Probabilistical Robust Power Control for Cognitive Radio Networks under Interference Uncertainty Conditions

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Abstract—The focus of this paper is to find a robust power control strategy with uncertain noise plus interference (NI) in cognitive radio networks (CRNs)in an under orthogonal frequency-division multiplexing (OFDM) framework. The optimization problem is formulated to maximize the data rate of secondary users (SUs) under the constraints of transmission power of each SU, probabilistic the transmit rate of each SU at each subcarrier and robust interference constraint of primary user. In consideration of the feedback errors from the quantization due to uniform distribution, the probabilistic constraint is transformed into closed forms. By using Lagrange relaxation of the coupling constraints method and subgradient iterative algorithm in a distributed way, we solve this dual problem. Numerical simulation results show that our proposed algorithm is superior to the robust power control scheme based on interference gain worst case approach and non-robust algorithm without quantization error in perfect channels in the improvement of data rate of each SU, convergence speed and computational complexity.

Keywords—Cognitive radio networks, robust power control, probability constraints, orthogonal frequency-division multiplexing (OFDM)

1 Introduction

In recent decade, the explosive growth of various wireless services has led to the increasing demand for limited radio spectrum. In addition, the traditional fixed spectrum allocation strategies and the inefficiency of utilized spectrum are great bottleneck and largely challenged by many wireless applications [1]. In order to solve the problem of the spectrum shortage and inefficient utilization and to satisfy the user needs, cognitive radio (CR) is developed to improve the network spectrum efficiency by allowing secondary users (SUs) to intelligently sense and opportunistically access those spectrum holes temporarily unused by licensed primary users (PUs) [2] and [3-

4]. That means the CR has to be the frequency-agile radio with flexible spectrum shaping abilities [5].

In CR system, the transmit power of each user is the main source of interference to other users. Therefore, the power control is necessary and naturally one of the key technologies of this system. A power allocation strategy is proposed to either maximize the average data rate or minimize the outage probability of SU in cooperative and non-cooperative spectrum sensing in [6]. In [7], an optimal power control scheme is presented in cooperative dynamic spectrum access networks with diverse the quality of service (QoS) constraints. In downlink and uplink scenarios, two-phase mixed distributed/centralized control algorithm is proposed that requires minimal cooperation between secondary and primary devices in [8]. In order to maximize the output SNR and limit the interference to one PU in Rayleigh fading channel, an adaptive-power control scheme is given in [9]. In [10], with perfect interference power information, a distributed power control algorithm is proposed for cognitive radio networks (CRNs). In [11-12], transmit power and data rate allocation algorithms are presented based on the lower bound of the signal-to-interference-plus-noise ratio (SINR) of each SU. Unfortunately these algorithms do not consider the influence from the uncertainty of interference-plus-noise (NI) to the communication quality of SU. A robust power control scheme using the transition matrices to capture the channel information is proposed by robust dynamic programming for the optimization of the worst-case performance in [13]. Since the statistical behavior of PU and the state transition probabilities of the channel are difficult to accurately described, the interval matrix uncertainty model and the likelihood uncertainty model are introduced to solve robust power control problems. However, the interference uncertainty in the channel is often not considered, which will increase the outage probability of users in CRNs. In underlay CRNs, a robust distributed uplink power allocation algorithm to maximize the social utility of SUs is presented in [14], when the interference from PUs to the base station of SUs is uncertain.

After the analysis of the above literatures, we proposed a probabilistically robust power control (PRPC) algorithm for OFDM based cognitive radio networks under noise plus interference uncertainty. Specifically, our objective is to maximize the data rate of SU on all subcarriers to satisfy the probability constraint which the transmit rate of each SU less than the desired transmit rate at each subcarrier for the quantized NI error. We also give the comparison to show the performance of PRPC algorithm with the interference gain worst case approach given in [15] and the non-robust algorithm by computer simulation results.

The rest of this paper is organized as follows. The system model of the CR networks under the frame of OFDM and non-robust resource allocation problem are described in Section 2. Section 3 gives a probabilistical robust power control problem formulation. A robust distributed scheme derived from Lagrange optimization method is proposed to maximize transmit data rate of each SU on all subcarriers in Section 4. Numerical results are given to demonstrate the effectiveness and performance of the proposed algorithm by the comparison of several existing algorithms in Section 5. Finally, the conclusion is given in section 6.

2 System model

In this paper, we assume that there are N secondary users (SUs) and K subcarriers in OFDM-based cognitive radio network. In order to ensure the reliable communication of each SU, the transmit power should not be more than its maximum threshold, that is power budget. Thus we have.

$$\sum_{k=1}^{K} p_k^i \le P_{\max}^i \tag{1}$$

Where p_k^i represents the transmit power of the transmitter i of SU at the subcarrier k . $P_{\max}^i$ is the maximum transmitting power of the SU .

