_{k=2}^{K} \log_2\left(1+\left|h^{[k]}\right|^2 \frac{P_t^{[k]}}{\sigma^2}\right) \\ s.\ t. \quad & P_t^{[k]} \ge 0,\ \forall k = 2, \ldots, K \\ & \sum_{k=2}^{K} P_t^{[k]} = P_t^{max} - P_{t-min}^{[1]}. \end{aligned} \tag{10}$$

From (P1), we can see that it is similar to the PA problem in multiple parallel channels. Thus the famous waterfilling PA strategy [32] can exploited to solve (P1) when $P_{t-min}^{[1]} < P_t^{max}$, and its closed-form solution can be represented as

$$P_t^{*[k]} = \left(\nu - \frac{\sigma^2}{|h^{[k]}|^2}\right)^+, k = 2, 3, \ldots, K, \tag{11}$$

where $x^+ \triangleq \max(x, 0)$, and ν should satisfy

$$\sum_{k=2}^{K} \left(\nu - \frac{\sigma^2}{|h^{[k]}|^2}\right)^+ = P_t^{max} - P_{t-min}^{[1]}. \tag{12}$$

The closed-form solution of (P1) expressed in (11) and (12) is easy to obtain, and thus its computational complexity can be significantly reduced. The PAMRSU algorithm in each time slot can be expressed in Algorithm 1.

Algorithm 1 PAMRSU

1: A time slot starts. Calculate $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$, $k = 1, \ldots, K$.
2: $P_{t-min}^{[1]}$ is calculated according to (8).
3: **if** $P_{t-min}^{[1]} < P_t^{max}$, **then**
4: $\quad P_t^{[1]} = P_{t-min}^{[1]}$.
5: $\quad P_t^{max} - P_{t-min}^{[1]}$ is allocated to SUs by (11) and (12).
6: **else**
7: $\quad$ Allocate P_t^{max} to the PU.
8: $\quad$ SUs are switched into sleep mode.
9: **end if**
10: Transmission for duration T with the power allocated.
11: The time slot ends.

C. PA Algorithm for Maximizing the EE of the Network

Energy efficiency becomes an important design criterion recently in wireless communications due to rapidly rising energy consumption in information and communication technology [33]–[36]. The EE of IA-based CR networks can be defined as the transmitted information per unit frequency per Joule energy consumption (bits/Hz/Joule). The PA problem aiming at maximizing the EE of the whole CR network with $R_{th}^{[1]}$ constraint of the PU, can be formulated as

$$\begin{aligned} \text{(P2)} \quad & \max_{P_t^{[1]}, P_t^{[2]}, \ldots, P_t^{[K]}} \frac{\sum_{k=1}^{K} R^{[k]}}{\sum_{k=1}^{K} P^{[k]}} = \frac{\sum_{k=1}^{K} \log_2\left(1+\left|h^{[k]}\right|^2 \frac{P_t^{[k]}}{\sigma^2}\right)}{\sum_{k=1}^{K}\left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right)} \\ s.\ t. \quad & P_t^{[k]} \ge 0,\ \forall k = 2, \ldots, K \\ & P_t^{[1]} \ge P_{t-min}^{[1]} \\ & \sum_{k=1}^{K} P_t^{[k]} \le P_t^{max}, \end{aligned} \tag{13}$$

where $P^{[k]}$ is the total power consumption of user k, which comprises the transmitter-circuit power consumption $P_{ct}^{[k]}$, receiver-circuit power consumption $P_{cr}^{[k]}$ and transmitted power $P_t^{[k]}$ [35], [37]. The objective function of (P2) has a concave numerator and an affine denominator with linear constraints, and thus (P2) is a concave-convex fractional programming [38]. When $P_{t-min}^{[1]} \le P_t^{max}$, (P2) has optimal solution. To obtain the closed-form solution of (P2), Lemma 1 and Lemma 2 are first provided.

Lemma 1: When $\sum_{k=1}^{K} P_t^{[k]} = P_t^{max}$, the closed-form solution of (P2) can be calculated as

$$\begin{aligned} P_t^{*[1]} &= \left(\nu - \frac{\sigma^2}{\left|\widehat{h}^{[1]}\right|^2}\right)^+ + P_{t-min}^{[1]}, \\ P_t^{*[k]} &= \left(\nu - \frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)^+, k = 2, 3, \ldots, K, \end{aligned} \tag{14}$$

where ν should satisfy

$$\left(\nu-\frac{\sigma^2}{\left|\widehat{h}^{[1]}\right|^2}\right)^+ +\sum_{k=2}^{K}\left(\nu-\frac{\sigma^2}{|h^{[k]}|^2}\right)^+ = P_t^{max} - P_{t-min}^{[1]}. \quad (15)$$

$\left|\widehat{h}^{[1]}\right|$ can be denoted as

$$\left|\widehat{h}^{[1]}\right| = \frac{\left|h^{[1]}\right|^2}{1+\frac{\left|h^{[1]}\right|^2 P_{t-min}^{[1]}}{\sigma^2}}. \quad (16)$$

Proof: See Appendix B. ■

The solution of (P2) when $\sum_{k=1}^{K} P_t^{[k]} = P_t^{max}$ as in Lemma 1 is different from that of (P1). This is because in (P1) it is required that $P_t^{[1]} = P_{t-min}^{[1]}$, while in (P2) the constraint is changed into $P_t^{[1]} \geq P_{t-min}^{[1]}$. Besides, when SNR is low, $\sum_{k=1}^{K} P_t^{[k]} = P_t^{max}$ can be satisfied after optimization of (P2), and Lemma 1 can be leveraged to obtain the solution. However when SNR becomes higher, $\sum_{k=1}^{K} P_t^{[k]}$ will become smaller than P_t^{max} to maximize the EE of the network, and the waterfilling strategy is no longer suitable. We will obtain the optimal solution of (P2) through fractional programming as in Lemma 2 and Theorem 1.

Lemma 2: We have an equation with variable λ as

$$\sum_{k=1}^{K}\log_2\left(\frac{\left|h^{[k]}\right|^2}{\sigma^2\lambda\ln 2}\right) = K\frac{1}{\ln 2}+\lambda\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right). \quad (17)$$

The solution of (17) λ^* can be expressed as (18) (on the next page), where $\Psi(\cdot)$ denotes the Lambert W function.

Proof: See Appendix C. ■

Therefore based on Lemma 1 and Lemma 2, we can obtain the closed-form solution of (P2) as in Theorem 1 when $P_{t-min}^{[1]} < P_t^{max}$.

Theorem 1: We define

$$\begin{aligned} P_t^{[1]} &= \max\left\{\frac{1}{\lambda\ln 2}-\frac{\sigma^2}{\left|h^{[1]}\right|^2}, P_{t-min}^{[1]}\right\}, \\ P_t^{[k]} &= \max\left\{\frac{1}{\lambda\ln 2}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}, 0\right\}, k=2,\ldots,K, \end{aligned} \quad (19)$$

and

$$\sum_{k=1}^{K}\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)-\lambda\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}+P_t^{[k]}\right)=0. \quad (20)$$

Substitute $P_t^{[k]}$ in (20) by (19), and the solution of (20), λ^*, can be obtained. Thus we can also define

$$\begin{aligned} P_t^{*[1]} &= \max\left\{\frac{1}{\lambda^*\ln 2}-\frac{\sigma^2}{\left|h^{[1]}\right|^2}, P_{t-min}^{[1]}\right\}, \\ P_t^{*[k]} &= \max\left\{\frac{1}{\lambda^*\ln 2}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}, 0\right\}, k=2,\ldots,K. \end{aligned} \quad (21)$$

(P2) can be solved by the fractional programming, and its closed-form solution can be discussed as

1) $\sum_{k=1}^{K} P_t^{*[k]} < P_t^{max}$: The closed-form solution of (P2) can be defined as in (21).
2) $\sum_{k=1}^{K} P_t^{*[k]} \geq P_t^{max}$ and $P_{t-min}^{[1]} \leq P_t^{max}$: The closed-form solution of (P2) can be defined as in (14).

Proof: See Appendix D. ■

Remark 2: When SNR becomes lower, (P2) may have no solutions. This happens when

$$P_{t-min}^{[1]} = \frac{\left(2^{R_{th}^{[1]}}-1\right)\sigma^2}{\left|h^{[1]}\right|^2} > P_t^{max}. \quad (22)$$

That is to say, when the lower bound of the PU's transmitted power $P_{t-min}^{[1]}$ is larger than the constraint of P_t^{max} as in Fig. 2, the three constraints in (P2) cannot be satisfied simultaneously, and thus (P2) does not have any solutions.

Thus we propose a PA algorithm for Maximizing the EE of the Network (PAMEEN) based on (P2). The PAMEEN algorithm can be represented in Algorithm 2.

Algorithm 2 PAMEEN

1: A time slot starts. Calculate $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$, $k=1,\ldots,K$.
2: $P_{t-min}^{[1]}$ is calculated according to (8).
3: **if** $P_{t-min}^{[1]} < P_t^{max}$, **then**
4: Solve the energy-efficient PA problem in (P2) through the fractional programming according to Theorem 1.
5: **else**
6: Allocate P_t^{max} to the PU.
7: SUs are switched into sleep mode.
8: **end if**
9: Transmission for duration T with the power allocated.
10: The time slot ends.

