A Novel Joint Precoding and Association Optimization Framework for C-RANs with Restricted Fronthauls

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***Abstract*—Joint optimization of associations and precoders in wireless communication networks has become a crucial problem, due to the growing density of network infrastructure and users. Furthermore, network operators continue to show interest in improved energy efficiency and less power consumption. Due to the non-convex structure of the joint optimization problem, current methods and solvers struggle to offer satisfactory solutions. In the present paper, we provide a novel approach for joint optimization of the precoders and associations in a cooperative network with limited fronthaul capacity links. The proposed joint optimization method provides an iterative approximation of the original problem in the form of a mixed integer quadratic program (MIQP), solved via off the shelf numerical solvers. The second contribution of our work is a distributed hybrid association strategy, which serves as an alternative to the joint optimization framework. The performance of both methods is evaluated, suggesting that the proposed joint optimization framework can be used as a benchmark for other heuristic methods, due to its better performance and higher complexity. Meanwhile, the hybrid association strategy is deemed suitable for a distributed implementation in less computationally advanced networks.**

I. Introduction

With the continuous growth of mobile devices and services globally, the traffic load is set to increase 1000-fold in the next 10 years [1]. This leaves the network operators facing a difficult challenge in meeting these demands, as they also aim to lower their power consumption. With the spectral efficiency of the developed solutions nearing the Shannon limit, viable methods for improving services include multiple-input multiple-output (MIMO) antennas and dense heterogeneous networks [2]. However, managing the high density of both users and infrastructure leads to further complications. For instance, base stations (BSs) not only constitute a considerable portion of a networks' power consumption, but their performance is limited by their backhaul links. Furthermore, with the increasing number of users and overlapping cells, the association of the users in the interference limited network is by itself a major challenge. In this regard, the centralized cloud-radio access network (C-RAN) continues to emerge as a strong candidate for accommodating future network generations. By separating the baseband processing units (BBUs) from the remote radio heads (RRHs), the C-RAN allows for more efficient resource management and better supports dense networks. Furthermore, C-RAN brings forth vast opportunities to implement cooperative solutions, which are long known to have substantial gains. An example of this, directly involving associations, is coordinated multipoint-joint transmission (CoMP-JT), which thrives in interference limited networks.

Joint precoding and association optimization is an interesting open research problem, which comes at the cost of a non-convex, combinatorial structure. Therefore, existing works in literature often choose to neglect one component, in order to obtain a more desirable mathematical structure. The authors in [3] and [4], achieve this by assuming that the associations are already given. In other works, [5]–[7], heuristic solutions are offered to the joint optimization problem. The authors in [8] study joint precoding and association optimization in a heterogeneous network, while making use of BS sleep modes. However, their work does not take into consideration backhaul (in C-RAN referred to as fronthaul) limitations. Moreover, obtaining the optimal solution requires an exhaustive search over all possible BS mode combinations.

Our first contribution in this work is a novel iterative approximation framework for joint precoding and association optimization under limited fronthaul capacity. Note that there exists no similar work in the current literature, deploying such a method for this problem and using off the shelf solvers for joint precoding and association optimization of a C-RAN with restricted fronthaul links. The second contribution of this paper, is to extend our previous work on hybrid association strategies [7]. For this purpose, a distributed algorithm is proposed for setting the cooperation threshold values of the RRHs based on their fronthaul load. The centralized joint precoding and association optimization framework may serve as a benchmark for heuristic solutions, due to its lower power consumption and higher percentage of feasible solutions in high signal-to-interference-plus-noise-ratio (SINR) requirement scenarios. Meanwhile. the hybrid strategy presents a purely heuristic alternative with lower complexity, suitable for distributed implementation. It is also noteworthy that our defined system model allows for the number of RRH antennas, fronthaul capacity and power constraints to be defined individually.

