Small Base Station Association and Cooperative Receiver Design for HetNets via Distributed SOCP

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Abstract

How to determine the right number of small base stations to activate in multi-cell uplinks to match traffic from a fixed quantity of K users is an open question. This paper analyses the uplink cooperative that jointly receives base stations activation to explore this question. This paper is different from existing works only consider transmitting power as optimization objective function. The global objective function is formulated as a summation of two terms: transmitting power for data and coordinated overhead for control. Then, the joint base stations activation and beamforming problem is formulated as a mixed integer second order cone optimization. To solve this problem, we develop two polynomial-time distributed methods. Method one is a two-stage solution which activates no more than K small base stations (SBSs). Method two is a heuristic algorithm by dual decomposition to MI-SOCP that activates more SBSs to obtain multiple-antennae diversity gains. Thanks to the parallel computation for each node, our methods are more computationally efficient. The strengths and weaknesses of these two proposed two algorithms are also compared using numerical results.

Keywords: user-base station association, coordinated beamforming, mixed integer programme, convex relaxation, QoS

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1. Introduction

The heterogeneous network (HetNet) is made up of macro base stations (BSs), which have large coverage and highly densely deployed small BSs, which are low-cost and low-power [1] [22]. Both types of BSs are equipped with multiple antennae and share the same frequency band. Recently, to cope with the explosive growth of mobile Internet data, deploying small-cell networks in the same frequency band has been receiving more attention [28] [29].

In order to guarantee quality of service (QoS) for users, the radio resource management usually has two phases. The first phase is to determine the user-base station association, in which the random access problem is used to obtain fixed network connectivity. In the following phase, the power control to the transmitter and the beamforming in the receiver is designed to support all data links. However, users' traffic demands are time-varying. Most of the time, only a few small BSs in HetNets are enough to meet the QoS requirements. Therefore, it is necessary to select sets of cooperative BSs and turn off others to decrease power consumption. An important and open question is how to activate the small base stations to serve a fixed quantity of K users. In this paper, a joint optimization of the user-base station association and linear receiver for uplink HetNets is presented to address this problem.

1.1 Motivation

Coordinated beamforming is a critical technology to manage the interference from multiple densely-packed small cells. It has already been advocated within industry and standardization fora, which have helped to design the receivers in small base stations. In LTE-A [2], two categories of modes have been considered for uplink coordinated multiple point reception: Joint Reception (JR) and Coordinated Scheduling and Beamforming (CS/CB). Unlike JR, which shares users' data through high speed backhauls, small BSs mitigate interference in CS/CB without exchanging data information.

The first step for coordinated beamforming is to select a cluster of small base stations that can satisfy the users currently being served. As the exact capacity region of multi-cell interference channels is not understood, whether for homogeneous or heterogeneous multi-cells, there might be unsupported users or extra active BSs. One existing method for user association is based on the "greedy criterion," in which users always select the "max-SINR" small BS that has the strongest measured/sensed signal of all. This method has already been used in random access control in LTE R8 [3] and Wi-Fi [4].

Following this rule in the uplink of multi-cell SIMO channels is not optimal. The small BSs that are located in the hotspot will accommodate too many users, resulting in increased uplink transmitting power and system interference. A more beneficial approach is to combine the user association and linear receiver (coordinated beamforming) design together to simultaneously determine the right number of cooperative BSs and the optimal beamforming vectors to guarantee the users' QoS requirements. Here, the QoS constraints are considered to be the target SINR for multiple users along orthogonal resource dimensions. This paper is motivated by designing schemes that use the full degree of freedom in small networks, including connectivity, power control, and multiple antennae to balance the uplink co-channel interference (CCI).

1.2 Related Work

Recently, many works have been devoted to clustering a number of small BSs together to achieve high spectrum efficiency, so that JR can be used within each BS cluster [5]. These solutions obviously require most BSs in the network to remain active, even for a few diffuse users. Substantial operational costs are incurred [6], and the network costs usually take the form of a power control signal, an ACK/NACK signal, or interference terms exchanged between small BSs. It is necessary to consider the gain in data links and the overhead consumption to select the right number of small BSs to be associated and activated. However, the research around BS activation with beamforming is not significant: we only know of [7], [8], and [9]. Among them, only one takes the extra consumption of coordinated beamforming (CoMP overhead) into account in their optimization models [8].

Reference [7] is the first to prove that the joint user association and beamforming problem is NP-hard for a well-known family of system utility functions (alpha-fairness utilities). Then an MMSE filter-based algorithm that relaxes the binary variable is proposed in [7] to approximately solve this problem. To attain the optimal activating set of BSs for downlink, Yong Cheng et al. have modelled a standard big-M mixed integer conic programming formulation to address the base station activation problem [8]. Then, a SOCP-based polynomial-time inflation and deflation procedure is presented to speed up the BnC (branch and cut) algorithm. As the run-time is still high, especially for large-scale networks, Wei-Cheng Liao et al. [9] develop a distributed algorithm by applying the Alternating Direction Method of Multipliers (ADMM) framework.

1.3 Differences and Contributions

Compared to the downlink coordinated beamforming problem [7], [9], and [5], the uplink problem is addressed from the perspective of “On-Demand Activation.” When considering user-base station connectivity, the additional binary variable problem (comparing to the multi-cell beamforming problem) is a mixed integer program and non-convex, so that strong uplink-downlink duality is no longer tenable. We also find that the uplink SIMO beamforming has some differences from downlink MISO beamforming. For multi-cell downlinking, cooperative BSs exchange backhaul signalling, an interference term that consists of the interference information from neighbouring cells [10]. However, it is not necessary to exchange CSI or interference terms for uplink coordinated beamforming. The reason is that the receivers of small base stations can sense and estimate the channel state information (CSI) from interfering users in neighbouring cells.

This paper contributes a systematic scheme to select small base stations, and the idea is to obtain the optimal number of small BSs by considering a trade-off between the transmitting power diversity gain and the overhead cost for cooperative beamforming. This paper models the global network overhead cost for multiple small BS cooperations as a linear function of the number of existing data links. We develop two approaches to obtain the output connectivity and beamforming vectors. The first can be viewed as a conventional approach to obtain an upper (achievable) bound for network power costs. The second is to solve the continuous relaxed conic problem using dual decomposition technology. Both approaches can be implemented in a distributed fashion that has low computational time. We compare these two algorithms to the standard mixed-integer Gurobi solution, and the numerical results illustrate the efficiency and the efficacy of the proposed algorithms.

