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A Novel Robust Resource Allocation Algorithm for OFDM-based Cooperative Cognitive Radio Networks with Imperfect CSI considerations

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Abstract

In this paper, the robust resource allocation problem for the orthogonal frequency division multiplexing (OFDM) based cooperative cognitive radio networks (CRNs) with decode and forward (DF) protocol, considering the imperfect channel state information (CSI) is studied. The proposed resource allocation algorithm takes into account multiple kinds of channel uncertainty. On the basis of the resource allocation scheme with perfect CSI, robust resource allocation algorithm is proposed to maximize the data rate of the cognitive radio networks, while the interference to primary user (PU) is below a predefined interference threshold. The worst-case approach is applied to the robust resource optimization problem. Each channel uncertainty parameter is defined by a bounded distance between its estimated and exact values, and then the robust power allocation problem is formulated as a semi-infinite programming (SIP) problem. The worst-case approach is utilized to transform the infinite constraints into finite constraints and convert the robust power allocation problem into a deterministic convex optimization problem. Then, a closed form optimal power allocation solution for robust algorithm is derived by the dual decomposition method. Simulation results validate the effectiveness of the proposed robust resource allocation algorithm and demonstrate that the robust resource allocation algorithm is superior to the non-robust algorithm.

Keywords: Cognitive Radio Networks; Cooperative Communications; Multicarrier Systems; Resource Allocation; Imperfect CSI.

Introduction

Cognitive radio (CR) has been proposed as a promising technology to alleviate the contradiction between spectrum scarcity and underutilization of the licensed spectrum [1] [2]. In the cognitive radio networks (CRNs), the unlicensed users or the secondary users (SUs) can access to the spectrum of the licensed users or the primary users (PUs) under the interference threshold of PUs.

Orthogonal frequency division multiplexing (OFDM) has been recognized as a potential technology for CRNs [3] [8]. In the OFDM-based CRNs, the PUs might use any modulation technology, so the subcarriers may not be orthogonal, which will bring harmful interference to PUs [4]. Moreover, long distance and high transmit power will introduce some interference to PUs. As a result, the direct communication of cognitive source and cognitive destination is not reliable.

Using the cooperative communications, the cognitive source communicates with the cognitive destination via relays [5] [11] [13]. With the assistance of relays, the performance of CRNs can be improved. For instance, diversity gain can be acquired, data can be reliably transmitted with lower power and the interference to PUs can be reduced [6-7].

Most of the existing relay selection and power allocation schemes for OFDM-based cooperative CRNs are developed under perfect channel state information (CSI) [8-13]. Some robust resource allocation algorithms with imperfect CSI have been developed in [14-20]. According to different kinds of estimation errors, deterministic uncertainty models (i.e. worst-case model) [14-15] and distributional uncertainty models (i.e. probabilistic model) [16-17] have been introduced to the robust resource allocation algorithms. When the statistical knowledge of the estimation errors is available, probabilistic model is adopted. However, it is difficult to exactly obtain statistical information of the estimation errors due to time-varying channel parameters and dynamic nature of communication system. Under this circumstance, the estimation errors can be assumed to be in some bounded regions, where the size of the region stands for the accuracy of estimation errors and the shape of the region depends on the source of estimation errors.

In this paper, considering the worst-case channel estimation errors, the resource allocation in the OFDM-based cooperative CRN using decode and forward (DF) protocol is investigated. The major contributions of this paper are as follows.

- A heuristic relay selection scheme is proposed, which provides higher equivalent end-to-end signal to interference plus noise ratio (SINR) in CRN and lower interference to PU for the respective subcarriers and is robust against different channel uncertainties.
- Considering all channel uncertainties, the robust relay selection and power allocation optimization problem is formulated under the worst-case scenario by the bounded channel uncertainty region with ellipsoid sets and interval sets. We convert the proposed robust power optimization problem from a semi-infinite programming (SIP) problem into a deterministic convex optimization problem, which can be efficiently solved by Lagrange dual decomposition method. Moreover, a closed form power analytical solution for robust power allocation has been derived.

Section 2 describes the system model and problem formulation with perfect CSI. Section 3 discusses the robust resource allocation problem. Section 4 provides the simulation results and section 5 concludes the paper.

1. System Model and Problem Formulation

1.1 System Model

A multi-relay two hop OFDM-based cooperative CRN as shown in Fig. 1 is considered. It is assumed that the channel between secondary transmitter (ST) and secondary receiver (SR) is weak and as a result, ST communicates with SR taking advantage of the cooperation of K relays. The maximum total transmit power of the ST and the individual relay are P_S and P_{R_k}, respectively. The relays are assumed to operate in half duplex mode with DF protocol, thus the receiving/transmitting signals are in two different time slots. In the first time slot, the cognitive source transmits message to different relays, while in the second time slot, the relays decode the message and re-encode it, then forward it to the cognitive destination.