Paper Organization: A description of the multi-user C-RAN system model is first presented. Next, we provide the description of the original optimization problem and explain our proposed iterative MIQP approximation optimization strategy. A distributed method based on the hybrid association is then presented. The convergence behavior and performance of both developed tech-

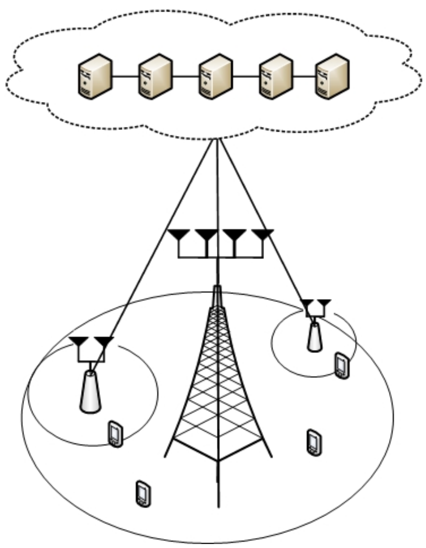

Fig. 1: A typical heterogeneous C-RAN architecture.

niques are investigated via Monte-Carlo simulations and a discussion is provided on their advantages and disadvantages. Lastly, we summarize the contributions of our work in the conclusion of this paper.

II. System Model

In this work we investigate a single cooperative heterogeneous C-RAN cluster operating in the downlink as depicted in Fig. 1. The cluster includes M_{RRH} RRHs, equipped with N_i transmit antennas and a maximum transmit power $P_{max,i}$, where i is the index of the corresponding RRH. There are M_{UE} co-channel single antenna users, each with an SINR requirement, denoted by γ_j, where j is the index of the corresponding user. The channel between the i-th RRH and the j-th user is indicated by $\mathbf{h}_{ij} \in \mathbb{C}^{N_i}$ and is assumed to adopt the uncorrelated block flat-fading model. The global channel vector of the j-th user may subsequently be shown by $\mathbf{h}_j \in \mathbb{C}^{N_{Tot}}$, where $N_{Tot} = \sum_i N_i$. Similarly, the concatenation of the individual precoding vectors, $\mathbf{w}_{ij} \in \mathbb{C}^{N_i}$, describe the global precoding vector of the j-th user, as $\mathbf{w}_j \in \mathbb{C}^{N_{Tot}}$. The fronthaul link connecting the i-th RRH to the BBUs, is assumed to have a maximum capacity denoted by C_i. In this work, we assume perfect channel state information (CSI) is available, although the model may be simply extended with minor modifications, in order to cater for imperfect CSI. For ease of mathematical notation, henceforth we let $\mathbb{K}_{UE}$ and $\mathbb{K}_{RRH}$ denote the set of users and RRHs, respectively.

With this, the signal model received by the j-th user can be shown as

$$y_j = \mathbf{h}_j^T \mathbf{w}_j x_j + \sum_{q \neq j} \mathbf{h}_j^T \mathbf{w}_q x_q + z_j,$$

where x_j is the uncorrelated complex zero mean data symbol transmitted for the j-th user, such that $\mathbb{E}\{|x_j^2|\} = 1$, and z_j is the complex additive white Gaussian noise (AWGN) with zero mean and variance σ_j^2. The achieved SINR for the j-th user is then given by

$$\frac{|\mathbf{h}_j^T \mathbf{w}_j|^2}{\sum_{q \neq j} |\mathbf{h}_j^T \mathbf{w}_q|^2 + \sigma_j^2}, \quad j \in \mathbb{K}_{UE}.$$

III. Optimization Model

A. Original Optimization Problem

In this section, we summarize the optimization strategy for minimizing the power consumption. The aim of the optimization problem is to satisfy the RRH fronthaul capacity constraints as well as the SINR demand of users, with the least overall transmit power possible. For the purpose of joint optimization, a binary association variable is introduced, denoted by α_{ij}. The association variable describes the connection between a user and an RRH as active or inactive. Furthermore, the association also has an influence on the fronthaul load, since an active association implies that the users' data must be present at the RRH. This allows the following representation of the optimization problem

$$\min_{\alpha_{ij}, \mathbf{w}_j} \quad \sum_j \|\mathbf{w}_j\|^2 \tag{1a}$$

$$\text{s.t.} \quad \sum_j \|\mathbf{w}_{ij}\|^2 \leq P_{max,i}, \quad i \in \mathbb{K}_{RRH}, \tag{1b}$$

