A Robust Distributed Power Control Algorithm for Minimum Interference to Primary Users in Underlay Cognitive Radio Networks

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***Abstract*—A robust distributed optimal power control (RDPC) scheme under worst case condition is proposed to make primary users (PUs) receive minimum interference generated from all secondary users (SUs) in underlay cognitive radio networks (CRNs). The strategy considers the transmit power of each SU below the maximum allowable power of the devices and interference plus noise ratio (SINR) of each SU under the minimum threshold. Simulation illustrate thatthe RDPC can lead SUs to reduce the interference to PUs, and simultaneously the better meet quality of service (QoS) requirement of SUs in comparison with the distributed power control algorithm (DPC) and the traditional iterative water filling algorithm (IWFA) in time-varying channel environment.**

***Index Terms*—cognitive radio networks, robust distributed power control (RDPC), worst case condition**

I. INTRODUCTION

Cognitive radio (CR) is one of the most promising technologies for future wireless communications [1-2] to resolve the limited radio spectrum resource shortage problem [3]. In underlay cognitive radio networks (CRNs) [4], secondary users (SUs) can share the frequency spectrum with primary users (PUs) and ensure the PU of the quality of service, simultaneously. Therefore, the transmit power control of SU [5], which is one of the spectrum sharing core technologies , are attracted widespread attention by researchers.

Currently, the problem of power control to SU in CR systemhas been an area of active research [6]-[10]. The adaptive power control problems based on game theory overcome the near-far effect, which studied in [11]. In [12], standard distributed power control algorithm (SDPCA) and an improved distributed power control algorithm (IDPCA) are proposed based on convex optimization theory in underlay cognitive radio networks (CRNs), which obtain the minimum the transmit power of SU. In [13], author consider a cognitive radio system the in fading wireless channels and propose an opportunistic power control strategy for cognitive users, which serves as an alternative way to protect the primary user's transmission and to realize spectrum sharing between the primary user and the cognitive users. The power control scheme is proposed to maximizes the SNR in [14]. All these papers can not consider uncertainty of these parameters, which only consider perfect channel estimation in communication systems.

Based on the above discuss, we can consider uncertainty in real communication systems. In this paper, a robust distributed power control algorithm (RDPC) is proposed to minimum the interference power from SU-Tx to PU-Rx under the worst case condition, which is appropriate in real system. In order to guarantee communication quality of PUs and SUs, our proposed power control scheme not only considers that the transmit power of each SU should not exceed its maximum power, but also takes the minimum SINR at secondary receivers into account. Simulation results show that the RDPC under the worst case condition is superior to the distributed power control algorithm (DPC) [12] the traditional iterative water filling algorithm (IWFA) [15] in time-varying channel environment.

II. SYSTEM MODEL

In this paper, a distributed spectrum sharing CRN is taken into consideration in underlay scenario, which consists of transmitter-receiver pairs of M SUs and K PUs.

For each SU transmitter, the transmit power should not be more than the maximum allowable power of the devices. So the power should be under this restriction

$$0 < p_m \le p_m^{\max} \ \forall m \in \{1, 2, \mathrm{L}\ \ , M\} \tag{1}$$

where p_m denotes the transmit power of the SU transmitter (SU-Tx) on link m . $p_m^{\max}$ represents the maximum value of transmission power provided by the SU-Tx.

Meeting the transmission quality of PU, the QoS of each SU should also be protected. That is to say, the signal-noise ratio (SINR) of each secondary receiver (SU-Rx) should not less than a threshold as follows

$$\gamma_m \ge \gamma_m^{th} \tag{2}$$

Where γ_m and γ_m^{th} ($\gamma_m^{th} > 0$) are the real value and the min-imum value of SINR at the SU-Rx on link m . The specific formula of γ_m is as follows

$$\gamma_m = \frac{G_{mm} p_m}{N_m} \tag{3}$$

G_{mm} denotes the direct channel gain from the active SU-Tx to the SU-Rx at link m. N_m is the sum of the interference powers and the background noise at the SU-Rx at link m. Its formula can be defined as follows

$$N_m = \sum_{j\neq m}^{M} G_{jm} p_j + \sigma_m + I_{mp} \forall k \in \{1,2,\ldots,K\} \tag{4}$$

where $I_{mp} = \sum_{k=1}^{K} G_{km} p_k$ represents the sum interference powers from all PU-Txs to the excited SU-Rxs of link m, G_{jm} and G_{km} are the interference gains from the SU-Tx of link j to the SU-Rx of link m and from the PU-Tx of link k to the SU-Rx of link m respectively. p_j represents the transmit power of the SU-Tx on link j. p_k denotes the transmit power of the PU-Tx on link k.

