Joint Base Station Association and Power Control for Uplink Cognitive Small Cell Network

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***Abstract*—In this paper, we propose a framework to jointly optimize user association and power control for the uplink cognitive small cell network (CSN). In the considered CSN, small cell base stations (SBSs) are deployed to serve a set of small cell user equipments (SUEs) by sharing the same licensed spectrum with a macrocell base station. The problem of joint user association and power allocation is formulated as an optimization problem, in which the goal is to maximize the overall uplink throughput while guaranteeing the SINR requirements of the served SUEs and MBS protection. To solve this problem, a distributed framework based on dual decomposition is proposed to find sub-optimal solution of the user association and transmit power in distributed manner. Moreover, distributed frameworks to achieve suboptimal solutions with low-computation complexity are also proposed. Simulation results show that the proposed approaches obtain suboptimal solutions with a small number of iterations.**

Keywords*—Cognitive small cell network, resource allocation, power allocation, optimization problem.

I. INTRODUCTION

THe use of small cell networks is a promising solution to improve the capacity and enhance the coverage for indoor and cell edge users in next-generation wireless cellular networks [1]. In order to utilize the limited licensed spectrum efficiently, SBSs will need to reuse the same radio resources with the macrocell network. This spectrum sharing network leads to severe co-channel cross-tier interference that requires smart adaptive scheduling algorithms [2] to mitigate interference and maximize the system throughput. A small cell network that reuses subchannels based on cognitive radio technology [3] is commonly known as the cognitive small cell network.

In the CSN deployment, some technical challenges need to be considered such as interference management, efficient spectrum usage, and cell association [3]–[5]. The goals of CSN deployment include the macrocell network protection and guaranteeing served SUEs' quality of service (QoS) while maximizing the overall network throughput. For the CDMA-based small cell network deployment, there have been some existing works studying the cell association and power control [6]–[12]. The studies in [6] and [7] only considered access control and power control to minimize the number of secondary users to be removed and to maximize the overall network throughput for efficient sharing in the CDMA-based network. For multiple cell cooperation, authors in [8] a distributed power control algorithm to address the uplink interference management problem for cognitive radio network in multi-cell environments, which is based on principles of the fixed point algorithm. However, they assumed a fixed base station assignment in both primary and secondary networks, i.e., each primary user (PU) or secondary user (SU) is already associated with a fixed base station (BS) in the corresponding cells. In [9], authors investigated the distributed power allocation strategies for a spectrum-sharing femtocell network. An effective distributed interference price bargaining algorithm based on the Stackelberg game is proposed to achieve the equilibrium, which does not consider the respect of the optimal power control. For optimal power control in multi-cell network, a framework based on geometric programming and dual decomposition is proposed to minimize the CO2 emissions in the cognitive femtocell network [10]. Obviously, the studies in [6]–[10] did not consider the base station association problem for the CDMA-based spectrum sharing.

For *joint power control and cell base station* for the CDMA network, some other works are proposed in [12]–[14]. In [13], the authors studied resource sharing and small cell access control in small cell networks, in which incentive mechanisms are proposed to encourage SUEs to share their SBSs with MUEs. However, this work considers only resource sharing without power control for the OFDMA-based small cell networks. In [12], authors proposed an universal joint BS association and power control algorithm for the CDMA-based heterogeneous cellular networks. In addition, authors in [12] developed the distributed base station association and power control algorithms to maintain the SINR requirements while exploiting the multiuser diversity gain to increase the system throughput. However, this algorithm cannot provide global optimal solution for users in the network. A framework addressed a joint user association and power control under the max-min fairness criterion are studied in [14]. Authors in [14] proposed a normalized fixed point iterative algorithm to directly solve the original problem and prove its geometric

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convergence to the global optimal solution, which implies the pseudo-polynomial time solvability of the considered problem. This work does not, however, consider the underlay spectrum sharing approach for two-tier network model. It can be seen that none of the existing works study optimal joint user association and power control in the uplink CSN. This paper aims to address this joint design problem.