In order to satisfy the communication quality of PU at each subcarrier, the crucial constraint is that the interference from all SUs at each subcarrier should not exceed the acceptable threshold at that subcarrier [16-17] as follows

$$p_k^i + I_k^i \le T_k^{\max} \tag{2}$$

Where $T_k^{\max}$ indicates the maximum allowable interference at the subcarrier k which the PUs can tolerant. I_k^i indicates the noise plus interference (NI) experienced by the SU i at the subcarrier k . It can be defined as

$$I_k^i = \sigma_k^i + \sum_{j=1, i \ne j}^{N} \alpha_k^{ij} p_k^j \tag{3}$$

Where σ_k^i and α_k^{ij} denote the normalized background noise power at the receiver input of the SU i on the kth subcarrier and the normalized interference gain between the transmitter of the SU j and the receiver of the SU i over the subcarrier k respectively.

The optimization objective is to maximize the transmit data rate of each SU at all subcarriers through adjusting transmit power of SU at each subcarrier. And simultaneously to satisfy constraints (1) and (2) respectively. To realize these goals, power allocation problem without imperfect system information can be expressed as

$$\begin{aligned} &\max \sum_{k=1}^{K} \log\left(1 + \frac{p_k^i}{I_k^i}\right) \\ &\text{s.t.} \begin{cases} p_k^i + I_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \end{cases} \end{aligned} \tag{4}$$

However, due to random nature of wireless channels and channel estimation errors in practical communication environment, the associated channel information is difficult to be obtained accurately.

Therefore, the robustness of power control problem should be considered.

3 Probabilistically robust power control problem formulations

Actually, due to imperfect channel estimation and quantization errors, the actual NI in (3) can not be reliable to obtain. In this case, parameter uncertainty is inevitable in real wireless communication systems. In order to alleviate the impact of such uncertainty impacts on the CR system, we guarantee the performance of SUs regarding d_k^i as existing the random variable by power allocation to maximize their data rate for all subcarriers, i.e.

$$p_r\left(d_k^i \le \log\left(1+\frac{p_k^i}{I_k^i}\right)\right) \ge \psi_k^i \tag{5}$$

Where $p_r\{.\}$ represents probability operator. d_k^i denotes an auxiliary variable that serves as a lower bound on the achievable rate on the kth subcarrier with probability ψ_k^i, where $\psi_k^i \in [0,1]$ denotes the probability that the power allocation $\{p_k^i\}$ can support the rates $\{d_k^i\}$.

Our objective is to maximize the transmit data rate of each SU at all subcarriers, simultaneously to satisfy constraints (1), (2) and (5). Then the robust power control problem under probability constraints can be formulated as

$$\max \sum_{k=1}^{K} d_k^i$$
$$\text{s.t.} \begin{cases} p_k^i + I_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \\ p_r\left(d_k^i \le \log\left(1+\frac{p_k^i}{I_k^i}\right)\right) \ge \psi_k^i \end{cases} \tag{6}$$

4 Robust power control algorithm

In this section, a robust power control algorithm is proposed to solve the transmit data rate problem of (6) for each SU on all subcarriers in CRNs.

After the simplification of (5), we can get

$$p_r(2^{d_k^i} - 1 \le \frac{p_k^i}{I_k^i})) \ge \psi_k^i \tag{7}$$

By introducing a new variable $\gamma_k^i = 2^{d_k^i} - 1$, problem (6) can be rewritten as

$$\max \sum_{k=1}^{K} \log(1+\gamma_k^i)$$
$$\text{s.t.} \begin{cases} p_k^i + I_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \\ p_r\left(\gamma_k^i \le \frac{p_k^i}{I_k^i}\right) \ge \psi_k^i \end{cases} \tag{8}$$

From (8), we can obtain

$$\max \sum_{k=1}^{K} \log(1+\gamma_k^i)$$
$$\text{s.t.} \begin{cases} p_k^i + \hat{I}_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \\ p_r\left(\theta_k^i \ge \frac{\hat{I}_k^i \gamma_k^i}{p_k^i} - 1\right) \ge \psi_k^i \end{cases} \tag{9}$$

Where θ_k^i describes the relative error in the NI on the kth subcarrier. It can be defined as follows

$$\theta_k^i = \frac{\hat{I}_k^i - I_k^i}{I_k^i} = \frac{\Delta I_k^i}{I_k^i} \tag{10}$$

Where $\hat{I}_k^i$ represents the estimate of the quantized NI of the i SU over the kth subcarrier. ΔI_k^i denotes the corresponding quantization error.

