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JOINT BEAMFORMING AND POWER ALLOCATION USING MIXED INTEGER NONLINEAR PROGRAMMING

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Abstract –**In this paper, Traditional beamforming and power control algorithms in cognitive radio (CR) are based on the assumption of perfect channel state information (CSI) however; this may lead to performance degradation in realistic systems. In this paper, the problem of joint beamforming and power control is investigated in underlay CR networks with imperfect CSI. Our objective is to maximize the sum utility of secondary users (SUs) under the primary users (PUs) interference power constraints and the transmission power constraint of SUs. First, the joint beamforming and power control problem is formulated under game theory framework, where the SUs compete with each other over the beamforming vectors and transmission power level made available by the PUs. Moreover, the channel uncertainty is described using ellipsoid sets and the interference power constraints can be converted into robust interference power constraints. Besides, Nash equilibrium (NE) is considered as the solution of this game. Finally, simulation results show that the proposed scheme can converge to a locally optimal pair of beamforming vector and transmission power level in the presence of channel uncertainty.**

Keywords – **Cognitive radio, Beamforming, power allocation, imperfect channel state information, Nash equilibrium.**

1. INTRODUCTION.

Cognitive radio (CR), as a promising technology to enhancing the utilization efficiency of the scarce radio spectrum, has attracted tremendous interests recently it has to access the opportunistic idle licensed spectrum without interference to PU. A key feature of the CR network is to allow a secondary user (SU) to simultaneously share a licensed spectrum as long as the secondary transmission does not interfere with the primary link. As a result, the challenge of the CR network is to protect the primary users (PUs) from harmful interference induced by the SUs as well as to meet the quality of service (QoS) demands of SUs [1].Cognitive beamforming and power control, as an effective interference suppression technology, has been widely used in CR from different aspects [2-4]. All these work are based on the assumption of perfect channel knowledge. However, in practical systems, perfect CSI is difficult to obtain due to the loose cooperation between PUs and SUs, as well as many other factors such as inaccurate channel estimation, limited feedback or lack of channel reciprocity. The worst-case approach has been used to design robust power for SUs in a multiple-input single-output (MISO) CR system [5, 6]. In [5], the software assisted method and a geometric method were considered for single SU and single PU to find suboptimal solution for the certainty and uncertainty models. A bounded region for channel matrices and channel covariance matrices was assumed to be known in [6]. The authors used a type of ellipsoid uncertainty problem to express the bound channel uncertainty.

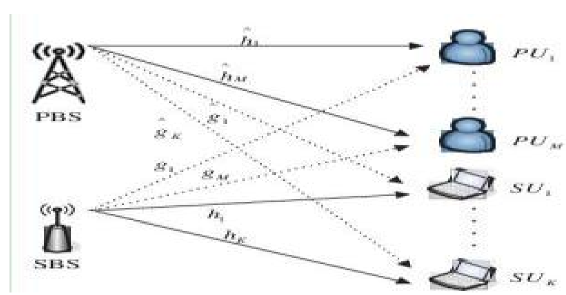

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Figure 1. Cognitive Radio System Model. Solid line Denotes Transmission Channel and Dotted line Denotes Interference Channel

For more SUs or PUs, [7] made some approximations for the uncertainty channel model between SUs and PUs. In [8], the worst-case of uncertainty was considered and the initially non-convex uncertainty problems are transformed into a second order cone programming (SOCP) or other convex problems, which can be solved by software.. The proposed scheme, with the consideration of both cooperative feedback from PUs and local feedback from SUs to the secondary base station (SBS), is robust to the channel uncertainties. Robust distributed power allocation algorithm for underlay CR networks was proposed in [10], which maximizes the sum utility of SUs when channel gains from SUs to primary base station (PBS) and interference introduced by PUs to the SBS are uncertain. In [11], the authors studied the problem of joint beamforming and power allocation in a cognitive MIMO system using game theory, where the imperfect CSI was taken into account by the robust interference constraint and the optimization problem in the formulated robust game is converted into a SOCP problem.