$$\sum_j \alpha_{ij} \log_2(1+\gamma_j) \leq C_i, \quad i \in \mathbb{K}_{RRH}, \tag{1c}$$

$$\|\mathbf{w}_{ij}\|^2 \leq \alpha_{ij} P_{max,i}, \quad i \in \mathbb{K}_{RRH}, j \in \mathbb{K}_{UE}, \tag{1d}$$

$$\mathbf{w}_j^H \mathbf{H}_j \mathbf{w}_j - (\sum_{q \neq j} \mathbf{w}_q^H \mathbf{H}_j \mathbf{w}_q + \sigma_j^2)\gamma_j \geq 0, \quad j, q \in \mathbb{K}_{UE}, \tag{1e}$$

$$\alpha_{ij} \in \{0,1\}, \quad i \in \mathbb{K}_{RRH}, j \in \mathbb{K}_{UE}, \tag{1f}$$

where $\mathbf{H}_j = \mathbf{h}_j \mathbf{h}_j^H$ and C_i is the available fronthaul capacity normalized to the bandwidth. The objective, (1a), represents the total network power. Constraints (1b) and (1c), represent the power and fronthaul capacity constraints, respectively. Constraint (1d) formulates the relationship between association and precoding vectors, i.e., a user is not associated to an RRH should not be receiving any power. Lastly, the users' SINR constraints are represented in (1e). Unfortunately, the above problem is not mathematically tractable, due to the combinatorial nature imposed by the discrete association variable, while constraint (1e) represents a non-convex set.

B. Iterative Approximation

We propose an iterative inner approximation of the above problem, where at each iteration the approximated sub-problem is cast as an MIQP and solved via a numerical solver. As the first term in (1e) is problematic, we write its affine approximation, shown below

$$\begin{aligned} &\mathbf{w}_j^H \mathbf{H}_j \mathbf{w}_j \geq \\ &\mathbf{w}_j^{\circ H} \mathbf{H}_j \mathbf{w}_j^\circ + (\mathbf{w}_j - \mathbf{w}_j^\circ)^H \mathbf{H}_j \mathbf{w}_j^\circ + \mathbf{w}_j^{\circ H} \mathbf{H}_j (\mathbf{w}_j - \mathbf{w}_j^\circ) \\ &-(\sum_{q \neq j} \mathbf{w}_q^H \mathbf{H}_j \mathbf{w}_q + \sigma_j^2)\gamma_j \geq 0, \quad j, q \in \mathbb{K}_{UE}, \end{aligned} \tag{2}$$

where $\mathbf{w}_\mathbf{j}^\circ$ is the optimal global precoding vector found in the previous iteration. Substituting the above approximation for the constraint (1e), provides us with the MIQP sub-problem.

The general procedure is described in Algorithm 1, where $P_{t,i}$, is the transmit power of the i-th RRH in the initial step. The numerical solver Gurobi [9], is then capable of solving each MIQP iteration, with a margin of optimality by employing branch and bound methods.

C. Convergence

It can be stated that at each iteration, the approximation in (2) is tight and leads to a global lower bound of the left hand side. With the monotonic improvement of the objective at each iteration, and the fact that the problems' objective is lower bounded from below by zero, the proposed iterative approximation leads to a necessary convergence. However, the resulting converging point is not necessarily the global optimum, due to the combinatorial and non-convex nature of the original problem. Numerical evaluation of the convergence behavior and the resulting performance of the proposed solution is given in Section V.

D. Initialization

For the initialization, a relaxed version of the problem is solved; with no fronthaul constraints, using a simple precoder, i.e., maximum ratio transmission (MRT) [10]. An equal power allocation is assumed in order to construct $\mathbf{w}_\mathbf{j}^\circ$ for the first iteration.