2. System Model and Problem Statement

2.1 System Model

Consider the uplink HetNet network as a multi-cell SIMO channel consisting of a set $\mathcal{L} \triangleq \{1,2,...,L\}$ of BSs and a set $\mathcal{K} \triangleq \{1,2,...,K\}$ of users. Each user has a single antenna, and the l-th BS is equipped with $M_l > 1$ antennae, $\forall l \in \mathcal{L}$, with $M \triangleq \sum_{l=1}^{L} M_l$. As shown in **Fig. 1**, small BSs are clustered, and all have radio control links to the Macro BS. We assume that the small BSs are synchronized and able to do coordinated beamforming under the control of the Macro BS. Instructed by the control signal from the Macro BS, each user can associate with one or several small BSs and then transmit data.

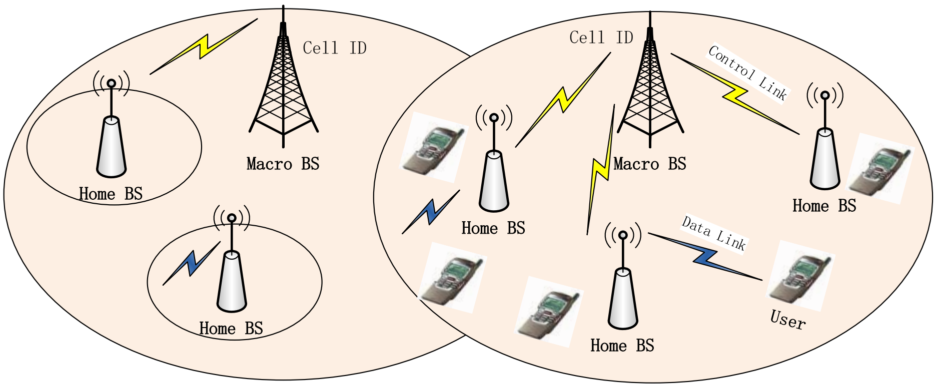

Fig. 1. The multi-tier heterogeneous cellular network

Let us denote $\mathbf{h}_{k,l} \in \mathbb{C}^{M_l \times 1}, \forall l \in \mathcal{L}, k \in \mathcal{K}$, as the frequency-flat channel vector from the k-th user to the l-th BS. We now can define a global channel vector for every user k as $\mathbf{h}_k \triangleq [\mathbf{h}_{k,1}^T, \mathbf{h}_{k,2}^T, ..., \mathbf{h}_{k,L}^T]^T \in \mathbb{C}^{M \times 1}, \forall k \in \mathcal{K}$. Each small BS has a linear filter for the multiple-antennae receiver that treats interference as noise. We use a universal frequency reuse approach in which all small cells operate on the same radio frequency. The received signals $\mathbf{y}_l \in \mathbb{C}^{M_l}$ at each BS constitute one collected signal $\mathbf{y} \in \mathbb{C}^M$,

$$\mathbf{y} = \mathbf{h}_k \sqrt{p_k} s_k + \sum_{i \neq k, i \in \mathcal{K}} \mathbf{h}_i \sqrt{p_i} s_i + \mathbf{z}. \tag{1}$$

where $s_k \in \mathbb{C}$ denotes the unit-power (scaled-power) data symbol transmitted from the k-th user, and $\mathbf{z} \in \mathbb{C}^M$ denotes the receiver noise in the network, consisting of M independent Gaussian random variables with distribution $\mathbf{z}_l^{m_l} \sim \mathcal{CN}(0, \sigma^2)$.

For the intended signal from user k, the three terms on the right hand side of (1) correspond to signal, interference, and noise, respectively. If employing a simple linear reception strategy for single user detection (without successive interference cancellation), let $\mathbf{w}_{k,l} \in \mathbb{C}^{M_l \times 1}$ denote the beam vector used at the l-th BS specifically for the k-th user's signal. And the global beam vector for every user k can be defined as $\mathbf{w}_k \triangleq [\mathbf{w}_{k,1}^T, \mathbf{w}_{k,2}^T, ..., \mathbf{w}_{k,L}^T]^T \in \mathbb{C}^{M \times 1}$. The interference is directly treated as noise, and the received SINR from the k-th user can be expressed as

$$\mathrm{SINR}_k = \frac{\left|\mathbf{w}_k{}^T \mathbf{h}_k\right|^2 p_k}{\sum_{j\neq k}\left|\mathbf{w}_k{}^T \mathbf{h}_j\right|^2 p_j + \mathbf{w}_k^T \sigma^2 \mathbf{I}_M \mathbf{w}_k}, \forall k \in \mathcal{K}. \tag{2}$$

where the above SINR is the summation of signal strength outputs at different radio-frequency antennae. The data are then jointly decoded by the baseband units of the central radio resource management unit. The unit designs optimal network connectivity by allocating a single or multiple small BSs to each user, and jointly computes the power $\{p_k, \forall k \in \mathcal{K}\}$ and beamformer used for uplink $\{\mathbf{w}_k, \forall k \in \mathcal{K}\}$. The Macro BS here does not receive data from the users, but it sends the control signals. If the l-th BS is not informed by the Macro BS to serve some users, it is always in the sleep state to save energy.

In the physical layer, SINR is an important metric for helping to evaluate the link performance. Regardless of traffic type, a minimum SINR is required at the receiver for a minimum data rate to be supported. While the maintenance of such minimum SINR targets is well-justified for delay-sensitive users to achieve a certain transmission rate, it is also applicable to non-delay-sensitive users in order to achieve a desired bit error rate (BER). For each active user, the network should provide at least one small BS to serve and provide quality of service. Similar to many works, such as [8], [12], and [13], the QoS constraints refer to the requirements of signal-to-interference-and-noise ratio (SINR) as

$$\frac{\left|\mathbf{w}_k{}^T \mathbf{h}_k\right|^2 p_k}{\sum_{j\neq k}\left|\mathbf{w}_k{}^T \mathbf{h}_j\right|^2 p_j + \mathbf{w}_k^T \sigma^2 \mathbf{I}_M \mathbf{w}_k} \geq \Gamma_k^{\min}, \forall k \in \mathcal{K}. \tag{3}$$

2.2 Problem Formulation

According to the power consumption model of cellular BSs [8] [11], power consumption can be categorized into non-transmission power dissipations. Therefore, a constant can be ignored in the problem formulation, and transmission-related power consumptions include power amplifier costs and control overhead for coordinated processing.

