A Novel User Association and Power Control Algorithm for Cell-free Massive MIMO

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A Novel User Association and Power Control Algorithm for Cell-free Massive MIMO

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***Abstract*—The vision of Industry 4.0 relies on advancements in wireless solutions; cell-free Massive Multiple Input Multiple Output (cf-mMIMO) is emerging as a promising physical layer technology for fifth-generation (5G) and beyond 5G technologies. However, industrial applications often demand varied and conflicting Quality-of-Service (QoS) requirements, and finding an optimal and scalable resource allocation strategy is challenging. This paper proposes a novel user association and power control algorithm to minimize the overall uplink (UL) transmit power while ensuring a given spectral efficiency (SE) requirement. The proposed solution identifies the best schedulable users to maximize the number of satisfied users without relying on instantaneous channel state information. Moreover, it adopts a game theory-based power control algorithm to minimize the total uplink power while ensuring the spectral efficiency requirement. Numerical results have shown significant gains in the number of satisfied users. A maximum gain of up to 15% is observed for a low SE requirement (0.25 bits/s/Hz), increasing to 50% for a SE requirement of 0.75 bits/s/Hz. Furthermore, the proposed solution has shown a great adaptability to varying requirements with respect to state-of-the-art schemes.**

***Index Terms*—5G, beyond 5G, Industry 4.0, cell-free Massive MIMO, user association, power control.**

I. Introduction

The rise of cyber-physical systems has brought in new applications like collaborative machines and predictive maintenance, leading to a new strategic journey of Industry 4.0 for intelligent production. The ubiquitous networking solutions promised by 5G and beyond 5G (B5G) technologies are envisioned to meet the critical communication requirements essential for Industry 4.0. Massive multiple-input multiple-output (mMIMO) is a multi-user MIMO technology that emerged as a crucial physical layer communication technology. Considering industrial scenarios, distributed mMIMO architecture has provided better link reliability compared to co-located mMIMO, [1]- [2]. Cell-Free Massive MIMO (cf-mMIMO), an alternative paradigm of distributed mMIMO providing uniform coverage to all users, has become a promising physical layer technology for B5G. The seminal work of cf-mMIMO assumed all access points (APs) are jointly connected to a central unit via fronthaul links serving all users, known as full-scale systems. These systems entail high computational complexity and fronthaul requirements, resulting in poor scalability [3]. User-centric cf-mMIMO schemes forming a serving cluster of APs for each user enable local processing, reducing complexity and signaling to model scalable cf-mMIMO systems. Different transmission modes for distributed mMIMO in industrial settings were investigated in [4], highlighting the benefits of user-centric cf-mMIMO transmission regarding achievable SINR and complexity.

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A scalable cf-mMIMO system needs an intelligent user association and power control strategy to choose the serving APs dynamically. A user-centric dynamic cooperation clustering (DCC) algorithm is proposed in [3] based on large-scale fading (LSF) values. Whereas, [6] proposed a Hungarian algorithm to maximize the uplink (UL) sum rate by formulating the association problem as a matching problem. Assuming APs equipped with multiple antennas and operating at mmWave bands with a well-defined beam space, [7] proposed a rate-constrained network decomposition algorithm that forms multiple weakly interfered serving clusters. Introducing a new performance indicator, user satisfaction rate (USR), [8] proposed a dynamic programming-based user scheduling algorithm to optimize throughput and USR.

Power control is an integral part of communication systems, controlling intra- and inter-cluster interference while improving the overall system performance. Finding an optimal power control is challenging for cf-mMIMO systems due to the involvement of a large set of optimization variables. In [9], the authors proposed a scalable LSF-based fractional power control technique. Alternatively, authors in [10] formulated power control as a non-cooperative game and presented a game-theoretic framework and model, which can be implemented in a distributed manner. Maximizing the sum SE (max-sum-SE) and maximizing the minimum SE (max-min-SE) are common utility functions used to improve the system overall performance or ensure fairness. However, these problems are non-convex and computationally challenging, particularly when the number of APs and users increases. A fractional programming-based approach is proposed in [11] targeting max-sum-SE and max-min-SE problems. Considering industrial scenarios with mission-critical applications and strict control loops, it is often necessary to guarantee user-specific quality of service (QoS) requirements. In [12], the authors formulated a mixed integer non-convex optimization problem with minimum QoS requirements and proposed a novel accelerated projected gradient method algorithm to solve it with a sub-optimal solution. Authors in [13] proposed a joint uplink power and computational resource allocation for energy-efficient allocation of computational resources using an iterative standard power control algorithm with the help of power feasibility conditions to satisfy the minimum QoS constraints based on instantaneous channel state information (CSI).