The main contribution of this paper is to introduce a distributed framework for joint user association and power allocation for the uplink small cell network in the CDMA-based two-tier network model, which is an NP-hard problem. The purpose of this paper is to find an optimal solution for associating SUEs to SBSs and allocating transmit power levels for SUEs to maximize the network utility while considering intra-tier and inter-tier interference. Additionally, the minimum SINR requirements of the served SUEs and MBS protection are also guaranteed. In summary, we make the following key contributions:

- We develop a distributed framework based on dual decomposition to solve the formulated optimization problem.
- We design a distributed algorithm that enable to determine the association of SUEs to SBSs and the power allocation for SUEs in an autonomous manner. Then, we prove that the proposed algorithm converges to a sub-optimal solution. Then, low computation complexity sub-optimal solutions are also proposed.
- Simulation results show that the proposed algorithms obtain sub-optimal solutions with a small number of iterations.

The remaining of this paper is organized as follows: Section II explains the system model and problem formulation. The NP-hard combinatorial optimization problem is solved based on the dual decomposition approach in Section III. Additionally, we also study the solution to archive near optimal solution. Section IV provides simulation results. Finally, conclusions are drawn in Section V.

II. System model and problem formulation

In this section, we present the system model and problem formulation.

A. System model

We consider the *uplink* of a cognitive small cell network, where a set $\mathcal{M} = \{1, 2, ..., M\}$ of SBSs operates inside the coverage of a macrocell network and serves a set $\mathcal{N} = \{1, 2, ..., N\}$ of SUEs as shown in Fig. 1. These SBSs adopt an open access mode which allows any SUEs to use the SBSs' services [15]. We consider the set N SUEs transmitting information to M SBSs on the same licensed spectrum. This licensed spectrum is reused from a macrocell base station using the underlay spectrum access model. SBSs are connected to a cognitive small cell management (CSM) controller that acts as a coordinator and spectrum manager. Moreover, we assume that SBSs and MBS have knowledge about channel state information of SUEs with perfect channel state information.

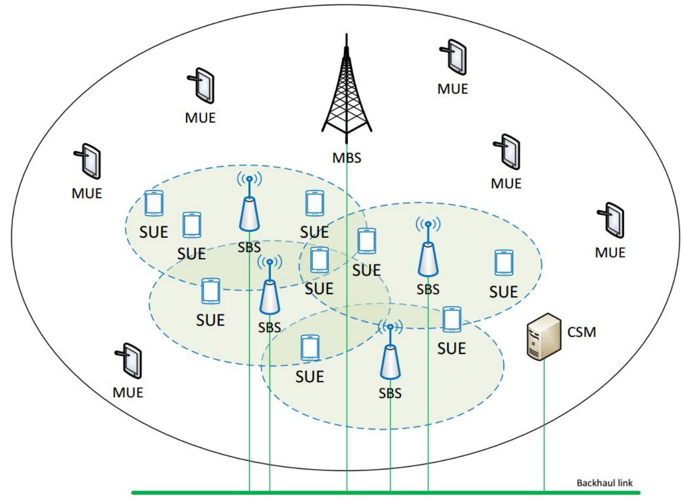

Fig. 1: System architecture of a cognitive small cell system.

Assuming that each SUE n associates with only one SBS at any time. Furthermore, we assume that each SUE is only permitted to access at most one subchannel. We will use the index 0 to denote the MBS.

B. Problem formulation

We first describe all constraints. After that, we formulate the optimization problem for the user association and power allocation.

SUE QoS. We assume that each SUE n requires the minimum QoS in term of a target signal-to-interference-plus-noise ratio (SINR) γ_n^{th} which can be written as follows:

$$\Gamma_{nm} \geq \gamma_n^{\text{th}}, \tag{1}$$

where the SINR of SUE n when the SUE n is served by SBS m with transmit power P_n will be given by

$$\Gamma_{nm}^k = \frac{g_{nm} P_n}{\sum\limits_{n' \in \mathcal{N} \setminus \{n\}} g_{n'm} P_{n'} + \sigma^2}, \tag{2}$$

where $\sum\limits_{n' \in \mathcal{N} \setminus \{n\}} g_{n'm} P_{n'}$ is the total interference from other SUEs to the SBS m; P_n and $P_{n'}$ denote the transmit powers of SUEs n and n' $(n' \neq n)$, respectively; g_{nm} and $g_{n'm}$ are the channel power gains from SUE n and from SUE $n' \neq n$ to SBS m, respectively. We assume the interference power from MUEs at the SBS is negligible which can be absorbed to the noise power σ^2.