Our objective is to minimize the sum interference caused by all SU-Txs, and simultaneously satisfy the conditions (1) and (2). Thus the power optimization problem can be expressed as

$$\min \sum_{m=1}^{M} h_{mk} p_m \\ s.t. \begin{cases} 0 < p_m \leq p_m^{\max} \\ \gamma_m \geq \gamma_m^{th} \end{cases} \tag{5}$$

where h_{mk} is the channel gain between the SU-Tx of the link m and the PU-Rx of the link k.

III. ROBUST PROBLEM FORMULATION

In practice, the channel gain and interference between SUs and PUs are uncertainties. In this section, according to the description method of additive uncertainty, we can get the description of uncertainty as follows

$$\Im = \{h_{mk} \mid \bar{h}_{mk} + \Delta h_{mk} : |\Delta h_{mk}| \leq \delta_{mk} \bar{h}_{mk}\} \tag{6}$$

$$\wp = \{g_{mm} \mid \bar{g}_{mm} + \Delta g_{mm} : |\Delta g_{mm}| \leq \omega_m \bar{g}_{mm}\} \tag{7}$$

$$\Re = \{g_{jm} \mid \bar{g}_{jm} + \Delta g_{jm} : \sum_{j\neq m} |\Delta g_{jm}|^2 \leq r_m^2\} \tag{8}$$

$$\aleph = \{\sigma_m \mid \bar{\sigma}_m + \Delta \sigma_m : || \leq \tau_m \bar{\sigma}_m\} \tag{9}$$

where $\bar{h}_{mk}$, $\bar{g}_{mm}$, $\bar{g}_{jm}$, $\bar{\sigma}_m$ are the nominal value of channel gains, and Δh_{mk}, Δg_{mm}, Δg_{jm}, $\Delta \sigma_m$ are the errors of the corresponding estimation ,respectively. $\delta_{mk} \in [0,1)$ denotes the upper bound of uncertainty, which describes the size of the uncertainty and represents the accuracy of parameter estimation. When the upper bound is zero $(\delta_{mk} = 0)$, there is no uncertainty in system. Obviously, the bigger δ_{mk} is, the more error is, the estimated channel gain is further away from the true value. In the same way, ω_m, r_m and τ_m are the upper bound of uncertainties of each parameter.

In combination with (6)-(9), the minimum interference problem can be written as

$$\min \sum_{m=1}^{M} h_{mk} p_m \\ s.t. \begin{cases} p_m \leq p_m^{\max} \\ \gamma_m \geq \gamma_m^{th} \\ h_{mk} \in \Im, g_{mm} \in \wp, g_{jm} \in \Re, \sigma_m \in \aleph \end{cases} \tag{10}$$

The above optimization problem (10) is a SIP (semi-infinite programming) problem, which is difficult to solve under the infinite number of constraints. To solve this problem, we use the worst case method to convert the SIP into a deterministic optimization problem under the finite number of constraints. It can be described by the following equation

$$\min_{h_{ik}\in\Im} \sum_{m=1}^{M} h_{mk} p_m \\ \begin{cases} \dfrac{\min_{g_{mm}\in\wp} p_m g_{mm}}{\max_{g_{jm}\in\Re,\sigma_m\in\aleph} (\sum_{j\neq m} g_{jm} p_m + \sigma_m)} \geq \gamma_m^{th} \\ p_m \leq p_m^{\max} \end{cases} \tag{11}$$