We introduce the binary indicators $\{a_{k,l} \in \{0,1\}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}\}$ to represent the user-SBS association output, with $a_{k,l} = 1$ indicating that the l-th BS is assigned to the k-th user, and $a_{k,l} = 0$ is opposite. We can also define the global BS assignment vector for the k-th user as $\mathbf{a}_k \triangleq [a_{k,1}, a_{k,2}, ..., a_{k,L}]^T$. If $a_{k,l} = 0$, then the SBS is not receiving, and the equality $\mathbf{w}_{k,l} = \mathbf{0}$ shall hold. The total uplink transmission-related power consumption, denoted by P^{ToT} after the assignment, is now expressed as

$$P^{\mathrm{ToT}} = \underbrace{\sum_{k=1}^{K}\left(\Lambda_k p_k\right)}_{(a)} + \underbrace{\sum_{l=1}^{L}\left(\sum_{k=1}^{K} a_{k,l} P_{k,l}^{(CO)}\right)}_{(b)}. \tag{4}$$

This power consumption consists of two terms in equation (4), respectively corresponding to part (A) **User-side cost**: the power cost; and (b) **Network-side cost**: the control link cost for cooperative reception. In part (a), constant $1/\Lambda_k$ is the PA efficiency at user k. In part (b), $P_{k,l}^{(CO)}$ is the control link power cost from the Macro BS. The Macro BS has to inform the small BS by transmitting the association indicator through wired or wireless links. After we formulate and solve the problem in a distributed manner, we will further discuss whether there are extra control overheads introduced from the power and beamformer allocation, e.g., the distributed implementation of the algorithm needs to exchange channel state information and beamforms vectors at the local small BS.

To operate the HetNet in a power-efficient way, our goal is to minimize the overall power cost while ensuring the target QoS requirements for all K active users. Now, the design of dynamic SBS activation and cooperative receiver design can be formulated as one joint optimization problem:

$$\begin{aligned} \min \quad & P^{\mathrm{ToT}} \\ s.t. \quad & \mathrm{C1}: \sum_{l=1}^{L} a_{k,l} \geq 1, \forall k \in \mathcal{K} \\ & \mathrm{C2}: \mathrm{SINR}_k \geq \Gamma_k^{\min}, \forall k \in \mathcal{K} \\ & \mathrm{C3}: p_k \leq P_k^{\mathrm{MAX}}, \forall k \in \mathcal{K} \\ & \mathrm{C4}: \left\| \mathbf{w}_{k,l} \right\|_2^2 \leq a_{k,l}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L} \\ & \mathrm{C5}: a_{k,l} \in \{0,1\}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L} \end{aligned} \quad . \tag{5}$$

where C1 states that the active user should be accommodated, and C2 is the QoS constraints in which the instantaneous SINR threshold should be met to guarantee QoS. In [23], the authors consider another way to formulate the problem. They put QoS constraints on the outage probability. C3 is the transmission power with the path loss constraint for each user. C4 is the SBS-user association constraints to ensure the SBS can satisfy $\mathbf{w}_{k,l} = 0$ if $a_{k,l} = 0$ and can satisfy $\mathbf{w}_{k,l} = 1$ if $a_{k,l} = 1$. At first glance, the input parameters $\Gamma_k^{\min}, \mathrm{M}, \mathrm{K}$ will determine the feasibility of this optimization problem. We can guarantee the QoS requirements for all users, if we allocate enough antennae M and power. Here, we make the assumption that for K users in the set of $\Gamma_k^{\min}$, it is feasible for at least one connection. Then, all the users can access the network without using admission control. C1 is not a tight constraint and can be neglected in the formulation. To further justify this assumption, we can view the above problem as a general case of the classic beamforming problem. If we have a special case of predefined $\{a_{k,l}, \forall k, l\}$, then problem (5) is transformed into the classic beamforming problem [12] [16], where the feasibility condition is completely discussed based on the Perron-Frobenius theorem.

3. A Suboptimal but Fast Solution by Direct Decomposition

3.1 The Structure of Suboptimal Solution

The optimization problem (5) is obviously non-convex and NP-hard. Finding the optimal solution is challenging, especially in a large-scale cellular network. We first derive a suboptimal solution by direct decomposing the original problem into two separate subproblems as in **Fig. 2**. The total power consumption obtained by this suboptimal solution can be viewed as a benchmark, explicitly a reliable cost upper bound, used for subsequent near-optimal algorithms.

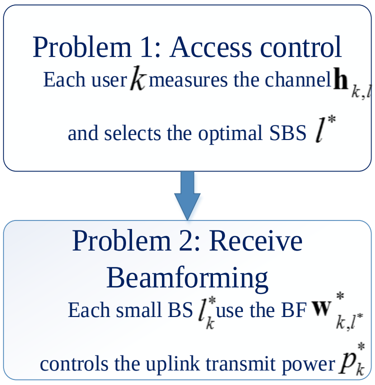

Fig. 2. To solve this intractable problem, the original problem is divided into two subproblems, and a two-stage optimization is derived.

We separately consider the user-SBS association and cooperative beamforming. The first stage is to select the optimal SBS to be associated. This is referred to the access control, which determines the connectivity of the network. The second stage is to obtain the cooperative beam vector with the associated SBS.

3.2 Detail Solution of Two-Stage Optimization

Consider the optimization variable $a_{k,l}$ in the first stage. For simplicity, each user selects the corresponding BS in a one-to-one ratio, only requiring one small BS to be accommodated.

$$\begin{aligned} &a_{k,l^*} = 1, \\ &l^* = \arg\max_{l \in \mathcal{L}} \left\| \mathbf{h}_{k,l} \right\|^2 . \end{aligned} \tag{6}$$

The above user-SBS association is following the "max-SINR" rule, a "greedy" selection. Each user picks the SBS that has the strongest signal strength. According to (6), a set of SBSs will be selected, and we need to design K reception filters even though the activated SBSs may be less than K. Once the connectivity is fixed, then $a_{k,l}$ is obtained and users start to transmit data.