MBS protection. In our model, each MUE is assumed to transmit at a fixed power level. In addition, the total interference from SUEs to the MBS is constrained to be below the threshold I_{th} to maintain the required QoS of the underlying MUE. This constraint can be expressed as

$$\sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{M}} x_{nm} g_{n0} P_n \leq I_{\text{th}}, \tag{3}$$

where $\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} x_{nm} g_{n0} P_n$ is the total interference generated by all SUEs to the MBS, and g_{n0} is the channel power gain from SUE n to MBS.

The joint user association and power control problem is formulated as an optimization problem that aims to maximize the overall network throughput as follows:

$$\textbf{OPT-1}: \quad \max_{(\boldsymbol{X},\boldsymbol{P})} \sum_{n\in\mathcal{N}} \log(\sum_{m\in\mathcal{M}} x_{nm}\Gamma_{nm}) \tag{4}$$

$$\text{s.t.} \quad (1),(3),$$

$$\sum_{m\in\mathcal{M}} x_{nm} = 1, \quad \forall n \in \mathcal{N}, \tag{5}$$

$$P_n^{\min} \le P_n \le P_n^{\max}, \quad \forall n \in \mathcal{N}, \tag{6}$$

$$x_{nm} = \{0,1\}, \forall m, n. \tag{7}$$

Here, we consider the network throughput in term of the fairness SINR of SUEs; the constraint (5) guarantees that each SUE can be associated with only one base station; constraint (6) guarantees that the transmit power of each SUE on each subchannel is adjusted within the desired range.

III. Dual decomposition based user association and power control

The $\mathbf{OPT}$-1 is a mixed integer non-linear programming problem because it contains binary variables $\boldsymbol{X}$ and continuous variables $\boldsymbol{P}$. Moreover, the $\mathbf{OPT}$-1 is an non-convex problem due to coupling power variable in the objective function and constrain (2). To solve the $\mathbf{OPT}$-1 problem, we first transform $\mathbf{OPT}$-1 into an equivalent convex problem following P variable. Then, we solve the reformulated problem by proposing series of updated primal-dual.

A. Reformulation and Lagrange dual problem

In this section we first transforms the $\mathbf{OPT\text{-}1}$ into a convex optimization problem. Note that what we actually maximize is $\sum_{n\in\mathcal{N}}\log(\sum_{m\in\mathcal{M}} x_{nm}\Gamma_{nm}) = \sum_{n\in\mathcal{N}}\max\{\log(\sum_{m\in\mathcal{M}} x_{nm}\Gamma_{nm}),0\}$. Moreover, since $\sum_{m\in\mathcal{M}} x_{nm} = 1$, we have $\sum_{n\in\mathcal{N}}\log(\sum_{m\in\mathcal{M}} x_{nm}\Gamma_{nm}) = \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} x_{nm}\log(\Gamma_{nm})$. Additionally, without loss of optimality, we use the logarithm change of power $\hat{P}_n = \log(P_n)$. Then, we have a reformulated optimization problem as follows:

$\mathbf{OPT\text{-}2}$:

$$\max_{\hat{\boldsymbol{P}}\in\hat{\mathcal{P}},\boldsymbol{x}\in\mathcal{X}} \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} x_{nm}\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) \tag{8}$$

subject to:

$$\sum_{m=1}^{M} x_{nm}\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) \ge \log(\Gamma_n^{\text{th}}), \ \forall n \tag{9}$$

$$\sum_{n=1}^{N}\sum_{m=1}^{M} x_{nm} e^{\hat{P}_k} g_{n0} \le I_{\text{th}}, \tag{10}$$

$$\sum_{m=1}^{M} x_{nm} = 1, \ \forall k, \tag{11}$$

where $\hat{\mathcal{P}} = [\log(P_n^{\min}), \log(P_n^{\max})]$, $\mathcal{X} = \{x_{nm}, \forall n, m| \ x_{nm} \in \{0,1\}\}$.

Theorem 1. *The transformed problem* $\mathbf{OPT\text{-}2}$ *is a convex optimization problem with respect to variable* $\hat{\boldsymbol{P}}$.