According to the Cauchy-Schwartz inequality, we have

$$\max_{g_{jm}\in\Re,\sigma_m\in\aleph} (\sum_{j\neq m} g_{jm} p_m + \sigma_m) = \max_{g_{jm}\in\Re,\sigma_m\in\aleph} [\sum_{j\neq m} (\bar{g}_{jm} + \Delta g_{jm}) p_j + (\bar{\sigma}_m + \Delta \sigma_m)] \\ \leq (\sum_{j\neq m} \bar{g}_{jm} p_j + \bar{\sigma}_m) + r_m \sqrt{\sum_{j\neq m} p_j^2} + \tau_m \bar{\sigma}_m \tag{12}$$

$$\min_{g_{mm}\in\wp} p_m g_{mm} = \min_{g_{mm}\in\wp} p_m (\bar{g}_{mm} + \Delta g_{mm}) = p_m \bar{g}_{mm} (1 - \omega_m) \tag{13}$$

The above robust optimization problem (12) can be written as

$$\min_{h_{ik}\in\Im} \sum_{m=1}^{M} h_{mk} p_m \\ s.t. \begin{cases} p_m \leq p_m^{\max} \\ \dfrac{p_m \bar{g}_{mm} (1-\omega_m)}{I_m} \geq \gamma_m^{th} \end{cases} \tag{14}$$

where $I_m = \sum_{j\neq m} \bar{g}_{jm} p_j + r_m \sqrt{\sum_{j\neq m} p_j^2} + (1+\tau_m) \bar{\sigma}_m$ denotes interference plus noise with uncertainties.

The above problem (13) can be transformed into the convex optimization problem as follows

$$\min_{h_{jk}\in\Im} \sum_{m=1}^{M} h_{mk} p_m$$
$$s.t. \begin{cases} p_m \le p_m^{\max} \\ \log \dfrac{p_m \bar{g}_{mm}(1-\omega_m)}{I_m} \ge \log \gamma_m^{th} \end{cases} \tag{15}$$

IV. ROBUST DISTRBUTED POWER CONTROL ALGORITHM

Considering the convexity of problem (13), the optimal solution can be obtained by Lagrange dual function as

$$L = (\{\alpha_m\},\{\beta_m\},\{p_m\}) = \sum_m p_m \bar{h}_{mk}(1-\delta_{mk}) + \sum_m \alpha_m (p_m - p_m^{\max}) + \sum_m \beta_m [\log(1+\gamma_m^{th}) - \log(1+\frac{p_m \bar{g}_{mm}(1-\omega_m)}{I_m})] \tag{16}$$

Where $\alpha_m \ge 0$ and $\beta_m \ge 0$ are Lagrange multipliers. The dual function of original problem is depicted as

$$D(\{\alpha_m\},\{\beta_m\}) = \min_{p_m} L(\{p_m\},\{\alpha_m\},\{\beta_m\}) = \sum_m \min L_m(p_m,\alpha_m,\beta_m) + \sum_m [\beta_m \log(1+\gamma_m^{th}) - \alpha_m p_m^{\max}] \tag{17}$$

Where single user optimization problem as

$$L_m(p_m,\alpha_m,\beta_m) = p_m[\bar{h}_{mk}(1-\delta_m)+\alpha_m] - \beta_m \log(1+\frac{p_m \bar{g}_{mm}(1-\omega_m)}{I_m}) \tag{18}$$

And, in order to obtain the fixed $(\{\alpha_m\},\{\beta_m\})$, we need to solve the following dual problem

$$\max D(\{\alpha_m\},\{\beta_m\}) \quad s.t.\ \alpha_m \ge 0, \beta_m \ge 0 \tag{19}$$

According to the KKT conditon [16],the optimal transmit power can be obtained by the following equation

$$\frac{\partial L_m(p_m,\alpha_m,\beta_m)}{\partial p_m} = 0 \tag{20}$$

And the optimal solution is

$$p_m^* = [\frac{\beta_m}{\alpha_m + \bar{h}_{mk}(1-\delta_m)} - \frac{I_m}{\bar{g}_{mm}(1-\omega_m)}]^+ \tag{21}$$

To obtain distributed solutions of (14), the dual problem can be solved by subgradient iteration algorithm to update the dual variables

$$\alpha_m^{t+1} = [\alpha_m^t + a(p_m - p_m^{\max})]^+ \tag{22}$$

$$\beta_m^{t+1} = [\beta_m^t + b\log(\frac{1+\gamma_m^{th}}{1+p_m \bar{g}_{mm}(1-\omega_m)/I_m})]^+ \tag{23}$$

Where $[X]^+ = \max[0, X]$, $a \ge 0$ and $b \ge 0$.