The second stage is to select adjustable receiving beamformers and control the user's transmission power directly by each selected SBS. The above one-to-one association can reduce the beamformer into a low dimensional vector $\mathbf{w}_{k,l^*} \in \mathbb{C}^{M_\ell} \times 1$. Therefore, it simplifies the optimization of the second stage. By substituting the association result a_{k,l^*} into the original problem (5), problem (7) is derived.

$$\begin{aligned} \min_{\mathbf{w}_{k,l^*(k)},\mathbf{p}} \quad & \sum_{k=1}^{K} \Lambda_k p_k + \sum_{k=1}^{K} P^{(\mathrm{CO})}_{k,l^*(k)} \\ s.t. \quad & \frac{\left| \mathbf{w}^T_{k,l^*(k)} \mathbf{h}_{k,l^*(k)} \right|^2 p_k}{\sum_{j \neq k} \left| \mathbf{w}^T_{k,l^*(k)} \mathbf{h}_{j,l^*(k)} \right|^2 p_j + \mathbf{w}^T_{k,l^*(k)} \sigma^2 \mathbf{I}_M \mathbf{w}_{k,l^*(k)}} \geq \Gamma_k^{\min}, \forall k \in \mathcal{K} \end{aligned} . \tag{7}$$

Let us make the assumption that the consumption of control links for different data links is the same $P_{k,l}^{(CO)} = P^{(CO)}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}$. Then, in the second phase of the two-stage solution, the control link cost is directly proportional to the number of users. In other words, the term (b) of (4) in the objective function now becomes (7) and equal to $KP^{(CO)}$. This term is not influenced by the optimization variables, so it can be ignored for the above optimization problem (7).

In the second stage, the main objective is to balance multiple selected SBSs by beamforming and power control to achieve the link quality thresholds $\Gamma_k^{\min}$. The second-stage optimization is the well-known multi-cell beamforming for uplink. It has two approaches to derive the optimal beamformer and power: an iterative algorithm based on the Perron-Frobenius theory of nonnegative matrix theorem in [12][17]; and the second order conic program (SOCP) based on uplink-downlink duality [18][19]. We here solve it by reformulating the dual downlink beamforming.

$$\begin{aligned} \min_{\mathbf{w}_{k,l^*(k)}^{VDL}} \quad & \sum_{k=1}^{K} \Lambda_k \left\| \mathbf{w}_{k,l^*(k)}^{VDL} \right\|^2 \\ s.t. \quad & \frac{\left| \mathbf{h}_{k,l^*}^{H} \mathbf{w}_{k,l^*(k)}^{VDL} \right|^2}{\sum_{j \neq k} \left| \mathbf{h}_{k,l^*(j)}^{H} \mathbf{w}_{j,l^*(j)}^{VDL} \right|^2 + \sigma^2} \geq \Gamma_k^{\min}, \forall k \in \mathcal{K} \end{aligned} \quad . \tag{8}$$

Here w_{k,l^*}^{VDL} is the beam vector for the virtual downlink transmission and the real uplink transmission. The duality property states that the achievable SINR region $\{\Gamma_k^{\min}, k \in \mathcal{K}\}$ for a downlink channel with joint transmitter beamforming and power control is the same as that of an uplink channel with joint receiver beamforming and power control, under the same sum power constraint $\sum_{k \in \mathcal{K}} p_k^{\mathrm{UL}} = \sum_{k \in \mathcal{K}} \left\| w_{k,l^*}^{\mathrm{VDL}} \right\|^2$.

3.3 Distributed Beamforming and Power Control

By establishing a virtual downlink problem, we can further transform (8) into a standard SOCP problem for most of cases of practical use. Observing the representation of (8), any phase rotation of the beam vectors w_{k,l^*}^{VDL} does not affect both the objective function $\sum_{k=1}^{K} \Lambda_k \left\| \mathbf{w}_{k,l^*(k)}^{VDL} \right\|^2$ and the SINR constraints. Therefore, (8) can be reformulated as a standard SOCP problem after convex relaxation [14]

$$\begin{aligned} \min_{\mathbf{w}_{k,l^*}^{\mathrm{VDL}}} \; & \sum_{k=1}^{K} \Lambda_k \left\| \mathbf{w}_{k,l^*(k)}^{VDL} \right\|^2 \\ s.t. \; & \sqrt{\sum_{j \in \mathcal{K}} \left| \mathbf{h}_{k,l^*(j)}^{H} \mathbf{w}_{j,l^*(j)}^{VDL} \right|^2 + \sigma_k^2} \leq \sqrt{1 + 1/\Gamma_k^{\min}} \, \mathrm{Re}\{\mathbf{h}_{k,l^*(k)}^{H} \mathbf{w}_{k,l^*(k)}^{VDL}\}, \forall k . \\ & \mathrm{Im}\{\mathbf{h}_{k,l^*(k)}^{H} \mathbf{w}_{k,l^*(k)}^{VDL}\} = 0, \forall k \end{aligned} \tag{9}$$

Because we assume the SBSs are synchronized, we add the phase synchronization constraints in (9). Without them, there will be multiple beam vectors achieving the same optimal objective value. For asynchronous SBSs where there are time or frequency offsets, cooperative beamforming can still be applied to have cooperative diversity gains. Interested readers can refer to [26] [27].

The above problem can then be solved in polynomial time by the interior point method [20], and the solution of (9) will be employed to have the uplink receive a beamformer and power for each link $\{k, l^*(k)\}$:

$$\mathbf{w}_{k,l^*(k)} = \frac{\mathbf{w}^{VDL}_{k,l^*(k)}}{\left\|\mathbf{w}^{VDL}_{k,l^*(k)}\right\|};\ p_k = \left\|\mathbf{w}^{VDL}_{k,l^*(k)}\right\|.$$

To get the numerical result quickly, CVX, a package for specifying and solving convex programs [15], can be directly used. However, for practical implementation, we solve the problem (9) here in a decentralized fashion on stage 2.

As the problem (9) has K separate parts for both objective functions and constraints, we can decompose the convex SOCP (9) into individual subproblems. Thus, each user only needs to adjust its own power and beamforming vector according to the separate minimization problem.

For Each User Solve:

$$\begin{aligned} \min_{\mathbf{w}^{\mathrm{VDL}}_{k,l^*}} \quad & \Lambda_k \left\|\mathbf{w}^{VDL}_{k,l^*(k)}\right\|^2 \\ s.t. \quad & \sqrt{\sum_{j\in\mathcal{K}} \left|\mathbf{h}^H_{k,l^*(j)} \mathbf{w}^{VDL}_{j,l^*(j)}\right|^2 + \sigma_k^2} \le \sqrt{1+1/\Gamma_k^{\min}}\,\mathrm{Re}\{\mathbf{h}^H_{k,l^*(k)} \mathbf{w}^{VDL}_{k,l^*(k)}\}, \\ & \mathrm{Im}\{\mathbf{h}^H_{k,l^*(k)} \mathbf{w}^{VDL}_{k,l^*(k)}\} = 0. \end{aligned} \tag{10}$$

(9) and (10) has the same KKT-condition [19], so therefore they have equivalent solutions. It is observed that each user can measure the global channel vector $\{\mathbf{h}^H_{k,l^*(j)}, j \in \mathcal{K}\}$ in the above problem to adjust the beamforming vector. With the local measurement of current interference level $\sum_{j\in\mathcal{K}} \left|\mathbf{h}^H_{k,l^*(j)} \mathbf{w}^{VDL}_{j,l^*(j)}\right|^2$ caused to user k, it is not necessary to exchange local CSI to solve this problem. To sum up, we present the two-stage algorithm as follows in **Table 1**.