In Step 7 of Algorithm 2, SUs are turned into sleep mode, and the power consumption of SUs mainly arise from the leaking current of the switching transistors when circuits are properly designed [37]. The power consumption of leaking current is usually much lower than the circuit power consumption in the active mode, and thus it can be neglected in the proposed PAMEEN algorithm in this paper, i.e., $P_{ct}^{[k]}=P_{cr}^{[k]}=P_t^{[k]}=0$, $k=2,3,\ldots,K$, when SUs are in the sleep mode.

D. PA Algorithm for Maximizing the Satisfaction of SUs

In the proposed PAMRSU and PAMEEN algorithms, the rate constraint is imposed only on the PU, and there is no requirement for the rate of SUs. If some rate constraints on SUs are also involved, they should also be met on condition that the PU's threshold is satisfied.

Assume that the rate requirements of the K users are $R_{th}^{[1]}$, $R_{th}^{[2]}$,..., $R_{th}^{[K]}$, and Proposition 1 is also suitable for SUs. Thus the minimal value of transmitted power of user k to met its rate requirement $R_{th}^{[k]}$ can be expressed as

$$P_{t-min}^{[k]} = \frac{\left(2^{R_{th}^{[k]}}-1\right)\sigma^2}{\left|h^{[k]}\right|^2}. \quad (23)$$

The rate threshold of the PU, $R_{th}^{[1]}$, should be satisfied primarily in the IA-based CR network. If $R_{th}^{[1]}$ can be met, we can allocate the remaining power to SUs to satisfy their

$$\lambda^* = \frac{K}{\ln 2 \sum\limits_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)}\Psi\left(\frac{\ln 2}{\mathrm{e}K}\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)\prod_{k=1}^{K}\left(\frac{\left|h^{[k]}\right|^2}{\sigma^2\ln 2}\right)^{\frac{1}{K}}\right). \tag{18}$$

requirements. We define a parameter to qualify the satisfaction of SUs (SSU) as

$$\begin{aligned}\Omega &= \sum_{k=2}^{K}\min\left(\frac{R^{[k]}}{R_{th}^{[k]}},1\right)\\ &= \sum_{k=2}^{K}\min\left(\frac{\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)}{R_{th}^{[k]}},1\right).\end{aligned} \tag{24}$$

The largest value of Ω is $K-1$ when rate requirements of all the SUs can be met, while its smallest value is 0 when no power is allocated to SUs and thus $R^{[k]}=0, k=2,\dots,K$. From (24), we can also know that still increasing $P_t^{[k]}$ when $R^{[k]} \geq R_{th}^{[k]}$ will decrease the value of Ω. This is because the QoS requirement of user k is already met, and increasing $P_t^{[k]}$ will result in the decrease of the power allocated to other SUs.

According to the definition of Ω in (24), we can define a PA optimization problem to maximize the SSU of SUs in the IA-based CR network as (P3).

$$\begin{aligned}\text{(P3)}\ &\max_{P_t^{[2]},P_t^{[3]},\dots,P_t^{[K]}}\ \sum_{k=2}^{K}\min\left(\frac{\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)}{R_{th}^{[k]}},1\right)\\ &s.\,t.\qquad P_t^{[k]}\geq 0,\ \forall k=2,\dots,K\\ &\qquad\quad \sum_{k=2}^{K}P_t^{[k]}=P_t^{max}-P_{t-min}^{[1]}.\end{aligned} \tag{25}$$

The solution of (P3) is difficult to obtain. To reduce the computational complexity in solving (P3), we propose a PA algorithm for Maximizing SSU (PAMSSU), and it is discussed in different cases as follows.

1) $P_t^{max} \leq P_{t-min}^{[1]}$:
The threshold of the PU $R_{th}^{[1]}$ cannot be met, and thus all the power P_t^{max} is allocated to the PU.

2) $P_t^{max} \geq \sum\limits_{k=1}^{K} P_{t-min}^{[k]}$:
The rate requirements of K users can all be satisfied. Thus $P_{t-min}^{[1]}$ is allocated to the PU, and the remaining power $P_t^{max}-P_{t-min}^{[1]}$ is allocated to SUs to maximize their sum rate with their rate requirements met. The PA problem can be expressed as

$$\begin{aligned}\text{(P4)}\ &\max_{P_t^{[2]},P_t^{[3]},\dots,P_t^{[K]}}\ \sum_{k=2}^{K}\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)\\ &s.\,t.\qquad P_t^{[k]}\geq P_{t-min}^{[k]},\ \forall k=2,3,\dots,K\\ &\qquad\quad \sum_{k=2}^{K}P_t^{[k]}=P_t^{max}-P_{t-min}^{[1]}.\end{aligned} \tag{26}$$

3) $P_{t-min}^{[1]} < P_t^{max} < \sum\limits_{k=1}^{K} P_{t-min}^{[k]}$:
$R_{th}^{[1]}$ can be met, and $P_{t-min}^{[1]}$ is allocated to the PU. The remaining power $P_t^{max}-P_{t-min}^{[1]}$ should be allocated to SUs to maximize the value of Ω, and the transmitted power of user k ($k=2,\dots,K$) cannot exceed $P_{t-min}^{[k]}$ to facilitate the maximizing of SSU. The PA problem can be expressed as

$$\begin{aligned}\text{(P5)}\ &\max_{P_t^{[2]},P_t^{[3]},\dots,P_t^{[K]}}\ \Omega=\sum_{k=2}^{K}\frac{1}{R_{th}^{[k]}}\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)\\ &s.\,t.\quad 0\leq P_t^{[k]}\leq P_{t-min}^{[k]},\ \forall k=2,3,\dots,K\\ &\qquad \sum_{k=2}^{K}P_t^{[k]}=P_t^{max}-P_{t-min}^{[1]},\end{aligned} \tag{27}$$

where Ω is not denoted as the expression in (24), because the transmitted power of each SU is already constrained to be lower than its minimal transmitted power to met its rate requirement.

According to Lemma 1, (P4) in (26) can be rewritten into a new format, and it can be solved by waterfilling strategy as

$$P_t^{*[k]}=\left(\nu-\frac{\sigma^2}{\left|\widehat{h}^{[k]}\right|^2}\right)^+ + P_{t-min}^{[k]},\quad \forall k=2,3,\dots,K, \tag{28}$$

where ν should satisfy

$$\sum_{k=2}^{K}\left(\nu-\frac{\sigma^2}{|\widehat{h}^{[k]}|^2}\right)^+ = P_t^{max}-\sum_{k=1}^{K}P_{t-min}^{[k]}. \tag{29}$$

$\left|\widehat{h}^{[k]}\right|^2$ can be denoted as

$$\left|\widehat{h}^{[k]}\right|^2=\frac{\left|h^{[k]}\right|^2}{1+\frac{\left|h^{[k]}\right|^2P_{t-min}^{[k]}}{\sigma^2}},\quad \forall k=2,3,\dots,K. \tag{30}$$

(P5) in (27) is a convex optimization problem, and it is easy to be solved by Karush-Kuhn-Tucker (KKT) conditions as

$$P_t^{*[k]}=\min\left(\left(\nu R_{th}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)^+, P_{t-min}^{[k]}\right),\ \forall k=2,3,\dots,K, \tag{31}$$

where ν should satisfy

$$\sum_{k=2}^{K}\min\left(\left(\nu R_{th}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)^+, P_{t-min}^{[k]}\right)=P_t^{max}-P_{t-min}^{[1]}. \tag{32}$$

The PAMSSU algorithm in each time slot can be expressed in Algorithm 3.

Algorithm 3 PAMSSU

A time slot starts. Calculate $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$, $k = 1, \ldots, K$.
$P_{t-min}^{[1]}$ is calculated according to (8).
if $P_t^{max} \geq \sum_{k=1}^{K} P_{t-min}^{[k]}$, **then**
  $P_t^{[1]} = P_{t-min}^{[1]}$.
  $P_t^{max} - P_{t-min}^{[1]}$ is allocated to SUs according to (P4).
else if $P_t^{max} \leq P_{t-min}^{[1]}$, **then**
  Allocate P_t^{max} to the PU.
  SUs are switched into sleep mode.
else
  $P_t^{[1]} = P_{t-min}^{[1]}$.
  $P_t^{max} - P_{t-min}^{[1]}$ is allocated to SUs according to (P5).
end if
Transmission for duration T with the power allocated.
The time slot ends.

E. Outage Probability Analysis of the PU and SUs

Outage probability simply means the probability that a given rate threshold cannot be satisfied because of channel variations [39], and it can reflect the variability of the transmission rate instantaneously. Thus it is suitable to be used in analyzing the rate performance of the PU in the IA-based CR networks. If the threshold of the PU's transmission rate is $R_{th}^{[1]}$ (bits/s/Hz), the outage probability of the PU in the IA-based CR network can be defined as

$$\begin{aligned}\Pr{}^{[1]}\{\text{outage}\} &= \Pr\left\{\log_2\left(1+\text{SINR}^{[1]}\right) < R_{th}^{[1]}\right\} \\ &= \Pr\left\{\log_2\left(1+\frac{\left|h^{[1]}\right|^2}{\sigma^2}P_t^{[1]}\right) < R_{th}^{[1]}\right\}, \quad (33)\end{aligned}$$

where $\text{SINR}^{[1]}$ is the SINR of the desired signal at the primary receiver.