Efficiently allocating limited resources to satisfy varied service requirements in dense industrial networks is challenging. Furthermore, in the context of cf-mMIMO, selecting appropriate serving clusters and power control for each scheduled user plays a significant role in ensuring a scalable system. However, the current state-of-the-art solutions either ignore QoS requirements or use standard optimization techniques that are not computationally scalable. Considering this gap, in this paper we consider joint user association and power control from a scheduling perspective. We propose a novel solution that takes into account power control constraints to identify and schedule the largest set of users that satisfies given QoS requirements. Our solution aims to solve two joint problems. The first is to maximize the number of satisfied users while meeting QoS requirements based on LSF values through a joint user association and scheduling algorithm using power feasibility conditions. The second involves minimizing uplink transmission power using a game theory-based power control algorithm, ensuring QoS requirements upon CSI acquisition at serving clusters only.

The rest of the paper is organized as follows: Section II outlines the system model, and Section III introduces the problem description. Section IV describes the proposed algorithm, and Section V presents the simulation results. Finally, Section VI provides the conclusion and outlines future work.

Notation: Boldface lowercase $\mathbf{x}$ and uppercase $\mathbf{X}$ denote column vectors and matrices respectively. $\mathcal{N}_{\mathbb{C}}$ represents the complex Gaussian distribution, $\mathbb{C}$ is complex sequence and $\mathbb{E}\{.\}$ denotes expected value. $^{\mathrm{T}}$, $^{\mathrm{H}}$, and † denote matrix operations transpose, hermitian, and pseudo-inverse, respectively. $\mathrm{diag}(.)$ transforms square matrices into block-diagonal matrix. $\mathbf{I}_{\mathrm{N}}$ and $\mathbf{0}_{\mathrm{N}}$, represents Identity and Zero matrix with size $\mathrm{N}\times\mathrm{N}$. $\setminus$, $\bigcup$, $\subset$, and $|\mathcal{X}|$ represent set difference, union, subset relation, and cardinality of a set, respectively.

II. System Model and Spectral Efficiency

A. System Model

Let us consider a time division duplex (TDD) cf-mMIMO system, equipped with a set $\mathcal{L}$ of distributed APs, where each AP with N antennas is connected to a central unit and coherently serving a set $\mathcal{K}$ of single-antenna users over the same radio resources. The cardinality $|\mathcal{L}| = L$ and $|\mathcal{K}| = K$ represents the number of APs and users. We assume time-varying channels whose response is constant over a block of τ_c symbols. Considering the TDD protocol, a UL frame of length $\tau_f < \tau_c$ is divided into UL pilot τ_p and UL data τ_{ul} samples. Acquisition of CSI using pilots plays a major role in formulating UL combiners. Limited orthogonal pilot sequences of length $\tau_p < K$ make the pilot assignment a key initial step to mitigate the pilot contamination effect; in this work, we adapted the pilot assignment strategy proposed in [14], based on LSF values. Given a k-th user assigned with a pilot sequence $\Phi_{tk} \in \mathbb{C}^{\tau_p}$, each l-th AP receives

$$\mathbf{y}_l^{ul} = \sum_{k=1}^{K} \sqrt{\eta_k}\mathbf{h}_{k,l}\Phi_{tk} + \mathbf{n}_l \tag{1}$$

, with transmit power η_k on channel $\mathbf{h}_{k,l} \in \mathbb{C}^N$, where $\mathbf{n}_l \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \sigma_{ul}^2\mathbf{I}_{\mathrm{N}}\right)$ is thermal noise with variance σ_{ul}^2. The collective channel of the k-th user is denoted as $\mathbf{h}_k = \begin{bmatrix}\mathbf{h}_{k1}^{\mathrm{T}} & .... & \mathbf{h}_{kL}^{\mathrm{T}}\end{bmatrix}^{\mathrm{T}} \in \mathbb{C}^M$, where $M = LN$. $\mathbf{h}_{k,l}$ are mutually independent Rayleigh fading channels, with $\mathbf{h}_{kl} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \mathbf{R}_{kl}\right)$. The complex Gaussian distribution models small scale fading where $\mathbf{R}_{kl} = \beta_{kl}\mathbf{I}_N$ is a spatial correlation matrix formulated considering LSF values describing geometric path loss and shadow fading.