Proof: All the constraint (9) and (10) are convex in $\hat{\mathcal{P}}$ since the log-sum-exp is convex in its domain. Similarly, the objective function is also convex function in $\hat{\mathcal{P}}$. Hence, $\mathbf{OPT\text{-}2}$ is a convex optimization problem respect to variable $\hat{\boldsymbol{P}}$. ■

B. Dual decomposition and optimal solution

From $\mathbf{OPT\text{-}2}$, the Lagrangian function is obtained by augmenting the objective function with a weighted sum of the constraints (9) and (10), as follows:

$$\begin{aligned} L(\boldsymbol{x},\hat{\boldsymbol{P}},\boldsymbol{\lambda},\boldsymbol{\mu}) &= \sum_{n=1}^{N}\sum_{m=1}^{M} x_{nm}\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) \\ &+ \sum_{n=1}^{N}\lambda_n(\sum_{m=1}^{M} x_{nm}\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) \\ &- \log(\Gamma_n^{\text{th}})) - \mu(\sum_{k=1}^{K}\sum_{m=1}^{M} x_{nm} g_{n0} e^{\hat{P}_n} - I_{\text{th}}). \end{aligned} \tag{12}$$

Then, dual problem of (12) can be represented as follows:

$$(\mathcal{D}): \quad \min_{\boldsymbol{\lambda}\ge 0,\boldsymbol{\mu}\ge 0} \ g(\boldsymbol{\lambda},\boldsymbol{\mu}), \tag{13}$$

where

$$g(\boldsymbol{\lambda},\boldsymbol{\mu}) = \max_{\boldsymbol{x}\in\mathcal{X},\hat{\boldsymbol{P}}\in\hat{\mathcal{P}}} L(\boldsymbol{x},\hat{\boldsymbol{P}},\boldsymbol{\lambda},\boldsymbol{\mu}), \tag{14}$$

subject to: (11)

By using dual decomposition mechanism, the problem (14) can be decomposed into two subproblems due to variables $\boldsymbol{x}, \hat{\boldsymbol{P}}$ appear in the sum of products.

Subproblem power control. Each SUE updates transmit power by solving a subproblem given a tuple of fixed primal variables $(\boldsymbol{x},\boldsymbol{\lambda},\boldsymbol{\mu})$ as follows:

$$\begin{aligned} \frac{\partial L(\boldsymbol{x},\hat{\boldsymbol{P}},\boldsymbol{\lambda},\boldsymbol{\mu})}{\partial \hat{P}_n} &= (1+\lambda_n - \mu g_{n0} e^{\hat{P}_n}) - \sum_{n'\neq n,m'} x_{n',m'}(1 \\ &+ \lambda_{n'})\frac{g_{nm'} e^{\hat{P}_n}}{\sum_{n''\neq n'} g_{n''m'} e^{\hat{P}_{n''}}}. \end{aligned} \tag{15}$$

For our convenient, we let $\tau_{n'm'} = \frac{(1+\lambda'_n)\Gamma_{n'm'}}{g_{n'm'}p_{n'}}$ denoting by transferable value from other user association. Then, (15) can be rewritten in the following.

$$\frac{\partial L(\boldsymbol{x}, \hat{\boldsymbol{P}}, \boldsymbol{\lambda}, \boldsymbol{\mu})}{\partial \hat{P}_n} = (1+\lambda_n - \mu g_{n0} e^{\hat{P}_n}) - \sum_{n',m'} x_{n',m'} \tau_{n'm'} g_{nm'} e^{\hat{P}_n}. \tag{16}$$

Due to $p_n = e^{\hat{P}_n}$ and $\nabla_n L_P(\boldsymbol{x}, \boldsymbol{P}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \frac{1}{p_n} \nabla_n L_{\hat{P}}(\boldsymbol{x}, \hat{\boldsymbol{P}}, \boldsymbol{\lambda}, \boldsymbol{\mu})$, the projected gradient-ascent method [16], [17] for SUE n power update can be given by:

$$\nabla_n L_P(\boldsymbol{x}, \hat{\boldsymbol{P}}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \frac{1+\lambda_n}{p_n} - \mu g_{n0} - \sum_{n',m'} x_{n',m'} \tau_{n'm'} g_{nm'}. \tag{17}$$