In this subsection, the outage probability of the PU in the IA-based CR Network is analyzed.

Lemma 3: In a K-user IA-based CR network with 1 data stream each user, if the interferences are eliminated perfectly, $\left|h^{[k]}\right|^2 = \left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}\right|^2$ follows exponential distribution.

Proof: See Appendix E. ∎

Based on the results in Lemma 3, we can derive the expression of the outage probability of the PU in the IA-based CR network.

Proposition 2: The outage probability of the PU in the IA-based CR network can be expressed as

$$\Pr{}^{[1]}\{\text{outage}\} = 1 - \exp\left\{-\frac{\sigma^2\left(2^{R_{th}^{[1]}}-1\right)}{P_t^{[1]}}\right\}. \quad (34)$$

Proof: See Appendix F. ∎

From Proposition 2, we can know that the outage probability of the PU in the IA-based CR network is determined by the transmit SNR, i.e., $\frac{P_t^{[1]}}{\sigma^2}$ (the ratio between the transmitted power and the noise power at the receiver). Thus through increasing the transmitted power $P_t^{[1]}$ of the PU, its outage probability performance can be improved.

The outage probability of SUs can also be similarly defined according to Proposition 2 as follows, when the rate requirement of user k, $R_{th}^{[k]}$, is deemed as its threshold, $k = 2, 3, \ldots, K$.

$$\Pr{}^{[k]}\{\text{outage}\}=1-\exp\left\{-\frac{\sigma^2\left(2^{R_{th}^{[k]}}-1\right)}{P_t^{[k]}}\right\}, k=2,3,\ldots,K. \quad (35)$$

In CR networks, we should try to satisfy the rate requirements of SUs with the QoS of the PU guaranteed. Nevertheless, the spectrum sharing is performed among the PU and SUs even when the rate requrements of SUs cannot be met, i.e., the outage probability of the PU is more important to achieve than that of SUs. Thus only the PU's outage probability is analyzed through simulation in Section V.

IV. Transmission-Mode Adaptation Based on Power Allocation in the IA-Based CR Network

When IA is performed in the CR network, we can know that it is equal to a single-input and single-output (SISO) channel for each user if 1 data stream is sent at each transmitter, and thus the rate of each user in IA (equal to SISO) is lower than that of the MIMO single-user channel [15]. On the other hand, in the proposed PAMRSU, PAMEEN and PAMSSU algorithms when $P_{t-min}^{[1]} \geq P_t^{max}$, the transmitted power is all allocated to the PU, and SUs are switched into sleep mode.

Thus we propose a transmission-mode adaptation (TMA) scheme when $P_{t-min}^{[1]} \geq P_t^{max}$ to change the transmission mode from IA to a single-user MIMO system with SUs sleeping to further improve the rate of the PU to approach its constraint $R_{th}^{[1]}$.

In the proposed TMA scheme, when $P_{t-min}^{[1]} \geq P_t^{max}$, SUs are switched into sleep mode, and the PU adopts MIMO to communicate in the time slot solely. The transmission rate of the PU using MIMO can be expressed as [32]

$$R_{MIMO}^{[1]} = \log_2\left|\mathbf{I}_{N^{[1]}} + \frac{P_t^{max}}{\sigma^2}\mathbf{H}^{[11]}\mathbf{Q}^{[1]}\mathbf{H}^{[11]\dagger}\right|. \quad (36)$$

The CSI at transmitters (CSIT) of the network is available due to the calculation of IA, and thus in (36) the transmitted power at each antenna can be optimized through using waterfilling strategy. The optimal signal covariance $\mathbf{Q}^{[1]} = \widetilde{\mathbf{V}}^{[1]}\mathbf{S}^{[1]}\widetilde{\mathbf{V}}^{[1]\dagger}$, and $\widetilde{\mathbf{V}}^{[1]}$ can be obtained by singular value decomposition of the channel matrix as $\widetilde{\mathbf{U}}^{[1]}\mathbf{D}^{[1]}\widetilde{\mathbf{V}}^{[1]\dagger} = \mathbf{H}^{[11]}$. The optimal diagonal PA matrix $\mathbf{S}^{[1]} = \text{diag}\left(s_1, \ldots, s_{\min\left(M^{[1]},N^{[1]}\right)}, 0, \ldots, 0\right)$. The optimal PA among antennas of user k can be achieved through using waterfilling strategy as

$$s_i=\left(\mu - \frac{\sigma^2}{P_t^{max}\delta_i^{[1]2}}\right)^+, i = 1, \ldots, \min\left(M^{[1]}, N^{[1]}\right), \quad (37)$$

where $x^+ \triangleq \max(x, 0)$. $\delta_1^{[1]}, \ldots, \delta_{\min\left(M^{[1]},N^{[1]}\right)}^{[1]}$ are the diagonal elements of $\mathbf{D}^{[i]}$, and μ should satisfy

$$\sum_{i=1}^{\min\left(M^{[1]},N^{[1]}\right)} s_i = 1. \quad (38)$$

We can easily obtain that

$$R_{MIMO}^{[1]} = \log_2\left|\mathbf{I}_{N^{[1]}} + \frac{P_t^{max}}{\sigma^2}\mathbf{H}^{[11]}\mathbf{Q}^{[1]}\mathbf{H}^{[11]\dagger}\right| > \log_2\left(1+\left|h^{[1]}\right|^2\frac{P_t^{max}}{\sigma^2}\right) = R_{IA-max}^{[1]}. \quad (39)$$

Thus all the proposed PAMRSU, PAMEEN and PAMSSU algorithms can be further combined with TMA scheme to improve the PU's rate when $R_{th}^{[1]}$ constraint cannot be guaranteed in the IA-based CR network, and we call them PAMRSU-TMA, PAMEEN-TMA and PAMSSU-TMA algorithms, respectively. Only Step 7 of PAMRSU, Step 6 of PAMEEN algorithms, and Step 7 of PAMSSU algorithm, should be changed accordingly when TMA is involved.

The TMA scheme can improve the transmission rate of the PU in the proposed algorithms when $P_{t-min}^{[1]} \geq P_t^{max}$, and the outage probability of the PU will be significantly reduced according to (33) and (39) when $P_{t-min}^{[1]} \geq P_t^{max}$.

V. Simulation Results and Discussions

In our simulations, we consider an 5-user IA-based CR network with $M^{[k]} = N^{[k]} = 3$ antennas equipped at each transceiver, and each transmitter sends 1 data stream to its corresponding receiver. The minimizing interference leakage (MinIL) algorithm is adopted to calculate the solutions of IA [18]. Rayleigh block fading [29] is adopted, and perfect CSI is assumed to be available at each node. According to [35], [37], the transmitter-circuit power consumption $P_{ct}^{[k]}$, the receiver-circuit power consumption $P_{cr}^{[k]}$ of all the users are set to 98mW and 112mW, respectively. P_t^{max}/K is set to 20dbm, and thus the constrained total transmitted power of the network (also the maximum transmitted power of each user) is equal to 500mW. The iterative algorithm is adopted to obtained the solutions of IA [18]. The performance of the proposed three PA algorithms is compared jointly to demonstrate that they are suitable to be applied in different scenarios.

The analytical values of the outage probability of the PU according to (34) and its simulated values in the IA-based CR network are shown in Fig. 3, with $R_{th}^{[1]}$ equal to 7.5 bits/s/Hz, 5 bits/s/Hz and 2.5 bits/s/Hz, respectively. From the results, we can see that the outage probability of the PU increases when its rate threshold $R_{th}^{[1]}$ becomes larger, which means the QoS requirement of the PU is becoming more rigorous. Besides, the simulated values of outage probability are quite consistent with its analytical values in (34), which proves the conclusions in Proposition 2.

In Proposition 1, we have derived the minimal transmitted power of the PU $P_{t-min}^{[1]}$ to guarantee its rate threshold $R_{th}^{[1]}$. Thus the values of $P_{t-min}^{[1]}$ and its achieved $R^{[1]}$ when $R_{th}^{[1]}$=5 bits/s/Hz are shown in Fig. 4 over 200 time slots with block fading is adopted. From the results, we can observe that with $P_{t-min}^{[1]}$ assigned to the PU, the rate of the PU $R^{[1]}$ is unchanged and equal to 5 bits/s/Hz, which proves the results in Proposition 1. In addition, the minimal transmitted power of the PU $P_{t-min}^{[1]}$ to guarantee its threshold varies dramatically over the time slots, and the largest value of $P_{t-min}^{[1]}$ is more

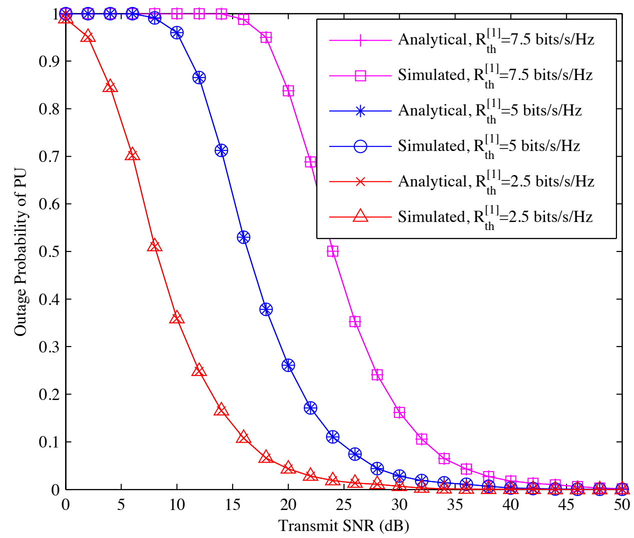

Fig. 3. Analytical and simulated values comparison of outage probability of the PU in the IA-based CR network with different values of $R_{th}^{[1]}$.