In the OFDM-based CRNs, we mainly consider feedback errors coming from quantization. If the receivers need finite number of bits to feedback the quantized NI, θ_k^i is assumed to follow uniform distribution on the interval $[-\zeta_k^i, \zeta_k^i]$ .Since the transmitters know the number of bits used for quantization of the NI, they can determine the maximum errors ζ_k^i . Thus the third constraint from (9) can be expressed as

$$p_r\left(\theta_k^i \ge \frac{\hat{I}_k^i \gamma_k^i}{p_k^i} - 1\right) = \int_{\bar{I}_k^i \gamma_k^i / p_k^i - 1}^{\zeta_k^i} \frac{1}{2\zeta_k^i} d\zeta_k^i = \frac{1}{2\zeta_k^i}\left(1 + \zeta_k^i - \frac{\hat{I}_k^i \gamma_k^i}{p_k^i}\right) \ge \psi_k^i \tag{11}$$

From (11), we have

$$\gamma_k^i \le \frac{p_k^i}{\hat{I}_k^i}(1+\zeta_k^i - 2\zeta_k^i\psi_k^i) \tag{12}$$

that is, (10) can be rewritten as follows

$$\max \sum_{k=1}^{K} \log(1+\gamma_k^i)$$
$$\text{s.t.} \begin{cases} p_k^i + \hat{I}_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \\ \gamma_k^i \le \frac{p_k^i}{\hat{I}_k^i}(1+\zeta_k^i - 2\zeta_k^i\psi_k^i) \end{cases} \quad (13$$

Since the constraints on $\{\gamma_k^i\}$ are decoupled across subcarriers, we can eliminate $\{\gamma_k^i\}$.Thus the power optimization problem can be formulated as

$$\max \sum_{k=1}^{K} \log\left(1+\chi_k^i \frac{p_k^i}{\hat{I}_k^i}\right)$$
$$\text{s.t.} \begin{cases} p_k^i + \hat{I}_k^i \le T_k^{\max} \\ \sum_{k=1}^{K} p_k^i \le P_{\max}^i \end{cases} \tag{14}$$

Where $\chi_k^i = 1+\zeta_k^i - 2\zeta_k^i\psi_k^i$ and $\psi_k^i > 0.5, \chi_k^i < 1$.

Obviously, the optimization problem (14) is a non-convex. According to convex optimization theory [18], the power control problem (14) can be converted into a convex one

$$\min - \sum_{k=1}^{K} \log\left(1+\chi_k^i \frac{p_k^i}{\hat{I}_k^i}\right)$$
$$\text{s.t.} \begin{cases} p_k^i + \hat{I}_k^i - T_k^{\max} \le 0 \\ \sum_{k=1}^{K} p_k^i - P_{\max}^i \le 0 \end{cases} \tag{15}$$

The Lagrange function of problem (15) can be defined as

$$L^i(\{p_k^i\},\lambda^i,\{\mu_k^i\}) = -\sum_{k=1}^{K} \log\left(1+\chi_k^i \frac{p_k^i}{\bar{I}_k^i}\right) + \lambda^i\left(\sum_{k=1}^{N} p_k^i - P_{\max}^i\right) + \sum_{k=1}^{K} \mu_k^i \left(p_k^i + \hat{I}_k^i - T_k^{\max}\right)$$

$$= \sum_{k=1}^{K}\left[-\log\left(1+\chi_k^i \frac{p_k^i}{\hat{I}_k^i}\right)+\lambda^i p_k^i+\mu_k^i\left(p_k^i+\hat{I}_k^i\right)\right]-\lambda^i P_{\max}^i-\sum_{k=1}^{K}\mu_k^i T_k^{\max} \tag{16}$$

Where $\lambda^i \geq 0$ and $\mu_k^i \geq 0$ represent Lagrange multipliers.

Therefore, according to the decomposition method of the Lagrange relaxation of coupling constraint proposed in [19], we provide a subgradient algorithm to solve the dual problem. Then the dual function of (15) is

$$\Im(\lambda^i,\{\mu_k^i\})=\sum_{k=1}^{N}\min L_k^i\left(\{p_k^i\},\lambda^i,\{\mu_k^i\}\right)-\lambda^i p_{\max}^i-\sum_{k=1}^{N}\mu_k^i \mathrm{T}_k^{\max} \tag{17}$$

Where

$$L_k^i\left(\{p_k^i\},\lambda^i,\{\mu_k^i\}\right)=-\log\left(1+\chi_k^i\frac{p_k^i}{\hat{I}_k^i}\right)+\lambda^i p_k^i+\mu_k^i\left(p_k^i+\hat{I}_k^i\right) \tag{18}$$