Table 1. Suboptimal Two-stage Algorithm

Algorithm 1

Initialization: Initialize uplink $\{a_{k,l}, \mathbf{w}_k, p_k, \forall k, \forall l\}$, set a very small constant ε.

Stage 1:

for i from 1 to K, $i \in \mathcal{K}$, each user **do**

Picks up the BS which has strongest signal strength,

obtain $l^*(k)$ and set $a_{k,l^*(k)} = 1$.

end for

Stage 2:

While $\left\|\{\mathrm{SINR}_i^{\mathrm{UL}}(\mathbf{w}_k, \mathbf{p}) - \Gamma_i^{\min}\}_{i\in\mathcal{K}}\right\|_2^2 \le \varepsilon$ **do**

Each user-SBS link solves the problem (10) to obtain $\mathbf{w}_{k,l^*(k)}$ and p_k.

end while

End Algorithm 1

4. A Near-Optimal Algorithm via Mixed Integer SOCP

We consider that if users are concentrated in one area, the two-stage optimization may cause congestion and will be more likely to result in an infeasible target SINRs. The user-SBS association of the first stage in the above algorithm does not connect with beamforming, missing the optimal user-SBS association strategy in certain scenarios. Therefore, we need to rethink the mixed integer programming problem, which is formulated as (5), that aims to research the user-SBS association strategy. However, problem (5) has a structure that is difficult to handle due to the integer user association variables. It is notorious for computational complexity, especially in large-scale networks. It drives us to derive a polynomial-time algorithm that is more efficient for the HetNet. Furthermore, we illustrate the distributed implementation of this algorithm.

The cooperative small BSs can be viewed as one virtual cloud-BS equipped with a large-scale number of antennae [24] [25]. In this virtual single-cell broadcast interference channel, we first introduce a new auxiliary variable I to represent the mutual interference, where $I_k^j \triangleq \mathbf{w}_k^T \mathbf{h}_j \in \mathbb{C}, \forall k, j \in \mathcal{K}$. Clearly, I_k^j is the interference level experienced at user k contributed by the user j, which is a linear mapping from $\mathbf{w}_k$. We further define new function to cost function as $g_k(p_k) = \Lambda_k p_k$ and $f_k(a_{k,l}) = \sum_{l=1}^{L} a_{k,l} = \left\|\mathbf{a}_k\right\|_0$. The L_0 norm here is defined as the number of nonzero components of $\mathbf{a}_k$. Just as in the two-stage solution, we make the assumption that the coordinated beamforming overhead for each data link is the same, which means $\{P_{k,l}^{(CO)} = P^{(CO)}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}\}$. Then, the original problem (5) can be equivalently expressed as

$$
\begin{aligned}
\min_{\mathbf{p}, a_{k,l}, \mathbf{w}_{k,l}} \quad & \sum_{k=1}^{K} \left(g_k(p_k) + P^{(CO)} f_k(a_{k,l}) \right) \\
s.t. \quad & \mathrm{C11.1:} \frac{1}{\Gamma_k^{\min}} |I_k^k|^2 \; p_k - \sum_{j \neq k} |I_k^j|^2 \; p_j \geq \sum_{l \in \mathcal{L}} a_{k,l} \sigma_k^2, \forall k \in \mathcal{K} \\
& \mathrm{C11.2:} \mathrm{Im}\{I_k^k\} = 0, \forall k \in \mathcal{K} \\
& \mathrm{C11.3:} \| \mathbf{w}_{k,l} \|_2^2 = a_{k,l}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L} \\
& \mathrm{C11.4:} a_{k,l} \in \{0,1\}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}
\end{aligned}
\quad . \qquad (11)
$$

where constraint $\| \mathbf{w}_{k,l} \|_2^2 = a_{k,l}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}$ is a tighter constraint compared to C4: $\left\|\mathbf{w}_{k,l}\right\|_2^2 \leq a_{k,l}$ in (5).

4.1 A Central and Global Solution

To solve this problem, we can employ the convex relaxation method to approximate it into a convex problem, and we do so by relaxing the integer value and constraints in (11). The original binary variables $a_{k,l}$ for any user or SBS become continuous optimization variables $\hat{a}_{k,l} \in [0,1]$. We call this integer relaxation, and after relaxation, the new continuous problem is obtained as:

$$\begin{aligned} \min_{\mathbf{p},\hat{a}_{k,l},\mathbf{w}_{k,l}} \quad & \sum_{k=1}^{K}\left(g_k(p_k)+P^{(CO)}f_k(\hat{a}_{k,l})\right) \\ s.t. \quad & \text{C11.1, C11.2} \\ & \|\mathbf{w}_{k,l}\|_2^2=\hat{a}_{k,l},\forall k\in\mathcal{K},\forall l\in\mathcal{L} \\ & \hat{a}_{k,l}\in[0,1],\forall k\in\mathcal{K},\forall l\in\mathcal{L} \end{aligned} \quad . \tag{12}$$

The objective function is now a linear function. The constraint C11.3 is obviously a second cone, and C11.1 with C11.2 can be formulated as

$$\sqrt{1+\frac{1}{\Gamma_k^{\min}}}\operatorname{Re}\{|I_k^k|\}\sqrt{p_k}\geq\left\|\left[|I_k^1|\sqrt{p_1},\ldots,|I_k^K|\sqrt{p_K},\sqrt{\sum_l\hat{a}_{k,l}}\sigma_k\right]\right\|_2,\forall k\in\mathcal{K}.$$

Therefore, the feasible set for $\mathbf{w}_{k,l}$, which was originally a disjunct set, now extends to a second order cone set. The MI-SOCP (11) is continuously relaxed into a convex problem to become the SOCP obtained in (12). Therefore, we can now solve this continuous problem (12) by some central path-following point method in polynomial time.