Inspired by the aforementioned work, in this paper, we consider the problem of joint beamforming and power control for underlay CR via game theory under imperfect CSI, where multiple SUs coexisting with multiple PUs. The objective is to maximize the sum utility of SUs under the interference power constraints at PUs, the total transmission power constraint of SUs, and SINR constraint of each SU. The joint problem is formulated as non-cooperative game, and then an ellipsoid model is adopted to describe the CSI uncertainty. By taking some approximation, the problem is reformulated as a SOCP problem. Simulation results show that the effectiveness of our proposed scheme.

The reminder of this paper is organized as follows. In section II, the system mode of CR is introduced and the optimization problem under imperfect CSI is formulated. In section III, the problem of joint beamforming and power control is formulated as non-cooperative game, and then the problem is transformed into a SOCP problem. In Section IV, numerical results are shown for our scheme. Finally, Section V draws some concluding remarks.

2. RELATED WORK

1. Introduction

Literature survey is carried out by analyzing many papers relevant to unreachability problem like hidden/exposed terminal problems ,packet dropping and distance based approach to reduce energy consumption of nodes cognitive radio networks. The researches carried out by different authors are surveyed and the analysis done by the researchers are discussed in the following paragraphs.

2. System Model and Problem Formulation

As illustrated in Fig. 1, we consider a cognitive network where a primary network consisting of a PBS and M Pus coexists with a secondary network with a SBS and K SUs. In the secondary network, SUs operate in the frequency band allocated to the PUs, thus the channels between the base stations and users are inherently interference channels.

3. Game under Imperfect CSI

Under the assumption of imperfect CSI between the SBS and PUs, in order to enable the SUs to share the spectrum with PUs, we should find appropriate power level and beamforming vectors to distribute them among the SUs so that the sum utility of SUs is maximized and the interference created to PUs is as low as possible. In this section, the problem of joint beamforming and power allocation under imperfect CSI will be described from the perspective of game theory.

4.Game-theoretic Formulation

Game theory is an effective tool to deal with the strategy choice and balancing among individuals who are of conflict interests. The players in a game with conflict interests will selfishly choose their own strategies to maximize their utility functions. In CR network,SUs share the spectrum bands of PUs in a competitive way, which will inevitably interfere with each other [12]. Therefore, the problem of joint beam- forming and power allocation is viewed as a non-cooperative game. Based on the system model described earlier, the non- cooperative game can be formulated as

$$G = [N, \{f_i, p_i\}_{i \in N}, \{u_i(\cdot)\}_{i \in N} \qquad (!)$$

and it has the following three major components.

1) **Players**: In this paper, players are SUs. A finite set of sensor nodes is denoted as $N = \{1, 2, \quad, K\}$.

2) **Strategic Space**: The strategic space is defined by the beamforming strategies f_i and power strategies p_i of SUs. The joint strategy spaces are defined as $\theta = f_1 \times f_2 \times \quad \times f_K$ and $P = p_1 \times p_2 \times \quad \times p_K$.

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3) **Utility Function**: In this paper, u_i is the corresponding utility function of SU$_i$.

A utility function of a player will assign numbers for every possible outcome in the game. In general, a higher number normally implies a more preferred outcome. The utilityfunction can be designed based on the achievable rate.

5. Second Order Cone Programming Solution

In this subsection, the optimization problem (9) is solved via a SOCP solution. As is known to all, the zero-forcing (ZF) scheme is a simple and efficient beamforming method which maximizes the sum utility by choosing appropriate f_k [14]. Here, we adopt the ZF beamforming that transforms the broadcast channel into multi-parallel independent and orthogonal sub-channels. The beamforming vectors are selected to satisfy $h_k\ f_i = 0,\ i \neq k$. Suppose that $F = [f_1, f_2\ ,\quad , f_K\ ]$ denotes the beamforming matrix, one easy way to choose the beamforming matrix F that gives the zero interference .

3. OVERVIEW OF BEAMFORMING

The evolution of multiple antenna systems has led to some important signal processing techniques such as beamforming [16] to substantially improve the performance of the wireless system. Beamforming exploits the benefits of antenna arrays for directional transmission or reception of a signal, which can be implemented at both receiver and transmitter. Specifically, interference reduction and SINR maximization are some of the key benefits that can be achieved with beamforming [46]. In literature, we can find two main categories of beamforming techniques [47]. They are called fixed beamforming and adaptive beamforming.

