Joint User Association and Resource Allocation in CoMP-Enabled Heterogeneous CRAN

Mohamed Labana and Walaa Hamouda
ECE, *Concordia University*, Montreal, QC, Canada
m_labana@ece.concordia.ca, Hamouda@encs.concordia.ca

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***Abstract*—In this paper, we consider jointly optimizing user association, resource allocation and power allocation in a two tier heterogeneous cloud radio access network (H-CRAN). Our objective is to utilize all the network resources in the most efficient way to maximize the network average throughput, while keeping some constraints such as the quality of service (QoS), interference protection to the devices associated with the Macro remote radio head (RRH), and fronthaul capacity. In our system, we propose using coordinated multi-point (CoMP) transmissions to utilize any excess resources to maximize the network performance. In contrast to the literature, in which CoMP is usually used only to support edge users. We divide our joint problem into three sub-problems: user association, radio resource allocation, and power allocation. We propose matching game based low complexity algorithms to tackle the first two sub-problems. For the power allocation sub-problem, we propose a novel technique to convexify the non-convex original problem to obtain the optimal solution. Given the conducted simulations, our proposed algorithms proved to enhance the network average weighted sum rate significantly, compared to the state of the art algorithms in the literature.**

***Index Terms*—coordinated multi-point, H-CRAN, matching game, resource allocation, user association.**

I. Introduction

With the developments in video broadcasting and virtual reality technologies, cellular data traffic is expected to continue growing exponentially over the years [1]. Moreover, due to emerging technologies such as automation and smart grid, it is expected that there will be billions of smart internet of things (IoT) devices operating by 2022 [2], in which all will need reliable network connections. These evolutionary expansions in different technologies has lead the researchers to think about new cellular network architectures that can face the new challenges. One of these proposed architectures is the cloud radio access network (CRAN), which is believed to have a great role in the 5G systems and beyond [1]. The CRAN architecture divides the base stations in the traditional cellular networks into remote radio heads (RRHs), which usually perform only the basic radio frequency functions; and baseband units (BBUs) that are aggregated in a centralized position. This architecture enables the centralized processing at the BBU pool which results in achieving much better network performance and lower power consumption, thanks to the statistical multiplexing gain.

Coordinated multipoint (CoMP) is a technique that enables serving a user by more than one base station in a cellular network. It helps to improve the network performance, such as enhancing the network throughput, increasing the coverage probability, and improving the quality of service (QoS) for the cell edge users [3].

In this work, we consider combining both emerging technologies. In particular, we consider a downlink heterogeneous H-CRAN system while implementing CoMP. We focus on jointly optimizing the user association, resource allocation, and power allocation to maximize the network throughput and utilize any available resources to enhance the network performance in the most efficient way.

The high ability of CoMP to cancel the inter-tier and intra-tier interference, and transferring the interfering signals into useful ones has driven many research works to start exploring how to use it to enhance the performance of CRAN networks. The authors in [4] solved the clustering problem through a cooperative bargaining game, while ensuring fairness amongst users. They utilized CoMP transmission in order to mitigate the interchannel interference (ICI). Nevertheless, their solution is only applicable to CRANs with high capacity fronthaul links. The clustering problem was also tackled in [5], in which a CoMP heuristic user association was proposed to maximize the energy efficiency. Their algorithm showed enhancement in the system energy performance when compared to the baseline nearest RRH user association scheme. However, they only focused on a single tier CRAN. In [6], authors proposed an algorithm to optimize the CoMP selection and resource allocation joint problem, where they considered only a single tier CRAN. The authors in [7] also considered the downlink power allocation problem in a single tier CRAN. They managed to reach the optimal solution but in a system model in which only one UE is served by multiple RRHs. Thus, there was no interference in their model, and the performance was only related to SNR.