The frequency spectrum is divided into N subcarriers each having a Δf bandwidth. The total interference introduced to PU by this CRN can be expressed as

$$I_{SPU} = \sum_{k=1}^{K}\sum_{i=1}^{N}\rho_k^i P_{Sk}^i \left|h_{SPU}^i\right|^2 \tag{1}$$

$$I_{RPU} = \sum_{k=1}^{K}\sum_{i=1}^{N}\rho_k^i P_{kD}^i \left|h_{kPU}^i\right|^2 \tag{2}$$

where I_{SPU} and I_{RPU} are the interference to PU by SR_k link and R_kD link, respectively, ρ_k^i is a binary decision variable indicating whether the *i*-th subcarrier is allocated to relay R_k, P_{Sk}^i and P_{kD}^i are the power of the *i*-th subcarrier transmitted on SR_k link and R_kD link. h_{SPU}^i and h_{kPU}^i denote the channel gain of the *i*-th subcarrier from the cognitive source to PU and from relay R_k to PU.

The capacity of the *i*-th subcarrier is given by

$$C_{Sk}^i = \frac{1}{2}\log_2\left(1+\frac{P_{Sk}^i\left|h_{Sk}^i\right|^2}{\sigma_k^2 + J_{ik}}\right) \tag{3}$$

$$C_{kD}^i = \frac{1}{2}\log_2\left(1+\frac{P_{kD}^i\left|h_{kD}^i\right|^2}{\sigma_d^2 + J_{id}}\right) \tag{4}$$

where C_{Sk}^{i} and C_{kD}^{i} present the capacity of the SR_k link and the $R_k D$ link, h_{Sk}^{i} and h_{kD}^{i} denote the instantaneous channel gain of the *i*-th subcarrier on the SR_k link and $R_k D$ link, respectively. σ_k^2 and σ_d^2 are the variance of the additive white Gaussian noise (AWGN) at R_k and D. J_{ik} and J_{id} are the interference introduced by the PU to the *i*-th subcarrier at R_k and D, which can be modeled as AWGN by the law of large numbers [21].

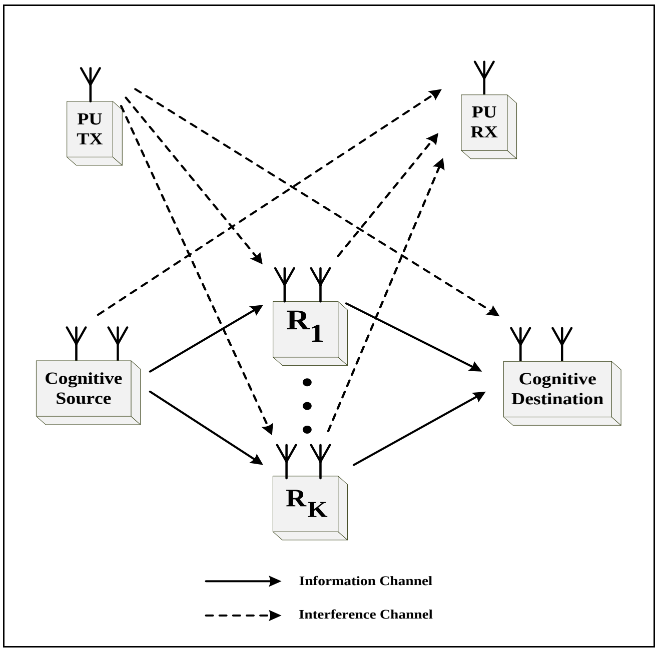

Fig. 1 System Model

1.2 Non-Robust Relay Selection and Power Allocation Algorithm

Before proposing the robust resource allocation algorithm, at first, the non-robust resource allocation algorithm is investigated. This problem can be expressed as

$$
\begin{aligned}
&P0: \max_{\rho_k^i, P_{Sk}^i \geq 0, P_{kD}^i \geq 0} \sum_{k=1}^{K}\sum_{i=1}^{N} \rho_k^i \min\left\{C_{Sk}^{i}, C_{kD}^{i}\right\} \\
&\text{subject to} \quad (C1): \sum_{k=1}^{K}\sum_{i=1}^{N} \rho_k^i P_{Sk}^i \leq P_S \\
&(C2): \sum_{i=1}^{N} \rho_k^i P_{kD}^i \leq P_{R_k}, \quad \forall k \in K \\
&(C3): \sum_{k=1}^{K}\sum_{i=1}^{N} \rho_k^i P_{Sk}^i G_{SPU}^{i} \leq I_{th}, \\
&(C3): \sum_{k=1}^{K}\sum_{i=1}^{N} \rho_k^i P_{kD}^i G_{kPU}^{i} \leq I_{th}, \\
&(C5): \sum_{k=1}^{K} \rho_k^i = 1, \forall i \\
&(C6): \rho_k^i \in \{0,1\}, \forall k, i
\end{aligned} \tag{5}
$$

