Yang and Zhao *EURASIP Journal on Wireless Communications and Networking* (2017) 2017:216
DOI 10.1186/s13638-017-1000-6

EURASIP Journal on Wireless Communications and Networking

RESEARCH
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Resource allocation in two-way OFDM-based cognitive radio networks with QoE and power consumption guarantees

Weiwei Yang and Xiaohui Zhao*

Abstract

In this paper, a resource allocation algorithm in two-way orthogonal frequency division multiplexing (OFDM) based cognitive radio networks with quality of experience (QoE) and power consumption guarantees is proposed. We define the overall QoE perceived by secondary users (SUs) per power consumption as *QoEW*. The power consumption model consists of fixed circuit power, dynamic circuit power, and transmit power which depends on the efficiency of the power amplifiers at different terminals. Under the constraint of total maximum transmit power, the optimization objective is to maximize *QoEW* while meeting the minimum QoE demands of SUs and maintaining interference threshold limitations of multiple primary users. The resource allocation problem is formulated into a nonlinear fractional programming and transformed into an equivalent convex optimization problem via its hypograph form. Based on the Lagrange dual decomposition method and cross-layer (CL) optimization architecture, this convex optimization problem is separately solved in the physical layer and the application layer. The optimal *QoEW* is achieved through the proposed CL alternate iteration algorithm. Numerical simulation results demonstrate the impacts of system parameters on *QoEW* and the effectiveness and superiority of the proposed algorithm.

Keywords: Cognitive radio network, Two-way relay, Resource allocation, Cross-layer, QoE and power consumption

1 Introduction

Cognitive radio (CR), as a promising technique to solve spectrum scarcity and improve spectrum utilization by means of dynamic spectrum access, has drawn intensive interests in recent years [1]. Orthogonal frequency division multiplexing (OFDM) is an effective technique to combat channel fading and multipath loss. And it has been widely accepted in CR networks (CRNs) owing to its advantages such as spectrum efficiency improvement and dynamic resource allocation. In an OFDM-based CRN, secondary users (SUs) are allowed to access the spectrum of primary users (PUs) as long as the interference to PUs below their thresholds, so that the transmission power of SUs is always limited and the communication quality of SUs cannot be guaranteed well [2, 3].

Recently, cooperative relay technique has been introduced into CRNs for throughput enhancement and coverage extension without large energy consumption [4]. Traditional one-way relay transmission has a 1/2 spectral efficiency loss than direct transmission, which is induced by half-duplex relay nodes [5]. In other words, since half-duplex relay nodes cannot simultaneously transmit and receive signals, one-way relay transmission needs four time slots to accomplish information exchange when two users communicate with each other. In order to overcome the inherent spectrum loss, two-way relaying transmission with physical-layer network coding (PNC) is proposed [6], in which only two time slots are required to finish information exchange. According to the difference of signal processing functions at relay nodes, PNC has several sub-protocols, such as decode-and-forward (DF) and amplify-and-forward (AF). Many previous works focus on PNC-AF protocol since it is easily realized in practical systems [7, 8]. Therefore, we focus on two-way OFDM-based CRN with PNC-AF protocol in this paper.

Radio resource allocation is very significant to performance enhancement for wireless networks. Most of the

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existing studies are carried out on radio resource allocation with quality of service (QoS) optimization target [9–11]. However, with the wide proliferation of mobile devices as well as the ubiquitous availability of multimedia services, traditional optimization metric (e.g., date rate and spectrum efficiency) cannot directly reflect end users' satisfaction, which may cause a waste of valuable radio resource. Quality of experience (QoE) is a widely used metric which can indicate not only multimedia service performance but also end users' subjective satisfaction of the multimedia service directly. Therefore, both academic studies and industries have turned their concentrations from network QoS parameters to QoE conception [12, 13]. Generally, an end user's QoE is affected by both physical layer and application layer parameters. There have been some researches that depend on cross-layer (CL) optimization architecture to solve QoE-oriented optimization problems [14–16]. In [14], a joint multi-user scheduling and multi-user rate adaptation strategy is proposed to provide an appropriate tradeoff between efficiency and fairness, while ensuring QoE. In [15], a near optimal power allocation scheme for transmitting scalable video coding based videos is proposed with the target to maximize QoE over multi-input multi-output systems. In [16], novel and practical CL QoE-aware radio resource allocation algorithms for the downlink of a heterogeneous OFDM access system are proposed. However, in [14–16], the energy consumption is not taken into consideration.

In recent years, rapid development of information and communications technology significantly contributes to the energy consumption and global warming, which is very crucial to the performance of wireless networks [17]. A power consumption model in wireless networks generally consists of the transmit power which depends on efficiency of power amplifier (PA) at different terminals, fixed circuit power, and dynamic circuit power related to data transmission rate [18]. How to maximize QoE perceived by end users while minimizing the power consumption is a challenging problem. Recently, some research works have been conducted on this topic [19, 20]. In [19], a QoE-driven resource allocation algorithm in the OFDM system is proposed to address the system energy efficiency and guarantee user-perceived QoE for different multimedia services. The power consumption model in [19] only consists of the transmit power. In [20], a joint optimization scheme of the fairness of users' QoE and power consumption for the OFDM access multi-cell networks is proposed. The power consumption model in [20] only has the fixed power and the transmit power with the assumption of identical efficiency values of PA at different terminals. However, this assumption is not practical since the efficiency value of PA varies with the design and the implementation of the terminals. Moreover, none of [19, 20] consider the dynamic power consumption. To our best knowledge, most of the existing resource allocation algorithms adopt the power consumption model ignoring dynamic circuit power and assuming identical efficiency values of PA at different terminals. In addition, there are barely resource allocation algorithms taking both QoE and power consumption-related issues into consideration for a two-way OFDM-based CRN.

Motivated by the aforementioned discussions, we investigate a QoE and power consumption-driven resource allocation problem in two-way OFDM-based CRN with PNC-AF protocol. The overall QoE perceived by SUs per power consumption is defined as $QoEW$. The optimization objective is to maximize $QoEW$ under the constraint of maximum total transmit power of SUs and the relay nodes, while guaranteeing the minimum QoE requirements of SUs and keeping the interference power to multiple PUs below their tolerable thresholds. The main contributions of this paper are summarized as follows.

- We adopt the power consumption model incorporates fixed circuit power, dynamic circuit power, and transmit power which depends on the efficiency of the PAs at different terminals. We define the tradeoff between overall QoE perceived by SUs and power consumption as $QoEW$.
- The resource allocation problem is formulated as a nonlinear fractional programming problem and converted it into an equivalent convex optimization problem via its hypograph form. Based on the Lagrange dual decomposition method and CL optimization architecture, the convex optimization problem is separately solved in the physical layer and the application layer.
- The optimal $QoEW$ is achieved through the proposed CL alternate iteration algorithm. Numerical simulation results show the impact of system parameters on $QoEW$ and the effectiveness and outperformance of the proposed algorithm through comparisons with other algorithms.

The rest of this paper is organized as follows. The system model and the formulation of QoE and power consumption oriented resource allocation problem is described in Section 2. A CL alternate iteration algorithm is proposed in Section 3. Simulation results and performance analysis are presented in Section 4. Finally, conclusions are drawn and future works are given in Section 5.