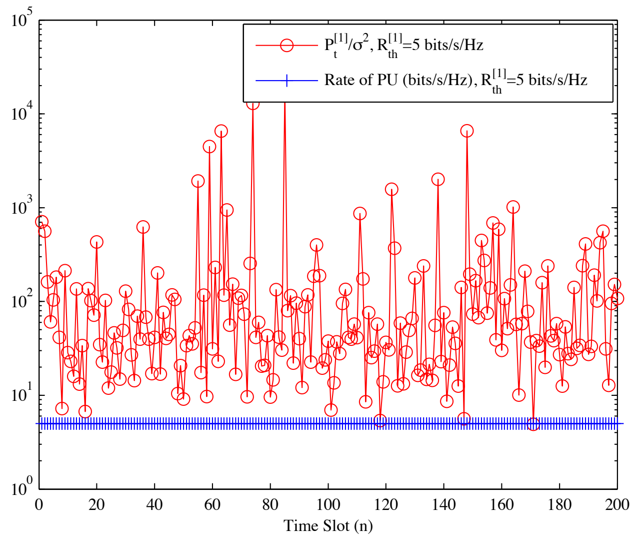

Fig. 4. Minimal transmitted power of the PU $P_{t-min}^{[1]}$ to guarantee the PU's threshold $R_{th}^{[1]}$=5 bits/s/Hz and its achieved rate of the PU over 200 time slots.

than 1000 times of its smallest value. Thus the transmitted power of the users in the IA-based CR network should be carefully allocated to guarantee the QoS of the PU while improving the performance of SUs.

The performance of the proposed PAMRSU, PAMEEN, PAMSSU, PAMRSU-TMA, PAMEEN-TMA, PAMSSU-TMA algorithms are compared. $R_{th}^{[1]}$ is set to 5 bits/s/Hz, and in PAMSSU and PAMSSU-TMA algorithms, $R_{th}^{[2]}$=0.5 bits/s/Hz, $R_{th}^{[3]}$=1 bits/s/Hz, $R_{th}^{[4]}$=5 bits/s/Hz and $R_{th}^{[4]}$=7.5 bits/s/Hz.

First the average SUs' sum rate of the IA-based CR network with these algorithms is compared in Fig. 5. It is shown that SUs' sum rate of the algorithms with TMA is the same as that of the algorithms without TMA. This is due to the fact that only the rate of the PU is changed when TMA is performed, and TMA has no affect on SUs. SUs' sum rate of PAMRSU(-

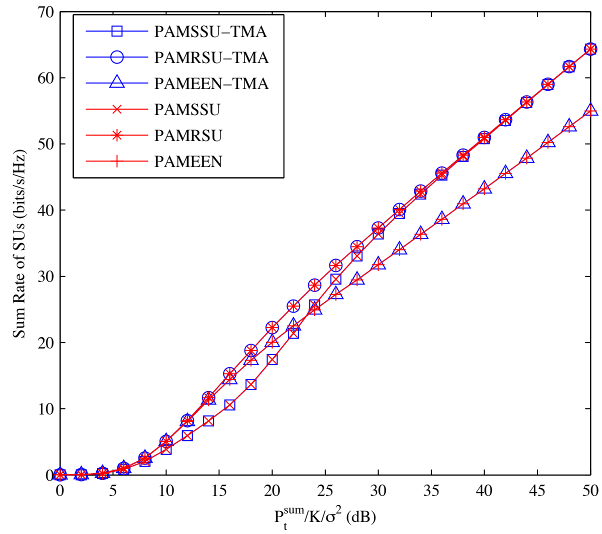

Fig. 5. Average SUs' sum rate comparison of different algorithms in a 5-user IA-based CR network.

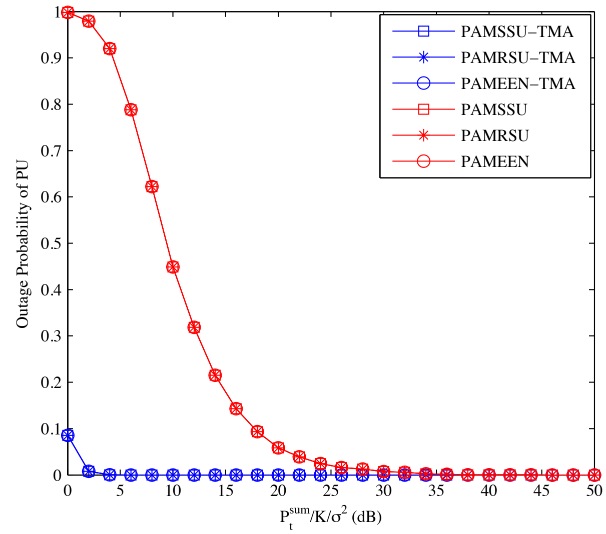

Fig. 7. The PU's average outage probability comparison of different algorithms in a 5-user IA-based CR network.

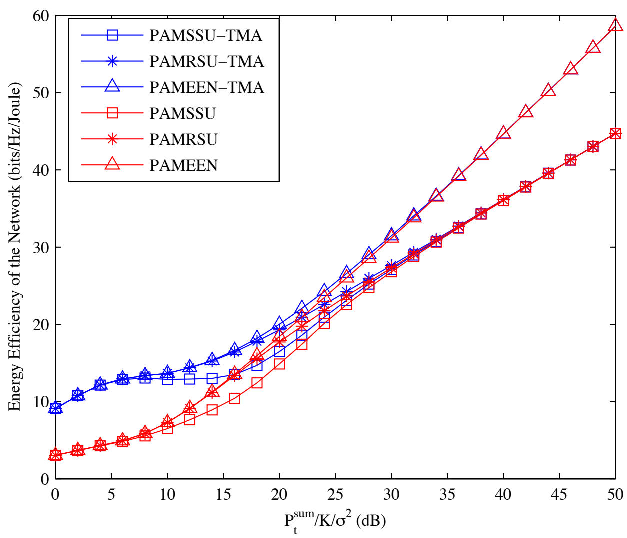

Fig. 6. Average energy efficiency comparison of different algorithms in a 5-user IA-based CR network.

TMA) algorithm is much larger than that of both PAMSSU(-TMA) and PAMEEN(-TMA) algorithms. Besides, SUs' sum rate of PAMSSU(-TMA) algorithm is larger than that of PAMEEN(-TMA) algorithm when the SNR is higher, due to smaller transmitted power of PAMEEN(-TMA) to enhance the EE of the network. SUs' sum rate of PAMSSU(-TMA) algorithm is becoming smaller than that of PAMEEN(-TMA) algorithm when the SNR becomes lower, because PAMEEN(-TMA) algorithm tends to be the same as PAMRSU(-TMA) algorithm when the SNR becomes lower.

Then the average EE of the IA-based CR network with different algorithms is compared in Fig. 6. From the results, we can see that when the SNR is larger ($P_t^{max}/K/\sigma^2$ >35dB), the EE of PAMRSU, PAMSSU, PAMRSU-TMA and PAMSSU-TMA algorithms are almost the same and much lower than that of PAMEEN and PAMEEN-TMA algorithms. This is because almost all of the rate requirements of the users can be met with IA, and PAMEEN(-TMA) algorithm is designed specially to optimize the EE of the network. When the SNR becomes smaller (15dB< $P_t^{max}/K/\sigma^2$ <35dB), EE of PAMRSU(-TMA) is becoming higher than that of PAMSSU(-TMA), and EE of PAMEEN(-TMA) is getting close to that of PAMRSU(-TMA). This is because TMA is performed sometimes to guarantee the threshold of the PU, PAMEEN is losing its advantage in improving the EE of the network, and PAMSSU focuses on the optimizing the parameter of SSU instead of sum rate or EE. When the SNR is extremely low ($P_t^{max}/K/\sigma^2$ <15dB), the EE of the algorithms with TMA is getting close to each other, which is much higher than that of the algorithms without TMA. It is because the probability of TMA is becoming higher with SNR becoming lower.