Algorithm 1 MIQP iterative approximation

1: **Initialize**: Associate to closest RRH
2: $\mathbf{v}_{ij} \leftarrow \frac{h_{ij}^*}{\|h_{ij}\|} \quad \forall i, j$
3: $P_{t,i} \leftarrow \frac{P_{max,i}}{\sum_i \alpha_{ij}} \quad \forall i$
4: $\mathbf{w}_{ij}^\circ \leftarrow \sqrt{P_{t,i}}\mathbf{v}_{ij}$
5: Solve a relaxed problem
6: **Repeat**
7: Solve approximated MIQP
8: **Until** Convergence
9: **Return** $\mathbf{w}_j, \alpha_{ij}$

IV. Cooperation Based on Hybrid Association

In this section we provide an extension to our previous work [7], which combined precoding optimization with a hybrid association strategy. Since the technique offered in the aforementioned paper separates the association problem from precoding optimization, by heuristically defining the associations, it represents a good case of comparison to the novel joint optimization method proposed in Section III. The hybrid association strategy proposed taking into consideration the distance of the link as well as the total resource (transmission power) available at the RRH, when defining associations. A hybrid quality indicator was defined, based on the ratio between the power constraint of the RRH ($P_{max,i}$), and the distance of the link (d_{ij}) raised to the power of the path loss exponent (ρ). This was done in provision of better load balancing, which is an important notion for limited fronthaul scenarios. The association of the j-th user was determined by taking the ratio of the quality indicators to the best link and comparing that ratio against a cooperation threshold, denoted by θ_i. For further details on the approach, we refer the reader to the original paper. With the hybrid association showing great potential in improving the energy efficiency performance of the network, we propose an iterative algorithm for setting the desirable θ_i values. The cooperation threshold, of the i-th RRH, is iteratively increased if its fronthaul constraint is violated. This results in a reduction in the number of users associated to the RRH and hence, lowering its fronthaul load. The power consumption is then minimized with the new associations, using the semidefinite programming relaxation (SDR) framework in [11], as shown below

$$\min_{\tilde{\mathbf{W}}_j} \quad \sum_j \mathrm{tr}(\tilde{\mathbf{W}}_j) \tag{3a}$$

$$\text{s.t.} \quad \sum_j \mathrm{tr}(\mathbf{\Pi}_i \tilde{\mathbf{W}}_j \mathbf{\Pi}_i) \leq P_{max,i}, \quad i \in \mathbb{K}_{RRH}, \tag{3b}$$

$$\mathrm{tr}(\mathbf{\Pi}_i \tilde{\mathbf{W}}_j \mathbf{\Pi}_i) \leq \alpha_{ij} P_{max,i}, \quad i \in \mathbb{K}_{RRH}, j \in \mathbb{K}_{UE}, \tag{3c}$$

$$\mathrm{tr}(\mathbf{H}_j \mathbf{W}_j) - \tag{3d}$$
$$(\sum_{q \neq j} \mathrm{tr}(\mathbf{H}_j \mathbf{W}_q) + \sigma_j^2)\gamma_j \geq 0, \quad j, q \in \mathbb{K}_{UE},$$

$$\tilde{\mathbf{W}}_j \succeq 0, \quad j \in \mathbb{K}_{UE}, \tag{3e}$$

$$\mathrm{rank}(\tilde{\mathbf{W}}_j) = 1, \quad j \in \mathbb{K}_{UE}, \tag{3f}$$

where $\tilde{\mathbf{W}}_\mathbf{j}$ is the transmit covariance matrix of the j-th user, while $\mathbf{\Pi}_i$ is merely an identity matrix designed to select the antennas corresponding to the i-th RRH. By dropping the rank constraint (3f), a relaxation of the above problem is obtained holding a complex-valued semidefinite programming structure. The relaxed problem may then be solved via numerical solvers, e.g., SeDuMi or SDPT3 [12]. Note that if $\mathrm{rank}(\tilde{\mathbf{W}}_j^*) = 1$ holds true for the obtained solutions, then the solutions of the relaxed problem are also the optimal solutions to the problem (3a)-(3f). However, it should be noted that since, an optimal solution of rank one is not in general guaranteed, a general rank covariance matrix may also be implemented via space time block coding schemes, such as [13]. Furthermore, it is worth mentioning that studies on rank constraint solutions for the above problem, i.e., [14], suggest that an optimal rank one solution is available if