2 System model and problem formulation

2.1 System model

We consider a two-way OFDM-based CRN as shown in Fig. 1. The secondary network shares the spectrum of primary network which has L PUs. A pair of SUs, S_1 and S_2 intend to communicate with each other. We assume that there is no direct path between them, so they exchange

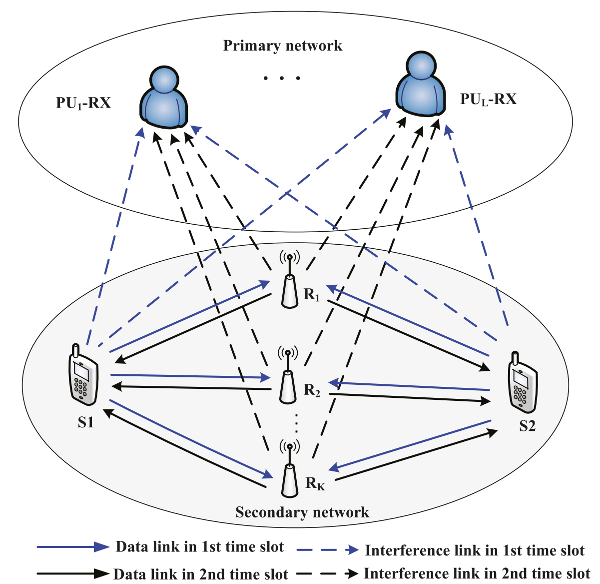

Fig. 1 System model

information with the assistance of K half-duplex relay nodes. It is also assumed that all the nodes in this network are equipped with a single antenna and operate in a time division duplexing (TDD) mode. Due to OFDM transmission technique, the channel is divided into N orthogonal subcarriers. We denote the channel coefficients from S_1 and S_2 to the $k_{th}, k \in [1:K]$ relay node on the $n_{th}, n \in [1:N]$ subcarrier are $h_{1,k}^n$ and $h_{2,k}^n$, respectively. Considering channel reciprocity nature, the duplexing period is smaller than channel coherence time, then the channel coefficients from the k_{th} relay node to S_1 and S_2 on the n_{th} subcarrier are the same as $h_{1,k}^n$ and $h_{2,k}^n$ [8].

In this CRN, we adopt PNC-AF protocol, so information exchange can be finished in two time slots. In order to simplify the analysis, we assume that the channel state information and the synchronization is perfect. In the first time slot or multiple access phase, S_1 and S_2 transmit their data symbols x_1^n and x_2^n on the n_{th} subcarrier to the k_{th} relay node simultaneously. The signals received by the k_{th} relay node on the n_{th} subcarrier can be expressed as

$$y_k^n = h_{1,k}^n\sqrt{p_{1,k}^n}x_1^n + h_{2,k}^n\sqrt{p_{2,k}^n}x_2^n + n_k^n \quad (1)$$

where $p_{1,k}^n$ and $p_{2,k}^n$ are the transmit power of S_1 and S_2 on the n_{th} subcarrier to the k_{th} relay node, respectively. n_k^n is the additive white Gaussian noise (AWGN) on the n_{th} subcarrier at the k_{th} relay node. In the primary network, PUs also receive the signals transmitted by S_1 and S_2. The interference introduced to the $l_{th}, l \in [1:L]$ PU's receiver (PU-RX) in the first time slot can be expressed as

$$I_{SP_l} = \sum_{i=1}^{2}\sum_{k=1}^{K}\sum_{n=1}^{N}\rho_k^n p_{i,k}^n |g_{i,l}^n|^2, \forall l \quad (2)$$

where $g_{i,l}^n, i \in [1{:}2]$ denotes the channel gains on the n_{th} subcarrier transmitted from S_i to the l_{th} PU-RX, respectively. ρ_k^n is a binary decision variable to indicate whether the n_{th} subcarrier selects the k_{th} relay node. If $\rho_k^n = 1$, it means the k_{th} relay node is allocated to the n_{th} subcarrier, otherwise not. We adopt the assumption that the interference from the primary network to secondary network is neglected according to the features of CRN [21, 22].

In the second time slot or broadcast phase, the k_{th} relay node amplifies the received signals on the n_{th} subcarrier with the amplification factor β_k^n given by

$$\beta_k^n = \sqrt{\frac{p_{r,k}^n}{|h_{1,k}^n|^2 p_{1,k}^n + |h_{2,k}^n|^2 p_{2,k}^n + \sigma^2}} \quad (3)$$

where $p_{r,k}^n$ denotes the transmit power on the n_{th} subcarrier at the k_{th} relay node which broadcasts the amplified signals for S_i. After each SU cancels its own transmit signal component from the received signal, the received signals at S_1 and S_2 on the n_{th} subcarrier can be written as

$$y_1^n = \sum_{k=1}^{K}\rho_k^n\beta_k^n h_{1,k}^n\left(\sqrt{p_{2,k}^n}h_{2,k}^n x_2^n + n_k^n\right) + n_1^n \quad (4)$$

$$y_2^n = \sum_{k=1}^{K}\rho_k^n\beta_k^n h_{2,k}^n\left(\sqrt{p_{1,k}^n}h_{1,k}^n x_1^n + n_k^n\right) + n_2^n \quad (5)$$

where n_1^n and n_2^n are also the AWGN on the n_{th} subcarrier at S_1 and S_2, respectively. Without loss of generality, we assume that n_1^n, n_2^n, and n_k^n follow the same distribution with $\mathcal{CN}(0, \sigma^2)$. Thus, the signal to noise ratio (SNR) for S_1 and S_2 on the n_{th} subcarrier can be written as

$$SNR_1^n = \frac{\sum\limits_{k=1}^{K}\rho_k^n|\beta_k^n|^2\left|h_{1,k}^n\right|^2\left|h_{2,k}^n\right|^2 p_{2,k}^n}{\left(1 + \sum\limits_{k=1}^{K}\rho_k^n|\beta_k^n|^2\left|h_{1,k}^n\right|^2\right)\sigma^2} \quad (6)$$

$$SNR_2^n = \frac{\sum\limits_{k=1}^{K}\rho_k^n|\beta_k^n|^2\left|h_{1,k}^n\right|^2\left|h_{2,k}^n\right|^2 p_{1,k}^n}{\left(1 + \sum\limits_{k=1}^{K}\rho_k^n|\beta_k^n|^2\left|h_{2,k}^n\right|^2\right)\sigma^2} \quad (7)$$

Let R_1 and R_2 denote the achievable data rate at S_1 and S_2 expressed as

$$R_1 = \frac{1}{2}\sum_{n=1}^{N}\log_2(1+SNR_1^n) \tag{8}$$

$$R_2 = \frac{1}{2}\sum_{n=1}^{N}\log_2(1+SNR_2^n) \tag{9}$$

where the pre-log factor 1/2 comes from the two time slots required by information exchange. In the broadcast phase, the interference generated by the secondary network to the l_{th} PU-RX can be expressed as

$$I_{RP_l} = \sum_{k=1}^{K}\sum_{n=1}^{N}\rho_k^n p_{r,k}^n |\tilde{g}_{k,l}^n|^2, \forall l \tag{10}$$

where $\tilde{g}_{k,l}^n$ denotes the channel gain of the n_{th} subcarrier transmitted between the k_{th} relay node and the l_{th} PU-RX.

2.2 Power consumption model

A general model of power consumption in wireless communication systems is determined by the sum of transmit power, fixed circuit power and dynamic circuit power. The transmit power depends on the efficiency of PA and is usually modeled as a product of the actual transmit power and the reciprocal of PA's drain efficiency. Thus, in this work, the total power consumption in secondary network can be expressed as

$$P_{tot} = \varepsilon_i \sum_{i=1}^{2}\sum_{k=1}^{K}\sum_{n=1}^{N}\rho_k^n p_{i,k}^n + \xi_k \sum_{k=1}^{K}\sum_{n=1}^{N}\rho_k^n p_k^n + P_C + \alpha\sum_{i=1}^{2} R_i \tag{11}$$

where the first term and the second term in (11) denote the transmit power of SUs and the relay nodes, respectively. The factors $\varepsilon_i > 1, \forall i$ and $\xi_k > 1, \forall k$ denote the reciprocal of the drain efficiency of PAs at SUs and the relay nodes, respectively. The third term P_C denotes the total fixed circuit power consumption usually consumed by electronics devices. The forth term denotes the dynamic circuit power consumption which is rate dependent, and the factor α denotes power consumption per unit data rate.