V. SIMULATION RESULTS

In this section, we use several computer simulations to demonstrate the theoretical results of the previous sections. We also compare the performance of robust distributed power control (RDPC) algorithm with that of distributed power control algorithm (DPC) [12] and the traditional iterative water filling algorithm (IWFA) [15].

In underlay network, we assume there is one primary link and three cognitive links, *i.e.*, M=1,N=3. The nominal values of g_{mm}, g_{jm}, h_{mk}, and σ_m are randomly chosen from the intervals [0,1],[0,0.01], [0,1], and [0,0.01]. The maximum transmission power of each SU is $p_m^{\max} = 1mW$, and the estimated interference from PU on the SU's link is $\bar{I}_{mp} = 2\sigma_m$. The threshold value of the minimum SINR on each SU-Rx is $\gamma_m^{th} = [2,2,2]^T$ dB. The following set of uncertain parameters $r_m = |r| = 15\%$, $\omega_m = |\omega| = 15\%$, $\tau_m = |\tau| = 15\%$, $\delta_m = |\delta| = 15\%$.

From Fig.1 (a), Fig.2 (a) and Fig.3 (a), we can clearly know that the transmit power of our proposed algorithm, DPC algorithm and IWFA are lower than the maximum allowable power of each secondary user's transmitter. From Fig.1 (b), Fig.2 (b) and Fig.3 (b), the SINR of each SU is higher than the minimum SINR threshold value in three algorithms.

Fig.4 and shows the total power consumption of the RDPC and other two algorithms. It is clearly know that it needs more transmit power and more time to conquer the channel uncertainty effect in our proposed algorithm, and the DPC algorithm can achieve the smaller total power consumption than IWFA in perfect channel. Specifically, we clearly know that the convergence value of the energy consumption in the RDPC algorithm is roughly the same as that of IWFA in Fig.4, but larger than the DPC algorithm, which considered the interference gain uncertainty($|\delta| = 15\%$). Furthermore, the interference power received at PU-Rx is the largest in the three algorithms under when the other gains are constant in Fig.5.

However, it is necessary to consider the channel uncertainty or users' mobility in real communication environment. When the number of the user of increasing the number,i.e. , M=3,N=3, $|\delta| = 60\%$. The simulations are shown from Fig.6 to Fig.10.

Compare Fig.6 (a) with Fig.1 (a), it clearly shows that the transmit power of SU-Tx for RDPC algorithm is lower than the transmit power in Fig.1 (a). Specifically, for the increasing the number of SUs, the total transmit powers of SUs must be reduced so that meet the QoS reqquirements of PUs. We can also obtain the same conclusion from the comparison of Fig.4 and Fig.9. It is obvious that the SU's SINR of our proposed algorithm is still bigger than the predefined threshold from Fig.6 (b).