The minimal transmitted power of the PU $P_{t-min}^{[1]}$ to guarantee its rate threshold $R_{th}^{[1]}$ is derived in Proposition 1, and it is adopted when $P_{t-min}^{[1]} < P_t^{max}$ in all the proposed algorithms. When $P_{t-min}^{[1]} > P_t^{max}$, TMA of the PU is performed and all the SUs are switched into sleep mode. Thus the average outage probability of the PU of these algorithms is compared in the IA-based CR network in Fig. 7. From the results, we can observe that the outage probability of the algorithms with TMA is the same, which is much lower than that of the algorithms without TMA. Thus TMA scheme can significantly improve the performance of the PU in the IA-based CR network, which is consistent with the discussion in Section IV.

The PAMSSU algorithm can maximize the requirements of SUs, measured by SSU Ω in Subsection III-D, while trying to satisfy the PU's threshold. Thus the average value of Ω is compared in the IA-based CR network in Fig. 8. From the results, we can see that Ω of PAMSSU algorithm is much larger than that of PAMRSU algorithm, and Ω of PAMRSU algorithm is larger than that of PAMEEN algorithm. This is

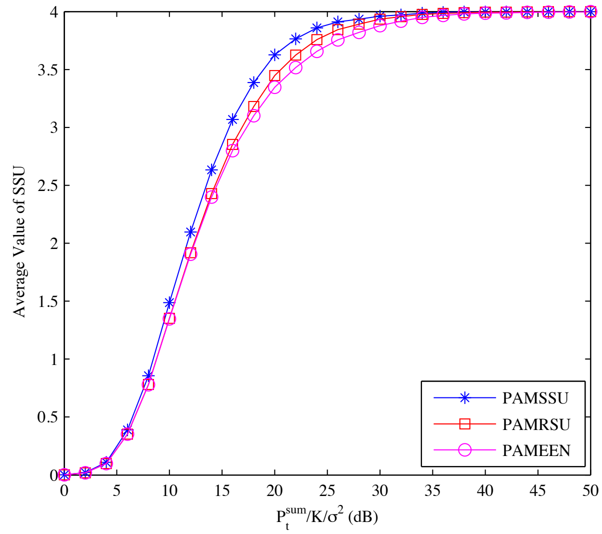

Fig. 8. Average value of SSU comparison of different algorithms in a 5-user IA-based CR network. $R_{th}^{[2]}$=0.5 bits/s/Hz, $R_{th}^{[3]}$=1 bits/s/Hz, $R_{th}^{[4]}$=5 bits/s/Hz and $R_{th}^{[4]}$=7.5 bits/s/Hz.

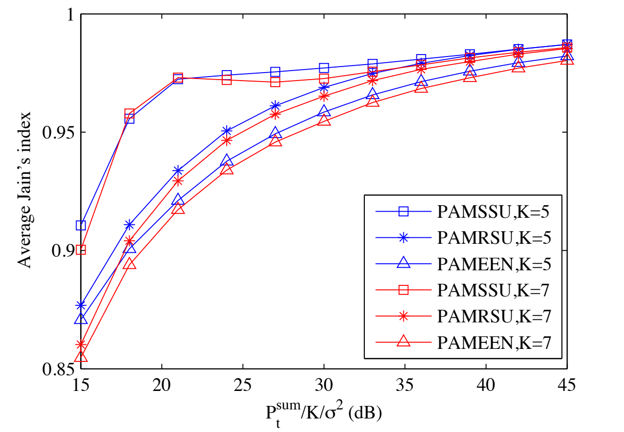

Fig. 9. Average Jain's index comparison of different algorithms in the IA-based CR network, when there are 5 users and 7 users, respectively. The rate requirements of all the users are set to 5 bits/s/Hz.

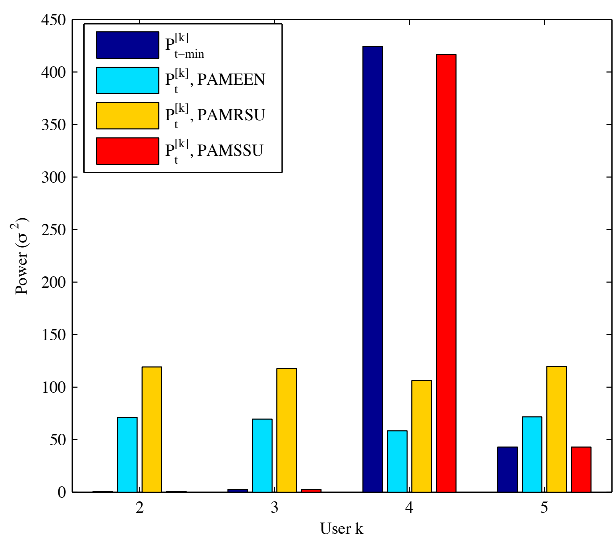

Fig. 10. Transmitted power comparison of SUs with different algorithms of the IA-based CR network in a certain time slot when $P_t^{max}/K/\sigma^2$ is equal to 20dB. $R_{th}^{[2]}$=0.5 bits/s/Hz, $R_{th}^{[3]}$=1 bits/s/Hz, $R_{th}^{[4]}$=5 bits/s/Hz and $R_{th}^{[5]}$=7.5 bits/s/Hz.

because the PAMSSU algorithm is designed to optimize Ω, and the PAMEEN algorithm mainly focuses the EE of the network instead of SUs' rate.

To further quantify the fairness of these algorithms, Jain's index is utilized to compare their fairness [40]. We define a length-$(K-1)$ vector $\mathbf{R}$ of non-negative real entries $\{R^{[k]}\}_{k=2}^{K}$, where $R^{[k]}$ is the transmission rate of SU k in the IA-based CR network. The Jain's fairness index J of vector $\mathbf{R}$ can be expressed as

$$J(\mathbf{R}) = \frac{\left(\sum_{k=2}^{K} R^{[k]}\right)^2}{(K-1)\sum_{k=2}^{K} R^{[k]2}}. \tag{40}$$

From (40), we can know that $\frac{1}{K} \leq J(\mathbf{R}) \leq 1$, and larger values of $J(\mathbf{R})$ means better fairness. Thus (40) can be leveraged as a metric to measure the fairness of the proposed algorithms. The average Jain's index of the proposed three algorithms is compared when $K = 5$ and $K = 7$ in Fig. 9, respectively. The rate requirements of all the users are set to 5 bits/s/Hz. From the results, we can know that the fairness of the PAMSSU algorithm is much better than the other two algorithms, and when the number of SUs increases, the fairness of the algorithm will decrease slowly. Besides, the Jain's index of the PAMSSU algorithm will not reach 1 when SNR is high, this is because when the rate requirements of all the SUs can be satisfied, it will not focus on the fairness any longer. Instead, the sum rate of SUs can be optimized with their rate requirements all satisfied.

In Fig. 3, and Fig. 5-9, the average performance of these algorithms is compared. Nevertheless, only the average performance cannot show their differences clearly, and we should compare the instantaneous performance of these algorithms to demonstrate their specific requirements. Therefore, the minimal transmitted power to guarantee rate requirement of each SU, and transmitted power of each SU of these three algorithms in a certain time slot are compared in Fig. 10 when $P_t^{max}/K/\sigma^2$ is equal to 20dB. The rate requirement of each SU, and achieved transmission rate of each SU of the three algorithms in this time slot are compared in Fig. 11 when $P_t^{max}/K/\sigma^2$ is equal to 20dB.

From the results, we can see that for user 2, user 3 and user 5, the minimal transmitted power to guarantee their rate requirements, $P_{t-min}^{[2]}$, $P_{t-min}^{[3]}$ and $P_{t-min}^{[5]}$, is relatively small, however, the transmitted power of these three users in the PAMEEN and PAMRSU algorithms is much higher than their requirements to maximize the EE of network and SUs' sum rate, respectively. On the other hand, in the PAMSSU algorithm, only the minimal required power $P_{t-min}^{[2]}$, $P_{t-min}^{[3]}$ and $P_{t-min}^{[5]}$ is assigned to these three users to satisfy their rate requirements. Thus transmitted power is saved and more

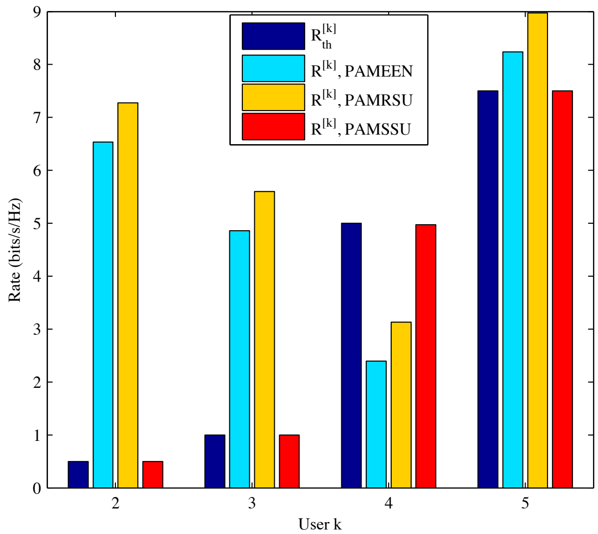

Fig. 11. Rate comparison of SUs with different algorithms of the IA-based CR network in a certain time slot when $P_t^{max}/K/\sigma^2$ is equal to 20dB. $R_{th}^{[2]}$=0.5 bits/s/Hz, $R_{th}^{[3]}$=1 bits/s/Hz, $R_{th}^{[4]}$=5 bits/s/Hz and $R_{th}^{[5]}$=7.5 bits/s/Hz.

power can be assigned to user 4 to achieve $R_{th}^{[4]}$ in PAMSSU algorithm than PAMEEN and PAMRSU algorithms.