where $(C1)$ and $(C2)$ are the transmit power constraints of the cognitive source and individual relay, $(C3)$ and $(C4)$ are the interference constraints in the first time slot and the second time slot, respectively, I_{th} is the interference threshold of PU. Here we denote $G_{kPU}^{i} = \left|h_{kPU}^{i}\right|^2$ and $G_{SPU}^{i} = \left|h_{SPU}^{i}\right|^2$. $(C5)$ and $(C6)$ are the relay selection constraints to express that only one relay can be assigned for each subcarrier, if $\rho_k^i = 1$, it means the relay R_k is allocated to the *i*-th subcarrier, otherwise it is not. Without loss of generality, the noise variance is assumed to be constant for all the subcarriers, and we denote $\sigma_k^2 + J_{ik} = \sigma_d^2 + J_{id} = \sigma^2$. The SINRs of the *i*-th subcarrier at R_k and D are $\gamma_{Sk}^i = \frac{\left|h_{Sk}^i\right|^2}{\sigma^2}$ and $\gamma_{kD}^i = \frac{\left|h_{kD}^i\right|^2}{\sigma^2}$, respectively. As for DF protocol, the maximum capacity of the *i*-th subcarrier in the CRN can be achieved when $P_{Sk}^i \gamma_{Sk}^i = P_{kD}^i \gamma_{kD}^i$. Therefore, the power allocated at R_k can be formulated as a function of the cognitive source power. When we denote $H_k^i = \left|h_{Sk}^i\right|^2 / \left|h_{kD}^i\right|^2$, thus $P_{kD}^i = P_{Sk}^i H_k^i$, and the objective function, $(C2)$ and $(C4)$ in $P0$ can be rewritten as

$$
\begin{aligned}
&P1: \max_{\rho_k^i, P_{Sk}^i \geq 0} \sum_{k=1}^{K} \sum_{i=1}^{N} \frac{\rho_k^i}{2} \log_2\left(1 + P_{Sk}^i \gamma_{Sk}^i\right) \\
&\quad \text{subject to } (C1),(C3),(C5),(C6) \\
&(C2): \sum_{i=1}^{N} \rho_k^i P_{Sk}^i H_k^i \leq P_{R_k}, \forall k \in K \\
&(C4): \sum_{k=1}^{K} \sum_{i=1}^{N} \rho_k^i P_{Sk}^i H_k^i G_{kPU}^i \leq I_{th},
\end{aligned} \tag{6}
$$

It can be seen that $P1$ is a mixed integer optimization problem and it is hard to find a joint optimal relay selection and power allocation solution. Therefore $P1$ should be solved in two steps. At First, the relay selection is performed under the equal power allocation of the cognitive source and individual relay. Second, the power is assigned under the given relay assignment. Considering the relay allocation constraints, in which only one relay can be allocated to each subcarrier, so the best relay must be selected for each subcarrier. The relay which provides the equivalent higher end-to-end SINR in the CRN and the lower interference to the PU can be selected for respective subcarriers. Therefore, we first take the harmonic mean of γ_{Sk}^i and γ_{kD}^i as the equivalent SINR for the *i*-th subcarrier selecting the relay R_k [22], the decision variable W_k^i can be expressed as

$$
W_k^i = \frac{2\gamma_{Sk}^i \gamma_{kD}^i}{\gamma_{Sk}^i + \gamma_{kD}^i} = \frac{2\gamma_{Sk}^i}{1 + H_k^i} \tag{7}
$$

The total interference introduced to the PU by the CRN is in proportion to $G_{SPU}^i + G_{kPU}^i$. We relax the integrality constraint on ρ_k^i, and the relay selection factor is denoted as follows

$$
\rho_k^i = \frac{W_k^i}{G_{SPU}^i + G_{kPU}^i} = \frac{2\gamma_{Sk}^i}{\left(G_{SPU}^i + G_{kPU}^i\right)\left(1 + H_k^i\right)} \tag{8}
$$