1. Fixed beamforming

Fixed beamforming uses a predefined set of beamforming weights and time-delays for each antenna at the transmitter or receiver. The beamforming weights and time-delays are basically calculated while exploiting the location and direction of the desired user. However, there is no correlation between the beamforming weights and the received signal in fixed beamforming. Hence, it can be identified as a multiple fixed beam switching technique.

2. Adaptive beamforming

Unlike fixed beamforming, adaptive beamforming technique dynamically computes the beamforming weights based on the properties (i.e., phase, amplitude fading) of the received signal. In other words, this technique tries to determine the optimal beamforming weights in such a way that they increase the quality of the desired received signal and minimize the interference to the other users. For instance, the least mean square algorithm [1], recursive least square algorithm [48] and sample matrix inversion [49] are some of the commonly used adaptive beamforming algorithms in literature.

3.Beamforming in Cognitive Radio Networks

We already mentioned that there are three dynamic spectrum access models, which are available to the SUs to initiate their communications. However, each dynamic spectrum access model introduces some amount of interference to the PU. Hence, the interference to the PU is inevitable in CRNs and sometimes it can be unintentional. Basically, interweave and overlay dynamic spectrum access models try to minimize the effect up to some extent by employing spectrum sensing and PU-association, respectively. In these kind of situations, SU's resources such as time and power are wasted and hence performance degradation in throughput is also possible. Inaddition to that, co-channel interference in wireless networks is another drawback due to the reusing of spectrum among the SUs.

In order to overcome those challenges, beamforming technique with multiple antenna system was introduced in CRNs [17]. For example, in hierarchical cellular network, using multiple antennas, SBS performs transmit beamforming to send multiple beams towards different SUs, which are located at various geographical locations. In such way, the energy of the transmitted signals is more concentrated at the intended receivers. As a result interference to the PU and other co-channel SUs are reduced. Furthermore, cooperative beamforming [50] is another type of beamforming method where a particular SU transmitter (i.e., source) uses some SU-relay nodes to send information to a particular SU receiver (i.e., destination). In this case, all users are equipped with single antenna transceivers. However, the SU-relay nodes act as a virtual array of antennas to focus the signal towards the intended SU-destination. Thus, it shows that even without implementation of multiple antennas at each SU, beamforming can be used to mitigate the interference and increase the received signal strength. However, association of the SUs could introduce significant complexity for beamforming in such system configu Related Works on Beamforming and Resources Allocation in CRNs.

In this section, we present a general survey about beamforming and resource allocation in CRNs. Specifically, in this survey, we consider resource allocation in CRNs with three

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different areas in terms of beamforming strategies, number of PU channels and network architectures.

1) Beamforming in single PU channel CRNs: In cognitive systems, resource allocation problems, i.e., power and channel allocation, have been widely deployed to increase the achievable sum-rate of the secondary network with simultaneously minimizing interference to the primary network. The authors in [51] considered a joint power and channel allocation problem to maximize the sum-rate of a secondary network with guaranteed protection to primary users. However, the work in [51] tried to control the transmit power of the SUs in order to reduce the interference to the PUs. Different from conventional power control, in [17] beamforming has been successfully adopted in CRNs to enhance SINR at each secondary user receiver (SU-RX) by exploiting the advantages of multiple antenna systems. In literature, joint beamforming and resources allocation have been widely studied for multiple-antenna CRNs. Xie et al. in [18] considered a sum-rate maximization problem with beamforming in a single PU channel CRN. In this work, the mutual interference between the SUs are nullified by deploying zero-forcing beamforming (ZFBF). ZFBF avoids the potential interference tolerance capabilities at SUs, the overall achievable sum-rate of the secondary network is degraded. The authors in [19, 20] explained that each SU or PU receiver is capable of tolerating some amount of interference, and they further proposed that underlay communication allows SUs to co-exist with PUs as long as the interference to the PU-RX is below the predefined threshold.