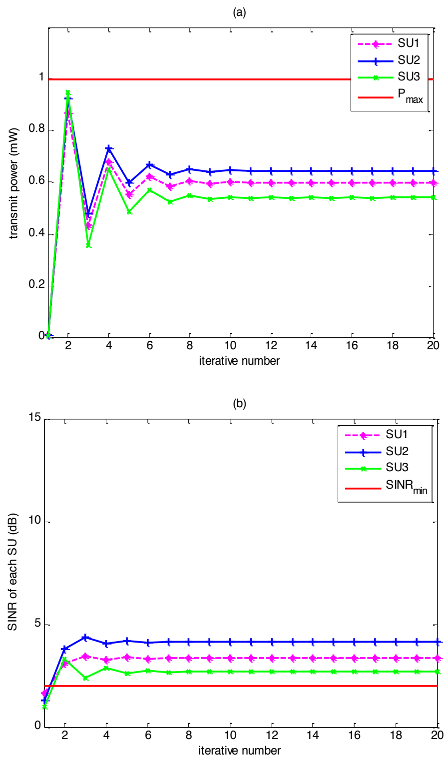

Figure 1. RDPC algorithm

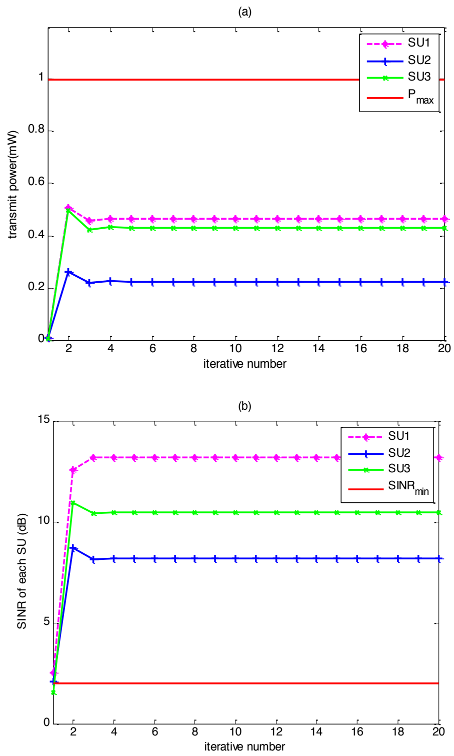

Figure 2. DPC algorithm

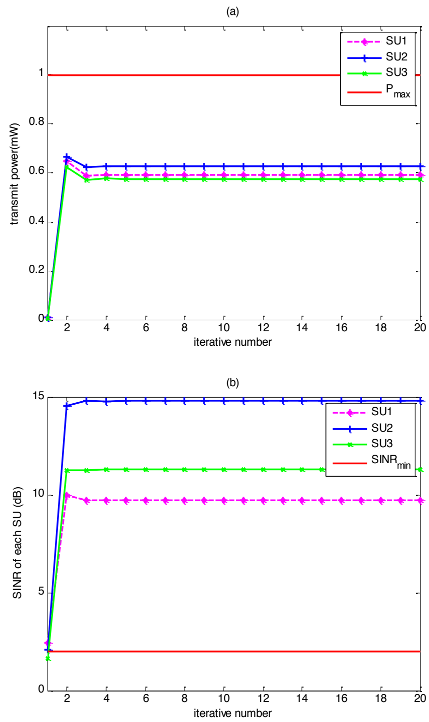

Figure 3. IWFA

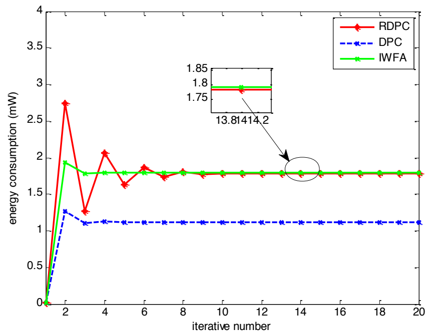

Figure 4. Energy consumption of three algorithms

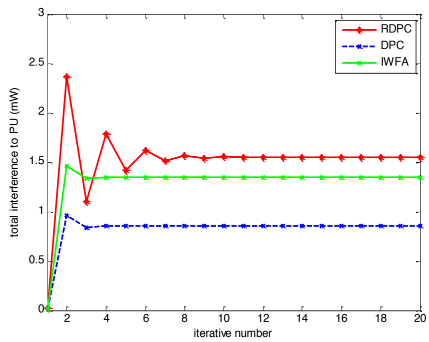

Figure 5. Total interference to PU of three algorithms

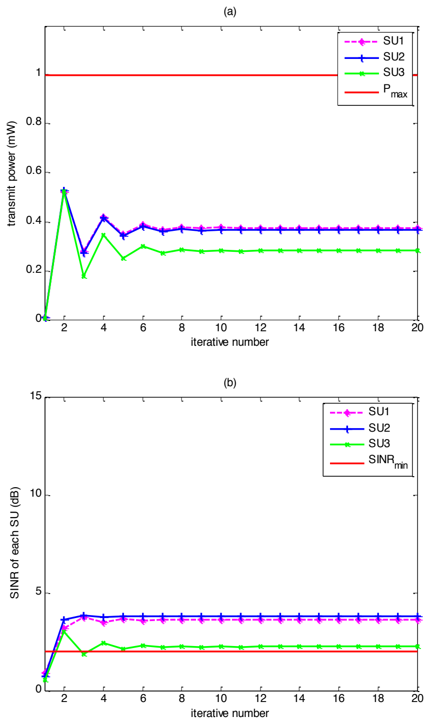

Figure 6. RDPC algorithm

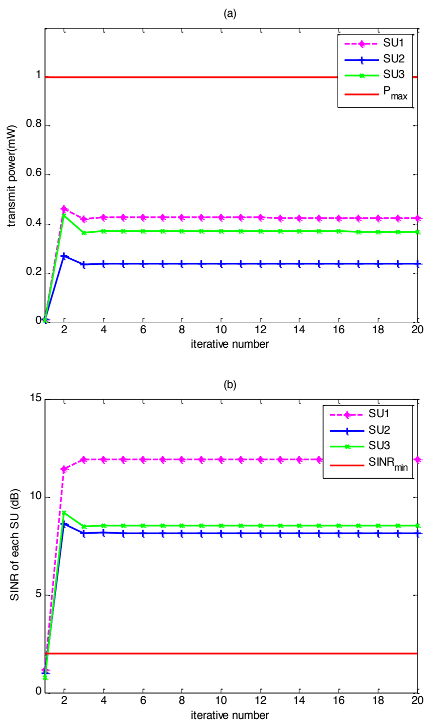

Figure 7. DPC algorithm

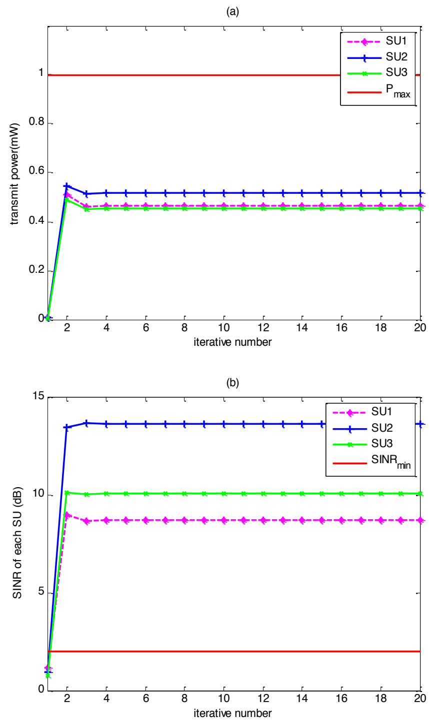

Figure 8. IWFA

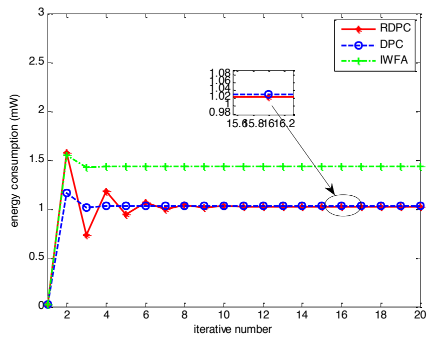

Figure 9. Energy consumption of three algorithms

In Fig.7 and Fig.8, we can obviously observe that the transmit power and SINR of three SUs demonstrate the same result as Fig.2 and Fig.3 with changing the number of users.

The total interference of SUs to three PUs is shown in Fig.10, which illustrates our proposed algorithm can effectively reduce the interference to the PUs when the communication environment changes.

In the following simulations, we will show the impact of channel estimation error and background noise quantization error to the communication status in Fig.11 to Fig.14.From Fig.11, Fig.12, Fig.13 and Fig.14, we can get the same conclusion that the total interference from SUs to PU monotonously increases with the minimum SINR threshold value γ_m^{th}. Specifically, For a given uncertainty, if γ_m^{th} increases, each SU needs transmit more power to meet the QoS requirements, Which also means that the transmit power of SU and the total interference to PU is positive correlation. From Fig.11, for a given γ_m^{th}, if the interference gain uncertainty δ decreases, the interference from SUs to PUs monotonously decreases. From Fig.12, Fig.13 and Fig.14, we can obtain similar results. But the influence of each uncertainty on the system is not the same. Furthermore, we give the variance of each uncertainty in Table 1.