2.3 Utility-based QoE model

Traditional QoS assessment provides an objective metric rather than a subjective opinion for end users, but it cannot directly reflect the perceived quality of end users and make full use of the radio resource. Currently, there are a growing number of studies on the assessment models of QoE instead of QoS, in which the mean opinion score (MOS) is the most widely used measure metric [23]. The MOS is the reflection of user data rate in application layer $\tilde{R}$ and modeled by utility function $U(\tilde{R}) \in [1, Q_{\max}]$, where $Q_{\max}$ is a positive upper bound of MOS. Generally, MOS from 1 to 4.2 can continuously describe the perceived quality of user from poor to excellent. The expression of $U(\tilde{R})$ varies with different multimedia traffic. Assurance of the appreciate level of QoE for heterogeneous services is an important consideration for future wireless communication system. Therefore, we consider two typical heterogeneous multimedia services, i.e. video application and best effort application in this work.

2.3.1 Video application

Video application is a special kind of QoS applications with certain demand of resource to maintain their requirements, and it is likely to be the most widely applied and the dominant service in future multimedia communications. Generally, users' QoE is related to transmission data rate and content of video. Therefore, we adopt the video application model proposed in [24] defined based on content features as

$$U(\tilde{R}) = \frac{a_1 + a_2 FR + a_3(\ln\tilde{R})}{1 + a_4 PER + a_5 (PER)^2} \tag{12}$$

where FR and PER denote the frame rate and packet error rate, respectively. The metric coefficients a_1 to a_5 are obtained by a nonlinear regression of the prediction model with training sets and they vary with different content. This model is strictly concave.

2.3.2 Best effort application

The most commonly used multimedia service of best effort application is file download (FD). The logarithmic MOS-throughput model proposed in [25] is used in our work. It is assumed that FD application is an elastic traffic and can be formulated as an increasing, strictly concave and continuously differentiable function of throughput described as

$$U(\tilde{R}) = \begin{cases} 1.0, & \tilde{R} \le \tilde{R}_{\min} \\ 0.16 + 0.8\ln(\tilde{R} - 0.3), & \tilde{R}_{\min} \le \tilde{R} \le \tilde{R}_{\max} \\ 4.2, & \tilde{R} \ge \tilde{R}_{\max} \end{cases} \tag{13}$$

where $\tilde{R}_{\min}$ and $\tilde{R}_{\max}$ denote the lower bound and upper bound of user data rate in the application layer.

2.4 Problem formulation

In this paper, we investigate a resource allocation problem in a two-way OFDM-based CRN with PNC-AF protocol under the consideration of QoE and power consumption. The tradeoff between the overall QoE perceived by SUs and power consumption is defined as $QoEW$, which can be formulated as

$$QoEW = \frac{\sum_{i=1}^{2} U_i\left(\tilde{R}_i\right)}{P_{tot}} \tag{14}$$

The physical meaning of $QoEW$ is the amount of QoE perceived by SUs at the cost of an amount of power. The greater $QoEW$ is, the higher SUs' satisfaction degree per watt is achieved. The objective is to maximize $QoEW$ through joint optimizing power allocation and subcarrier assignment while the following constraints are simultaneously satisfied: (i) in the application layer, QoE of each SU should be kept above the minimum MOS; (ii) in the physical layer, the interference to primary network should be under the interference threshold of each PU-RX in both two time slots, the transmit power of SUs and relay nodes should be below the total maximum power budget, and the exclusiveness of subcarrier assignment should be guaranteed. Therefore, this optimization problem can be mathematically formulated as

$$\begin{aligned}
\mathbf{P1} \quad & \max_{p_{i,k}^n, p_{r,k}^n, \rho_k^n} QoEW \\
s.t. \quad & C1: U_i(\tilde{R}_i) \geq MOS_i^{\min}, \forall i \\
& C2: R_i = \tilde{R}_i, \forall i \\
& C3: I_{SP_l} \leq I_l^{th}, \forall l \\
& C4: I_{RP_l} \leq I_l^{th}, \forall l \\
& C5: \sum_{i=1}^{2}\sum_{k=1}^{K}\sum_{n=1}^{N} \rho_k^n p_{i,k}^n + \sum_{k=1}^{K}\sum_{n=1}^{N} \rho_k^n p_{r,k}^n \leq P_{\max} \\
& C6: p_{i,k}^n \geq 0, p_{r,k}^n \geq 0 \\
& C7: \sum_{k=1}^{K} \rho_k^n = 1, \forall n \\
& C8: \rho_k^n \in \{0,1\}, \forall k, n
\end{aligned} \tag{15}$$

where $MOS_i^{\min}$ represents the minimum MOS of S_i required in the application layer. $C1$ guarantees the minimum perceived quality demand of S_i. If $C1$ is not satisfied, communication outage may happen, since terminating the multimedia service with poor satisfaction level can avoid power consumption and is very important to improve energy efficiency for green communications. R_i and $\tilde{R}_i$ are the user data rate in the physical layer and the application layer, respectively. $C2$ decouples the CL optimization problem and establishes the relationship between the physical layer and the application layer. R_i and $\tilde{R}_i$ will converge to the same value when a feasible solution to **P1** is achieved. I_l^{th} is the interference threshold of the l_{th} PU-RX. $C3$ and $C4$ are the interference threshold constraints of the l_{th} PU-RX in both two time slots. $P_{\max}$ is the maximum total power value of SUs and the relay nodes. $C5$ and $C6$ are the peak transmit power constraints of SUs and the relay nodes. $C7$ and $C8$ are the subcarrier assignment constraints to ensure that each subcarrier can select only one relay for itself.

3 Resource allocation algorithm with QoE and power consumption guarantees

The objective of this work is to find the optimal subcarrier assignment variables $\boldsymbol{\rho} = \{\rho_k^n\}$, power allocation $\mathbf{P_{S_1}} = \{p_{1,k}^n\}$, $\mathbf{P_{S_2}} = \{p_{2,k}^n\}$, and $\mathbf{P_R} = \{p_{r,k}^n\}$ to maximize $QoEW$ with the forementioned constraints. Obviously, although the utility functions defined in (12) and (13) are concave, **P1** is still a nonconvex optimization problem due to the integer constraints from the subcarrier assignment variables, which is NP-hard to find an optimal solution. Hence, we address this issue by dividing **P1** into a subcarrier assignment problem and a power allocation problem separately. First, we assume the n_{th} subcarrier is assigned to the m_{th} relay node, which can be expressed as

$$\rho_k^n = \begin{cases} 1, \ \forall k = m \\ 0, \ \forall k \neq m \end{cases} \tag{16}$$