2) Therefore, it is not necessary to null the interference all the time. For example, Jiang et al. in [22] employed a zero-gradient based iterative approach to determine the local optimal beamforming vectors while maximizing the energy efficiency of the CRN. In [23], beamforming vectors were calculated by using an iterative algorithm based on semidefinite programming to maximize the sum-rate with a total power constraint and co-channel interference constraints at both PU and SU receivers. This work was further extended in [24] by adding an extra quality of service (QoS) constraint. However, the authors in [22-24] only considered a single PU channel CRNs with their problem formulations. As a result, it reduces the degree of freedom available at the SBS on channel allocation for SUs. Therefore, joint beamforming and resource allocation with multiple PU channels were considered.

3) Beamforming in multiple PU channels CRNs: In fact, primary user network is not only confined to a single channel. It can employ multiple PU channels to achieve heterogeneous SINR targets at each receiver. Thus, availability of multiple PU channels in secondary network increases the selectivity on channel allocation, while beamforming helps to further reduce the unwanted obstructions to the PUs. Obviously, multiple PU channels access enhances the performance in terms of sum-rate over the single channel CRNs. In [17], a single secondary user transmitter (SU-TX)/SU-RX pair was considered with uniformly distributed primary user transmitters (PU-TXs) and PU-RXs in a circular disc area. Beamforming was implemented by the SU-TX to minimize the interference to the PU-RXs while the received signal strength was maximized at the SU-RX. The authors in [53] considered two beamforming and resource allocation optimization problems, i.e., sum-rate maximization and SINR balancing, in CRNs under the peak power constraints and interference constraints for SUs and PUs, respectively. Authors in [54] presented a framework to minimize the total transmit power of a secondary network subject to some

4. NETWORK ARCHITECTURES IN CRNS:

In literature, we can find different network architectures, which have been proposed for the secondary network. In fact, we can mainly classified them into two categories, i.e., infrastructure-based CR networks and cognitive radio ad-hoc networks (CRAHNs) [34]. The former consists of a central network entity, which is called as the SBS or access point (AP). A cellular network CRN is a common example for the infrastructure-based CR network. On the other hand, the later, i.e., CRAHN, does not have a central unit. Instead, SUs in those networks communicate with each other using the ah-hoc connections. Some works in this area include an adaptive intercell interference cancellation (ICIC) technique for MISO downlink cellular system with channel allocation and beamforming to maximize the weighted sum-rate [58]. Hamdi et al. in [59] considered joint beamforming with near-orthogonal user selection method to maximize the downlink throughput of a cellular CRN while subjecting to SINR constraint at each SU, interference constraint at the PU-RX and total power constraint. Authors in [60] presented a joint beamforming with PUs and SUs selection problem to maximize the sum-rate of the entire cellular networks (i.e., both primary and secondary network). In addition, the authors in [22-24] also studied resource allocation and beamforming under the cellular architecture. In [61] the authors discussed a weighted sum-rate maximization problem for ah-hoc networks constrained with per-node (i.e., each SU-TX) transmit power and PU interference. Furthermore, a resource control optimization problem with interference and delay requirements was formulated in [62] with beamforming in an ad-hoc CRN. Different from the traditional architecture, device-to-device (D2D) communication based secondary networks offer many benefits. Improved spectral efficiency,

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greater coverage with spatial diversity, higher data rates, lower energy consumption and delay are some of the potential advantages due to the direct and short distance communication used in D2D networks. In [63], the authors considered a power allocation problem for CRNs with D2D communications to maximize the data rates of both PU and SU networks without evaluating the effect of interference and beamforming. In [64], joint beamforming and power controlling were studied to minimize the sum power of the primary and D2D networks by subjecting to minimum rate targets both at each PU-RX and SU-RX. Different from all the existing works, in this thesis, we exploit a joint beamforming, channel and power allocation optimization problem for multi-user multi-channel MISO CRNs. Instead of performing beamforming at a single SBS, we consider beamforming at each SU-TX to mitigate interference and support more transmission opportunities with other benefits.

A. A two-stage solution approach

The problem P1 consists of continuous and discrete variables, and there are nonlinear terms in both objective function and constraints. It is a non-convex, mixed integer non-linear programming problem, which has been proved to be NP-hard as in [23]. In order to balance performance and computational complexity, in the following a two-stage solution approach is proposed. The idea is to separate the main problem into two sub-problems. In the first sub-problem, the power and beamforming vectors are calculated based on a given channel allocation. After that, the second sub-problem, which determines an optimal channel allocation, will be solved. For the second sub-problem, two algorithms are proposed with different computational complexity.