Considering a user-centric centralized architecture, an association matrix $\mathbf{D} \in \{0,1\}^{\mathrm{LN}\times\mathrm{KN}} = [\mathbf{D}_1 \dots \mathbf{D}_K]$ is defined, where $\mathbf{D}_k = [\mathbf{D}_{k1} \dots \mathbf{D}_{kL}]^{\mathrm{T}}$ represent the association to the k-th user. $\mathbf{D}_{kl} \in \{0,1\}^{\mathrm{N}\times\mathrm{N}}$ is either $\mathbf{I}_N$ or $\mathbf{0}_N$, depending on whether the l-th AP is in the k-th user's serving cluster or not. For a given k-th user, only the serving cluster participates in the UL processing, and channel estimates $\hat{\mathbf{h}}_k = \begin{bmatrix}\hat{\mathbf{h}}_{k1}^{\mathrm{T}} & .... & \hat{\mathbf{h}}_{kL}^{\mathrm{T}}\end{bmatrix}^{\mathrm{T}} \in \mathbb{C}^M$, are performed only at the serving APs. The minimum mean-square error (MMSE) channel estimator proposed in [15] is adopted in this work to obtain the CSI of each user.

Considering $\mathbf{O}_k = \mathrm{diag}\left(\mathbf{D}_k\right)$ as a block diagonal matrix with size $M \times M$, the combining vectors are formulated according to the channel estimates of the serving clusters. We adopted the *partial*-MMSE (P-MMSE) combiner (2) from [3], where the set of users $\mathcal{S}_k$ that are partially or completely served by the serving cluster of the k-th user are considered, i.e.

$$\begin{aligned}\mathbf{v}_k &= \eta_k\left(\sum_{i\in\mathcal{S}_k}\eta_i\mathbf{O}_k\hat{\mathbf{h}}_i\hat{\mathbf{h}}_i^{\mathrm{H}}\mathbf{O}_k + \mathbf{Z}_k\right)^{\dagger}\mathbf{O}_k\hat{\mathbf{h}}_k,\\ \mathbf{Z}_k &= \mathbf{O}_k\left(\sum_{i\in\mathcal{S}_k}\eta_i\mathbf{\Lambda}_i + \sigma_{ul}^2\mathbf{I}_M\right)\mathbf{O}_k,\end{aligned} \tag{2}$$

where $\mathbf{\Lambda}_i \in \mathbb{C}^{\mathrm{LN}\times\mathrm{LN}}$ is the error correlation matrix of the collective channel estimate of the i-th user [15].

The effective SINR of k-th user ρ_k using P-MMSE can be represented as:

$$\rho_k = \frac{\mathrm{DS}_k}{\mathrm{IUI}_k + \mathrm{n}_k} \tag{3}$$

where $\mathrm{DS}_k = \eta_k\mathbb{E}\left|\left\{\mathbf{v}_k^{\mathrm{H}}\mathbf{O}_k\mathbf{h}_k\right\}\right|^2$, $\mathrm{IUI}_k = \sum_{i=1}^{K}\eta_i\mathbb{E}\left\{\left|\mathbf{v}_k^{\mathrm{H}}\mathbf{O}_k\mathbf{h}_i\right|^2\right\} - \eta_k\mathbb{E}\left|\left\{\mathbf{v}_k^{\mathrm{H}}\mathbf{O}_k\mathbf{h}_k\right\}\right|^2$, and $\mathrm{n}_k = \sigma_{ul}^2\mathbb{E}\left\{||\mathbf{O}_k\mathbf{v}_k||^2\right\}$ denote desired signal, inter-user interference, and noise, respectively [3]. This results in an achievable SE for the k-th user as:

$$\mathrm{SE}_k = \underbrace{\left(1 - \frac{\tau_p}{\tau_f}\right)}_{\vartheta}\log_2\left(1 + \rho_k\right). \tag{4}$$

B. Closed-form expressions

In this article, we use achievable SE as a key performance indicator of QoS. SE_k (4) for each user is calculated using instantaneous CSI obtained at each $k-$th user serving cluster. Without an appropriate user association process, it is computationally inefficient to calculate instantaneous CSI at all APs, further contradicting the idea of scalable cf-mMIMO. On the other hand, the large-scale fading characteristics of the users are slowly varying, and, it is feasible for the network to estimate them accurately over time. The closed-form expressions for the uplink SE have been derived in [15], using LSF coefficients with different modes of Zero-Forcing (ZF) combining schemes. The usage of such approximations can provide insight into the impact of interference suppression when combiners such as P-MMSE (2), are applied. Considering $\mathcal{P}_k$ as the set of users assigned with the same pilot sequence as k-th user, including the k-th user itself, γ_{kl} is calculated as:

$$\gamma_{kl} = \frac{\eta_k \tau_p \beta_{kl}^2}{\tau_p \sum_{t\in\mathcal{P}_k} \eta_t \beta_{tl} + \sigma_{ul}^2}. \tag{5}$$