We define the set of subcarriers which select the m_{th} relay node as $\mathcal{N}_m$. Under the given subcarrier assignment scheme, the transmission data rate at S_1 and S_2 can be rewritten as

$$R_1 = \frac{1}{2}\sum_{n=1}^{N} \log_2\left(1 + \frac{p_{r,m}^n p_{2,m}^n H_{1,m}^n H_{2,m}^n}{p_{r,m}^n H_{1,m}^n + p_{1,m}^n H_{1,m}^n + p_{2,m}^n H_{2,m}^n + 1}\right) \tag{17}$$

$$R_2 = \frac{1}{2}\sum_{n=1}^{N} \log_2\left(1 + \frac{p_{r,m}^n p_{1,m}^n H_{1,m}^n H_{2,m}^n}{p_{r,m}^n H_{2,m}^n + p_{1,m}^n H_{1,m}^n + p_{2,m}^n H_{2,m}^n + 1}\right) \tag{18}$$

where $H_{1,m}^n = \left|h_{1,m}^n\right|^2 / \sigma^2$ and $H_{2,m}^n = \left|h_{2,m}^n\right|^2 / \sigma^2$. The sum power consumption P_{tot} can be rewritten as

$$P_{tot} = \varepsilon_i \sum_{i=1}^{2}\sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{i,m}^n + \xi_m \sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{r,m}^n + P_C + \alpha \sum_{i=1}^{2} R_i \tag{19}$$

Then **P1** can be reformulated as

$$\begin{aligned}
\mathbf{P2} \quad & \max_{p_{i,m}^n, p_{r,m}^n} QoEW \\
s.t. \quad & C1: U_i(\tilde{R}_i) \geq MOS_i^{\min}, \forall i \\
& C2: R_i = \tilde{R}_i, \forall i \\
& C3: \sum_{i=1}^{2}\sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{i,m}^n \left|g_{i,l}^n\right|^2 \leq I_l^{th}, \forall l \\
& C4: \sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{r,m}^n \left|\tilde{g}_{m,l}^n\right|^2 \leq I_l^{th}, \forall l \\
& C5: \sum_{i=1}^{2}\sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{i,m}^n + \sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{r,m}^n \leq P_{\max} \\
& C6: p_{i,m}^n \geq 0, p_{r,m}^n \geq 0
\end{aligned} \tag{20}$$

Note that **P2** is still a nonconvex problem. An equivalent transformation of **P2** via its hypograph form [26] can be expressed as

$$
\begin{aligned}
\mathbf{P3} \quad & \max_{p^n_{i,m}, p^n_{r,m}} z \\
s.t. \quad & C7: QoEW \geq z \\
& C8: z \geq 0
\end{aligned} \tag{21}
$$

where the constraints from $C1$ to $C6$ in **P3** are the same as **P2**. We substitute $QoEW \geq z$ with $\varphi(z) \geq 0$, where $\varphi(z) = \sum_{i=1}^{2} U_i(\tilde{R}_i) - zP_{tot}$, **P3** can be transformed into a convex optimization problem since the objective function and the constraints are all convex [26]. We maximize z over the hypograph of $QoEW$ with the constraints in **P3**, which is equivalent to solve **P2**. Considering there are many variables in **P3** which it is difficult to directly solve, we use the Lagrange dual method [27] to solve it. The Lagrange function of **P3** can be formulated as

$$
\begin{aligned}
&\mathcal{L}(\mathbf{P_{S_1}}, \mathbf{P_{S_2}}, \mathbf{P_R}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta) \\
&= z + \sum_{i=1}^{2} \gamma_i (U_i(\tilde{R}_i) - MOS_i^{\min}) + \sum_{i=1}^{2} \lambda_i (R_i - \tilde{R}_i) \\
&+ \sum_{l=1}^{L} \mu_l \left(I_l^{th} - \sum_{i=1}^{2} \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{i,m} \left| g^n_{i,l} \right|^2 \right) \\
&+ \sum_{l=1}^{L} \upsilon_l \left(I_l^{th} - \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{r,m} \left| \tilde{g}^n_{m,l} \right|^2 \right) \\
&+ \delta \left(P_{\max} - \sum_{i=1}^{2} \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{i,m} - \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{r,m} \right) + \varphi(z)
\end{aligned} \tag{22}
$$

where $\boldsymbol{\gamma} \geq \mathbf{0}$, $\boldsymbol{\lambda} \geq \mathbf{0}$, $\boldsymbol{\mu} \geq \mathbf{0}$, $\boldsymbol{\upsilon} \geq \mathbf{0}$, and $\delta \geq 0$ are the Lagrange multipliers. The dual optimization problem of **P3** can be written as

$$
\min \mathcal{D}(\boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta) \tag{23}
$$

The dual function of (22) is defined as

$$
\mathcal{D}(\boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta) \triangleq \max_{p^n_{i,m}, p^n_{r,m}} \mathcal{L}(\mathbf{P_{S_1}}, \mathbf{P_{S_2}}, \mathbf{P_R}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta) \tag{24}
$$

We can observe that the dual function $\mathcal{D}(\boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta)$ involves the parameters from the physical layer and the application layer. In other words, in order to achieve an optimal z, parameters from different layers are all needed. Inspired by the CL optimization architecture which periodically selects the best optimal parameters from different layers, we solve the dual function in the physical layer and application layer separately. Substituting $\varphi(z)$ into (22) and substituting (23) to (24), we can get

$$
\mathcal{D}(\boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\upsilon}, \delta) = \max_{P^n_{i,m}, P^n_{r,m}} (\mathcal{L}_{PHY} + \mathcal{L}_{APP}) \tag{25}
$$

where

$$
\begin{aligned}
\mathcal{L}_{PHY} &= z + \sum_{i=1}^{2} \lambda_i R_i + \sum_{l=1}^{L} \mu_l \left(I_l^{th} - \sum_{i=1}^{2} \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{i,m} \left| g^n_{i,l} \right|^2 \right) \\
&+ \sum_{l=1}^{L} \upsilon_l \left(I_l^{th} - \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{r,m} \left| \tilde{g}^n_{m,l} \right|^2 \right) \\
&+ \delta \left(P_{\max} - \sum_{i=1}^{2} \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{i,m} - \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{r,m} \right) \\
&- z \left(\varepsilon_i \sum_{i=1}^{2} \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{i,m} + \xi_m \sum_{m=1}^{K} \sum_{n \in \mathcal{N}_m} p^n_{r,m} + P_C + \alpha \sum_{i=1}^{2} R_i \right)
\end{aligned} \tag{26}
$$

$$
\mathcal{L}_{APP} = \sum_{i=1}^{2} \left[(1+\gamma_i) U_i(\tilde{R}_i) - \gamma_i MOS_i^{\min} - \lambda_i \tilde{R}_i \right] \tag{27}
$$

$\mathcal{L}_{PHY}$ and $\mathcal{L}_{APP}$ denote the Lagrangian sub-problems in the physical layer and the application layer, respectively. As for $\mathcal{L}_{PHY}$, it is extremely difficult to get closed-form optimal analytical solutions to $\mathbf{P_{S_1}}$, $\mathbf{P_{S_2}}$, and $\mathbf{P_R}$. In addition, the computation complexity would be unacceptable for implementation. Therefore, we formulate power allocation issue through solving N per-subcarrier optimization problems in which the closed-form optimal solutions to $\mathbf{P_{S_1}}$, $\mathbf{P_{S_2}}$, and $\mathbf{P_R}$ can be obtained with the following power constraint on each subcarrier

$$
\sum_{i=1}^{2} p^n_{i,m} + p^n_{r,m} = P^n_m \tag{28}
$$

where P^n_m is the maximum total power allocated to the n_{th} subcarrier at S_1, S_2, and the m_{th} relay node. Based on the approach in [18, 28], ${p^n_{r,m}}^* = \frac{P^n_m}{2}$, when the received SNR at S_1 and S_2 are identical, we can get the optimal power solutions to $p^n_{1,m}$ and $p^n_{2,m}$ expressed as

$$
{p^n_{1,m}}^* = \frac{P^n_m \left(1 + H^n_{2,m} P^n_m\right)}{2\left(1 + H^n_{2,m} P^n_m + \sqrt{\left(1 + H^n_{1,m} P^n_m\right)\left(1 + H^n_{2,m} P^n_m\right)}\right)} \tag{29}
$$

$$
{p^n_{2,m}}^* = \frac{P^n_m \sqrt{\left(1 + H^n_{1,m} P^n_m\right)\left(1 + H^n_{2,m} P^n_m\right)}}{2\left(1 + H^n_{2,m} P^n_m + \sqrt{\left(1 + H^n_{1,m} P^n_m\right)\left(1 + H^n_{2,m} P^n_m\right)}\right)} \tag{30}
$$