Therefore, R_k with maximum ρ_k^i is allocated to the *i*-th subcarrier, which can be expressed as

$$
K(i) = \arg\max_k \rho_k^i, \forall i \tag{9}
$$

where $K(i) \in [1:K]$ presents the relay selected by the *i*-th subcarrier. We denote $N_{K(i)}$ as the set of subcarriers selected in the relay $R_{K(i)}$. The computational complexity of this heuristic relay selection scheme is in $O(KN)$. Under this relay selection scheme, $P1$ can be converted into the following:

$$
\begin{aligned}
&P2: \max_{P_{SK(i)}^i \geq 0} \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} \frac{1}{2} \log_2\left(1 + P_{SK(i)}^i \gamma_{SK(i)}^i\right) \\
&\quad \text{subject to } (C1): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i \leq P_S, \\
&(C2): \sum_{i \in N_{K(i)}} P_{SK(i)}^i H_{K(i)}^i \leq P_{R_{K(i)}}, \forall K(i) \in K \\
&(C3): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i G_{SPU}^i \leq I_{th}, \\
&(C4): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i H_{K(i)}^i G_{K(i)PU}^i \leq I_{th},
\end{aligned} \tag{10}
$$

We can see that $P2$ is a convex optimization problem [23] and an optimal power allocation can be found by using the Karush-Kuhn-Tucker (KKT) conditions.

2. Robust Resource Allocation Algorithm

In practical communication systems, it is extremely difficult to obtain perfect CSI. Thus it is necessary to develop robust resource allocation scheme in a more practical scenario without the availability of CSI. We adopt the worst-case approach with the bounded estimation errors. CSI uncertainty is generally modeled by the sum of the estimated values and additive error. In this paper, we consider five types of uncertain CSI parameters: 1) the CSI between cognitive source and relay receivers (h_{Sk}^i), 2) the CSI between relay transmitters and cognitive destination (h_{kD}^i), 3) the CSI between the cognitive source and PU receiver (G_{SPU}^i), 4) the CSI between relay transmitters to PU receiver (G_{kPU}^i), 5) the interference caused by PU plus the noise in CRN. H_k^i is used to express the two hop CSI uncertainty and we use γ_{Sk}^i to express the normalized interference uncertainty. The ρ_k^i can be rewritten as

$$\rho_k^i = \frac{2\left(\hat{\gamma}_{Sk}^i + \Delta\gamma_{Sk}^i\right)}{\left(\hat{G}_{SPU}^i + \Delta G_{SPU}^i + \hat{G}_{kPU}^i + \Delta G_{kPU}^i\right)\left(1 + H_k^i + \Delta\hat{H}_k^i\right)} \tag{11}$$

Using definition of the convex ellipsoid uncertainty region [24], G_{SPU}^i, $G_{K(i)PU}^i$ and $H_{K(i)}^i$ can be formulated by

$$\Phi = \left\{ G_{SPU}^i \left| \hat{G}_{SPU}^i + \Delta G_{SPU}^i : \sum_{i \in N_{K(i)}} \left|\Delta G_{SPU}^i\right|^2 \le \eta_{K(i)}^2, \forall K(i) \in K \right. \right\} \tag{12}$$

$$\Theta = \left\{ G_{K(i)PU}^i \left| \hat{G}_{K(i)PU}^i + \Delta G_{K(i)PU}^i : \sum_{i \in N_{K(i)}} \left|\Delta G_{K(i)PU}^i\right|^2 \le \delta_{K(i)}^2 \right. \right\} \tag{13}$$

$$\Xi = \left\{ H_{K(i)}^i \left| \hat{H}_{K(i)}^i + \Delta H_{K(i)}^i : \sum_{i \in N_{K(i)}} \left|\Delta H_{K(i)}^i\right|^2 \le \varepsilon_{K(i)}^2, \forall K(i) \in K \right. \right\} \tag{14}$$

where Φ, Θ and Ξ are the sets of different kinds of channel CSI uncertainty. $\eta_{K(i)}$, $\delta_{K(i)}$ and $\varepsilon_{K(i)}$ are the upper bounds of the uncertainty parameters. Ψ is defined as the set of the normalized interference uncertainty formulated by

$$\Psi = \left\{ \gamma_{SK(i)}^i \left| \hat{\gamma}_{SK(i)}^i + \Delta\gamma_{SK(i)}^i : \left|\Delta\gamma_{SK(i)}^i\right| \le \kappa_{SK(i)}^i \hat{\gamma}_{SK(i)}^i \right. \right\} \tag{15}$$