The optimal solution for problem (12) can be obtained as $\{\mathbf{w}_k^*,\mathbf{p}^*,\hat{a}_{k,l}^*\}$, and it will almost obtain a fully supported beamformer vector $\mathbf{w}_k^*$ from the SOCP solver. Each user selects the whole connected topology to have maximum antennae diversity, but a weighted value $\hat{a}_{k,l}^*$ for the SBSs selection $\hat{a}_{k,l}^*$ might be called as the cooperative probability for each active link k,l. After solving this convex SOCP, we can define the obtained optimal objective value as $\Omega_{relax}^*=\sum_{k\in\mathcal{K}}(\Lambda_k p_k^*+P^{(CO)}\sum_{l\in\mathcal{L}}\hat{a}_{k,l}^*)$ from the above relaxing continuous problem. Although this kind of direct relaxation of integer variables does not truly show the impact of the user-SBS association $a_{k,l}$, the total power consumption obtained Ω_{relax}^* can be viewed as a loose lower bound for the original problem (11). While the obtained objective power consumption from Section 3 can be viewed as an upper bound, we define it as Ω_1^*. Then, we denote the realistic total power consumption from the solution of MI-SOCP (11) as Ω^*. Ω^* must satisfy $\Omega^*\in[\Omega_1^*,\Omega_{relax}^*]$.

4.2 Distributed Solution through Dual Decomposition

The branch and cut (BnC) method is a commonly used algorithm for the mixed integer programming problem [21]. BnC involves running a branch and bound (BnB) algorithm and using cutting planes to tighten the region after continuous relaxation. When considering a minimization problem such as our problem (11), a node and its descendants (i.e., the subtree rooted at that node) can be removed from the BnC search tree if one of the following pruning conditions is satisfied: The optimal objective value of the SOCP continuous relaxation at the node is larger than the best-known objective value (i.e., the smallest upper bound) among the recorded integer-feasible solutions (deleting the node and the associated subtree).

We propose a distributed heuristic method that reduces the search complexity from that of BnC for MI-SOCP in the practical scenarios of large-scale L and middle-sized K. See **Fig. 3** for the detailed procedure.

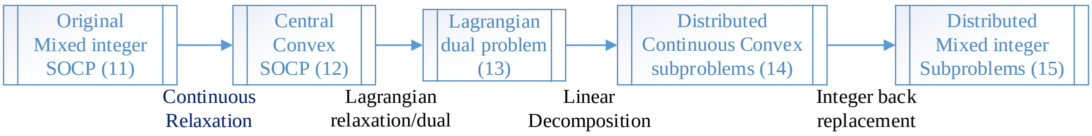

Fig. 3. The detailed procedure for the distributed implementation of MI-SOCP

We first transform the problem into the dual problem. The basic idea in Lagrangian duality is to take the constraints in (12) into account by augmenting the objective function with a weighted sum of the constraint functions. Introducing Lagrange multipliers λ_k and $\mu_{k,l}$ for each constraint, the transformed unconstraint problem can be written as

$$\begin{aligned}&\max_{\lambda_k,\mu_{k,l}}\ \min_{p_k,\hat{a}_{k,l},\mathbf{w}_{k,l}} \sum_k (\mathrm{g}_k(p_k)+\mathrm{P}^{(\mathrm{CO})} f_k(\hat{a}_{k,l}))+\\ &\sum_k \lambda_k(\sum_{j\neq k}|I_k^j|^2 p_j+\sum_{l\in\mathcal{L}}\hat{a}_{k,l}\sigma_k^2-\frac{1}{\Gamma_k^{\min}}|I_k^k|^2 p_k)+\sum_k\sum_l \mu_{k,l}(\|\mathbf{w}_{k,l}\|_2^2-\hat{a}_{k,l})\end{aligned} \tag{13}$$

Observing the above (13), this problem can be separated into K different problems using the linear differentiation operation.

$$\max_{\lambda_k,\mu_{k,l}}\ \min_{p_k,\hat{a}_{k,l},\mathbf{w}_{k,l}} \mathrm{g}_k(p_k)+\mathrm{P}^{(\mathrm{CO})} f_k(\hat{a}_{k,l})+\lambda_k(\sum_{j\neq k}|I_k^j|^2 p_j+\sum_{l\in\mathcal{L}}\hat{a}_{k,l}\sigma_k^2-\frac{1}{\Gamma_k^{\min}}|I_k^k|^2 p_k)+\sum_l \mu_{k,l}(\|\mathbf{w}_{k,l}\|_2^2-\hat{a}_{k,l}) \tag{14}$$

This means that each user, e.g., the k-th user, only needs to individually solve its own optimization problem. It is easy to derive the optimal result for the k-th user as $\{p_k^*,\mathbf{w}_k^*,\hat{a}_{k,l}^*\}$ and a power consumption lower bound Ω_k^* by solving distributed convex subproblems (14). Because of the (assumptive) feasibility and convexity, subproblem (14) and continuous problem (12) are equivalent. Then, replacing $\hat{a}_{k,l}\in[0,1]$ with $a_{k,l}\in\{0,1\}$, we have the K subproblem as

$$\begin{aligned}&\text{For User } k \text{ Solve:}\\ &\min_{\mathbf{p},a_{k,l},\mathbf{w}_{k,l}} && \Lambda_k p_k + P^{(CO)}\sum_l a_{k,l}\\ &s.t. && \frac{\Gamma_k^{\min}+1}{\Gamma_k^{\min}}|I_k^k|^2 p_k-\sum_{j\in K}|I_k^j|^2 p_j \geq \sum_{l\in\mathcal{L}} a_{k,l}\sigma_k^2,\\ &&& \mathrm{Im}\{I_k^k\}=0,\\ &&& \|\mathbf{w}_{k,l}\|_2^2\leq a_{k,l},\forall l\in\mathcal{L}\\ &&& a_{k,l}\in\{0,1\},\forall l\in\mathcal{L}\end{aligned} \tag{15}$$

To get high quality integer values of user-SBS association $a_{k,l}$ of the above subproblems (15), we develop a heuristic algorithm based on designed qualification indices. We define in this paper the qualification index measure, denoted by $\mathrm{QI}_{k,l}$, of assigning the l-th BS to serve the

k-th user, as:

$$\mathrm{QI}_{k,l} \triangleq \frac{\left|\mathbf{w}_{k,l}^{*T}\mathbf{h}_{k,l}\right|^2}{\Lambda_k p_k^* + P_{k,l}^{\mathrm{CO}}}. \tag{16}$$

This qualification index can be interpreted as the utility obtained for the k-th user to access the l-th SBS. The numerator in (16) is the receiving gain while the denominator is the power consumption. With this qualification index and $\{p_k^*, \mathbf{w}_k^*, \hat{a}_{k,l}^*, \Omega_k^*\}$, user k selects the associated SBS in sequence by an iteration algorithm. To describe this algorithm, we define n as the number of iterations of searching integer variables $a_{k,l}^*$, and $\mathcal{Q}_k(n)$ is the Small BS sets that are selected by the k-th user in the iterations. We summarize the complete description of the presented distributed joint user-SBS association and uplink beamforming algorithm in **Table 2**. It should be noted here that the computational complexity of the above algorithm is worst-case $n \le L-1$ times SOCP (14) for each user. Therefore, it is a low-complexity polynomial-time algorithm.