The user data rate on the n_{th} subcarrier at S_i can be reformulated as

$$R_i^{n*} = \frac{1}{2}\log_2\left(1+\frac{H_{1,m}^n H_{2,m}^n (P_m^n)^2}{\left(\sqrt{\left(1+H_{1,m}^n P_m^n\right)}+\sqrt{\left(1+H_{2,m}^n P_m^n\right)}\right)^2}\right) \tag{31}$$

Obviously, R_i^{n*} is determined by one dimensional variable P_m^n. The optimal solution to P_m^n can be obtained through one dimensional linear search method [28, 29]. After we get ${P_m^n}^*$, we substitute it into (26), we can reformulate

$$\mathcal{L}_{PHY} = \mathcal{G}_0 + \sum_{n=1}^{N} \mathcal{G}({P_m^n}^*) \tag{32}$$

where

$$\mathcal{G}_0 = z + \sum_{l=1}^{L} \mu_l I_l^{th} + \sum_{l=1}^{L} \upsilon_l I_l^{th} + \delta P_{\max} - zP_C \tag{33}$$

$$\begin{aligned}\mathcal{G}({P_m^n}^*) = &\sum_{i=1}^{2}(\lambda_i - z\alpha)R_i^{n*} - \sum_{i=1}^{2}\sum_{l=1}^{L}\mu_l {p_{i,m}^n}^* |g_{i,l}^n|^2 \\ &- \sum_{l=1}^{L}\upsilon_l {p_{r,m}^n}^* |\tilde{g}_{m,l}^n|^2 - \delta {P_m^n}^* - z\varepsilon_i \sum_{i=1}^{2} {p_{i,m}^n}^* - z\xi_m {p_{r,m}^n}^*\end{aligned} \tag{34}$$

As for the n_{th} subcarrier, the best relay node which maximizes $\mathcal{G}({P_m^n}^*)$ can be selected by

$$m^* = \arg\max_{m=1,2,\ldots,K}\{\mathcal{G}({P_m^n}^*)\} \tag{35}$$

In order to maximize the dual function $\mathcal{L}_{PHY}$, we need to obtain the optimal Lagrange multipliers $\boldsymbol{\mu}^*$, $\boldsymbol{\upsilon}^*$, and δ^*. We employ sub-gradient method [26] to update the Lagrange multipliers with recursive forms until $\boldsymbol{\mu}^*$, $\boldsymbol{\upsilon}^*$, and δ^* are achieved

$$\mu_l(t_1+1) = \left[\mu_l(t_1) - s_1^l\left(I_l^{th} - \sum_{i=1}^{2}\sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{i,m}^n \left|g_{i,l}^n\right|^2\right)\right]^+, \forall l \tag{36}$$

$$\upsilon_l(t_1+1) = \left[\upsilon_l(t_1) - s_2^l\left(I_l^{th} - \sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{r,m}^n \left|\tilde{g}_{m,l}^n\right|^2\right)\right]^+, \forall l \tag{37}$$

$$\delta(t_1+1) = \left[\delta(t_1) - s_3\left(P_{\max} - \sum_{i=1}^{2}\sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{i,m}^n - \sum_{m=1}^{K}\sum_{n\in\mathcal{N}_m} p_{r,m}^n\right)\right]^+ \tag{38}$$

where $[x]^+ \triangleq \max(0,x)$. s_1^l, s_2^l, and s_3 are the small positive step sizes. t_1 is the number of iteration in the physical layer. Finally, pseudo code of the physical layer algorithm also called inner loop algorithm is listed in Algorithm 1.

Algorithm 1: Physical layer algorithm

```
Input: convergence accuracy of the physical layer
algorithm ε_phy, convergence accuracy of power
 search method
ε_S, maximum number of iterations in physical layer
T_phy, z, λ, ρ, μ, υ, δ, s_1^l, s_2^l, s_3 and t_1 = 0.
while R_i(t_1 + 1) − R_i(t_1) ≥ ε_phy, ∀i or t_1 < T_phy do
  repeat
    for n=1:N do
      repeat
        update p_m^n with power search method;
      until p_m^n reaches ε_S;
      calculate p_{1,m}^n, p_{2,m}^n and p_{r,m}^n;
    end for
  calculate R_i^n(t_1 + 1) according to (31);
  update ρ according to (35);
  update μ_l(t_1 + 1), υ_l(t_1 + 1) and δ(t_1 + 1)
according to (36)-(38);
  t_1 = t_1 + 1;
  until R_i(t_1 + 1) − R_i(t_1) < ε_phy, ∀i or t_1 ≥ T_phy reaches;
end while
```

In the application layer, with Karush-Kuhn-Tucker (KKT) conditions $\frac{\partial \mathcal{L}_{APP}}{\partial \tilde{R}_i} = 0$, the optimal user rate in the application layer can be formulated as

$$\tilde{R}_i^* = {U_i'}^{-1}\left(\frac{\lambda_i}{1+\gamma_i}\right), \forall i \tag{39}$$

where ${U_i'}^{-1}(\cdot)$ is the inverse function of the derivation of $U_i(\cdot)$. The Lagrange multipliers can also be updated by the sub-gradient method with recursive forms as

$$\gamma_i(t_2+1) = \left[\gamma_i(t_2) - s_4^i\left(U_i(\tilde{R}_i) - MOS_i^{\min}\right)\right]^+, \forall i \tag{40}$$

$$\lambda_i(t_2+1) = [\lambda_i(t_2) - s_5^i(R_i - \tilde{R}_i)]^+, \forall i \tag{41}$$

where s_4^i and s_5^i are the small positive step sizes. t_2 is the number of iteration in the application layer. Then, the pseudo code of the application layer algorithm also called an outer loop algorithm is listed in Algorithm 2. We alternate iterations of the physical layer algorithm and the application layer algorithm, which is defined as the CL alternate iteration algorithm until the convergence of the optimal z^* is obtained.

The computational complexity of the proposed CL alternate iteration algorithm can be estimated roughly as follows. In the physical layer (i.e., inner loop), we first

---

Algorithm 2: Application layer algorithm

Input: convergence accuracy of the application layer algorithm ε_{app}, maximum number of iterations in application layer T_{app}, $MOS_i^{\min}$, $\boldsymbol{\lambda}$, $\boldsymbol{\gamma}$, s_4^i, s_5^i and $t_2 = 0$.
while $z(t_2+1) - z(t_2) \geq \varepsilon_{app}, \forall i$ or $t_2 < T_{app}$ **do**
  repeat
    solve (26) to obtain P_{tot} and R_i by **Algorithm 1**;
    calculate $\tilde{R}_i\,(t_2+1)$ and $z(t_2+1)$;
    update $\lambda_i\,(t_2+1)$ and $\gamma_i\,(t_2+1)$ according to (40)-(41);
    $t_2 = t_2 + 1$;
  until $z(t_2+1) - z(t_2) < \varepsilon_{app}, \forall i$ or $t_2 \geq T_{app}$ reaches;
end while

---

perform the power allocation under the given subcarrier assignment scheme. Then the power allocation problem is decomposed into N parallel power allocation subproblems. Thus, the power allocation algorithm requires N evaluations for all subcarriers. In every evaluation, we assume I_S is the number of iterations to obtain the optimal power solution $P_m^{n\,*}$ with the search method. The subcarrier assignment scheme is carried out after we obtain $P_m^{n\,*}$ with the computational complexity K. After N evaluations, the computational complexity of the power allocation and subcarrier assignment procedure is $N(I_S + K)$. The iteration number of sub-gradient method for maximizing $\mathcal{L}_{PHY}$ is I_{phy}. Then, the computational complexity required in the physical layer is $\mathcal{O}(I_{phy}N(I_S + K))$. In the application layer (i.e., outer loop), the number of iterations of sub-gradient method for z^* is I_{app}. To sum up, the overall computational complexity is $\mathcal{O}(I_{app}I_{phy}N(I_S + K))$ when optimal z^* is obtained.