$\kappa_{SK(i)}^i$ is the upper bound of the uncertainty, which determine the size of the uncertainty region. $P2$ can be rewritten as

$$\begin{aligned}
& P3: \max_{P_{SK(i)}^i \ge 0} \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} \frac{1}{2} \log_2\left(1 + P_{SK(i)}^i\left(\hat{\gamma}_{SK(i)}^i + \Delta\gamma_{SK(i)}^i\right)\right) \\
& \quad \text{subject to } (C1): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i \le P_S, \\
& (C2): \sum_{i \in N_{K(i)}} P_{SK(i)}^i\left(\hat{H}_{K(i)}^i + \Delta H_{K(i)}^i\right) \le P_{R_{K(i)}}, \forall K(i) \in K \\
& (C3): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i\left(\hat{G}_{SPU}^i + \Delta G_{SPU}^i\right) \le I_{th}, \\
& (C4): \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^i\left(\hat{H}_{K(i)}^i + \Delta H_{K(i)}^i\right)\left(\hat{G}_{K(i)PU}^i + \Delta G_{K(i)PU}^i\right) \le I_{th}, \\
& (C5): \sum_{i \in N_{K(i)}} \left|\Delta G_{SPU}^i\right| \le \eta_{K(i)}^2, \forall K(i) \in K, \sum_{i \in N_{K(i)}} \left|\Delta H_{K(i)}^i\right| \le \varepsilon_{K(i)}^2, \forall K(i) \in K, \\
& \sum_{i \in N_{K(i)}} \left|\Delta G_{K(i)PU}^i\right| \le \delta_{K(i)}^2, \forall K(i) \in K, \left|\Delta\gamma_{SK(i)}^i\right| \le \kappa_{SK(i)}^i \hat{\gamma}_{SK(i)}^i
\end{aligned} \tag{16}$$

$P3$ is a semi-infinite programming (SIP) problem [25] and is very hard to solve due to the infinite constraints. In order to transform the infinite constraints into finite constraints, we should convert $P3$ into the deterministic optimization problem under the estimation errors in worst-case scenario:

Constraints $(C2)$, $(C3)$ and $(C4)$ in $P3$ can be separately transformed into

$$(C2): \max_{H^i_{K(i)}\in\Xi} \sum_{i\in N_{K(i)}} P^i_{SK(i)} H^i_{K(i)} \le P_{R_{K(i)}}, \forall K(i)\in K \tag{17}$$

$$(C3): \max_{G^i_{SPU}\in\Phi} \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{G}^i_{SPU} + \Delta G^i_{SPU}\right) \le I_{th} \tag{18}$$

$$(C4): \max_{H^i_{K(i)}\in\Xi, G^i_{K(i)PU}\in\Theta} \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} H^i_{K(i)} G^i_{K(i)PU} \le I_{th} \tag{19}$$

According to the Cauchy-Schwartz inequality, $(C2)$ in $P3$ can be further converted as follows

$$\begin{aligned}(C2): &\max_{H^i_{K(i)}\in\Xi} \sum_{i\in N_{K(i)}} P^i_{SK(i)} H^i_{K(i)} = \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{H}^i_{K(i)} + \max_{\sum_{i\in N_{K(i)}} \left|\Delta H^i_{K(i)}\right| \le \varepsilon^2_{K(i)}} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \Delta H^i_{K(i)} \\ &\le \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{H}^i_{K(i)} + \sqrt{\sum_{i\in N_{K(i)}} \left(P^i_{SK(i)}\right)^2} \sqrt{\sum_{i\in N_{K(i)}} \left|\Delta H^i_{K(i)}\right|^2} = \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{H}^i_{K(i)} + \varepsilon_{K(i)} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \le P_{R_{K(i)}}, \forall K(i)\in K\end{aligned} \tag{20}$$

Similarity, $(C3)$ and $(C4)$ in $P3$ can be expressed as

$$(C3): \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{G}^i_{SPU} + \sum_{K(i)=1}^{K} \eta_{K(i)} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \le I_{th} \tag{21}$$

$$(C4): \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{H}^i_{K(i)} \hat{G}^i_{K(i)PU} + \sum_{K(i)=1}^{K} \delta_{K(i)} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{H}^i_{K(i)} + \sum_{K(i)=1}^{K} \varepsilon_{K(i)} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \hat{G}^i_{K(i)PU} + \sum_{K(i)=1}^{K} \varepsilon_{K(i)} \delta_{K(i)} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \le I_{th} \tag{22}$$

According to Eq.(17-22), $P3$ can be rewritten as

$$\begin{aligned} &P4: \max_{P^i_{SK(i)}\ge 0} \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} \frac{1}{2}\log_2\left(1 + P^i_{SK(i)}\left(\hat{\gamma}^i_{SK(i)} + \Delta\gamma^i_{SK(i)}\right)\right) \\ &\quad \text{subject to } (C1): \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \le P_S, \\ &(C2): \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{H}^i_{K(i)} + \varepsilon_{K(i)}\right) \le P_{R_{K(i)}}, \forall K(i)\in K \\ &(C3): \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{G}^i_{SPU} + \eta_{K(i)}\right) \le I_{th}, \\ &(C4): \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{H}^i_{K(i)} + \varepsilon_{K(i)}\right)\left(\hat{G}^i_{K(i)PU} + \delta_{K(i)}\right) \le I_{th} \end{aligned} \tag{23}$$