$$|\upsilon| + 3 > |\zeta| \tag{4}$$

where υ and ζ denote the number of variables and constraints of the problem respectively and can are calculated as shown below

$$\upsilon = |\mathbb{K}_{UE}|, \tag{5}$$

$$\zeta = |\mathbb{K}_{UE}| + |\mathbb{K}_{RRH}| + (|\mathbb{K}_{UE}||\mathbb{K}_{RRH}|). \tag{6}$$

Note that the aforementioned condition (4) does not imply that an optimal rank one solution is attainable for any setup, but merely describes the setups for which the relaxation is tight. Furthermore, since the product term in equation (6) results from constraint (3c), we provide a equivalent reformulation, which reduces the number of constraints and hence, increases the number of possible setups that satisfy the rank one constraint. The formulation below is equivalent to constraint (3c)

$$\sum_{ij}(1-\alpha_{ij})\,\mathrm{tr}(\mathbf{\Pi}_i\tilde{\mathbf{W}}_j\mathbf{\Pi}_i) \leq 0 \tag{7}$$

with the above formulation, it is possible to reduce the number of constraints to the following

$$\zeta = |\mathbb{K}_{UE}| + |\mathbb{K}_{RRH}| + 1 \tag{8}$$

Lastly, it must also be stated that even in the case the above conditions do not hold and the optimal solution is not rank one, the obtained optimal covariance matrix has a leading eigenvalue. This allows a well approximated rank-one solution to be obtained by rank reduction via singular value decomposition.

It must be noted, that in the proposed hybrid strategy, the fronthaul constraints and associations are essentially moved from the optimization problem to the algorithm. This is in contrast to the MIQP framework, which carries out joint optimization. In the initial state of the proposed hybrid strategy, the SDR optimization problem is solved in full cooperation mode, where all the users are associated to all the RRHs. The fronthaul constraints are then checked for violation, and if so the cooperation threshold of the RRH is increased, in order to reduce the number of users associated, thus reducing its fronthaul load. The cooperation threshold can be calculated as per RRH with the equation below

$$\theta_i = 1 - exp(-\tau_i(\frac{FronthaulConsumption_i}{C_i})) \tag{9}$$

where τ_i grows for each iteration that does not satisfy the fronthaul constraint. Note that the update function for the algorithm should monotonically increase the cooperation threshold from zero to one. However, the growth of τ_i can be left up to the given scenario, for instance smaller increments would result in the fronthaul constraint being satisfied more tightly at the expense of slower convergence. The details of the algorithm are presented in Algorithm 2, while numerical evaluation of its convergence is demonstrated in Section V.

V. Simulation Results & Discussion

In this section, we investigate the performance of the described iterative MIQP approximation joint optimization framework and the hybrid strategy via Monte-Carlo simulations, using 500 feasible realizations. The simulation scenarios are setup to follow the 3GPP LTE specification [15]. The simulated model consists of three RRHs, each equipped with two antennas and uniformly distributed in a single cluster. Four single antenna users populate the cluster with uniform distribution. The channel model between the i-th RRH and j-th user, is comprised of large scale fading and small scale fading. The large scale fading consisting of both path loss and shadowing, whilst the small scale fading follows a complex Gaussian distribution with zero mean and unit variance. Table I describes the rest of our simulation setup along with the other system parameters.