4 Simulation results

In this section, we use computer simulation to validate the effectiveness of our proposed resource allocation algorithm and show its outperformance than the fixed relay selection with equal power allocation (FRS-EPA) scheme, random relay selection with equal power allocation (RRS-EPA) scheme, fixed relay selection with optimal power allocation (FRS-OPA) scheme, random relay selection with optimal power allocation (RRS-OPA) scheme, and QoE maximization algorithm. Simulation parameters are assumed as follows unless specified otherwise. We assume $L = 2$, $K = 2$, and $N = 16$. The interference thresholds of PU1 and PU2 are $I_1^{th} = 4 \times 10^{-10}W$ and $I_2^{th} = 6 \times 10^{-10}W$, respectively. The maximum total transmit power, the fixed circuit power, and the dynamic circuit power consumption factor are $P_{\max} = 10W$, $P_C = 0.05W$, and $\alpha = 0.01$, respectively. The reciprocal of PAs' drain efficiency at SUs and the relay nodes are $\varepsilon_1 = 4$, $\varepsilon_2 = 4$, $\xi_1 = 2$, and $\xi_2 = 2$, respectively. The channel gains are assumed to be the frequency flat Rayleigh fading channels. They are independent and identically distributed (i.i.d.) circularly symmetric complex Gaussian (CSCG) random variables (RVs) and distributed as $h \sim \mathcal{CN}\left(0,\ \frac{1}{(1+d)^\tau}\right)$, where $\tau = 4$ is the path loss coefficient and d is the distance among different nodes in the system. We adopt rapid movement video application, thus the coefficients a_1 to a_5 are set to be −0.0228, −0.0065, 0.6582, 10.0437, and 0.6865. We assume there are no packet loss and $FR = 10$. The minimum required MOS for S_1 and S_2 are 3.6 and 4, respectively.

Figure 2 demonstrates the interference power to PUs in both two time slots in the physical layer. We set PU1 and PU2 with different interference threshold which is more practical to real wireless systems than the scenario that different PUs have the same interference level. We can observe that the interference powers to PUs are all below their individual interference thresholds in both two time slots which shows that our proposed algorithm can strictly guarantee the quality of service for each PU.

Figure 3 presents the QoE of SUs versus the increasing number of iteration in the application layer. We can find that U_1 and U_2 can quickly converge to the equilibrium points with the increase of iteration numbers. Moreover, U_1 and U_2 are all exceed the minimum MOS requirements, which proves that this proposed algorithm can guarantee the QoE for SUs. We also observe that U_2 converges to 4.2 which means the perceived quality of S_2 is high. However, U_1 is only little higher than 3.6 which implies the perceived quality of S_1 is acceptable. U_1 and U_2 converge to different values under the same physical layer sending rates indicates that the equal date rates have unequal contribution to QoE in terms of different traffic features.

Figure 4a, b show the effect of relay number on sum QoE and $QoEW$, respectively. From Fig. 4a, we can observe that the QoE maximization algorithm achieves the maximum sum QoE of SUs while the proposed method keeps the minimum sum QoE requirements of SUs. Figure 4b illustrates that $QoEW$ of these two algorithms increases with the relay number since more spatial diversity gain can be obtained, but with limitation when $K \geq 3$. Additionally, $QoEW$ of the proposed method is higher than that of the QoE maximization algorithm. The reason is that the optimization objective of the QoE maximization algorithm is to maximize the sum QoE of SUs without considering power consumption.

Figure 5 presents the effect of subcarrier number on $QoEW$ with $K = 2$. We assume $I_{th} = I_1^{th} = I_2^{th} = 5 \times 10^{-9}W$ to simplify the analysis. We can see that $QoEW$ increases as the subcarrier number increases, since it is more likely for the controller to assign subcarriers to the users with good channel conditions and then to optimize the power allocation. However, when the subcarrier

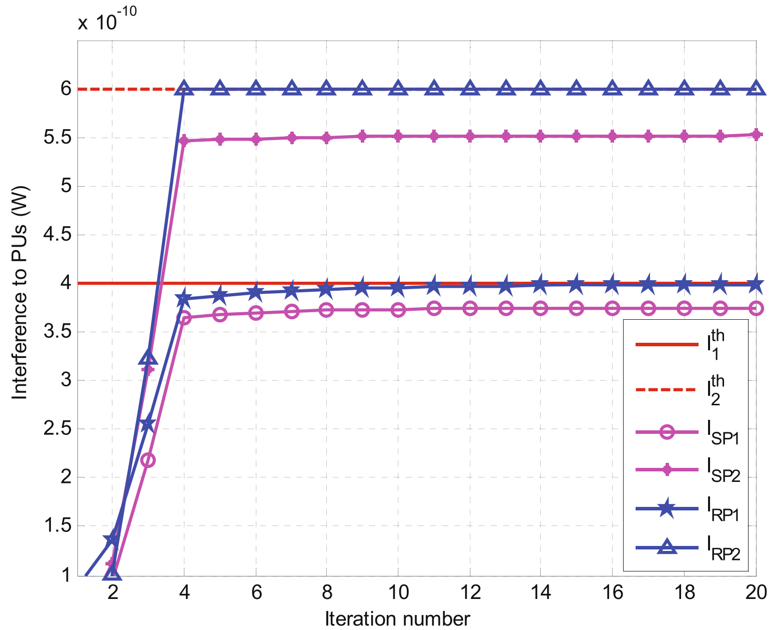

Fig. 2 Interference to PUs

number increases to some extent, the growth of $QoEW$ becomes slowly because of the limitation of the interference threshold.

Figure 6 shows $QoEW$ from different algorithms versus the minimum MOS requirement. In order to simplify the analysis, we assume S_1 and S_2 have an equal minimum MOS requirement. It can be observed that $QoEW$ decreases with the increase of the minimum QoE requirement since the growth of the minimum QoE requirement results in the increase of the power consumption. In addition, Fig. 6 also validates that our proposed relay selection and power allocation algorithm is superior to FRS-EPA scheme, RRS-EPA scheme, FRS-OPA scheme, and RRS-OPA scheme.