Here, and different from previous works, we propose using generalized CoMP transmissions to utilize any excess resources in the network to obtain higher throughput. To the best of our knowledge, no research work considered solving a similar joint user association, resource allocation, and power allocation optimization problem in H-CRAN, while implementing CoMP. We propose matching game based low complexity algorithms to tackle the user association and resource allocation sub-problems. Matching game was also proposed in [8] to solve a similar optimization problem. However, CoMP was not supported in their proposed algorithms. Our user association algorithm proved to realize a good tradeoff between the cooperation gain and fronthaul consumption, to achieve a cooperation gain even in case of tight fronthaul constraints. Furthermore, we propose a novel approach to convexify the power allocation sub-problem to obtain an optimal solution.

The rest of this paper is organized as follows: in section II, we discuss the system model and formulate our problem; our proposed algorithms are presented in section III; the performance analysis and numerical results are investigated in section IV; and finally, our conclusions are drawn in section V.

II. System Model and Problem Formulation

We consider the downlink transmission in a H-CRAN with the architecture shown in figure 1. Our system model includes a Macro remote radio head (MRRH) associated with some users denoted as MUs, and belong to the set U^{MUs}. Within the area of the MRRH coverage, several Pico remote radio heads (PRRHs) are deployed to serve a set of devices denoted as PUs, and belong to the set U^{PUs}. The MRRH and the PRRHs are assigned the same orthogonal radio resources from the set $\mathcal{N} = 1, 2, 3..N$. All the RRHs are connected to a baseband unit (BBU) pool via fronthaul links.

It can be noticed that the devices served by different PRRHs will suffer high interference from the MRRH and the non-serving PRRHs that use the same radio resources. Consequently, we implement the CoMP transmission technique to ensure that the QoS is satisfied for the PRRHs users (PUs), and to utilize the additional resources to optimize the network performance.

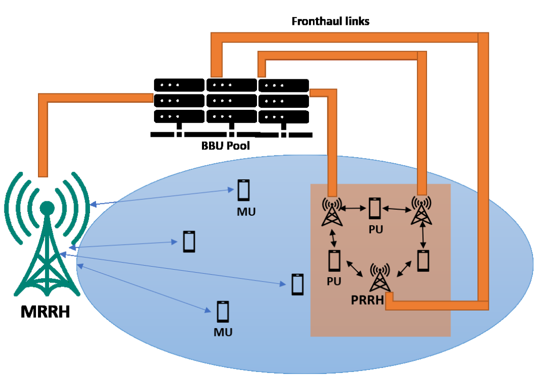

Fig. 1: Our Network Architecture

One of the great advantages of the CRAN architecture is that RRHs are connected to a central BBU pool, where computations can be done in a centralized manner; and hence, obtaining significant performance gain. Thus, in our model, the processing of all the proposed algorithms is performed at the BBU pool assuming perfect channel state information (CSI). The rate achieved by PU i on radio resource n:

$$R_i^n = B^n \log_2(1 + SINR_i^n) \tag{1}$$

where B^n is the bandwidth of radio resource n, $SINR_i^n$ is the signal to interference plus noise ratio received by PU i at n,

$$SINR_i^n = \frac{\sum_{j\in\Upsilon} y_{ij} P_j^n g_{ji}^n}{P_M^n g_{Mi}^n + \sum_{k\in\rho_n^i} P_k^n g_{ki}^n + \sigma^2}, \tag{2}$$

where i, j and n are the indices for PUs, PRRHs and radio resources, respectively; y_{ij} is the association coefficient, where $y_{ij} = 1$ if PU i is served by PRRH j, and $y_{ij} = 0$ otherwise; Υ is the set of PRRHs; the index M is used to denote the MRRH; P_j^n and P_M^n are the transmission powers of PRRH j and the MRRH on radio resource n, respectively; ρ_n^i is the set of PRRHs which use radio resource n and do not serve PU i. Finally, g_{ji}^n, and g_{Mi}^n are the channel gains on radio resource n between PU i and PRRH j or the MRRH, respectively.