The dual problem (15) is given by

$$\begin{aligned} &\max \quad \Im(\lambda^i,\{\mu_k^i\}) \\ &\text{s.t.} \quad \lambda^i \geq 0, \mu_k^i \geq 0, \forall k \end{aligned} \tag{19}$$

According to KKT conditions, the optimal transmit power of each SU at the subscribe k can be obtained by solving the following equation

$$\frac{\partial L_k^i(\{p_k^i\},\lambda^i,\{\mu_k^i\})}{\partial p_k^i}=0 \tag{20}$$

and the solution is

$$p_k^{i,opt}=\frac{1}{(\lambda^i+\mu_k^i)\ln 2}-\frac{1}{\chi_k^i}\hat{I}_k^i \tag{21}$$

We can update the Lagrange multipliers by the subgradient iteration algorithm as follows

$$\lambda^i(t+1)=\left[\lambda^i(t)+\alpha(t)\left(\sum_{k=1}^{N}p_k^i-p_{\max}^i\right)\right]^+ \tag{22}$$

$$\mu_k^i(t+1)=\left[\mu_k^i(t)+\beta(t)\left(p_k^i+\hat{I}_k^i-T_k^{\max}\right)\right]^+ \tag{23}$$

Where $[y]^{+} = \max\{0, y\}$. t denotes the iteration time, and $\alpha(t), \beta(t)$ are the nonnegative step sizes.

The robust distributed power control algorithm is summarized as follows.

Step1.Initialized $t = 0$, $\hat{I}_k^i(0) > 0$, $0 \le p_k^i(0) \le p_{\max}^i$, $p_{\max}^i > 0$, $p_k^{\max} > 0$, $\lambda^i > 0$, $\mu_k^i > 0$, $\chi_k^i > 0$, $\psi_k^i \in [0,1]$, $\alpha_k^{ij} > 0$, $\forall i$, $\forall k$.

Step2. Measured the interference gain between the transmitter of the SU j and the receiver of the SU i over the subcarrier k , and background noise power at the receiver input of the SU i on the kth subcarrier.

Step3. Updated the Lagrange multipliers according to (22) and (23). Increase the current iteration number by 1.

Step4. Calculated $p_k^i(t+1) = \frac{1}{\left[\lambda^i(t+1) + \mu_k^i(t+1)\right]\ln 2} - \frac{1}{\chi_k^i}\left(\sigma_k^i + \sum_{j=1, i\neq j}^{N} \alpha_k^{ij} p_k^j\right)\left[1 + \theta_k^i(t+1)\right]$.

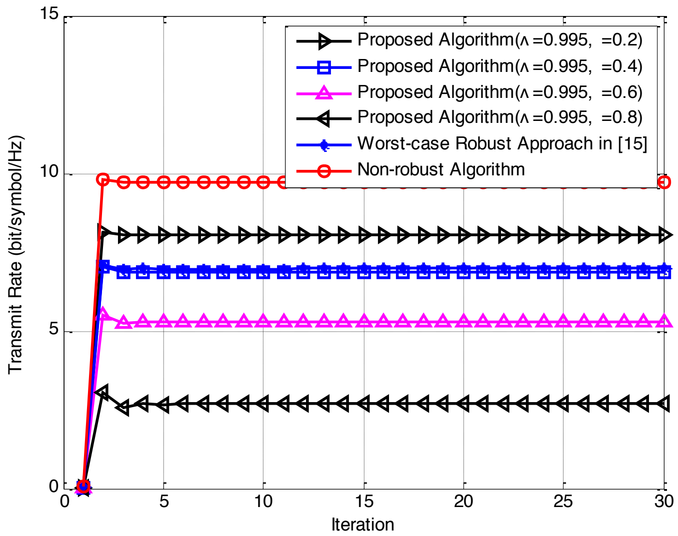
Step5. Determined the transmit power vector satisfies $\left\| p_k^i(t+1) - p_k^i(t) \right\| \le \vartheta$, (where ϑ is an error tolerance factor), stop the iteration; otherwise, go to step 2.