Algorithm 2 Distributed hybrid association algorithm

Initialize: Full cooperation, $\theta_i \leftarrow 0.01, \alpha_{ij} \leftarrow 1 \quad \forall i,j$
$\Phi_{ij} \leftarrow \frac{P_{max,i}}{d_{ij}^{\rho}} \quad \forall i,j$
$\beta_j \leftarrow \max(\mathbf{\Phi_j}) \quad \forall j$
while Any fronthaul constraint violated **do**
  if $\frac{\Phi_{ij}}{\beta_j} < \theta_i$ **then**
    $\alpha_{ij} \leftarrow 0$
  end if
  Increase τ_i
  Update θ_i using (9)
  Solve (3a)-(3e)
end while
Return $\tilde{\mathbf{W}}_j, \alpha_{ij}$

TABLE I: Simulation Parameters

Parameter	**Settings**
Carrier Frequency	2GHz
Bandwidth	10MHz
Cluster Radius	250m
Maximum Transmission Power	40dBm
Path Loss (dB), d[km]	LOS: $103.4 + 24.2\log_{10} d$ NLOS: $131.1 + 42.8\log_{10} d$
LOS Probability, d[km]	$\min(\frac{0.018}{d}, 1)(1-\exp(-\frac{d}{0.063}))$ $+\exp(-\frac{d}{0.063})$
Shadowing	8dB
Noise level	-164dBm/Hz

For the implementation of the distributed algorithm, the path loss exponent is set to $\rho = 3$. As the cooperation threshold should be a low value for the first iteration, in order to impose full cooperation mode, we set $\theta_i = 0.01$. Furthermore, our choice of update function for increasing τ_i is simply, $\tau_i = 5\tau_i$, however, this can be left up to the individual scenario.

The convergence of the iterative MIQP approximation optimization framework is displayed in Fig. 2, with a fronthaul capacity of 75 Mbps. Since the hybrid association algorithm aims to find associations such that the fronthaul constraints are satisfied, its convergence behaviour is studied with the average RRH fronthaul load as shown in Fig. 3. With an individual fronthaul capacity constraint of 75 Mbps. It can be seen that in the case of three users, the fronthaul constraints are satisfied and hence the hybrid association strategy equates to full cooperation. It is worth clarifying that the reason behind the converged fronthaul load being less than the constraint is that the average is used, which essentially includes instances where an RRH was not connected to any users, hence lowering the average load. The resulting power consumption behavior of the distributed algorithm is investigated in Fig. 4, where it can be seen that the power increases until convergence. This is due to the fact that, as the algorithm reduces cooperation in a bid to reduce the fronthaul load, the RRHs satisfy the SINR demands by increasing the transmitted power. A preliminary comparison between Fig. 2 and Fig. 4, shows the difference between the power consumption of the two approaches at the point of convergence. It can be observed that the hybrid strategy consumes 16% more power relative to the proposed joint optimization approach. It can also be observed that having the RRHs equipped with more antennas can reduce power consumption. Furthermore, for both proposed methods, the complexity of the system does not significantly impact the number of iterations required for convergence. Instead, the complexity can be seen to have an impact on the iteration time as presented in Table II. An advantage of the hybrid strategy is the faster convergence time, due to the efficiency of the SDR framework. The convergence studies indicated that the average iteration time for the MIQP approximation joint optimization framework is more greatly affected by the complexity of the system, where the simulations were carried out in MATLAB, with a single core 2 GHz processor. These findings suggest that the joint optimization may be used in more computationally powerful networks or serve as a benchmark to distributed heuristic methods, which are solved more efficiently. The difference in implementation of the two approaches is also noteworthy, the hybrid strategy allows the RRHs to decide their level of cooperation based on their fronthaul load, while with the joint optimization framework all the decisions will be carried out at the central unit.

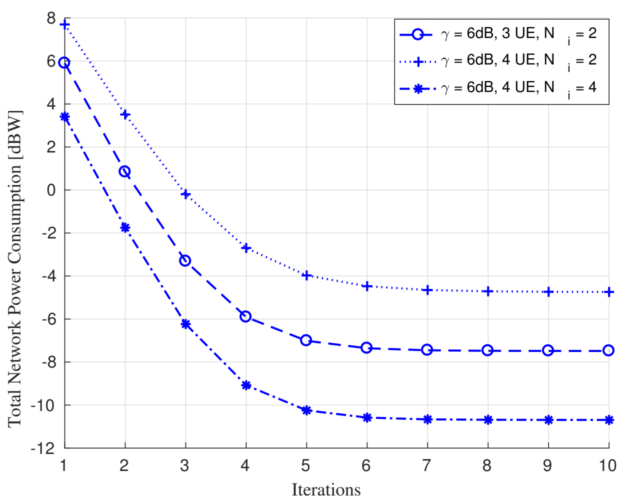

Fig. 2: Network power consumption vs. iterations. Convergence of the joint optimization framework, where $C_i = 75$ Mbps.