Obviously, $P4$ is also a convex problem. The Lagrange function of $P4$ is

$$\begin{aligned} L = &\sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} \frac{1}{2}\log_2\left(1 + P^i_{SK(i)} \hat{\gamma}^i_{SK(i)} \left(1 + \kappa^i_{SK(i)}\right)\right) + \lambda\left(I_{th} - \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{G}^i_{SPU} + \eta_{K(i)}\right)\right) \\ &+ \sum_{K(i)=1}^{K} \nu_{K(i)} \left(P_{R_{K(i)}} - \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{H}^i_{K(i)} + \varepsilon_{K(i)}\right)\right) + \beta\left(P_S - \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)}\right) \\ &+ \mu\left(I_{th} - \sum_{K(i)=1}^{K} \sum_{i\in N_{K(i)}} P^i_{SK(i)} \left(\hat{H}^i_{K(i)} + \varepsilon_{K(i)}\right)\left(\hat{G}^i_{K(i)PU} + \delta_{K(i)}\right)\right) \end{aligned} \tag{24}$$

where λ, $\nu_{K(i)}$, β and μ are the Lagrange multipliers. Eq. (24) can be solved by the dual decomposition method:

$$\min_{\beta\ge 0, \nu_{K(i)}\ge 0, \lambda\ge 0, \mu\ge 0} g\left(\beta, \nu_{K(i)}, \lambda, \mu\right) \tag{25}$$

The dual function of Eq. (25) is denoted as

$$g\left(\beta, \nu_{K(i)}, \lambda, \mu\right) \triangleq \max_{P_{SK(i)}^{i} \geq 0} L \tag{26}$$

Substituting Eq. (24) to Eq. (26), we can get

$$g\left(\beta, \nu_{K(i)}, \lambda, \mu\right) \triangleq \max_{P_{SK(i)}^{i} \geq 0} \left[D_0 + \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} D\left(P_{SK(i)}^{i}\right) \right] \tag{27}$$

$$D_0 = \beta P_S + \sum_{K(i)=1}^{K} \nu_{K(i)} P_{R_{K(i)}} + (\lambda + \mu) I_{th} \tag{28}$$

$$D\left(P_{SK(i)}^{i}\right) = \frac{1}{2}\log_2\left(1 + P_{SK(i)}^{i}\hat{\gamma}_{SK(i)}^{i}\left(1+\kappa_{SK(i)}^{i}\right)\right) - \beta P_{SK(i)}^{i} - \nu_{K(i)} P_{SK(i)}^{i}\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right) - \lambda P_{SK(i)}^{i}\left(\hat{G}_{SPU}^{i} + \eta_{K(i)}\right) - \mu P_{SK(i)}^{i}\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right)\left(\hat{G}_{K(i)PU}^{i} + \delta_{K(i)}\right) \tag{29}$$

Then we can get the optimal solution of Eq. (27) as

$$\max_{P_{SK(i)}^{i} \geq 0} D\left(P_{SK(i)}^{i}\right) \tag{30}$$

Therefore, the optimal power can be obtained as

$$P_{SK(i)}^{*i} = \left[\frac{1}{2\ln 2A} - \frac{1}{\hat{\gamma}_{SK(i)}^{i}\left(1+\kappa_{SK(i)}^{i}\right)}\right]^{+} \tag{31}$$

where $A = \beta + \nu_{K(i)}\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right) + \lambda\left(\hat{G}_{SPU}^{i} + \eta_{K(i)}\right) + \mu\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right)\left(\hat{G}_{K(i)PU}^{i} + \delta_{K(i)}\right)$. The Lagrange multipliers in (31) can be updated by the subgradient method with the following recursive forms

$$\beta(t+1) = \left[\beta(t) - a(t)\left(P_S - \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^{i}\right)\right]^{+} \tag{32}$$

$$\lambda(t+1) = \left[\lambda(t) - c(t)\left(I_{th} - \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^{i}\left(\hat{G}_{SPU}^{i} + \eta_{K(i)}\right)\right)\right]^{+} \tag{33}$$

$$\nu_{K(i)}(t+1) = \left[\nu_{K(i)}(t) - b(t)\left(P_{R_{K(i)}} - \sum_{i \in N_{K(i)}} P_{SK(i)}^{i}\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right)\right)\right]^{+} \tag{34}$$

$$\mu(t+1) = \left[\mu(t) - d(t)\left(I_{th} - \sum_{K(i)=1}^{K} \sum_{i \in N_{K(i)}} P_{SK(i)}^{i}\left(\hat{H}_{K(i)}^{i} + \varepsilon_{K(i)}\right)\left(\hat{G}_{K(i)PU}^{i} + \delta_{K(i)}\right)\right)\right]^{+} \tag{35}$$

where t is the iteration number, $a(t)$, $b(t)$, $c(t)$, and $d(t)$ are step sizes. The iterations are repeated until the convergence.