To guarantee the required QoS, a constraint must be defined. Accordingly, the data rate assigned for each PU must be greater than or equal to a predefined threshold R_i^{min}. Thus,

$$\sum_{n\in\aleph} \propto_i^n R_i^n \geq R_i^{min}, \forall i \in U^{PUs} \tag{3}$$

where $\propto_i^n$ is the binary resource allocation coefficient. $\propto_i^n = 1$ only if the radio resource n is assigned to PU i. Another constraint must be set in order to protect the MRRH users (MUs) from the interference caused by the PRRHs. Consequently, the interference on the MU m that is allocated radio resource n must be less than a predefined threshold I_{m}^n.

$$\sum_{j\in\Upsilon} P_j^n g_{jm}^n \leq I_{\mathrm{m}}^n, \ \forall n \in \aleph, \ m \in U^{MUs}. \tag{4}$$

Additionally, we set a constraint to ensure that the sum of the achievable rates of the PUs associated with each PRRH j is less than the fronthaul capacity Ca_j^{PRRH}.

$$\sum_{n\in\aleph} \sum_{i\in U^{PUs}} \propto_i^n y_{ij} R_i^n \leq Ca_j^{PRRH}, \forall j \in \Upsilon. \tag{5}$$

Consequently, with an objective function to maximize the weighted sum rate of the network, our joint user association, resource allocation, and power allocation optimization problem can be formulated as follows:

$$\mathbf{P1}: max. \ (y, \propto, P) \sum_{j\in\Upsilon} \sum_{i \in U^{PUs}} \sum_{n\in\aleph} \propto_i^n \ R_i^n \tag{6}$$

s.t. (3), (4), (5),

$$\sum_{n\in\aleph} \propto_i^n \leq 1, \forall i \in U^{PUs} \tag{7}$$

$$P_j^{\min} \leq \sum_{n\in\aleph} P_j^n \leq P_j^{\max}, \ \forall \ j \in \Upsilon \tag{8}$$

$$y_{ij} = \{0, 1\} \tag{9}$$

$$\propto_i^n = \{0, 1\} \tag{10}$$

Note that the constraint (7) indicates that a user can only be assigned one resource block (RB). Nevertheless, such a RB can be served by numerous PRRHs, according to the network status. On the other hand, constraint (8) limits the total power of PRRH j to some maximum value. Finally, constraints (9), and (10) indicate that y_{ij} and $\propto_i^n$ are binary coefficients. Thus we can easily conclude that $\mathbf{P1}$ is NP-Hard problem, which is computationally intractable. Therefore, we consider a sub-optimal solution by dividing $\mathbf{P1}$ to three sub-problems considering the user association $(\mathbf{P1-UA})$, resource allocation $(\mathbf{P1-RA})$, and power allocation $(\mathbf{P1-PA})$, respectively.

$$\mathbf{P1-UA}\ max.\ (y) \sum_{j\in\Upsilon} \sum_{i\ \in U^{PUs}} R_i^n \tag{11}$$

s.t. (5), (9).

The first sub-problem will consider the user association using a many-to-many matching game [9] between PUs and PRRHs, while considering the fronthaul capacity constraint.

$$\mathbf{P1-RA}\ max.\ (\propto) \sum_{j\in\Upsilon} \sum_{i\ \in U^{PUs}} \sum_{n\in\aleph} \propto_i^n\ R_i^n \tag{12}$$

s.t. (4), (7), (10)

The second sub-problem that considers the resource allocation is solved using a many-to-many matching game between PUs and radio resources, while taking the interference protection on MUs into account

$$\mathbf{P1-PA}\ max.\ (P(\omega_n)) \sum_{i\in\omega_n} R_i^n. \tag{13}$$

s.t. (3), (4), (5), (8).

The third sub-problem is the power allocation, where ω_n is the set of PUs using radio resource n and their serving PRRHs. The power allocation sub-problem is in general non-convex. However, we will introduce an additional constraint to transform the problem to be a convex one. The additional constraint and the proof of convexity of the new problem will be discussed later on.

The fronthaul communications in CRAN architectures can be based on several technologies. For instance, wireless fronthaul networks were proposed based on microwave links, or WiFi standard in indoor environments [10]. Optical fiber based networks are always very efficient candidates due to their large capacities [10]. In many of these fronthaul network architectures, the transmission medium might be shared, especially among the RRHs serving at the same geographical area.