User 4 is a specific case to be further demonstrated. For the PAMEEN and PAMRSU algorithms, the allocated power to user 4 is much lower than that of its minimal required power $P_{t-min}^{[4]}$, which results in the lower rate of user 4 than $R_{th}^{[4]}$. This is because the effective channel of user 4, $\left|h^{[4]}\right|^2$, is the worst in this time slot due to the channel variation, and thus more power should be allocated to other users to achieve much higher sum rate or EE. On the contrary, in the PAMSSU algorithm, the objective is to satisfy the requirements of all the SUs, and only the minimal required power is assigned to user 2, user 3 and user 5 to satisfy their rate requirements. The transmitted power is thus saved and more power can be assigned to user 4 to achieve $R_{th}^{[4]}$ in PAMSSU algorithm due to its poor effective channel $\left|h^{[4]}\right|^2$. According to the definition of SSU in (24), the value Ω of PAMSSU algorithm in this time slot is close to its largest value 4, which is larger than that in PAMEEN and PAMRSU algorithms. Besides, although $R_{th}^{[5]}$ is larger than $R_{th}^{[4]}$, $P_{t-min}^{[5]}$ is much smaller than $P_{t-min}^{[4]}$. This is because the effective channel $\left|h^{[5]}\right|^2$ of user 5 is much higher than $\left|h^{[4]}\right|^2$ of user 4 in this time slot due to the channel variation.

VI. Conclusions

In this paper, we have developed several PA algorithms for IA-based CR networks. The minimal transmitted power of the PU to guarantee its rate threshold was derived. Then three PA algorithms, PAMRSU, PAMEEN and PAMSSU, were proposed for IA-based CR networks to maximize the SUs' rate, the EE of the network, and the SSU, respectively. To evaluate the rate performance, and the outage probability of PU and SUs with different value of its transmitted power was also derived. To further guarantee the rate constraint of the PU, we proposed a transmission-mode adaptation scheme to adapt the transmission mode to improve the performance of the PU, and it can be combined with the proposed PA algorithms easily. Simulation results were presented to show the effectiveness of the proposed adaptive PA algorithms for IA-based CR networks.

Appendix A
Proof of Proposition 1

Proof: When the power allocation is considered in the IA-based CR network, the transmission rate of the PU can be calculated as

$$R^{[1]} = \log_2\left(1+\frac{\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[11]}\mathbf{v}^{[1]}\right|^2 P_t^{[1]}}{\sum\limits_{k=2}^{K}\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[1k]}\mathbf{v}^{[k]}\right|^2 P_t^{[k]}+\sigma^2}\right). \quad (41)$$

The QoS requirement of the PU should be guaranteed, and thus from (41) and (7), we can obtain

$$P_t^{[1]} \geq \frac{\left(2^{R_{th}^{[1]}}-1\right)\left(\sum\limits_{k=2}^{K}\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[1k]}\mathbf{v}^{[k]}\right|^2 P_t^{[k]}+\sigma^2\right)}{\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[11]}\mathbf{v}^{[1]}\right|^2}. \quad (42)$$

In the feasible IA-based CR networks, the interferences are constrained in certain subspaces at the unintended receivers, and the interference leakage at the receivers is trivial. Besides, $P_t^{[k]}$ is larger than 0. Thus we have

$$\begin{aligned}&\frac{\left(2^{R_{th}^{[1]}}-1\right)\left(\sum\limits_{k=2}^{K}\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[1k]}\mathbf{v}^{[k]}\right|^2 P_t^{[k]}+\sigma^2\right)}{\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[11]}\mathbf{v}^{[1]}\right|^2}\\ \approx\ &\frac{\left(2^{R_{th}^{[1]}}-1\right)\sigma^2}{\left|\mathbf{u}^{[1]\dagger}\mathbf{H}^{[11]}\mathbf{v}^{[1]}\right|^2}=\frac{\left(2^{R_{th}^{[1]}}-1\right)\sigma^2}{\left|h^{[1]}\right|^2}=P_{t-min}^{[1]}. \quad (43)\end{aligned}$$

Thus $P_{t-min}^{[1]}$ is the minimal value of the PU's transmitted power $P_t^{[1]}$ to guarantee its threshold $R_{th}^{[1]}$. ■

Appendix B
Proof of Lemma 1

Proof: When $\sum_{k=1}^{K} P_t^{[k]} = P_t^{max}$, we have

$$\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}+P_t^{[k]}\right)=\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}\right)+P_t^{max}=\text{constant}. \quad (44)$$

We also define $\widehat{P}_t^{[1]} = P_t^{[1]} - P_{t-min}^{[1]}$. Therefore, (P2) can be rewritten as (45) (on the next page). In (45), $\left|\widehat{h}^{[1]}\right|$ can be denoted as (16).

The optimization problem in (45) is similar to the PA problem in multiple parallel channels, and the waterfilling strategy can be leveraged to obtain the optimal solution. Thus the closed-form solution of (P2) when $\sum_{k=1}^{K} P_t^{[k]} = P_t^{max}$ can be denoted as (14), where ν should satisfy (15). ■

$$\max_{P_t^{[1]},P_t^{[2]},\ldots,P_t^{[K]}} \log_2\left(1+\left|h^{[1]}\right|^2 \frac{\left(\widehat{P}_t^{[1]}+P_{t-min}^{[1]}\right)}{\sigma^2}\right)+\sum_{k=2}^{K}\log_2\left(1+\left|h^{[k]}\right|^2 \frac{P_t^{[k]}}{\sigma^2}\right)$$
$$= \log_2\left(\left(1+\frac{\left|h^{[1]}\right|^2 P_{t-min}^{[1]}}{\sigma^2}\right)\left(1+\frac{\sigma^2\left|h^{[1]}\right|^2}{\left|h^{[1]}\right|^2 P_{t-min}^{[1]}+\sigma^2}\frac{\widehat{P}_t^{[1]}}{\sigma^2}\right)\right)+\sum_{k=2}^{K}\log_2\left(1+\left|h^{[k]}\right|^2 \frac{P_t^{[k]}}{\sigma^2}\right)$$
$$= \log_2\left(1+\left|\widehat{h}^{[1]}\right|^2 \frac{\widehat{P}_t^{[1]}}{\sigma^2}\right)+\sum_{k=2}^{K}\log_2\left(1+\left|h^{[k]}\right|^2 \frac{P_t^{[k]}}{\sigma^2}\right)+\text{constant}$$
$$s.t.\quad \widehat{P}_t^{[1]}\geq 0,\ \ P_t^{[k]}\geq 0,\ \forall k=2,\ldots,K$$
$$\widehat{P}_t^{[1]}+\sum_{k=2}^{K}P_t^{[k]}\leq P_t^{max}-P_{t-min}^{[1]}. \tag{45}$$

$$\frac{\ln 2}{\mathrm{e}K}\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)\prod_{k=1}^{K}\left(\frac{\left|h^{[k]}\right|^2}{\sigma^2\ln 2}\right)^{\frac{1}{K}}=\frac{\ln 2}{K}\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)\lambda \mathrm{e}^{\lambda\frac{\ln 2}{K}\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}\right)}. \tag{46}$$

Appendix C
Proof of Lemma 2

Proof: (17) can be rewritten as (46).

Therefore, according to the definition of the Lambert W function, (46) can be changed into (18), which is the solution of (17). ■

Appendix D
Proof of Theorem 1

Proof: As (P2) is a concave-convex fractional programming, we can optimize the following problem in (47) to obtain the optimal solution of (P2) [41].

$$F(\lambda) = \max_{P_t^{[1]},P_t^{[2]},\ldots,P_t^{[K]}}\sum_{k=1}^{K}\log_2\left(1+\left|h^{[k]}\right|^2\frac{P_t^{[k]}}{\sigma^2}\right)-\lambda\sum_{k=1}^{K}\left(P_{ct}^{[k]}+P_{cr}^{[k]}+P_t^{[k]}\right)$$
$$s.t.\quad P_t^{[k]}\geq 0,\ \forall k=2,\ldots,K$$
$$P_t^{[1]}\geq P_{t-min}^{[1]}$$
$$\sum_{k=1}^{K}P_t^{[k]}\leq P_t^{max}. \tag{47}$$

The optimization in (47) is a convex optimization problem, and it is easy to solve by applying KKT conditions. The optimal solution of (47) can be expressed as (19) with the constraint $\sum_{k=1}^{K}P_t^{[k]}\leq P_t^{max}$.

Let $F(\lambda)=0$, we can obtain (20). Then $P_t^{[k]}$ in (20) is substituted by the optimal solution in (19).

When $P_t^{[k]}$ can all be expressed as $\frac{1}{\lambda\ln 2}-\frac{\sigma^2}{\left|h^{[k]}\right|^2}$ in (19), $k=1,\ldots,K$, (20) is equivalent to (17) and difficult to solve. The solution λ^* can be calculated as (18) in Lemma 2. When some of $P_t^{[k]}$ is 0 or $P_t^{[1]}=P_{t-min}^{[1]}$ in (19), (20) is much easier to solve, and we can refer to Lemma 2 to obtain λ^* similarly.