3. Simulation Results

In this section, the simulation results are presented. Here σ^2 is assumed to be 2×10^{-13} W. The OFDM system of $N = 6$ subcarriers is assumed with $K = 2$ relays. The frequency flat Rayleigh fading channels is assumed throughout the simulations and the path loss exponent is 4. It is further assumed that $P_S = P_{R_k}$ and $\kappa = \kappa_{SK(i)}^{i}$, $\varepsilon_{K(i)} = \varepsilon\hat{H}_{K(i)}^{i}$, $\delta_{K(i)} = \delta\hat{G}_{K(i)PU}^{i}$ and $\eta_{K(i)} = \eta\hat{G}_{SPU}^{i}$, respectively. Let $\zeta = \kappa = \varepsilon = \delta = \eta$, represents the normalized error bound for all parameters' uncertainty regions [26]. The simulations were performed for 10000 channel realizations. From Fig. 2 to Fig. 4, it is assumed $P_S = P_{R_k} = 10^{-3}\ W$ and $I_{th} = 10^{-13}\ W$. Based on Fig. 2, the proposed algorithm can guarantee the interference threshold of PU in both SR_k link and R_kD link, but the interference power to PU in both SR_k link and R_kD link produced by non-robust algorithm is all above the interference threshold of PU. From Fig. 3, we find the two algorithms can quickly converge to the equilibrium points. Additionally, when these two algorithms get their optimal solutions, the individual relay can take advantage of the power, but the cognitive source cannot make full use of the power. Based on Fig. 4, the two algorithms can quickly converge to the optimal points. Fig. 5 gives the capacity of the two algorithms under the cognitive source and individual relay power budget with $\zeta = 0.5$. The capacity of the non-robust algorithm is higher than that of the robust one. When we take $P_S = P_{R_k} = 8\times10^{-3}\ W$, the interference threshold of PU becomes the limiting constraint and the capacity is constant.