Considering the set of $\mathcal{L}_k$ serving APs, the approximated achievable $\text{SINR}_k(\tilde{\rho}_k)$, can be calculated as [15]:

$$\tilde{\rho}_k = \frac{\eta_k g_{kk}}{\sum_{t=1}^{K} c_{kt} + \sum_{t\in\mathcal{P}_k\setminus\{k\}} i_{kt} + u_k}, \tag{6}$$

where, $g_{kk} = \left|\sum_{l\in\mathcal{L}_k} \gamma_{kl}\right|^2$, $c_{kt} = \sum_{l\in\mathcal{L}_k} \gamma_{kl}\left(\beta_{tl} - \gamma_{tl}\right)$, $i_{kt} = \left(\sum_{l\in\mathcal{L}_k} \gamma_{tl}\right)^2$, and $u_k = \sigma_{ul}^2 \sum_{l\in\mathcal{L}_k} \gamma_{kl}$.

The minimum SE requirement for all users is denoted as SE_{req}. Assuming Shannon rates, the minimum SINR (ρ_{th}) to meet SE_{req} can be calculated as:

$$\rho_{th} = 2^{\frac{\vartheta}{\text{SE}_{\text{req}}}} - 1. \tag{7}$$

Defining $\boldsymbol{\eta} = [\eta_1, \ldots, \eta_K]$ as the vector of transmit powers for all users satisfying: $\tilde{\rho}_k \geq \rho_{th}, \forall k \in \mathcal{K}$, the following inequality holds: $\boldsymbol{\eta} \geq \boldsymbol{\Delta}\mathbf{G}^{-1}\left(\mathbf{Z}\boldsymbol{\eta} + \mathbf{u}\right)$, where $\mathbf{G}$ and $\mathbf{Z}$ are given by:

$$\left[\mathbf{G}_{ki}\right] = \begin{cases} g_{kk} - c_{kk}\rho_{th}, & \text{if} \quad k = i \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$\left[\mathbf{Z}_{ki}\right] = \begin{cases} 0, & \text{if} \quad k = i \\ c_{ki} + i_{ki} & i \in \mathcal{P}_k \setminus \{k\} \\ c_{ki}, & \text{otherwise} \end{cases} \tag{9}$$

$\mathbf{u} = \begin{bmatrix} u_1 & \ldots & u_K \end{bmatrix}^{\text{T}}$, and $\boldsymbol{\Delta}$ is a diagonal matrix containing the target SINR (ρ_{th}) values for all scheduled users as diagonal elements. In Section IV, the above expressions are used to derive the proposed solution.

III. Problem Formulation

This section presents the problem of joint user association and power control. The goal is to maximize the number of satisfied users; due to limited resources in a dense industrial network, it is challenging to allocate them in a way that guarantees SE_{req} for all scheduled users. Therefore, it is essential to identify the largest set of schedulable users. In addition, selecting an appropriate serving cluster and optimal power control is necessary to develop an efficient, scalable cf-mMIMO system.

Considering a single antenna per AP, we formulate our optimization problem as:

$$\begin{aligned}
\mathcal{P}_0: \ \underset{\mathbf{D}, \boldsymbol{\eta}}{\text{minimize}} \quad & \sum_{k=1}^{|\mathcal{U}_{\text{schd}}|} \eta_k && \text{(10a)} \\
\text{subject to} \quad & \text{SE}_k \geq \text{SE}_{\text{req}} \quad, \forall k \in \mathcal{U}_s, && \text{(10b)} \\
& d_{l,k} \in \{0, 1\} \qquad , && \text{(10c)} \\
& 0 \leq \eta_k \leq \eta_{max}, && \text{(10d)}
\end{aligned}$$