5 Simulation result and analysis

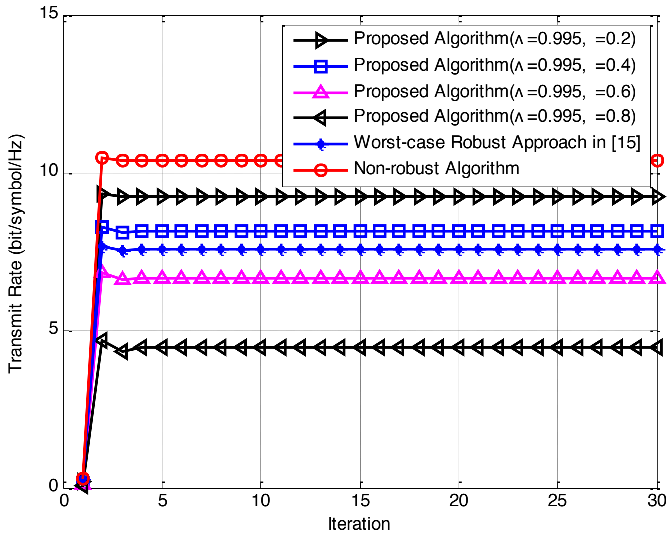
In this section, simulation results are presented to verify the effectiveness of our proposed probabilistically robust power control algorithm (PRPC) in the previous section. We also compare the performance in the proposed algorithm with the robust power control scheme (RPC) based on interference gain worst-case approach in [15] and the non-robust algorithm which ignores the quantized NI error under perfect channels.

Under our OFDM framework, we suppose that there are three active SUs and three subcarriers, i.e. $N = 3, K = 3$,. The maximum transmit power $p_{\max}^i$ for each SU is 1 to guarantee the QoS of SUs. The background noise and the interference gain are randomly chosen from the intervals $(0, 0.1/\mathrm{N}-1)$ and $(0, 1/\mathrm{N}-1)$ respectively. For the proposed PRPC, the quantized NI relative error follows a uniform distribution for all SUs over $[-\zeta_k^i, \zeta_k^i]$. For description convenience, let $\zeta_k^i = \zeta \in [0,1]$ for all $i \in N, k \in K$. The simulation results are given from Fig. 1 to Fig. 7.

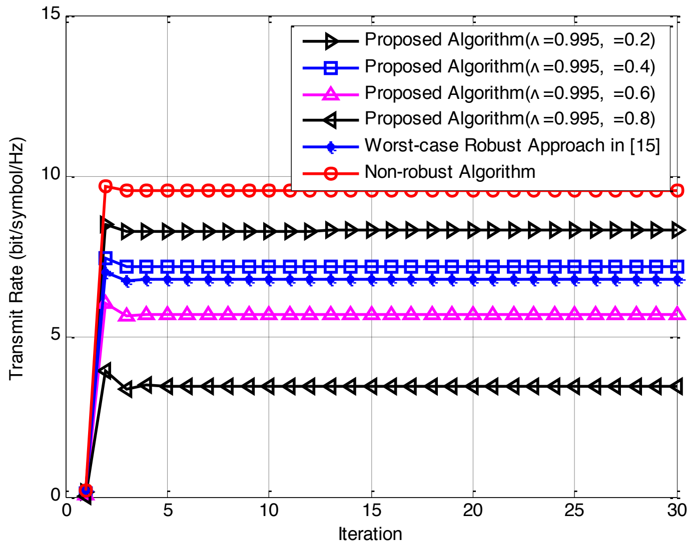
First, we give the robustness of our algorithm on the transmit rate of each SU and the sum-rate of three SUs in the exited quantized NI relative errors in Fig.1 and Fig.2 to show the effects of the quantized NI uncertainty in the feedback channel, we assume that the probability $\psi_k^i = \psi$ is 0.995 which implies large quantized NI relative errors.



(a) The transmit rate of SU1 in all subcarriers



(b) The transmit rate of SU2 in all subcarriers



(c) The transmit rate of SU3 in all subcarriers

Fig. 1. Transmit rate of each SU at all subcarriers by different algorithms

In Fig.1, we compare the transmit rate of each SU at each subcarrier under different given algorithms with the proposed algorithm. Since the estimated quantized NI error is ignored in the non-robust algorithm, the transmit rate of each SU in the proposed algorithm is less than that of the non-robust algorithm. Under our proposed algorithm, it is shown that the transmit rate monotonously decreases with the increasing quantized NI relative errors ζ. When ζ is randomly selected from the interval $[0,0.4]$, we can obtain that the transmit rate of each SU at all subcarriers of PRPC algorithm is more than that of the robust algorithm with consideration of the background noise and interference gain uncertainties.

When ζ is randomly chosen from the interval $[0.6,1]$, the transmit rate of each SU at all subcarriers is less than that of RPC algorithm. Because the background noise and interference gain uncertainties in the proposed algorithm are greater than that of the RPC algorithm.

In Fig.2, we can obviously observe that the sum-rate of three SUs demonstrates the same result as the transmit rate of individual SU with different ζ.