TABLE II: Iteration time vs. complexity

	Average Iteration Time (s)	
Complexity	**Hybrid Strategy**	**Joint Opt**
$M_{UE} = 3, N_i = 2$	0.94	1.17
$M_{UE} = 4, N_i = 2$	1.62	3.05
$M_{UE} = 4, N_i = 4$	2.45	6.21

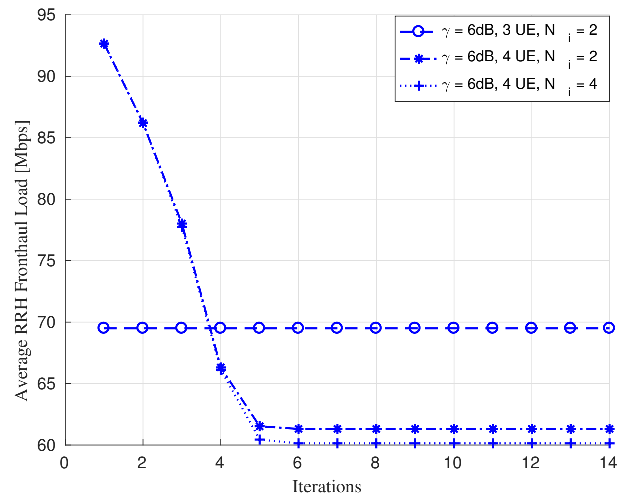

Fig. 3: Average RRH fronthaul load vs. iterations. Convergence of the hybrid association strategy framework, where $C_i = 75$ Mbps.

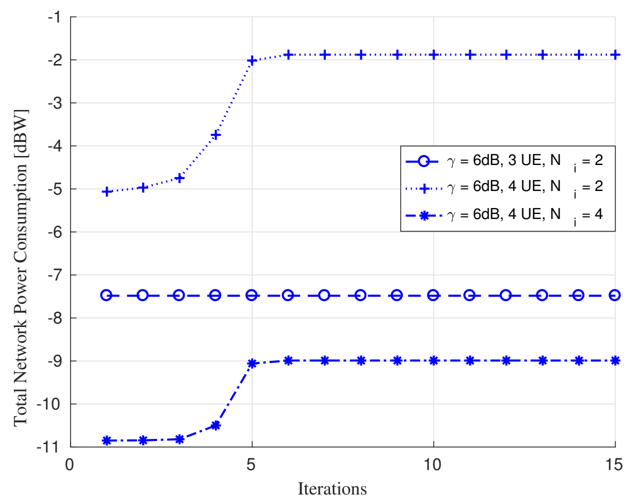

Fig. 4: Network power consumption vs. iterations. The overall power consumption, using the hybrid association strategy framework, increases as less cooperation is compensated by higher transmit powers, where $C_i = 75$ Mbps.

Henceforth, we refer to the proposed iterative MIQP approximation joint optimization framework as "Joint Opt", since cooperation and subsequently the associations are left entirely up to the framework. The hybrid strategy, indicated by "Hybrid Strategy", serves as a good representation of approaches in literature which propose a heuristic algorithm for determining the associations, complemented by an efficiently solvable optimization problem i.e., SDR power minimization. Two more common heuristic methods are provided for the purpose of comparison, named "Single Association" and "Full CoMP", which represent association to their nearest RRH and full cooperation (association to all RRHs), respectively. Furthermore, these two conventional methods represent two extremes in terms of the incurred fronthaul load, with single association imposing the least and full cooperation the most.