The constraints (10b), ensures all the scheduled users

$$\mathcal{U}_{\text{schd}} = \left\{k|\mathbf{D}\left[:, k\right] \neq \mathbf{0}_{\text{L}\times 1}\right\}, \forall k \in \mathcal{K} \tag{11}$$

have a guaranteed SE_{req}, (10c) binary association variable, where $d_{lk} = 1$ if l-th AP is assigned to k-th user, otherwise 0. The final constraint (10d) ensures that UL transmits power does not violate given power budget requirements. We address this problem by splitting it into two sequential joint sub-problems; we define the first problem $\mathcal{P}_1$, to find the best schedulable set of users to maximize the number of satisfied users $\mathcal{U}_{\text{sat}}$ based on LSF values, as it is not scalable to estimate instantaneous CSI before user association.

$$\begin{aligned}
\mathcal{P}_1: \ \underset{\mathbf{D}}{\text{maximize}} \quad & \mathcal{U}_{\text{sat}} && \text{(12a)} \\
\text{subject to} \quad & d_{l,k} \in \{0, 1\} \qquad , && \text{(12b)} \\
& \eta_k = \eta_{max}, \quad \forall k \in \mathcal{U}_{\text{schd}}, && \text{(12c)} \\
& \text{SE}_k \geq \text{SE}_{\text{req}} \quad \forall k \in \mathcal{U}_{\text{schd}} && \text{(12d)}
\end{aligned}$$

Where,

$$\mathcal{U}_{\text{sat}} = \sum_{k=1}^{|\mathcal{U}_{\text{schd}}|} \mathbb{1}_{\{\text{SE}_k \geq \text{SE}_{\text{req}}\}}, \tag{13}$$

represents the number of satisfied users. Upon identifying the best set of $\mathcal{U}_{\text{schd}}$ and their respective association matrix $\mathbf{D}$, we assume that instantaneous CSI only at serving clusters is obtained. We introduce our second sub-problem $\mathcal{P}_2$ as minimization of the total UL transmit power while guaranteeing SE_{req}:

$$\begin{aligned}
\mathcal{P}_2: \ \underset{\boldsymbol{\eta}}{\text{minimize}} \quad & \sum_{k=1}^{|\mathcal{U}_{\text{schd}}|} \eta_k && \text{(14a)} \\
\text{subject to} \quad & \text{SE}_k \geq \text{SE}_{\text{req}} \quad, \forall k \in \mathcal{U}_s, && \text{(14b)} \\
& 0 \leq \eta_k \leq \eta_{max}. && \text{(14c)}
\end{aligned}$$

We can see that a solution to problem $\mathcal{P}_2$ is feasible if and only if $\eta_k, \forall k \in \mathcal{U}_{\text{schd}}$ do not exceed η_{max} and still meet SE_{req}. Solution to $\mathcal{P}_2$ exists if and only if the following conditions are satisfied [9]:

- All the diagonal elements of $\mathbf{G}$ (8) are non-negative.
- Perron-Forbenious eigenvalue r of the matrix $\mathbf{C} = \boldsymbol{\Delta}\mathbf{G}^{-1}\mathbf{Z}$, is real, non-negative and < 1, where,

$$\left[\mathbf{C}_{ki}\right] = \begin{cases} 0, & \text{if} \quad k = i \\ \frac{\rho_{th}\mathbf{Z}_{ki}}{\mathbf{G}_{ki}}, & \text{otherwise} \end{cases} \tag{15}$$

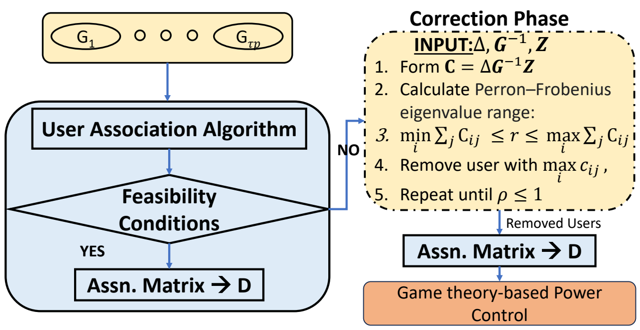

Fig. 1: Proposed joint user association and power control algorithm

Hence, it is important to satisfy feasibility conditions of $\mathcal{P}_2$ while solving $\mathcal{P}_1$. The following section will introduce the proposed solution, where the solution of $\mathcal{P}_1$ provides the desired association matrix $\mathbf{D}$ and the solution of $\mathcal{P}_2$ results in minimum UL transmit power vector $\boldsymbol{\eta}$ ensuring targeted SE_{req}.