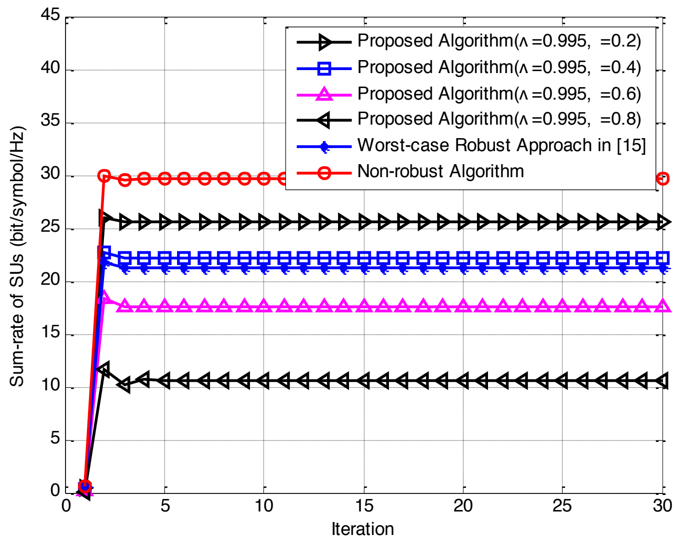
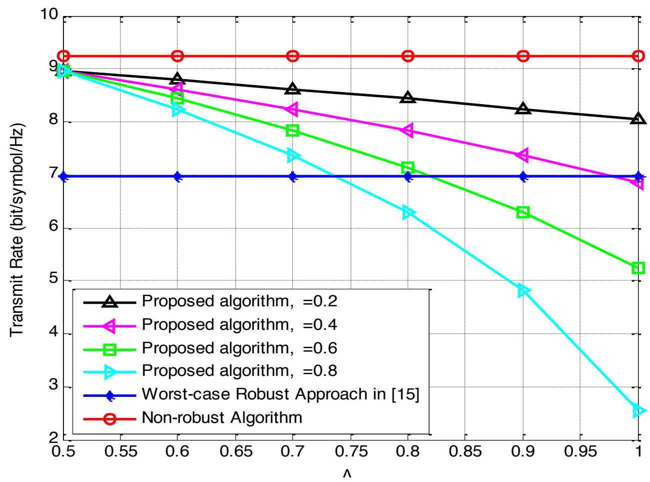
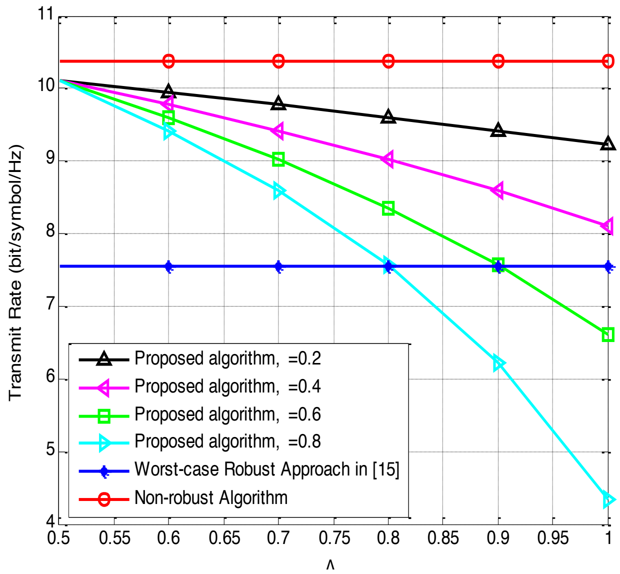


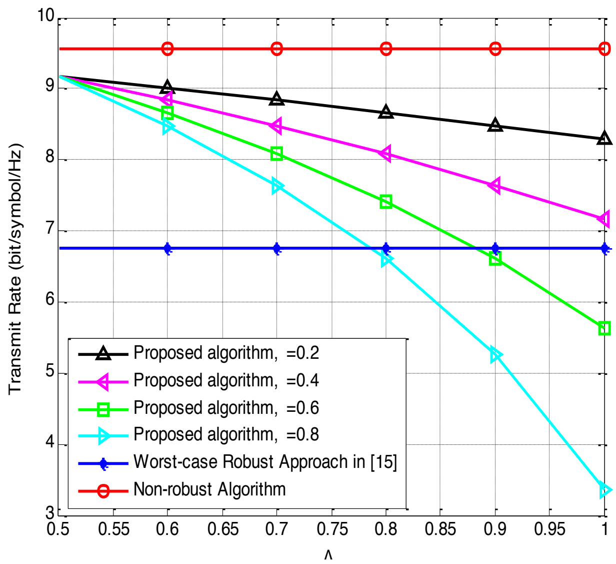
Fig. 2. Sum-rate of three SUs by different algorithms