Table 2. Near-optimal Distributed SOCP Algorithm

Algorithm 2

Initialization: Initialize a full SBS set $\mathcal{Q}_k(0) = \mathcal{L}$ and accordingly $\{a_{k,l}(0) = 1, \forall k, \forall l\}$.

Step 2:

for user k from 1 to K **do**

solve (14) to obtain $\{p_k^*, \mathbf{w}_k^*, \hat{a}_{k,l}^*, \Omega_k^*\}$. Then calculate the association SBSs set $\{l \mid l \in \mathcal{L}, a_{k,l}^* \neq 0\}$, let $\mathcal{Q}_k(1) = \{l \mid l \in \mathcal{L}, a_{k,l}^* \neq 0\}$

end for

Step 3: start from $n = 1$

for user k from 1 to K **do**

for $l \in \mathcal{Q}_k^*(n)$ **do**

Calculate $l^* = \arg\min QI_{k,l}, l \in \mathcal{Q}(n)$,

Update the indicators $a_{k,l^*} = 0$.

Solve the problem (12) with substituting updated $\{a_{k,l}(n), \forall l\}$.

if problem (15) is infeasible or the optimal objective value $\Omega_k(n) > \Omega_k(n-1)$.

end iteration save current n.

end for

End Algorithm 2

5. Numerical Examples and Discussions

In this section, we test and compare the presented two solutions in a 7-cell cellular network with L = 70 small BSs, and we randomly pick up K = 7 users in the same frequency band. The distance between the centres of adjacent cells is set as 2000 meters. The macro BSs are located in the centre of the cell. We deploy the small BSs and users uniformly randomly in the two-dimensional area as in **Fig. 4**. Each user has the ability to sense and access all small BSs. The 3GPP log-distance path loss model is used here: $\mathrm{PL} = 128 + 37.6\ log10(d)$, with d (kilometres) denoting the user-BS distance. The shadow fading is a log-normal distribution with zero mean and 8 dB variance. The noise power at all receivers is set to −112.45 dBm, which corresponds to thermal noise at room temperature and a bandwidth of 180 kHz. Small scale Rayleigh multi-paths fading is zero mean and unit variance. We assume homogeneous parameter settings of small-cell networks and that all user equipment has the same power amplifier efficiency $\Lambda_k = 25\%$, a maximum power of 20 mw ($P_{\mathrm{MAX}} = 13\ dBm$), and target SINRs of $\{\Gamma_k^{\min} = 3dB, \forall k \in \mathcal{K}\}$. The simulation results presented are averaged over 500 Monte Carlo runs for both Algorithms 1 and 2. One hundred runs using CVX+Gurobi directly solves the mixed-integer problem (11).

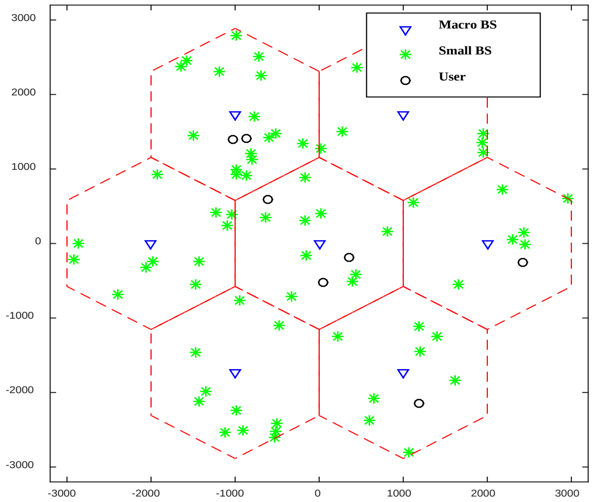

Fig. 4. A randomly generated network location of the Small Bss and users

We first illustrate the total power consumption of our proposed algorithms and set the convergence tolerance in Alg.1 as $\varepsilon = 10^{-5}$. It is difficult to quantify the amount of cooperation overhead $P^{(\mathrm{CO})}$. Because it depends on the detailed implementation of the distributed algorithm, we set it as an independent variable from 0 dBm to 10 dBm. Then, the overall transmitted power versus the system parameter $P^{(\mathrm{CO})}$ is displayed in **Fig. 5**. Fig. 5 draws four curves: the first curve is the power cost obtained from the continuous relaxation problem (12) and can be viewed as the lower bound for network power consumption, though it is not achieved in the actual networks. By using the optimization tools CVX+Gurobi, the optimal value for the association problem (5) is obtained, which has a tiny gap of about $2\% - 5\%$ power consumption compared to the first curve. The other two curves are from our proposed algorithms. The result of **Alg. 2** is very close to the second curve that uses CVX+Gurobi. The numerical results show that **Alg. 2** is more power efficient compared to **Alg. 1**, especially for low control overhead power of 0 dBm.