In what follows, it will be more convenient to reformulate the fronthaul capacity constraint as a sum fronthaul constraint. Thus, our new constraint can be represented as follows:

$$\sum_{i\in U^{PUs}} \sum_{n\in\aleph} \sum_{j\in\Upsilon} \propto_i^n y_{ij} R_i^n \leq Ca^{Total} \tag{14}$$

where Ca^{Total} is the total capacity of the fronthaul network.

III. Proposed Algorithms

In CRAN, all RRHS are connected to a centralized BBU pool, where our algorithms are assumed to be implemented, with PRRHs and PUs being mapped to virtual nodes. In the rest of this section we will discuss the matching game algorithms used to solve the user association and resource allocation sub-problems. Finally, we introduce our novel approach to convexify the power allocation sub-problem.

A. Many-to-many Matching Game Based User Association

We use a matching game based on the deferred acceptance scheme [9]. Our algorithm simply works as follows: each PU i proposes to be matched to its preferred PRRH j, which initially accepts the proposal if there is enough capacity to serve i in its fronthaul link, according to the minimum data rate needed for i, R_i^{min}. If there is not enough capacity, j starts to sequentially reject the previously initially accepted PUs which are less preferred than i until there is enough fronthaul capacity to admit i or there are not other PUs to reject. If the latter case occurs, i and all the rejected PUs will have to remove j from their preference lists, and the same should be done by j. These steps should be repeated multiple times until convergence is reached. Additionally, the whole previously mentioned steps should also be repeated while updating the preference lists to ensure that the already matched PUs will not be considered again for matching with PRRHs they are associated with. The outputs are the user association sets Θ_j, and Θ_i.

To determine the preferred PRRHs for each PU, the utility of each PU i with respect to each PRRH j (u_i^j) and the utility of each PRRH j with respect to each PU i (u_j^i) must be calculated. The result is applied as an input to the algorithm, where,

$$u_i^j = \log_2(1 + \sum_{n\in\aleph} SINR_{ij}^n) \tag{15}$$

$$u_j^i = \sum_{n\in\aleph} P_j^{max} g_{ji}^n. \tag{16}$$

Consequently, the preference list for each PU i (PL_i) is simply calculated by arranging the PRRHs in a descending order according to the values of u_i^j. The same process is done to calculate the preference list of each PRRH j (PL_j). Hence, each PU ranks PRRHs according to which will serve it with the highest rate, averaged on all radio resources. Also, each PRRH ranks PUs according to which will receive the highest power form it, averaged over all radio resources. During the user association and the radio resource allocation phases of our problem, the PRRHs will be virtually assumed to be operating with the maximum power P_j^{max}

When the fronthaul capacity is limited, we can approximately assume that the rates achieved by the PUs connected to a specific PRRH is tied by the capacity of its fronthaul. Thus, one can roughly approximate the initial rate that will be achieved by PU i from PRRH j as:

$$R_i^j = max(R_i^{min}, \frac{Ca_j^{PRRH}}{|\Theta_j|}) \tag{17}$$

where $|\Theta_j|$ is the number of PUs associated to PRRH j. Now assume that i is associated to some PRRHs $j_1, j_2, j_3...etc$. The rate achieved by i will be tied by the lowest rate it can achieve at $j_1, j_2, j_3...etc$, according to their fronthaul capacities, and the number of PUs associated to each. This rate can be initially approximated as:

$$R_i^{init} = min(R_i^{j_1}, R_i^{j_2}, R_i^{j_3}, ...). \tag{18}$$

Consequently, we can avoid cooperations that will actually lead to data rate loss based on the approximate equations (17), and (18). In algorithm I, the term Co is true only if a cooperation gain is expected. Thus, no PU will be associated with more than one PRRH, unless cooperation gain is guaranteed, or in the worst case, no performance degradation will occur.