Hence, the optimal solution of the SUE n can be obtained by:

$$P_n^* = \left[\frac{1+\lambda_n}{\mu g_{n0} + \sum\limits_{n',m'} x_{n',m'} \tau_{n'm'} g_{nm'}} \right]^+. \tag{18}$$

Subproblem user association. In (17), when a tuple of primal variables $(\boldsymbol{x}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ is fixed, $\{(1+\lambda_n)\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) - \mu g_{n0} e^{\hat{P}_n}\}_{\forall m,n}$ are constant weighted values. Then, the problem (14) is equivalent to a maximum weighted matching problem as follows:

$$\max_{\boldsymbol{x} \in \mathcal{X}} \sum_{n=1}^{N} \sum_{m=1}^{M} x_{nm} \left[(1+\lambda_n)\log(\Gamma_{nm}(e^{\hat{\boldsymbol{P}}})) - \mu g_{n0} e^{\hat{P}_n} \right], \tag{19}$$

subject to: (11).

Subsequently, after power updated phase, the optimal user association of FUEs to maximize (19) are determined as follows:

$$x_{nm}^* = 1 \; |m^* = \arg\max\nolimits_m \Gamma_{nm}(\boldsymbol{P}), \forall n. \tag{20}$$

From results in (20), we can see that given fixed transmit power, user associations only depends on value $\Gamma_{nm}(\boldsymbol{P})$.

Lagrange multiplier update. By solving dual problem (13) using projection gradient-decent method, the optimal multiplier is found by updating as follows:

$$\lambda_n^{(t+1)} = \left[\lambda_n^{(t)} - s_2(t) \left(\sum_{m=1}^{M} x_{nm}^{(t)} \Gamma_{nm}(\boldsymbol{P}_n^{(t)}) - \Gamma_n^{\text{th}} \right) \right]^+, \tag{21}$$

$$\mu^{(t+1)} = \left[\mu_m^{(t)} + s_3(t) \left(\sum_{k=1}^{K} \sum_{m=1}^{M} x_{nm}(t) g_{n0} P_n^{(t)} - I_{\text{th}} \right) \right]^+, \tag{22}$$

where the parameters $s_i(t)$ $(i = 1, 2, 3)$ represent the step sizes which are chosen to satisfy

$$\sum_{t=0}^{\infty} s_i(t)^2 < \infty, \quad \text{and} \quad \sum_{t=0}^{\infty} s_i(t) = \infty, \quad \forall i = 1, 2, 3, \tag{23}$$

Algorithm 1 JUP: Optimal joint user association and power allocation.

Initialization: $\boldsymbol{P}^{(0)}$, $\boldsymbol{x}^{(0)}$, $\boldsymbol{\lambda}^{(0)}$, $\boldsymbol{\mu}^{(0)}$.
Repeat:
Algorithm at each SUE:
Calculate and broadcast $\tau_{nm}^{(t+1)} = \frac{(1+\lambda_n^{(t)})\Gamma_{nm}^{(t)}}{g_{nm} P_n^{(t)}}$
Transmit power update: $P_n^* = \left[\frac{1+\lambda_n}{\mu g_{n0} + \sum\limits_{n',m'} x_{n',m'} \tau_{n'm'} g_{nm'}} \right]^+$
User association update:
$x_{nm}^{(t+1)} = 1 \; |m^* = \arg\max_m \Gamma_{nm}(\boldsymbol{P}^{(t+1)}), \forall n$
SUEs' QoS updates using (21)
Algorithm at the MBS:
Measures and broadcast the interference price updates using (22)
Until convergence.

which leads to the convergence of algorithm [18], and $[a]^+ = \max\{a, 0\}$.

Next, we propose a distributed algorithm to achieve sub-optimal solution of joint user association and power allocation, namely, the JUP algorithm.