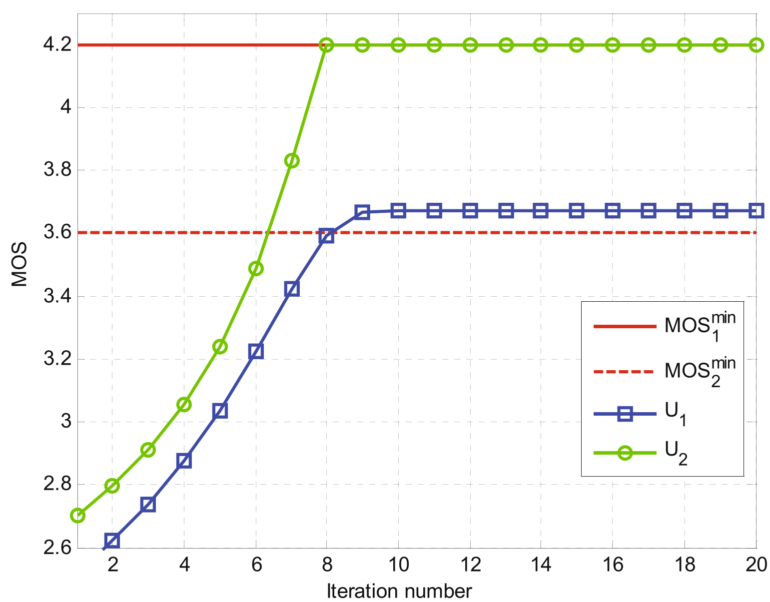

Fig. 3 QoE of SUs

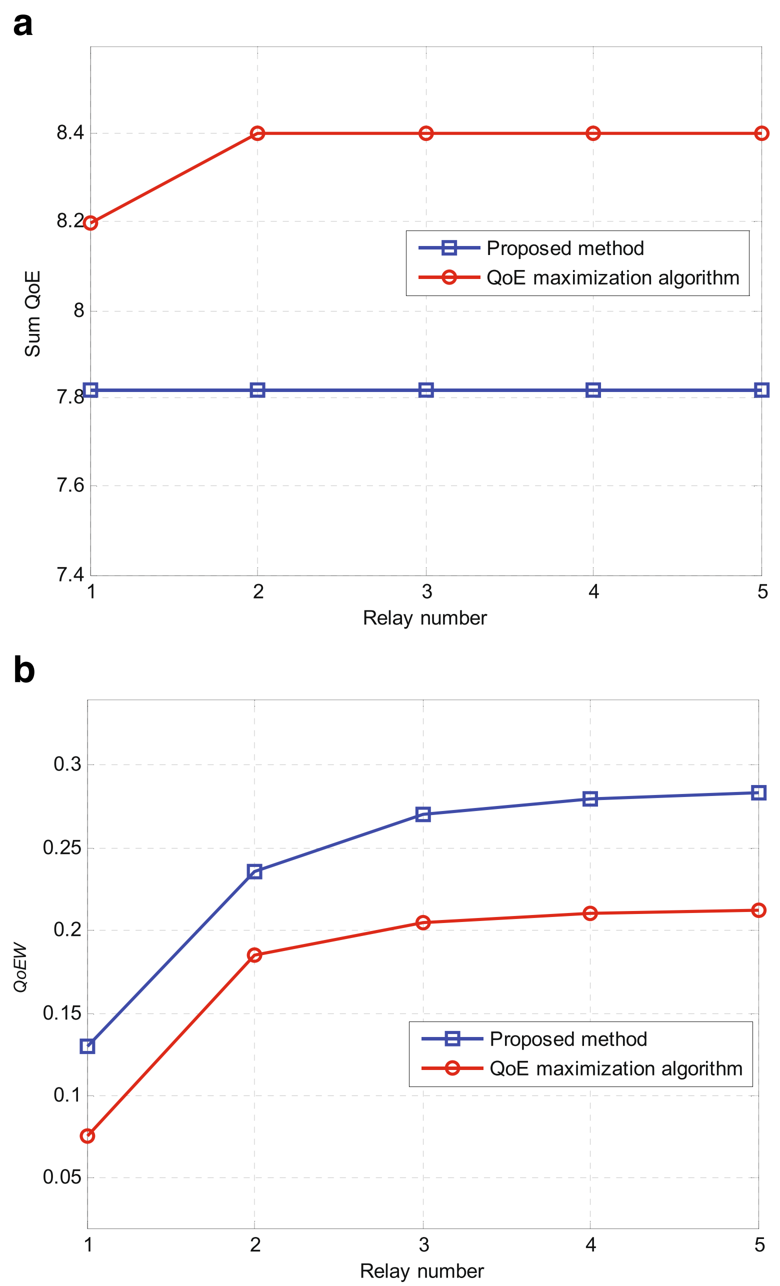

Fig. 4 Sum QoE and *QoEW* versus relay number. **a** Effect of relay number on sum QoE. **b** Effect of relay number on *QoEW*

Figure 7 illustrates $QoEW$ of the proposed algorithm and QoE maximization algorithm versus the maximum transmit power budget. We can see that the proposed algorithm achieves higher $QoEW$ than that of QoE maximization algorithm which always attempts to maximize the QoE regardless of the power consumption. It can also be observed that $QoEW$ of these two algorithms increases initially with the increase of $P_{\max}$ when $P_{\max}$ is the limitation constraint. However, when $P_{\max}$ increases to some extent, $QoEW$ becomes nearly constant since interference threshold becomes a dominant constraint in this region. In addition, the larger interference threshold is configured, the higher $QoEW$ will be obtained.

Figure 8 demonstrates $QoEW$ versus P_C and α, respectively. We can find that $QoEW$ converges with the increase of iteration number and increases when $P_{\max}$ increases from 8 W to 10 W under the given interference threshold. Moreover, under the same $P_{\max}$, $QoEW$ increases with the decrease of P_C and α. And α has bigger influence on the $QoEW$ than P_C under this circumstance.

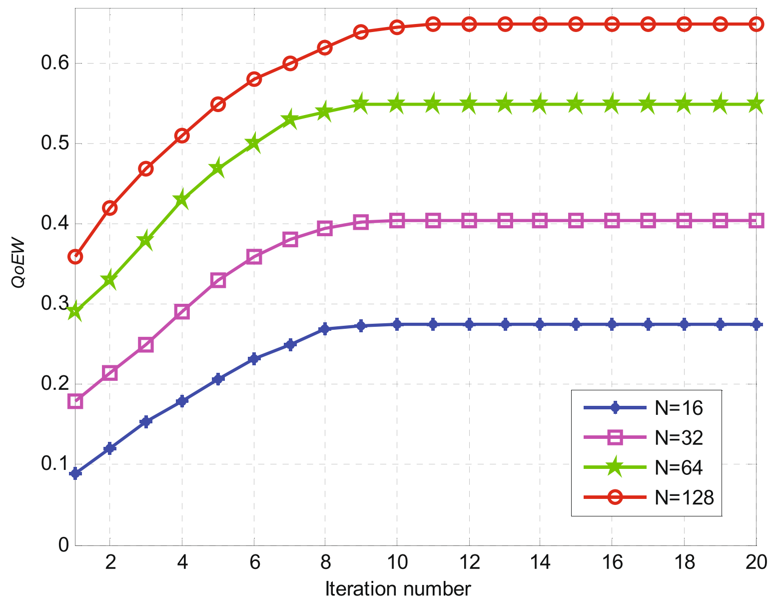

Fig. 5 Effect of subcarrier number on *QoEW*

Figure 9 gives the drain efficiency impact of PAs on $QoEW$. Obviously, the proposed method outperforms the QoE maximization algorithm as we expect it. Comparing the performance of these two algorithms with different drain efficiency of PAs at SUs and the relay nodes, we can see that these two algorithms achieve the lowest $QoEW$ with $[\varepsilon_1, \varepsilon_2, \xi_1, \xi_2] = [2, 2, 4, 4]$ and the highest $QoEW$ with $[\varepsilon_1, \varepsilon_2, \xi_1, \xi_2] = [4, 4, 2, 2]$, which indicates that $QoEW$ achieves the best value when PAs at the relay nodes with high drain efficiency, since the allocated transmit power to the relay nodes is higher than that to SUs.