(a) The transmit rate of SU1 in all subcarriers



(b) The transmit rate of SU2 in all subcarriers



(c) The transmit rate of SU3 in all subcarriers

Fig. 3. Transmit rate of each SU at all subcarriers by different algorithms

In Fig.3, we present the impact of the probability ψ ($\psi \in [0.5,1]$) on the transmit rate of each SU at each subcarrier under different algorithms. It is clear that the region of the quantized NI relative error extends with the increasing φ. For a given ζ, if ψ increases, the transmit rate of each SU over all subcarriers decreases. In addition, for a given ψ, if ζ increases, this transmit rate decreases. Therefore, ψ and ζ are the two major factors that can affect the transmit rate of each SU at each subcarrier.

From Fig.4, when ψ is chosen in the interval $[0.5, 0.77]$ and $\zeta < 0.6$, we can see that the sum-rate of three SUs at all subcarriers is more than that of RPC algorithm based on worst-case approach. Because the background noise and interference gain uncertainties in our proposed algorithm are less than that of the worst-case for RPC algorithm.

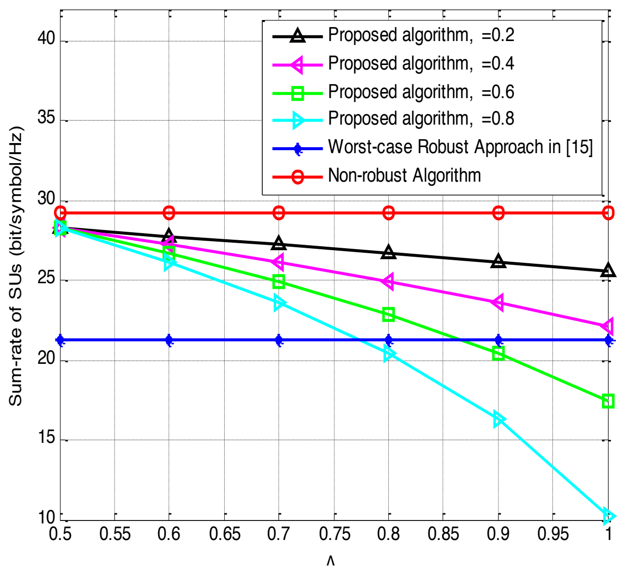


Fig. 4. Sum-rate of three SUs at all subcarriers by different algorithms

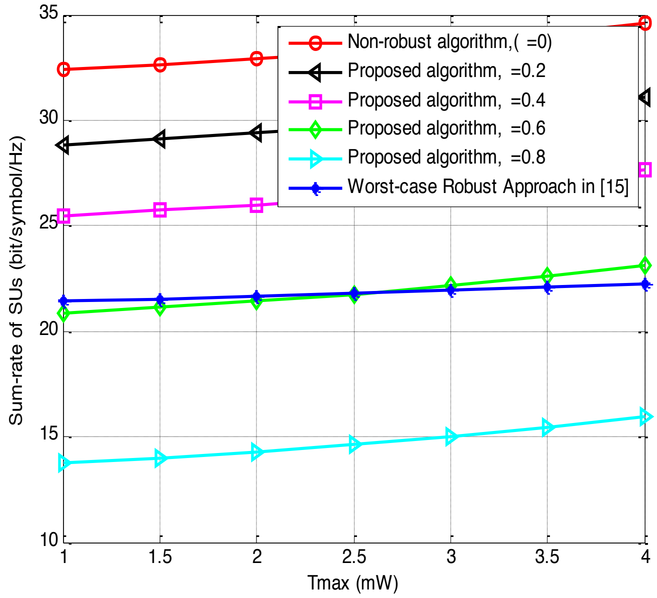


Fig. 5. Sum-rate of SUs vs. the quantized NI relative errors uncertainty ζ

From Fig.5, we know that the sum-rate of three SUs decreases with the increasing ζ. According to the inequality $p_k^i + \hat{I}_k^i \le T_k^{\max}$, for a fixed interference from all SUs at each subcarrier, if ζ increases, the interference constraint can satisfy at cost of reduction of the transmission power of SUs. Thus, there is a trade off between robustness and the sum-rate of SUs. Moreover, the region of maximum transmit power of SUs will shrink with the increasing ζ. When the interference constraint satisfies $T_k^{\max} << P_{\max}^i / K$ for all SUs, the constraint $\sum_{k=1}^{K} p_k^i \le P_{\max}^i$ is inactive. Therefore, the upper bound of the optimal power is determined by the interference threshold $T_k^{\max}$. In other words, for the same uncertainty in NI, the higher $T_k^{\max}$ is, the more the sum-rate of all SUs is, Since big interference threshold (e.g. $T_k^{\max} = 4\,\text{mW}$) may allow more transmit power for the improvement of the sum-rate of all SUs.