Lemma 1. *For any initial feasible solution of the user association $\boldsymbol{x}^{(0)}$ and power allocation $\boldsymbol{P}^{(0)}$, the* JUP *algorithm converges to the sub-optimal solution $\boldsymbol{x}^*, \boldsymbol{P}^*$.*

Proof: Because the problem $\mathbf{OPT\text{-}2}$ is a convex optimization problem respect to variable $\hat{\boldsymbol{P}}$ given vector $\boldsymbol{x}$, the Slater condition is also satisfied so the optimal duality gap given use association is equal to zero, and step-sizes satisfy (23). However, the non-convex mixed-integer program of the OPT-2 there may exist non-zero dual gap; hence solving the optimization OP may not yield the global optimal solution. Nevertheless, the JUP algorithm can be proved using the gradient-based standard technique. ■

C. Suboptimal solution

By observing the solution based on the JUP algorithm, we can see that the MBS has to update and broadcast the interference price and channel gain between the MBS and SUEs. Moreover, the τ_{nm} of each SUE has to exchange between itself and other SUEs. Hence, these exchanges cause the increment of message passing. In order to reduce the number of message passing in the network, we divide the maximum interference level I_{th} into I_{th}/N, which the interference causes by each SUE to the MBS is not exceed I_{th}/N [19]. Then, the JUP algorithm leads to a suboptimal solution, namely, JUP-S.

IV. Simulation results

In order to evaluate our proposed algorithm, we use the following simulation setup. We simulate an MBS and 5 SBSs ($M = 5$) with the coverage radii of 500 m and 25 m, respectively. The SBSs are deployed in a small indoor area of 250×250 m^2 to serve $N = 10$ SUEs. In the CSN, we