B. Many-to-one Matching Game Based Resource Allocation

Regarding the resource allocation (RA) algorithm, it will follow procedures similar to the user association (UA) algorithm that is already explained in details in Algorithm I, and it is also based on deferred acceptance [9]. The utilities that will be input to the algorithm are:

$$u_n^i = \sum_{j\in\ \Theta_i^j} P_j^{max} g_{jm}^n \tag{19}$$

$$u_i^n = \log_2(1 + \sum_{j\in\ \Theta_i^j} SINR_{ij}^n) \tag{20}$$

$$u_n^j = P_j^{max} g_{jm}^n \tag{21}$$

$$u_i^{(n)(j)} = \log_2(1 + SINR_{ij}^n) \tag{22}$$

where u_n^i is the utility of each n with respect to each PU i which is equal to the interference caused on MU m (allocated radio resource n) by the PRRHs associated with i. u_i^n is, similarly, the utility of each PU i with respect to each radio resource n and is equal to the rate achieved on n using CoMP transmission from the associated PRRHs. u_n^j is the interference caused on MU m by PRRH j. $u_i^{(n)(j)}$ is the rate achieved by PU i when allocated radio resource n and associated with PRRH j.

In addition to the utilities, PL_n, PL_i, Θ_i , Θ_j should also be input to the resource allocation (RA) algorithm. In which PL_n^i, PL_i^n are the preference lists that can be obtained as explained before, and Θ_i, Θ_j are the user association sets obtained from Algorithm I.

Now we illustrate the operation of the RA algorithm. Firstly, matching is done between PUs and radio resources based on the interference caused by the PRRHs associated with i, according to the predefined interference threshold I_m^n. If a PU is initially accepted on a radio resource n, it competes with the PUs that were previously initially accepted on the same n and associated with the same PRRHs. The PU that achieves higher rate from each PRRH will be associated with it on radio resource n. If a PU losses all its associated PRRHs on a specific radio resource n, the radio resource will be removed from its preference list, and this PU will propose its second preferred n in the subsequent cycle. Additionally, all the utilities and preference lists should be updated after any change in the user association set. These steps will be repeated