Through applying λ^* to (19), we can obtain the optimal solution of (P2) as (21). However, the constraint $\sum_{k=1}^{K}P_t^{[k]}\leq P_t^{max}$ has not been considered. Thus we should discuss the validity of the optimal solution in (21) as follows.

1) $\sum_{k=1}^{K}P_t^{*[k]}<P_t^{max}$: The closed-form solution of (P2) can be defined as in (21).

2) $\sum_{k=1}^{K}P_t^{*[k]}\geq P_t^{max}$ and $P_{t-min}^{[1]}\leq P_t^{max}$: The closed-form solution of (P2) can be defined as in (14). ■

Appendix E
Proof of Lemma 3

Proof: In the design of $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ in the K-user IA-based CR network, $k=1,2,\ldots,K$, it only concentrates on the condition in (2) without involving $\mathbf{H}^{[kk]}$ in (3), i.e., only the channel matrices between different users, $\mathbf{H}^{[kj]}$, $\forall j\neq k$, are utilized to achieve IA. The condition (3) will be satisfied naturally when the condition (2) is met. Thus $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are i.i.d., and independent of $\mathbf{H}^{[kk]}$, and we can obtain that

$$\mathbb{E}(\left|h^{[k]}\right|^2)=\mathbb{E}\left[\sum_{i=1}^{N^{[k]}}\sum_{j=1}^{M^{[k]}}\left|\left(\mathbf{u}^{[k]}\right)_i\right|^2\left|\left(\mathbf{v}^{[k]}\right)_j\right|^2\left|\left(\mathbf{H}^{[kk]}\right)_{ij}\right|^2\right]$$
$$=\sum_{i=1}^{N^{[k]}}\left|\left(\mathbf{u}^{[k]}\right)_i\right|^2\sum_{j=1}^{M^{[k]}}\left|\left(\mathbf{v}^{[k]}\right)_j\right|^2\mathbb{E}\left[\left|\left(\mathbf{H}^{[kk]}\right)_{ij}\right|^2\right]. \tag{48}$$

As mentioned in Section II, $\left(\mathbf{H}^{[kk]}\right)_{ij}$ is i.i.d. $\mathcal{CN}(0,1)$, and $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are unitary vectors, thus we can achieve

$$\mathbb{E}\left(\left|h^{[k]}\right|^2\right)=1. \tag{49}$$

Thus $h^{[k]}$ is a complex Gaussian random variable with zero mean and unit variance, and $\left|h^{[k]}\right|^2$ follows exponential distribution with unit mean and variance. ■

APPENDIX F
PROOF OF PROPOSITION 2

Proof: From (33), we can obtain that

$$\begin{aligned}\Pr{}^{[1]}\{\text{outage}\} &= \Pr\left\{\log_2\left(1+\frac{\left|h^{[1]}\right|^2}{\sigma^2}P_t^{[1]}\right) < R_{th}^{[1]}\right\} \\ &= \Pr\left\{\left|h^{[1]}\right|^2 < \frac{\sigma^2\left(2^{R_{th}^{[1]}}-1\right)}{P_t^{[1]}}\right\}. \qquad (50)\end{aligned}$$

In Lemma 1, we see that $\left|h^{[k]}\right|^2$ follows exponential distribution with unit mean and variance. Thus the cumulative distribution function (c.d.f.) of $\left|h^{[k]}\right|^2$ can be expressed as

$$\Pr\left\{\left|h^{[1]}\right|^2 \le x\right\} = \begin{cases} 1-e^{-x}, & x \ge 0 \\ 0, & x < 0 \end{cases} \qquad (51)$$

The rate threshold of the PU $R_{th}^{[1]}$ should be set positive, and we have

$$\frac{\sigma^2\left(2^{R_{th}^{[1]}}-1\right)}{P_t^{[1]}} > 0 \qquad (52)$$

From (50) and (51), we can obtain the expression of the outage probability of the PU as (34). ■

REFERENCES

[1] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[2] T. Luan, F. Gao, and X.-D. Zhang, "Joint resource scheduling for relay-assisted broadband cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 11, no. 9, pp. 3090–3100, Sept. 2012.

[3] P. Si, H. Ji, F. R. Yu, and V. C. M. Leung, "Optimal cooperative internetwork spectrum sharing for cognitive radio systems with spectrum pooling," *IEEE Trans. Veh. Tech.*, vol. 59, no. 4, pp. 1760–1768, May 2010.

[4] N. Zhao and H. Sun, "Robust power control for cognitive radio in spectrum underlay networks," *KSII Trans. Internet Inf. Syst.*, vol. 5, no. 7, pp. 1214–1229, Jul. 2011.

[5] J. T. MacDonald and D. R. Ucci, "Interference temperature limits of ieee 802.11 protocol radio channels," in *Proc. IEEE EIT'07*, pp. 64–69, Chicago, IL, May 2007.

[6] T. C. Clancy, "Dynamic spectrum access using the interference temperature model," *Ann. Telecomm.*, vol. 64, no. 7-8, pp. 573–592, Aug. 2009.

[7] B. Wang and K. J. R. Liu, "Advances in cognitive radio networks: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, Feb. 2011.

[8] S.-J. Kim and G. B. Giannakis, "Optimal resource allocation for MIMO ad hoc cognitive radio networks," *IEEE Trans. Inf. Theory*, vol. 57, no. 5, pp. 3117–3131, May 2011.

[9] V. R. Cadambe and S. A. Jafar, "Interference alignment and degrees of freedom of the *K*-user interference channel," *IEEE Trans. Inf. Theory*, vol. 54, no. 8, pp. 3425–3441, Aug. 2008.

[10] M. A. Maddah-Ali, A. S. Motahari, and A. K. Khandani, "Communication over MIMO X channels: interference alignment, decomposition, and performance analysis," *IEEE Trans. Inf. Theory*, vol. 54, no. 8, pp. 3457–3470, Aug. 2008.

[11] B. Nosrat-Makouei, J. G. Andrews, and R. W. Heath, "MIMO interference alignment over correlated channels with imperfect CSI," *IEEE Trans. Signal Proc.*, vol. 59, no. 6, pp. 2783–2794, Jun. 2011.

[12] B. Xie, Y. Li, H. Minn, and A. Nosratinia, "Adaptive interference alignment with CSI uncertainty," *IEEE Trans. Commun.*, vol. 61, no. 2, pp. 792–801, Feb. 2013.

[13] O. E. Ayach and R. W. Heath, Jr., "Interference alignment with analog channel state feedback," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 626–636, Feb. 2012.

[14] X. Li, N. Zhao, Y. Sun, and F. R. Yu, "Interference alignment based on antenna selection with imperfect channel state information in cognitive radio networks," *IEEE Trans. Veh. Tech.*, to appear.

[15] N. Zhao, F. R. Yu, H. Sun, A. Nallanathan, and H. Yin, "A novel interference alignment scheme based on sequential antenna switching in wireless networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 10, pp. 5008–5021, Oct. 2013.

[16] N. Zhao, F. R. Yu, H. Sun, H. Yin, A. Nallanathan, and G. Wang, "Interference alignment with delayed channel state information and dynamic AR-model channel prediction in wireless networks," *Wireless Netw.*, vol. 21, no. 4, pp. 1227–1242, May. 2015.

[17] N. Zhao, F. R. Yu, and V. C. M. Leung, "Opportunistic communications in interference alignment networks with wireless power transfer," *IEEE Wireless Commun.*, vol. 22, no. 1, pp. 88–95, Feb. 2015.

[18] K. Gomadam, V. R. Cadambe, and S. A. Jafar, "A distributed numerical approach to interference alignment and applications to wireless interference networks," *IEEE Trans. Inf. Theory*, vol. 57, no. 6, pp. 3309–3322, Jun. 2011.

[19] H. Farhadi, C. Wang, and M. Skoglund, "Distributed interference alignment and power control for wireless MIMO interference networks," in *Proc. IEEE WCNC'13*, pp. 3077–3082, Shanghai, China, Apr. 2013.

[20] F. Shu, X. You, M. Wang, Y. Han, Y. Li, and W. Sheng, "Hybrid interference alignment and power allocation for multi-user interference MIMO channels," *Sci. China-Inf. Sci.*, vol. 56, no. 4, pp. 1–9, Apr. 2013.

[21] Y. Yi, J. Zhang, Q. Zhang, and T. Jiang, "Exploring frequency diversity with interference alignment in cognitive radio networks," in *Proc. IEEE Globecom'12*, pp. 5579–5583, Anaheim, CA, Dec. 2012.

[22] J. Tang, S. Lambotharan, and S. Pomeroy, "Interference cancellation and alignment techniques for multiple-input and multiple-output cognitive relay networks," *IET Signal Process.*, vol. 7, no. 3, pp. 188–200, May 2013.

[23] T. Xu, L. Ma, and G. Sternberg, "Practical interference alignment and cancellation for MIMO underlay cognitive radio networks with multiple secondary users," in *Proc. IEEE Globecom'13*, pp. 1031–1036, Atlanta, GA, Dec. 2013.