4.1.1 Power and beamforming vector determination based on a given channel allocation .In this section, the beamforming vector and power allocation for each SU-TX will be determined given a channel allocation, X˜ . Given X˜ , constraints(3.11) and (3.13) can be transformed to a summation of quadratic terms and norms so that they become convex. However, the problem is still non-convex because neither the objective function (3.10) nor the constraint (3.12) are convex similar to analysis in [23] and [24], respectively. To overcome this issue, we use semidefinite programming (SDP) approach [66], which allows to express the quadratic terms with some equivalent affine expressions. With SDP, the quadratic terms,

. Following the similar method in [23], we introduce the following iterative algorithm for P3.

(i) **Initialization**: Relax the intra-user interference constraint (4.13) by assigning a feasible non-negative large value for ϕ. Then, solve the problem P3 to find outa feasible value of W, called each user as ϕk0) = ∑W(0) . Set the intra-user interference thresholds for Tr(W˜ m0)Hmk), ∀k ∈ S and calculate the sum-rate, m∈Sn m=k R(W˜ (0) , ϕ(0)), based on (4.11). Define SU pair index, k = 1, 1 ≤ k ≤ K and the iteration index, a = 1.

(ii) Update: Update ϕ(a) by ϕ(a) = ϕ(a−1) − (1 − δ)ϕka−1)Ik where δ is a fixed step size, 0 < δ < 1, and Ik is the kth column of an K × K identity (iii) Iteration results: Calculate the new value for R(W˜ (a) , ϕ(a)) using W(a) .

(iv) Check improvements: Calculate ∆R = R(W˜ (a) , ϕ(a)) − R(W˜ (a−1) , ϕ(a−1)). The non-negativity of ∆R can be proved as in [24]. If ∆R is greater than a predefined threshold, let a = a+1 and repeat steps (ii) and (iii) till it is below a predefined threshold. After that, set W(a) = W˜ (a−1) , R(W˜ (a) , ϕ(a)) = R(W˜ (a−1) , ϕ(a−1)) and update the intra-user interference for each user as ϕka) = ∑Tr(W˜ ma)Hmk), ∀k ∈ S . m∈Sn m=k

(v) Continue iterations and pick the next user: Set k = k + 1 and continue steps (ii) - (iv)for the newly selected user.

(vi) Termination: If k > K , stop the iterations. matrix.

At each iteration, the problem P3 needs to be solved given a channel allocation and ϕ. Since most of the convex optimization toolboxes (e.g., CVX) use the interior-point algorithm [69] as a basic solution platform, considering the worst-case scenario as in [67], the computational complexity of a SDR problem P3 can be expressed as O(max{ξ , κ}4 κ(1/2)log(1/ϵ)) (4.14)where κ and ξ describe the problem size (i.e., number of PSD matrices) and the number of constraints involved in the optimization problem P3, respectively. ϵ is the given accuracy of the solution defined by the solver. Let tT denotes the total number of iterations taken by the iterative algorithm to produce a feasible solution for total K SU pairs. Then, the overall complexity to find beamforming and power vectors for a given channel allocation can be derived as

O(max{ξ , κ}4 κ(1/2)log(1/ϵ)) × tT (4.15) Let W˜ = [W˜ 1 . . . W˜ K] and ϕ˜ = [ϕ˜1 , . . . ,ϕ˜K]T be the feasible solutions of the problem P3. Then, W is optimal if and only if the rank of each Wk , ∀k ∈ S , is equal to one, i.e., rank(Wk) = 1. If such condition is not satisfied, appropriate rank one approximation methods, e.g., eigen-decomposition method [67], can be deployed to get the final solution of

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W. By using eigen-decomposition method, each beamforming matrix Wk can beequivalently represented as

∑ Wk = λkjckjckj j =1

where λkj and ckj denote the jth eigenvalue and the corresponding eigenvector of the kth beamforming matrix Wk , respectively. If Wk is a rank one matrix, then there exists exactly one non-zero eigenvalue, say λkJ .