Algorithm 1: Many to many matching user association

Input: $u_i^j,\ u_j^i,\ PL_i,\ PL_j,\ \ \forall j \in \Upsilon, i \in U^{PUs}$
1 **Initialize:** $t_1 = 0$, $t_2 = 0$, $\Theta_j(0) = \emptyset\ \forall j \in \Upsilon$, $Ca_j^{av} = Ca_j^{PRRH}$
2 **do**
3 $\quad t_1 \leftarrow t_1 + 1$
4 $\quad$ **for** $j \in \Upsilon$ **do**
5 $\quad\quad$ **for** $i \in U^{PUs}$ **do**
6 $\quad\quad\quad$ **if** $i \in \Theta_j(t_1)$ **then**
7 $\quad\quad\quad\quad u_i^j(t_1) = 0,\ u_j^i(t_1) = 0$
8 $\quad\quad\quad$ **else**
9 $\quad\quad\quad\quad u_i^j(t_1) = u_i^j(t_1 - 1)$, $u_j^i(t_1) = u_j^i(t_1 - 1)$
10 $\quad PL_i(t_1) = update(PL_i(t_1 - 1))$
11 $\quad PL_j(t_1) = update(PL_j(t_1 - 1))$
12 $\quad$ **do**
13 $\quad\quad \Psi_j = \emptyset\ \forall j \in \Upsilon$
14 $\quad\quad t_2 \leftarrow t_2 + 1$
15 $\quad\quad$ **for** $j \in \Upsilon$ **do**
16 $\quad\quad\quad$ **for** $i\ with\ j\ as\ its\ most\ preferred\ in\ PL_i$ **do**
17 $\quad\quad\quad\quad$ **while** $i \notin \Psi_j$ **do**
18 $\quad\quad\quad\quad\quad$ **if** $Ca_j^{av} \geq R_i^{min}$ **then**
19 $\quad\quad\quad\quad\quad\quad \Psi_j(t_2) \leftarrow \Psi_j(t_2) \cup i$, $Ca_j^{av} \leftarrow Ca_j^{av} - R_i^{min}$
20 $\quad\quad\quad\quad\quad$ **else**
21 $\quad\quad\quad\quad\quad\quad PL_j'(t_2) = \{i' \in \Psi_j(t_2)\ |i \succ_j i'\}$
22 $\quad\quad\quad\quad\quad\quad$ Remove least preferred $i' \in PL_j'(t_2)$ from $\Psi_j(t_2)$ till $(PL_j'(t) = \emptyset)$ Or $(Ca_j^{av} \leq R_i^{min})$
23 $\quad\quad\quad\quad\quad\quad$ **if** $Ca_j^{av} \geq R_i^{min}$ **then**
24 $\quad\quad\quad\quad\quad\quad\quad$ do step 19
25 $\quad\quad\quad\quad\quad\quad$ **else**
26 $\quad\quad\quad\quad\quad\quad\quad D_{Lp} \leftarrow i$, $z_j = \{z \in PL_j(t_2)\ |D_{Lp} \succ_j z\} \cup D_{Lp}$
$\quad\quad\quad\quad\quad\quad\quad$ **for** $z \in z_j$ **do**
27 $\quad\quad\quad\quad\quad\quad\quad\quad PL_i(t_2) = PL_i(t_2) \setminus \{j\}$ $PL_j(t_2) = PL_j(t_2) \setminus \{z\}$
28 $\quad$ **while** $\Psi_j(t_2) \neq \Psi_j(t_2 - 1),\ \forall j \in \Upsilon$
29 $\quad$ **for** $j \in \Upsilon$ **do**
30 $\quad\quad$ **for** $i \in U^{PUs}$ **do**
31 $\quad\quad\quad$ **if** $(i \in \Psi_j(t_1)) \cap (i \notin \Theta_j(t_1),\ \forall j \in \Upsilon)$ **then**
32 $\quad\quad\quad\quad \Theta_j(t_1) \leftarrow \Theta_j(t_1) \cup \{i\}$
33 $\quad\quad\quad$ **else if** $(i \in \Psi_j(t_1)) \cap (i \notin \Theta_j(t_1)) \cap Co$ **then**
34 $\quad\quad\quad\quad \Theta_j(t_1) \leftarrow \Theta_j(t_1) \cup \{i\}$
35 **while** $\Theta_j^i(t_1) \neq \Theta_j^i(t_1 - 1)$
Output: $\Theta_j, \Theta_i,\ \ \forall j \in \Upsilon, i \in U^{PUs}$

until convergence. The output from the RA algorithm will be the set κ_n containing the PUs assigned each radio resource n, and their serving PRRHs.

C. Power Allocation (PA) Algorithm

Given that the set κ_n was obtained by applying the user association and resource allocation algorithms, the power allocation problem can now be solved. We can write the objective function of our power allocation sub-problem as:

$$\sum_{n\in\aleph}\sum_{i\in\kappa_n} R_i^n = \sum_{n\in\aleph}\sum_{i\in\kappa_n} B^n \log_2(1+SINR_i^n) = \sum_{n\in\aleph}\sum_{i\in\kappa_n} B^n \log_2\Big(1+\frac{\sum_{j\in\tau_i} P_j^n g_{ji}^n}{P_M^n g_{Mi}^n + \sum_{j\notin\tau_i} P_j^n g_{ki}^n + \sigma^2}\Big) \quad (23)$$

where τ_i is the set of PRRHs serving PU i. To transform $(\mathbf{P1-PA})$ to a convex problem, we introduce an additional constraint. Thus, the resultant modified problem $(\mathbf{P1-PA})$ can be stated as follows,

$$\mathbf{P1-PA} \quad max.\ (P(\kappa_n)) \sum_{n\in\aleph}\sum_{i\in\kappa_n} R_i^n \quad (24)$$

s.t. (3), (4), (8),

$$P_M^n g_{Mi}^n + \sum_{j\notin\tau_i} P_j^n g_{ji}^n + \sigma^2 \leq \sum_{j\in\tau_i} P_j^n g_{ji}^n \quad \forall\, i\in\kappa_n, n\in\aleph. \quad (25)$$

Constraint (25) is simply stating that $SINR \geq 1$ for all the associated PUs. The proof of the convexity of $(\mathbf{P1-PA})$ is provided in the appendix. Since our new problem is convex, it can be solved with any of the well known convex optimization tools to obtain the optimal solution.