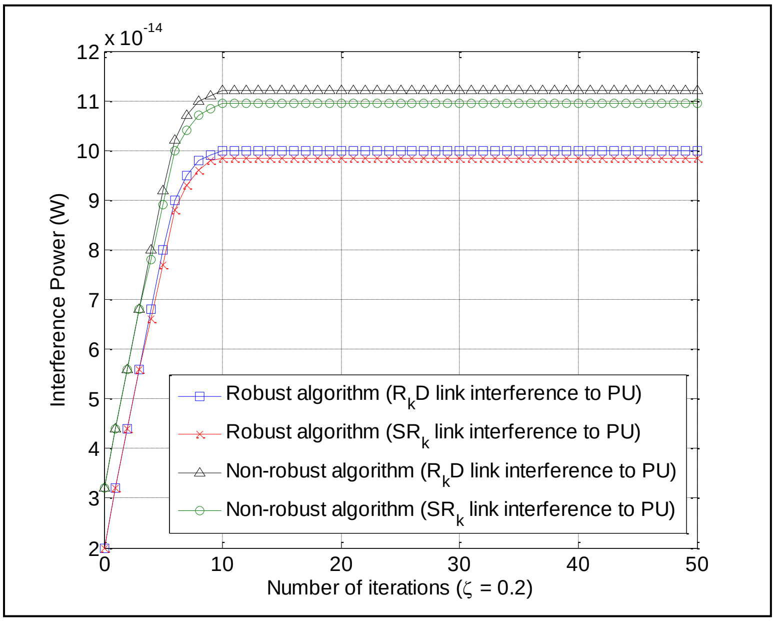

Fig. 2 Interference power of different links to PU

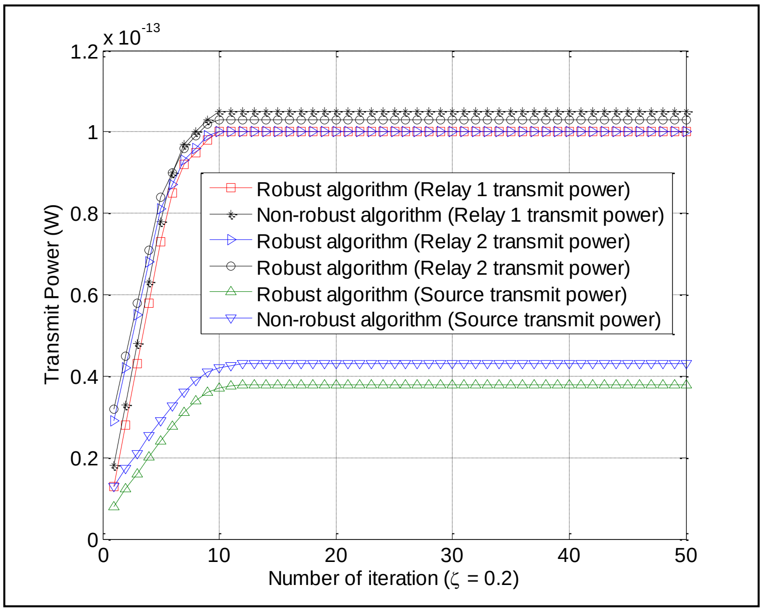

Fig. 3 Transmit power at cognitive source and individual relay

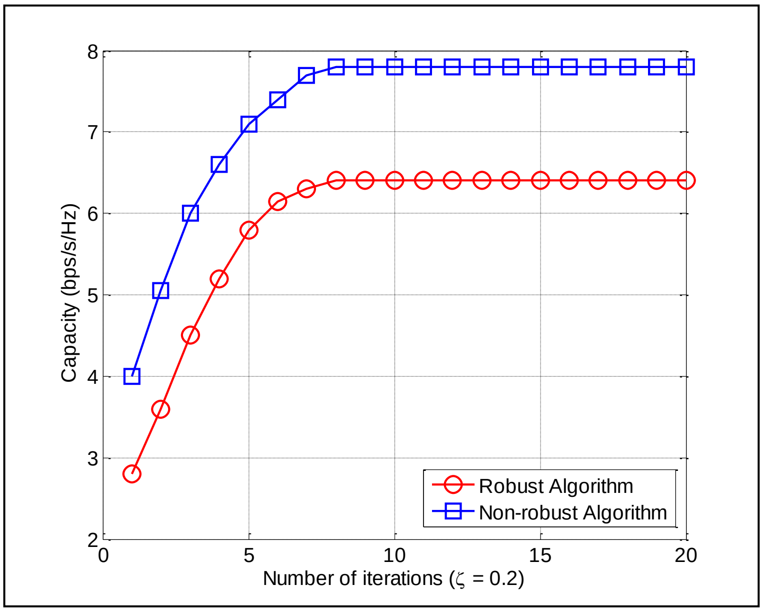

Fig. 4 Capacity versus cognitive source and individual relay power budget

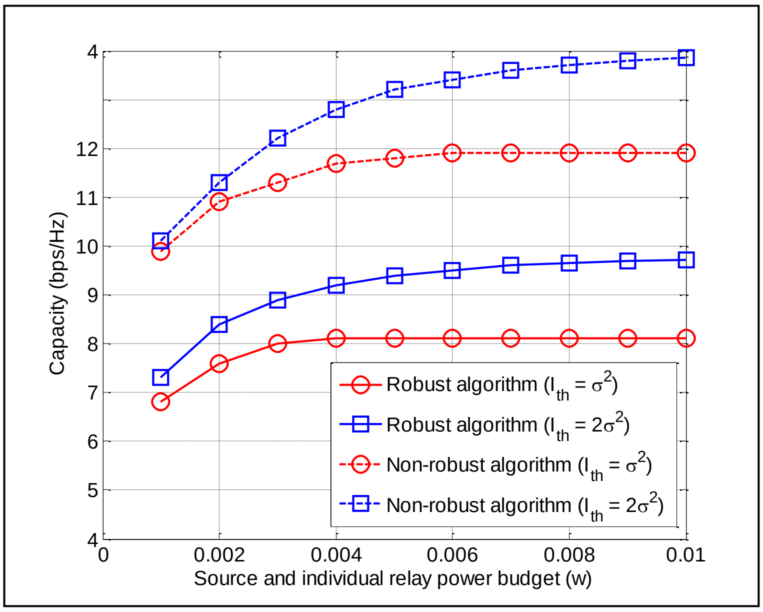

Fig. 5 Convergence of capacity

4. Conclusions

In this paper, a robust resource allocation algorithm in OFDM-based cooperative CRN was proposed, taking into account multiple kinds of channel uncertainty. The worst-case approach was applied to the robust resource optimization problem. The robust resource optimization problem was converted into a deterministic convex optimization problem. Then, a closed form optimal power allocation solution for robust algorithm was derived by dual decomposition method. The numerical results demonstrate that the robust resource allocation algorithm is superior to the non-robust algorithm.

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