B. Finding the optimal channel allocation

In the previous section, we have determined the optimal power and beamforming vectors for a known channel allocation. In order to find the optimal channel allocation, an exhaustive searching algorithm can be used, which needs to compute beamforming vectors, power allocations and sum-rates for all possible channel allocations. With N PU channels and K SU pairs, the searching space size of the exhaustive searching algorithm is (N + 1)K , which increases exponentially with K . Obviously, this searching method is practically infeasible. Hence, for practical applications, we propose a channel allocation algorithm based on discrete stochastic algorithm to find optimal channel allocations.

Algorithm : Discrete Stochastic Approximation

In order to determine the beamforming vector and channel allocation for each SU-TX, we considered the perfect knowledge of the channel state information (CSI) at secondary base station (SBS). Hence, problem formulation with imperfect CSI is one of the possible extensions to this work. We can use the training sequence channel estimate method [76] to find CSI at the beginning of each time slot. In addition to that, we can use discrete stochastic approximation (DSA)-based channel allocation method [77] to find out the suboptimal channel allocation. Errors in the estimates of the CSI is inevitable due to some sensing limitations. Let Φ as in section (4.1.2). Hence, each Xl ∈ Φ indicates a certain feasible channel allocation in the CRN. Therefore, the corresponding channel gain matrix for Xl is defined as C [Xl], l = 1, . . . , L = (N + 1)K . In general, the optimization problem is expressed as in (4.21). However, due to the estimation errors, the estimated channel gains matrix at the tth time slot, denoted as C [t, Xl], may produce a noisy estimate of R(Xl), which is defined as r(Cˆ[t, Xl]). Infact, for different iteration times, the value of r(Cˆ[t, Xl]) becomes random. Hence, if we assume those estimates are unbiased, then we can have a sequence of independent and identically distributed random variables corresponding to each iteration time t. Therefore, the suboptimal channel allocation problem can be approximated by DSA as

X⋆ = arg max E {r(Cˆ[t, Xl])} (5.1)

At the beginning of the algorithm, we set the iteration index, t to be one. Then, a channel allocation is randomly selected from Φ, which is denoted as X(1) . Furthermore, a state probability is assigned to each channel allocation in Φ including X(1) . Define the set of probabilities for all channel allocations at the tth iteration to be π[t]=∑π[t, 1], π[t, 2], . . . , π[t, L], where

l π[t, l] = 1. At t = 1, we set π[t, X(1)] = 1 andπ[t, X] = 0, ∀X = X(1) . In addition, L × 1 auxiliary vector, el , is defined with all elements equal to zero except the lth element, which has a value equals to one. For notation simplicity, the value of el at the tth iteration is mapped to a L × 1 column matrix D[t]. Next, at each iteration a new channel allocation,X˜ , is randomly selected from the set Φ. Afterward, we compute the corresponding sum-rates for the two selected channel allocation (i.e., r(Cˆ[1, X(1)]) and r(Cˆ[1,X˜ (1)]). Two sum-rates are then compared to determine the better channel allocation. Finally, the state probabilities of each channel allocation is updated using π[t + 1] = π[t] + ϵ[t](D[t + 1] − π[t]) with a step size of ϵ[t] = 1/t. The implementation of the DSA algorithm is summarized as in Algorithm.

1:Initialization: Given K, N , Φ
2:Set t = 1,
3:Randomly select a channel allocation from $\Phi \leftarrow X^{(1)}$
4:Set $\pi[1, X^{(1)}] \leftarrow 1$, $\pi[1, X_l] \leftarrow 0$, $\forall X_l = X^{(1)}$, $X_l \in \Phi$ and $D[1] \leftarrow e_l$
5:for t = 1, 2, . . . do
6:Randomly select a new channel allocation from $\Phi \leftarrow \tilde{X}^{(t)}$, $\forall \tilde{X}^{(t)} = X^{(t)}$
7:$[T] \leftarrow \{X^{(t)}, \tilde{X}^{(t)}\}$
8:Compute two rates, $r(\hat{C}[t, X^{(t)}])$, $r(\hat{C}[t, \tilde{X}^{(t)}])$
9:if $\{r(\hat{C}[t, X^{(t)}]) \leq r(\hat{C}[t, \tilde{X}^{(t)}])\}$ then
10:$X^{(t+1)} \leftarrow \tilde{X}^{(t)}$
11:else
12:$X^{(t+1)} \leftarrow X^{(t)}$
13:end if
14:$D[t + 1] \leftarrow e_{index}$
15:$\pi[t + 1] = \pi[t] + \epsilon[t](D[t + 1] - \pi[t])$, where $\epsilon[t] = 1/t$
16:if $\pi[t + 1, X^{(t+1)}] > \pi[t + 1, X^\star]$ then
17:$X^\star \leftarrow X^{(t+1)}$
18:else
19:$X^\star \leftarrow X^{(t)}$