For the fronthaul capacity constraint in (5) to be satisfied, after applying the UA, RA, and PA algorithms, each PRRH checks the total rate of its associated PUs. Then PRRHs start to reject the ones with the smallest achievable rates until the constraint is satisfied.

It is important to note that, for the special cases when the fronthaul links are shared among the RRHs or the fronthaul capacity is unlimited, the same algorithms and steps are employed to solve the problem. However, in the user association algorithm, PUs can freely be associated with numerous PRRHs, as using CoMP will not result in overloaded fronthaul links. In contrast, it will help achieving much higher network throughput.

IV. Simulation Results

Our simulation model considers six PRRHs of a maximum transmission power of $20dBm$ placed inside the coverage area of a single MRRH with a constant transmission power of $46dBm$. The PRRHs and PUs are uniformly distributed at an indoor area of $300m^2$. The MUs are placed outdoors directly beside the $300m^2$ indoor area, in order to have the worst case inter-tier interference scenario. The MRRH and the PRRHs use the same orthogonal six radio resources, each of which is $180KHz$ bandwidth. We assume that each radio resource is already allocated to a MRRH user (MU), and that the

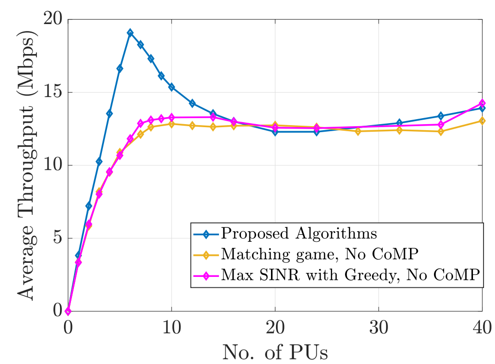

Fig. 2: Weighted sum rate of the network versus number of PUs- large fronthaul capacity

interference threshold of each of the six MUs is $-100dBm$. The noise power spectral density (PSD) is $-174\ dBm/Hz$. The wireless channel follows a Rayleigh fading model, with the path-loss and shadowing models implemented as [11]. The distance between the MRRH and the indoor area is $600m$.

In Fig. 2, we consider that our network has fronthaul links with unlimited capacity. Thus, constraints (5) or (14) are not taken into account. To assess the performance of our proposed algorithms, we compare the performance of our network while implementing three different settings:

- Our proposed generalized CoMP with matching game UA and RA algorithms
- No CoMP, user association is done with the high SINR algorithm, and resource allocation with greedy algorithm.
- No CoMP, with matching game UA and RA algorithms [8]

In the three settings, the optimal power allocation is obtained.

We can see that significantly higher throughput could be obtained with CoMP, as the excess resources are utilized to achieve much higher rate for the connected PUs. The network performance with CoMP tends to become closer to the non-CoMP algorithms as the number of the served PUs increases, due to the decrease in the available excess resources. Thus, when the network is overloaded, our generalized CoMP algorithm is equivalent to non-CoMP algorithms.

To assess the performance of our network in the case of limited capacity fronthaul, we consider the both cases of either individual or shared fronthaul links. The capacity of the shared fronthaul $Ca^{Total} = 9Mbps$. On the other hand, the capacity of each individual fronthaul link $Ca_j^{PRRH} = 1.5Mbps$. Fig. 3 represents the weighted sum rate of the network versus the number of served PUs. We can see that our proposed CoMP algorithms can achieve considerable gains even in the case of tight individual fronthaul constraints. This is due to the fact that our user association algorithm can create a good tradeoff between fronthaul consumption and cooperation gain.