[24] N. Zhao, T. Qu, H. Sun, A. Nallanathan, and H. Yin, "Frequency scheduling based interference alignment for cognitive radio networks," in *Proc. IEEE Globecom'13*, pp. 3469–3473, Atlanta, GA, Dec. 2013.

[25] N. Zhao, F. R. Yu, and H. Sun, "Power allocation for interference alignment based cognitive radio networks," in *Proc. IEEE Infocom Workshop on GCCCN'14*, pp. 742–746, Toronto, Canada, April. 2014.

[26] J. Zou, H. Xiong, D. Wang, and C. W. Chen, "Optimal power allocation for hybrid overlay/underlay spectrum sharing in multiband cognitive radio networks," *IEEE Trans. Veh. Tech.*, vol. 62, no. 4, pp. 1827–1837, May 2013.

[27] Y. Xu and X. Zhao, "Optimal power allocation for multiuser underlay cognitive radio networks under QoS and interference temperature constraints," *China Commun.*, vol. 10, no. 10, pp. 91–100, Oct. 2013.

[28] P. He, L. Zhao, S. Zhou, and Z. Niu, "Optimal recursive power allocation for energy harvesting nodes with multiple antennas," *IEEE Trans. Veh. Tech.*, to appear.

[29] E. Biglieri, J. Proakis, and S. Shamai, "Fading channels: information-theoretic and communications aspects," *IEEE Trans. Inf. Theory*, vol. 44, no. 6, pp. 2619–2692, Oct. 1998.

[30] C. Yetis, T. Gou, S. A. Jafar, and A. Kayran, "On feasibility of interference alignment in MIMO interference networks," *IEEE Trans. Signal Proc.*, vol. 58, no. 9, pp. 4771–4782, Sep. 2010.

[31] D. Niyato, E. Hossain, and Z. Han, "Dynamics of multiple-seller and multiple-buyer spectrum trading in cognitive radio networks: A game-theoretic modeling approach," *IEEE Trans. Mobile Comput.*, vol. 8, no. 8, pp. 1009–1022, Aug. 2009.

[32] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge, U.K.: Cambridge Univ. Press, 2005.

[33] F. R. Yu, X. Zhang, and V. C. M. Leung, *Green Communications and Networking*. CRC Press, 2012.

[34] R. Xie, F. R. Yu, H. Ji, and Y. Li, "Energy-efficient resource allocation for heterogeneous cognitive radio networks with femtocells," *IEEE Trans. Wireless Commun.*, vol. 11, no. 11, pp. 3910–3920, Nov. 2012.

[35] O. Amin and L. Lampe, "Opportunistic energy efficient cooperative communication," *IEEE Wireless Commun. Lett.*, vol. 1, no. 5, pp. 412–415, Oct. 2012.

[36] L. Liu, Y. Yi, J. Chamberland, and J. Zhang, "Energy-efficient power allocation for delay-sensitive multimedia traffic over wireless systems," *IEEE Trans. Veh. Tech.*, vol. 63, no. 5, pp. 2038–2047, Jun. 2014.

[37] S. Cui, A. J. Goldsmith, and A. Bahai, "Energy-constrained modulation optimization," *IEEE Trans. Wireless Commun.*, vol. 4, no. 5, pp. 2349–2360, Sep. 2005.
[38] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2009.
[39] A. Goldsmith, *Wireless communications*. Cambridge, UK: Cambridge University Press, 2005.
[40] A. B. Sediq, R. H. Gohary, and H. Yanikomeroglu, "Optimal tradeoff between efficiency and jain's fairness index in resource allocation," in *Proc. IEEE PIMRC'12*, pp. 577–583, Sydney, Australia, Sep. 2012.
[41] S. Schaible, "Fractional programming," *Zeitschrift fur Operations Research*, vol. 27, no. 1, pp. 39–54, Jan. 1983.

Nan Zhao (S'08-M'11) is currently an Associate Professor in the School of Information and Communication Engineering at Dalian University of Technology, China. He received the B.S. degree in electronics and information engineering in 2005, the M.E. degree in signal and information processing in 2007, and the Ph.D. degree in information and communication engineering in 2011, from Harbin Institute of Technology, Harbin, China. From Jun. 2011 to Jun. 2013, Nan Zhao did postdoctoral research in Dalian University of Technology, Dalian, China. His recent research interests include Interference Alignment, Cognitive Radio, Wireless Power Transfer, and Optical Communications. He has published more than 50 papers in refereed journals and international conferences. Prof. Zhao is a member of the IEEE. He serves as an Area Editor of AEU-International Journal of Electronics and Communications, and an Editor of Ad Hoc & Sensor Wireless Networks. Additionally, he served as a technical program committee (TPC) member for many interferences, e.g., Globecom, VTC, WCSP.

F. Richard Yu (S'00-M'04-SM'08) received the PhD degree in electrical engineering from the University of British Columbia (UBC) in 2003. From 2002 to 2004, he was with Ericsson (in Lund, Sweden), where he worked on the research and development of wireless mobile systems. From 2005 to 2006, he was with a start-up in California, USA, where he worked on the research and development in the areas of advanced wireless communication technologies and new standards. He joined Carleton School of Information Technology and the Department of Systems and Computer Engineering at Carleton University in 2007, where he is currently an Associate Professor. He received the IEEE Outstanding Leadership Award in 2013, Carleton Research Achievement Award in 2012, the Ontario Early Researcher Award (formerly Premiers Research Excellence Award) in 2011, the Excellent Contribution Award at IEEE/IFIP TrustCom 2010, the Leadership Opportunity Fund Award from Canada Foundation of Innovation in 2009 and the Best Paper Awards at IEEE ICC 2014, Globecom 2012, IEEE/IFIP TrustCom 2009 and Int'l Conference on Networking 2005. His research interests include cross-layer/cross-system design, security, green IT and QoS provisioning in wireless-based systems.

He serves on the editorial boards of several journals, including Co-Editor-in-Chief for Ad Hoc & Sensor Wireless Networks, Lead Series Editor for IEEE Transactions on Vehicular Technology, IEEE Communications Surveys & Tutorials, EURASIP Journal on Wireless Communications Networking, Wiley Journal on Security and Communication Networks, and International Journal of Wireless Communications and Networking, a Guest Editor for IEEE Transactions on Emerging Topics in Computing special issue on Advances in Mobile Cloud Computing, and a Guest Editor for IEEE Systems Journal for the special issue on Smart Grid Communications Systems. He has served on the Technical Program Committee (TPC) of numerous conferences, as the TPC Co-Chair of IEEE GreenCom15, INFOCOM-MCV15, Globecom14, WiVEC14, INFOCOM-MCC14, Globecom13, GreenCom13, CCNC13, INFOCOM-CCSES12, ICC-GCN12, VTC12S, Globecom11, INFOCOM-GCN11, INFOCOM-CWCN10, IEEE IWCMC09, VTC08F and WiN-ITS07, as the Publication Chair of ICST QShine10, and the Co-Chair of ICUMT-CWCN09. Dr. Yu is a registered Professional Engineer in the province of Ontario, Canada.

Hongjian Sun (S'07-M'11-SM'15) received his Ph.D. degree in Electronic Engineering from the University of Edinburgh, U.K., in 2010. He then joined Kings College London, U.K., as a Postdoctoral Research Associate. In 2011-2012, he was a visiting Postdoctoral Research Associate at Princeton University, USA. Since 2013, he has been a Lecturer in Smart Grid at the University of Durham, U.K. His recent research interests include Smart Grids, Wireless Communications, and Signal Processing. He has made one contribution to the IEEE 1900.6a Standard, and published two book chapters and more than 50 papers in refereed journals and international conferences.

He is on the Editorial Board of the Journal of Communications and Networks, and EURASIP Journal on Wireless Communications and Networking, and was a Guest Editor for the special issue Industrial Wireless Sensor Networks for the International Journal of Distributed Sensor Networks. Additionally, he served as an organizing chair for the Workshop on Integrating Communications, Control, Computing Technologies for Smart Grid, Glasgow, U.K., in May 2015, and the Workshop on Communications Technologies for Smart Grid, Shanghai, China, in August 2015. He also served (or is serving) as a technical program committee (TPC) member for many international conferences, e.g., ICC, Globecom, VTC. He is a peer-reviewer for a number of international journals and was nominated as an Exemplary Reviewer by IEEE Communications Letters in both 2011 and 2012.

Ming Li (S'05, M'11) received the M.S. and Ph.D. degrees in electrical engineering from the State University of New York at Buffalo, Buffalo, in 2005 and 2010, respectively. From Jan. 2011 to Aug. 2013, he was a Post-Doctoral Research Associate with the Signals, Communications, and Networking Research Group, Department of Electrical Engineering, State University of New York at Buffalo. From Aug. 2013 to June 2014, Dr. Li joined Qualcomm Technologies Inc. as a Senior Engineer. Since June 2014, he has been with the School of Information and Communication Engineering, Dalian University of Technology, Dalian, China, where he is presently an Associate Professor. His research interests are in the general areas of communication theory and signal processing with applications to interference channels and signal waveform design, secure wireless communications, cognitive radios and networks, data hiding and steganography, and compressed sensing.