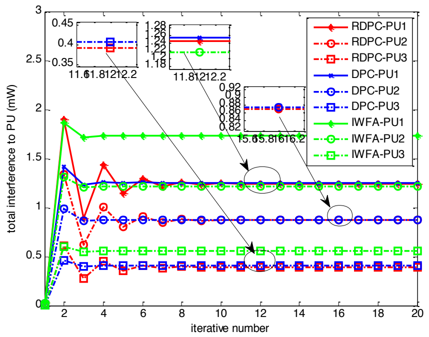

Figure 10. Total interference to PU of three algorithm

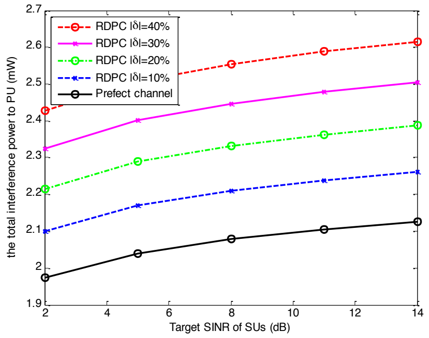

Figure 11. Total interference to PU versus Total interference to PU versus γ_m^{th} with interference gain uncertainty δ

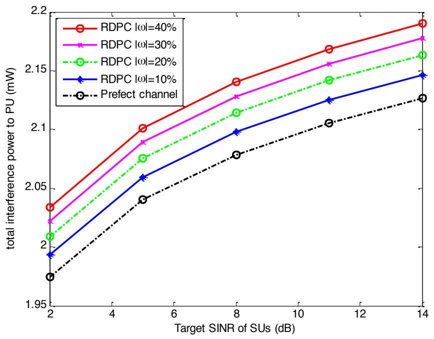

Figure 12. Total interference to PU versus γ_m^{th} with direct channel gain uncertainty ω

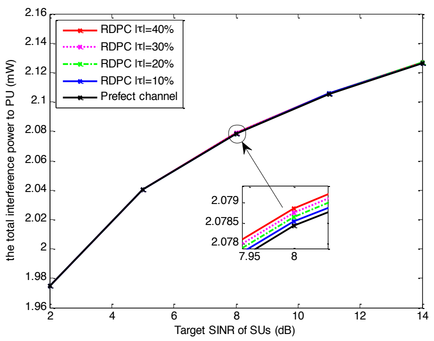

Figure 13. Total interference to PU versus γ_m^{th} with background noise uncertainty τ

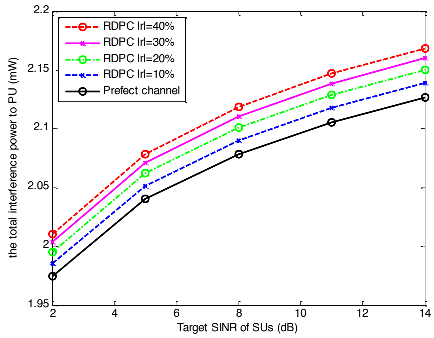

Figure 14. Total interference to PU versus γ_m^{th} with channel gain uncertainty τ

Through the calculation of variances, we can clearly know the size of the influence of different parameters on the system from Table 1. Among them, we can see that the δ deviates from the center value is the greatest with ω, r and τ, which means the greatest effect in real communication system.

TABLE I.
INTERFERENCE TO PU WITH DIFFERENT PARAMETERS OF UNCERTAINTIES

Parameter	Interference to PU (mW) $(\gamma_m^{th}=8)$					Variance
	0%	10%	20%	30%	40%	
δ	2.0784	2.2099	2.3325	2.4472	2.5546	2.8* 10^{-2}
ω	2.0784	2.0979	2.1143	2.1283	2.1404	4.8* 10^{-4}
r	2.0784	2.0901	2.1010	2.1106	2.1184	2.0* 10^{-4}
τ	2.0784	2.0785	2.0786	2.0787	2.0788	2.0* 10^{-8}

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