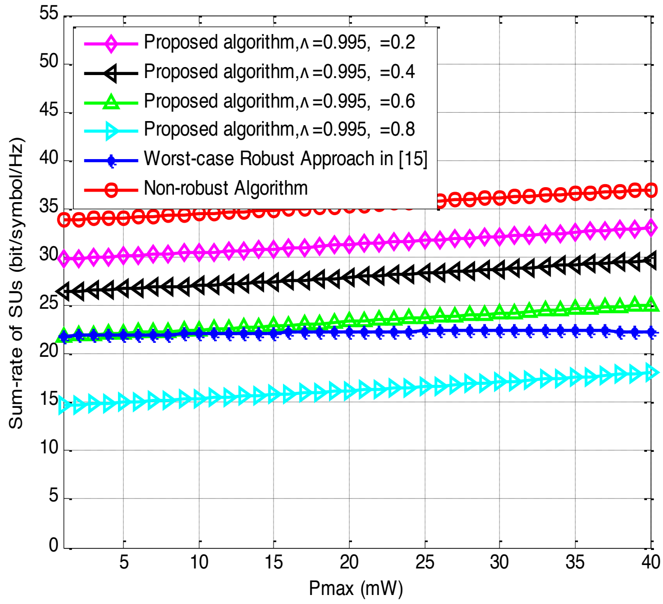


Fig. 6. Sum-rate of three SUs vs. maximum transmit power of each SU at all subcarriers

In order to describe the effects of $\sum_{k=1}^{K} p_k^i \le P_{\max}^i$ vs. the sum-rate of SUs, we assume that the interference threshold is larger than the average maximum transmit power of each SU at each subcarrier, that is $T_k^{\max} >> P_{\max}^i / K$, and $p_k^i + \overline{I}_k^i \le T_k^{\max}$ is inactive. Hence according to $\sum_{k=1}^{K} p_k^i \le P_{\max}^i$, for a given ζ, if the maximum transmit power $P_{\max}^i$ of the SU i increases, the sum-rate of SUs increases too in Fig.6.

In Fig.7, we show the system performance under multiple SUs and multiple sub-carriers. As expected, the total throughput of all SUs increases with the decrease of ζ in different combinations. Since the transmission power of each SU at all subcarriers should not be more than its maximum transmit power and the received SINR decreases with the increasing number of SUs and ζ, there are much more interference at the SU-Rx for a given number of subcarriers. With the increasing number of subcarriers or ζ, the system throughput gradually increases for a given number of SUs.

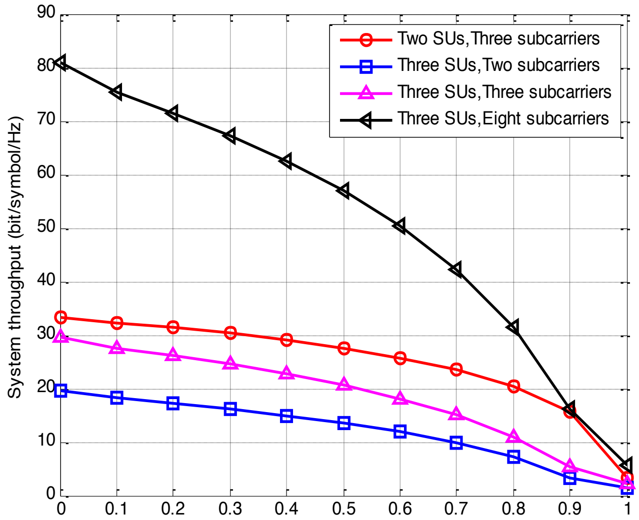


Fig. 7. System throughput vs. number of SUs, subcarriers and ζ

6 Conclusions

In this paper, we pay more attention to the robustness consideration that it is difficult for secondary users (SUs) to obtain exact information of wireless channel in cognitive radio networks (CRNs), which may cause communication interruption for SUs, and becomes one of major concerns in multiuser OFDM-based CRNs. By taking the transmission rate of each SU over each subcarrier as a main performance metric, we transform this optimization problem into a tractable convex problem solved by dual decomposition method to obtain a new robust power control algorithm under the uncertainty of interference plus noise power, the introduced probability constraint, and the other two constraints. Simulation results prove that the proposed robust power control approach can improve the transmission rate of each SU, and satisfy the QoS constraints of both PUs and SUs. Additionally, the performance of the proposed algorithm is superior to that of RPC algorithm based on interference gain worst-case approach and non-robust algorithm (i.e., without considering quantization error on perfect channel condition).

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