In Fig. 5. the total network power consumption of all strategies were investigated, with varying SINR requirements, neglecting results with less than 70% feasibility. It is clearly evident that not only does the Joint Opt outperform other solutions, but it is able provide more feasible solutions for high SINR demands. In contrast, single RRH association and full cooperation fall short in supporting high SINR requirements, due to the effect of heavy interference and limited fronthaul capacities, correspondingly. Considering that the heuristic methods are all solved via the SDR framework, the differences in their performance highlights the impact of associations on the system performance and subsequently, the potential performance gains of the proposed joint optimization framework.

Lastly, Fig. 6. studies the feasibility performance of different methods. It can be seen that for the two conventional methods, single association and full cooperation, an increase in SINR requirement results in a rapid reduction of the percentage of feasible realizations. In contrast the two proposed methods are able to sustain a high percentage of feasibility for much longer. Note that this can be regarded as an important metric of performance as it indicates the frameworks' ability to provide feasible precoding and association solutions for different realizations. It is also evident that the joint optimization framework outperforms all others by providing more feasible solutions even when the users SINR requirements are high.

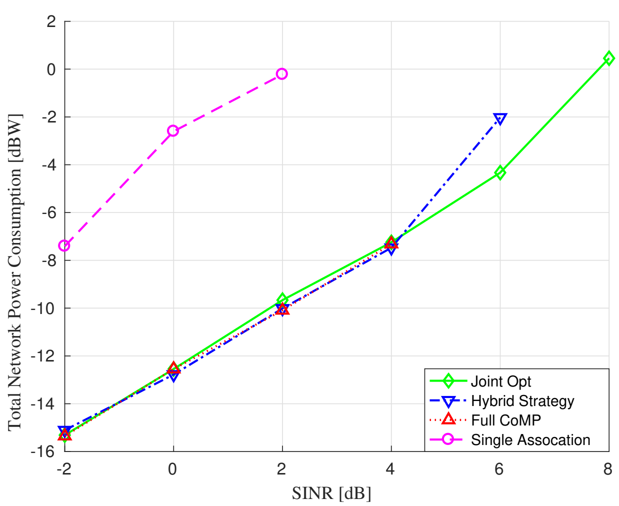

Fig. 5: Network power consumption vs. SINR. Joint Opt outperforms other methods and is able to support higher SINR requirements, where $C_i = 75$ Mbps.

VI. Conclusion

In this work, we have offered a novel approach towards joint precoding and association optimization of C-RAN networks with limited fronthaul links. The developed framework jointly determines the precoders and associations, while minimizing the networks' power consumption. Therefore, providing an indispensable tool for improving the performance of future generation networks. Additionally, a faster distributed heuristic algorithm is developed, providing an alternative for less computationally advanced networks. Simulation results prove that the proposed joint optimization framework outperforms other techniques, in consuming less power as well as offering more feasible realizations at high SINRs, and can serve as a benchmark to other heuristic solutions, especially when the fronthaul capacities are limited.

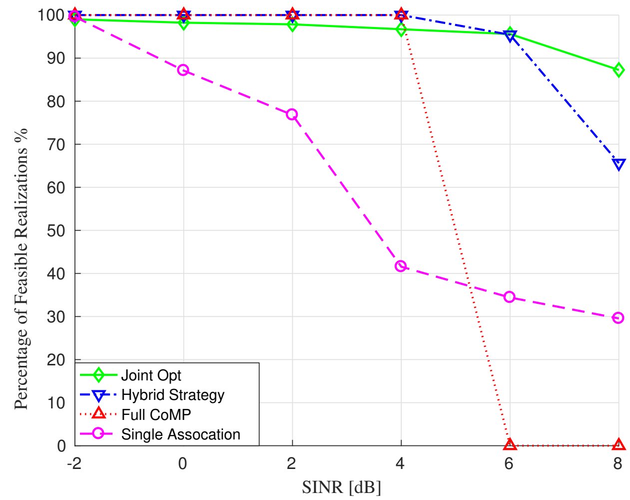

Fig. 6: Percentage of feasible realizations vs. SINR. The percentage of feasible realization scenarios drops rapidly for conventional methods, while the Joint Opt is able to sustain a reasonably high level, where $C_i = 75$ Mbps.

Acknowledgements

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