To further assess the performance of our algorithms in more random environments, our parameters will be changed such that the PRRHs will be Poisson distributed with density

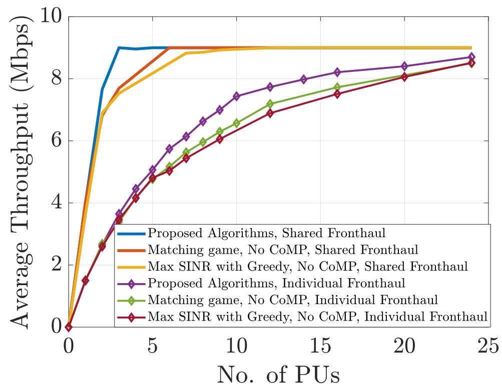

Fig. 3: Weighted sum rate of the network versus number of PUs- limited fronthaul capacity

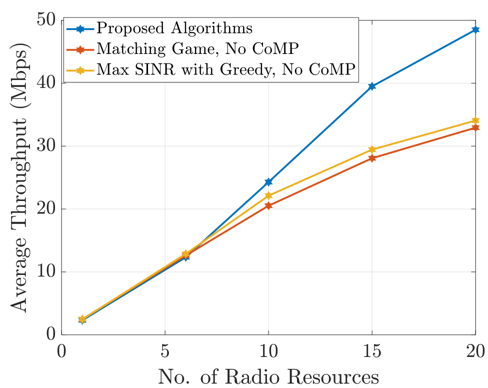

Fig. 4: Weighted sum rate of the network versus number of radio resources- large fronthaul capacity

$\lambda_{PRRH} = 6PRRHs$, and the PUs will also follow the same distribution with $\lambda_{PU} = 16PUs$. The efficiency of our generalized CoMP algorithm can be more realized from Fig. 4, in which the weighted sum rate of the network is plotted against the number of radio resources available for each PRRH. It can be seen that the performance of our CoMP algorithm is close to the non-CoMP algorithms when the number of available resources is small. However, as the number of available resources, and accordingly, excess resources increase, the throughput of the network becomes much higher when employing the proposed algorithms.

V. Conclusions

We proposed generalized CoMP in order to utilize any excess resources in the network to improve the throughput. The simulation results proved the significant improvements in the network performance when utilizing our proposed algorithms. The performance of our generalized CoMP scheme becomes more superior when excess radio resources and high capacity fronthaul links are available in the network. Moreover, our proposed user association algorithm proved to achieve cooperation gains even with very tight fronthaul constraints.

Appendix
Proof of Convexity of **P1-PA**

To prove the convexity of our maximization optimization problem, we need to prove that the objective function is concave, and inequality constraints are convex functions. For the objective function of **P1-PA** (equation 23), we can easily rewrite it as follows:

$$\sum_{n\in\aleph} B^n \sum_{i\in\kappa_n} \log_2\Big(\sum_{j\in\tau_i} P_j^n g_{ji}^n + P_M^n g_{Mi}^n + \sum_{j\notin\tau_i} P_j^n g_{ki}^n + \sigma^2\Big) + \log_2\Big(\frac{1}{P_M^n g_{Mi}^n + \sum_{j\notin\tau_i} P_j^n g_{ki}^n + \sigma^2}\Big) \quad (26)$$

Apparently, the first logarithmic term in the objective function, $\log_2(\sum_{j\in\tau_i} P_j^n g_{ji}^n + P_M^n g_{Mi}^n + \sum_{j\notin\tau_i} P_j^n g_{ki}^n + \sigma^2)$ is concave, while the second logarithmic term is convex. Thus, the sum of the two terms is generally neither concave or convex. However, if the additional constraint (25) can be satisfied and our problem is feasible, the first logarithmic concave term will be always greater that the second logarithmic convex term, and any increase in the second term will result in a higher increase in the first. Hence, the sum of the two logarithmic terms will be monotonically increasing in the feasible region, and consequently, concave. Since the sum of concave functions is also concave, our whole objective function is concave. Regarding the constraints, (3) can be easily proved to be a convex function in a similar way as above; while constraints (4), and (8) are clearly affine functions. Accordingly, **P1-PA** is a convex problem.

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