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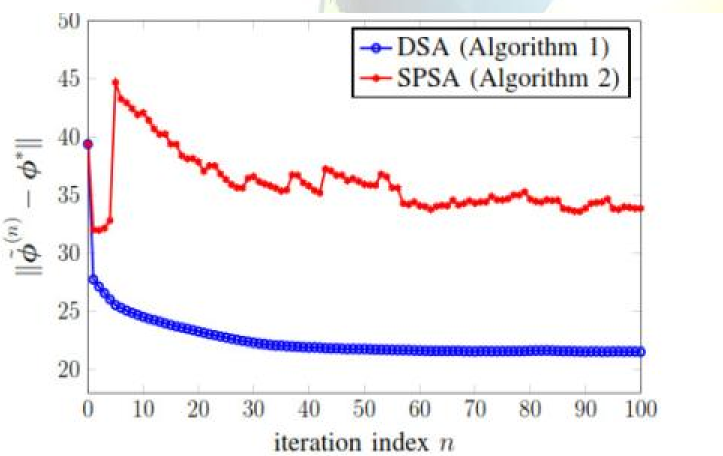
20:end if
21:t ← t + 1
22:end for
23:Output: X* , W*

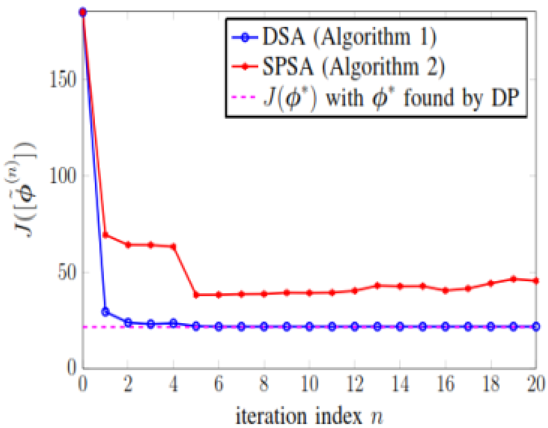
5. Simulation Results

In this section, the performance of both BPCA-GA and BPCA-SA algorithms are evaluated using computer simulations.

Simulation environment

Consider a CRN with three PU-TX/PU-RX pairs (i.e., N =3). The locations of the PU-TXs are given by the x-y plane coordinates (300, 0), (−4000) and (0, −100), and their associated PU-RXs are situated at (600, 0), (−400, 300) and (0, −400), respectively, where all the distances are measured in meters. There are six SU-TX/SU-RX pairs (i.e., K = 6) randomly located within a square area of 600m × 600m. For each SU-TX, its associated SU-RX is randomly located in a circle centered at the SU-TX with a radius of 100m





6. Conclusion

In this paper, the problem of joint beamforming and power control in underlay CR with multiple PUs and multiple SUs was studied. Imperfect CSI between the SBS and PUs was considered. The problem was formulated as non-cooperative game, and then an ellipsoid model was adopted to describe the CSI uncertainty. After making some approximations, the problem was reformulated as a SOCP problem. Simulation results shown that the proposed scheme converges to an equilibrium state. And the sum utilities of SUs were also presented to illustrate the performance of the secondary network under perfect and imperfect CSI. Furthermore, we assumed that each SU-TX/SU-RX pair is only allowed to utilize at most one PU channel at a time. However, we may allow each SU-TX to use more than one channel to communicate with a single SU-RX. Hence, this could help to significantly improve the performance of the secondary network in term of achievable throughput while simultaneously satisfying the quality-of-service (QoS) requirement of each user. In addition, we can improve the spectrum utilization of both primary and secondary networks with greater extend.

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