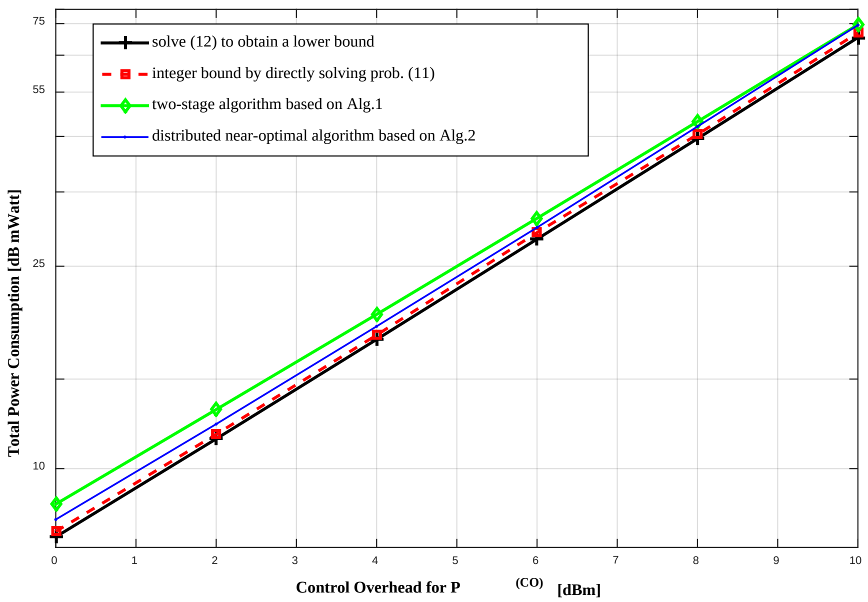

Fig. 5. Total Transmitted power vs. control overhead

The **Fig. 6** shows the average number of cooperative BSs using different central and distributed algorithms. Every user picks up cooperative SBSs to associate with in the coordinated multi-cell. The continuous relaxation problem will select full connectivity, while Alg.1 will select only one BS to access for each user. The average number of BSs that Alg.2 selects by applying Gurobi to the problem (7a) ranges from 5.4 to 32.7, as the power overhead P (CO) is increased from 0 to 10 dBm.

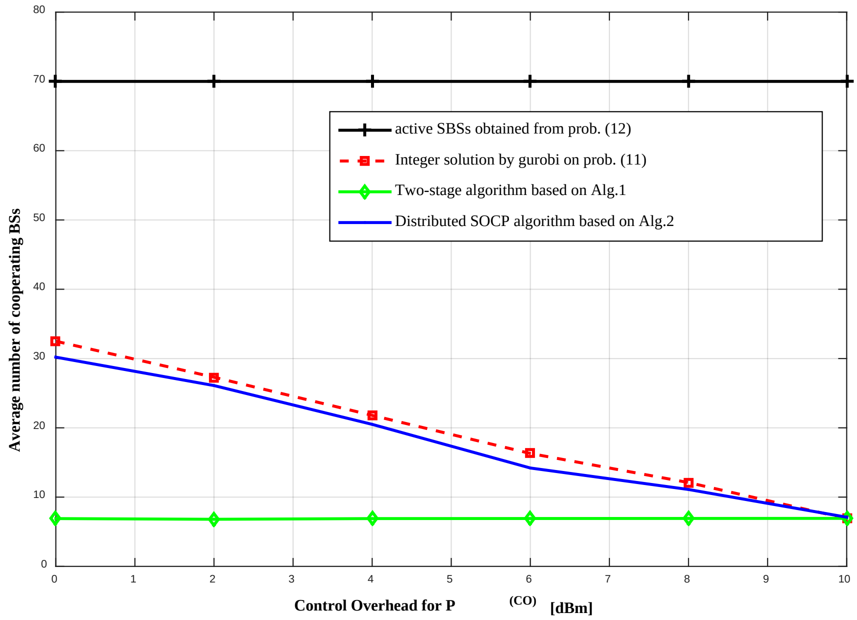

Fig. 6. Average number of BSs cooperated vs. control overhead

As displayed in **Fig. 7**, the run-time of different solutions are depicted. It is obvious that the proposed Alg. 1 consumes the least time among all the solutions. The proposed Alg. 1 and Alg. 2 also consume much less time than the Gurobi solver. The simulation is on the platform, the Pentium Dual-Core CPU 3.07GHZ and Gurobi 5.6.3. Because the computations of our simulations are completed on one computer, it is notable that the algorithm can further speed up in parallel implementation.

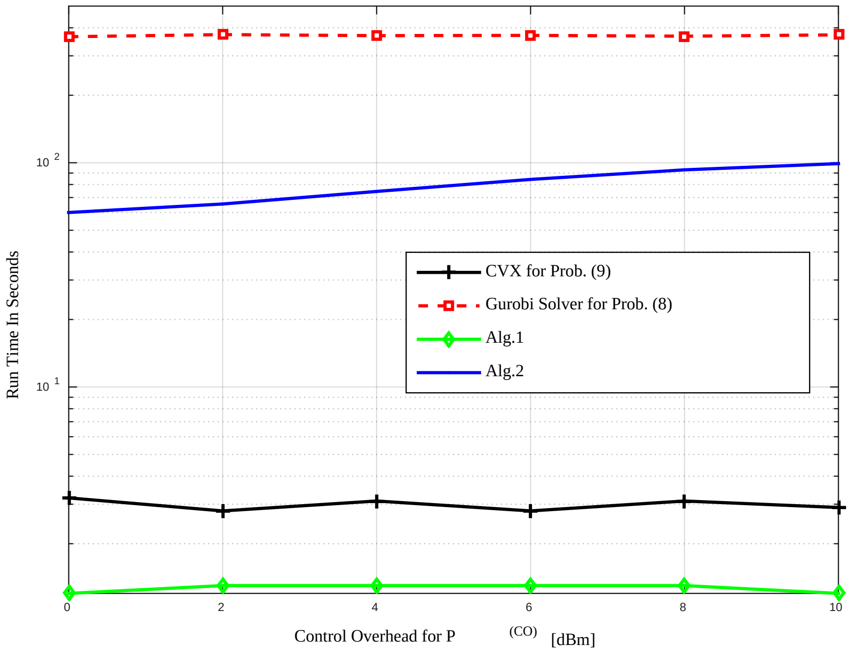

Fig. 7. Average run time consumption vs. control overhead

6. Conclusion

It is observed that the power consumption for data links is decreasing, along with a number of small BSs being activated because of the multiple antennae diversity gain. However, the overhead for control links consumption is increasing because of more active links in the networks. The basic question for coordinated receiving is how to achieve a good trade-off by activating the right number of small BSs for the user-base station association procedure. To address this problem, the network power cost is taken as the objective utility for designing association rules. Two polynomial-time distributed methods are presented to optimize both user-SBS association and receiver design. These two algorithms are computationally efficient, and are also cost efficient in power consumption, as a lower bound of power cost is also obtained by integer relaxation (a central SOCP). As base station activation is a fresh but important topic, it will be useful to explore this problem in more practical cases, such as a time-space correlation small-scale fading channel (like the channel model in this paper). Rethinking this problem in the case where only the imperfect statistical channel information state is available, the formulating optimization will be an objective function that averages power consumption and outage QoS constraints in future work.

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