5 Conclusions

In this paper, a QoE and power consumption-driven resource allocation problem in a two-way OFDM-based CRN is studied. The tradeoff between the sum of QoE perceived by SUs and power consumption is defined as $QoEW$

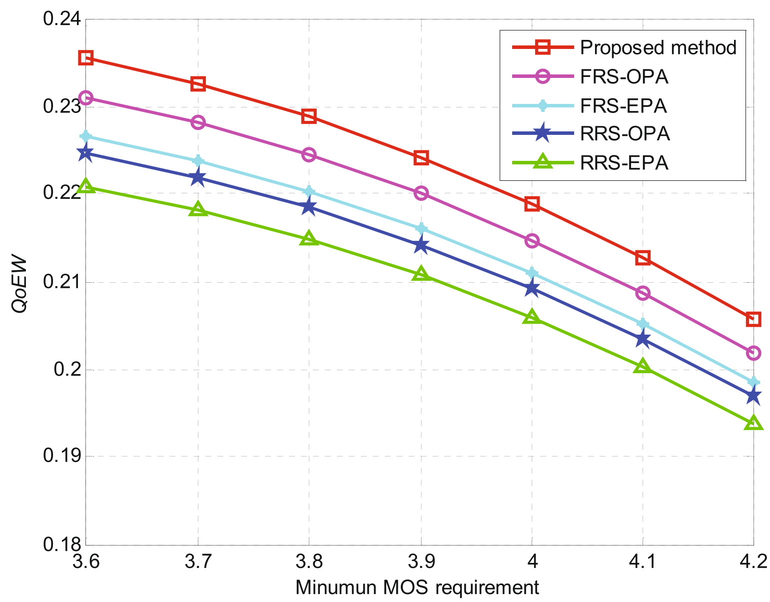

Fig. 6 *QoEW* versus minimum MOS requirement

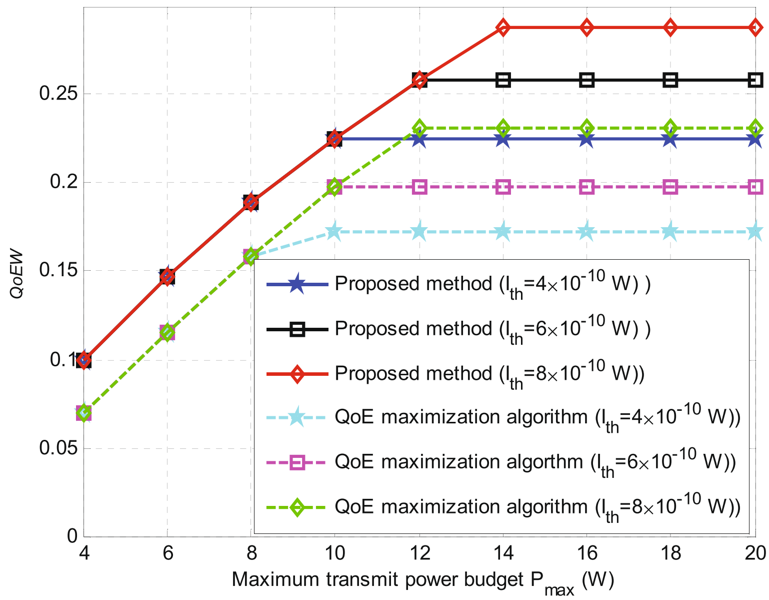

Fig. 7 *QoEW* versus the maximum transmit power budget

and adopted as a new performance metric. A CL alternate iteration algorithm is proposed to solve this resource allocation problem. Numerical simulation results show the outperformance of the proposed algorithm through comparisons with other algorithms and validate the effectiveness of the proposed algorithm for the satisfaction of the minimum QoE demands of SUs and the guarantee of the interference thresholds of multiple PUs. In addition, the impacts of the fixed power, the dynamic circuit power consumption factor and the drain efficiency of PAs on *QoEW* are also given. In our future work, we will extend this framework for multiple SUs with various multimedia services and different QoE requirements under green communications considerations.

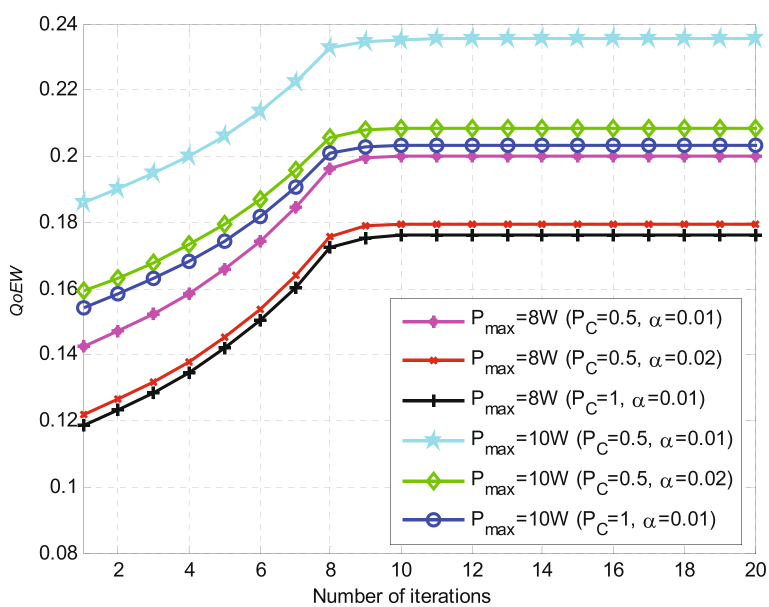

Fig. 8 *QoEW* versus P_C and α

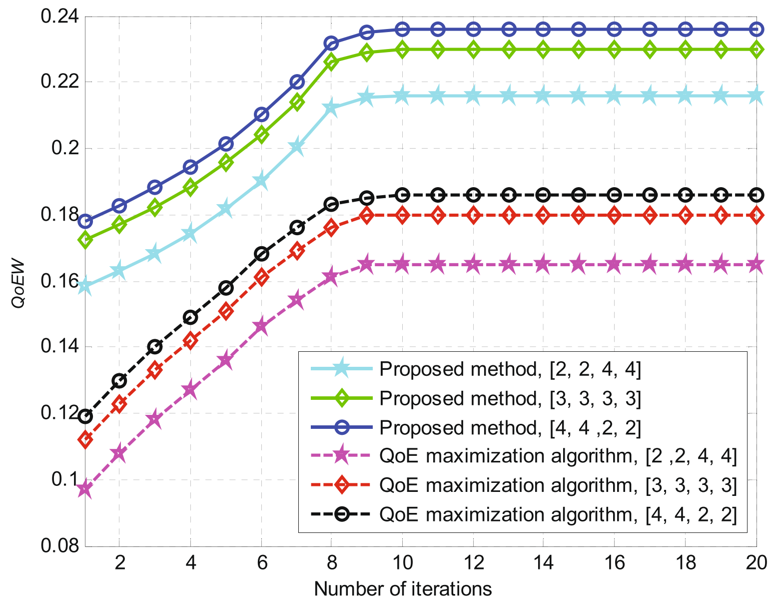

Fig. 9 Drain efficiency impact of PAs on *QoEW*

Acknowledgements
The work of this paper is supported by the National Natural Science Foundation of China under grant No.61171079.

Authors' contributions
WY contributed in the conception of the study and design of the study and wrote the manuscript. Furthermore, WY carried out the simulation and revised the manuscript. XH helped to perform the analysis with constructive discussions and helped to draft the manuscript. All authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

Publisher's Note
Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Received: 9 May 2017 Accepted: 5 November 2017
Published online: 19 December 2017

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