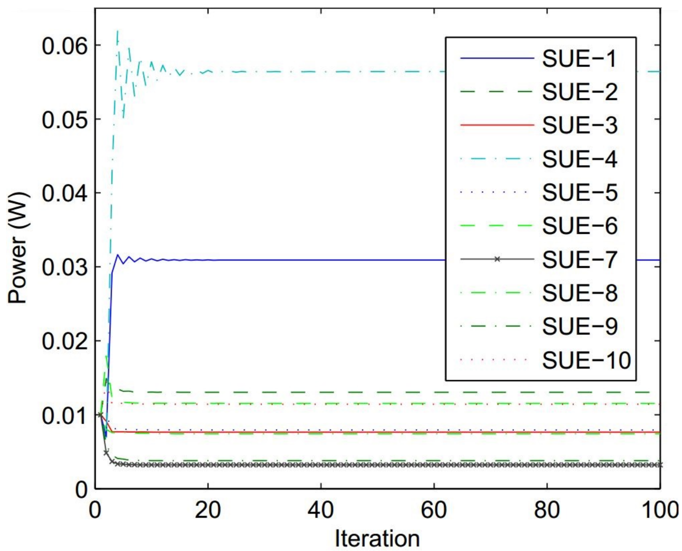

Fig. 2: Transmit power of SUEs

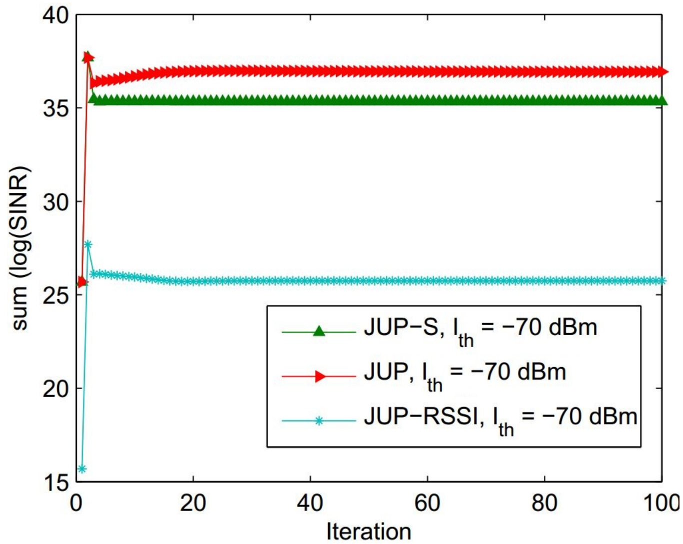

Fig. 4: Transmit power of SUEs

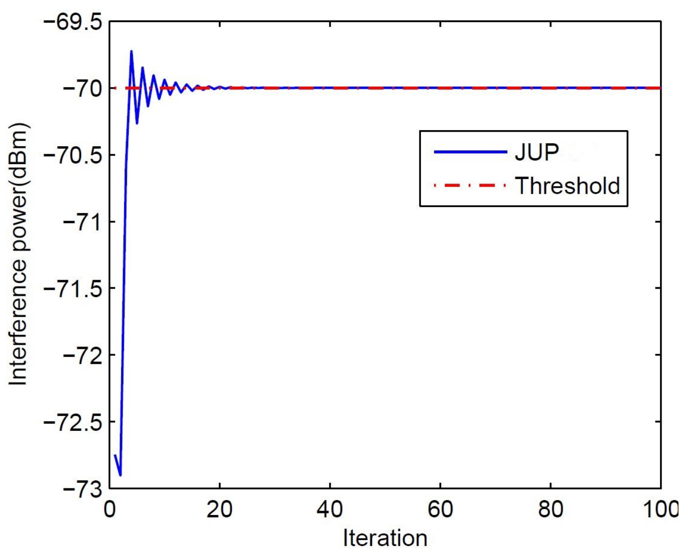

Fig. 3: Transmit power of SUEs

reuse a bandwidth $B = 5$Mhz, which are allocated to the macrocell network. The power channel gains are assumed to be flat fading. The path loss model is followed by the log-distance path loss model [20], [21]. In the SUE-to-MBS path-loss for distance d, $L_d = 15.3 + 37.6 \log_{10}(d) + \rho$. The wall penetration loss ρ equals to 10 dB. In the SBS-to-same-cell-SUE path-loss for distance d, $L_d = 38.46 + 20 \log_{10}(d)$. In the SUE-to-other-cell-SBS path-loss for distance d, $L_d = \max\{38.46 + 20 \log_{10}(d), 15.3 + 37.6 \log_{10}(d)\} + 2\rho$. The maximum interference power on each subchannel at the MBS is -70 dBm. The noise power is set to -114 dBm. Each SUE has a minimum SINR threshold of -18 dB. Each SUE has a maximum transmit power of 100 mW.

The results of the distributed user association and power allocation based on the JUP algorithm for given network settings are presented in Fig. 2, Fig. 3, and Fig. 4. Fig. 2 presents the power convergence properties of each SUE in the JUP algorithm separately. We can see that, in order to satisfy SUEs'QoS and MBS protection, SUEs perform user association based on the updated transmit power levels that are shown in Fig. 2. Moreover, in Fig. 3 illustrate the total interference power from SUEs to the MBS is guaranteed under power control policies of SUEs. The simulation results in Fig. 2 and Fig. 3 show that the JUP algorithm can converge to the sub-optimal solution very fast (around iteration).

In Fig. 4, we show the convergence the overall utility of all SUEs by comparing with other methods, i.e., the JUP algorithm, the JUP-S algorithm, and the JUP-RSSI algorithm. The sub-optimal solution performance is based on the JUP algorithm. In order to reduce message passing in the network, which archives the near optimal solution, we use the JUP-S algorithm. For the JUP-RSSI, SUEs are associated with their SBSs based on the RSSI signal. However, the transmit power levels of SUEs are updated as in the JUP. We can see from Fig. 4 that the total utility of the low-complexity sub-optimal solution can archive a gap of 5.4% compared to the JUP algorithm. Additionally, Fig. 4 also shows that the joint user association and power control using JUP and JUP-S can reach up to 42.3% and 34.61% gain over the approach using JUP-RSSI algorithm. This is shown that SUEs perform user association based on the proposed approach obtained a better performance in term of total utility in the cognitive small cell network deployment.

V. Conclusions

In this paper, we has proposed a framework to jointly optimize user association and power allocation in the uplink CSN. In the considered CSN, SBSs have deployed to serve a set of

SUEs by sharing the same licensed spectrum with a macrocell base station. The problem of optimal joint user association and power allocation has formulated as an optimization problem, in which the goal is to maximize the overall uplink throughput while guaranteeing the SINR requirements of the served SUEs and MBS protection. A distributed framework based on dual decomposition has proposed to find the optimal solution of the user association and transmit power. Simulation results has showed that the proposed approach yields a performance improvement in terms of the overall network throughput with a limited number of iterations to converge.

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