IV. Proposed Solution

This section introduces a joint user association and scheduling algorithm to solve $\mathcal{P}_1$. The proposed algorithm determines the best schedulable user set and their respective serving clusters based on LSF characteristics considering the power feasibility conditions, such that a solution to $\mathcal{P}_2$ exists. A power control algorithm is proposed to solve $\mathcal{P}_2$, assuming that instantaneous CSI is available from the scheduled users and their respective serving APs. As we consider the power feasibility conditions required for $\mathcal{P}_2$ while solving $\mathcal{P}_1$, our solution is to be intended as a joint solution for user association and power control.

The proposed joint user association and scheduling solution have two phases: Association and Correction, shown in Fig. 1. To limit the pilot contamination effect, we prohibit two users from sharing the same pilot sequence to be served by the same AP. To accomplish this, we divide the users $\mathcal{K}$ into groups $\mathcal{G}_{total} = \left\{\mathcal{G}_1, \ldots, \mathcal{G}_{\tau_p}\right\}$ based on their assigned pilots and $\mathcal{K}_{\mathcal{G}} = \left\{\mathcal{K}_{\mathcal{G}_1}, \ldots, \mathcal{K}_{\mathcal{G}_{\tau_p}}\right\}$ represents users in each pilot group. For each user in a chosen group, APs are sorted according to strongest γ_{kl} values, and $j-$ strongest APs are allocated to each user. This association strategy might result in overlapping associations within the group; for each conflicting association, we calculate the relative pilot contamination ratio, and the user with the lowest ratio will be chosen as the desired user for that AP. Considering l' as the conflicting AP and $\mathcal{K}_{conflict}$ as the set of conflicting users with the same pilot sequence choosing l' AP, pilot contamination ratio for $k-$th user, using (6), can be defined as:

$$\zeta_k = \frac{\sum_{t \in \mathcal{K}_{conflict} \setminus \{k\}} \left(\gamma_{tl}\right)^2}{\left(\gamma_{kl}\right)^2} \tag{16}$$

Once we have found the serving APs for each selected user group, using (8) and (9), the feasibility check matrix

Algorithm 1 Proposed Algorithm

Input: $\boldsymbol{\Gamma}, \mathcal{K}_{\mathcal{G}}, \mathcal{L}, \text{SE}_{\text{req}}$

Initialization : $\mathbf{D} = \mathbf{0}^{\text{L}\times\text{K}}$
for $\mathcal{K}_{\mathcal{G}_i}$ in $\mathcal{K}_{\mathcal{G}_1}, \ldots, \mathcal{K}_{\mathcal{G}_{\tau_p}}$ **do**
  $\mathcal{K}_{nonSat} \leftarrow \{\}$, to store non satisfied users.
  for $i = 1, 2, \ldots |\mathcal{K}_{\mathcal{G}_i}|$ **do**
    Sort APs in descending order based on γ_{il} (5).
    Select j strongest APs for $i-th$ user $\rightarrow \mathcal{L}_i$.
    $\mathbf{D}[\mathcal{L}_i, i] = 1 \leftarrow$ update assn.matrix
  end for
  Calculate the conflicting set of APs ($\mathcal{L}_{conflict}$) where each AP has more than one user associated in $\mathcal{K}_{\mathcal{G}_i}$
  for l' in $\mathcal{L}_{conflict}$ **do**
    Calculate the conflicting users $\mathcal{K}_{conflict}$
    Calculate $\zeta_{k'} \quad \forall k' \in \mathcal{K}_{conflict}$ using (16)
    $k_{sel} = \arg\min_{k'} \zeta_{k'}$
    $\mathbf{D}[l', k_{sel}] = 1$ & $\mathbf{D}[l', \mathcal{K}_{conflict} \setminus k_{sel}] = 0$
  end for
end for
Form $\mathbf{C} = \boldsymbol{\Delta}\mathbf{G}^{-1}\mathbf{Z}$, using (8), (9) and Check feasibility conditions (13)
if Not Satisified **then**
  $\mathcal{K}_{remov} \leftarrow \{\}$
  repeat
    Calculate $k^* = \arg\max_i \sum_j c_{ij}$
    $\mathcal{K}_{remov} \leftarrow \mathcal{K}_{remov} \cup \{k^*\}$
    Update $\mathcal{K}_{\text{schd}} \leftarrow \mathcal{K}_{\text{schd}} \setminus k^*$
    Update $\mathbf{C}$ using (8), (9), with $\mathcal{K}_{\text{schd}}$
  until feasibility conditions met
end if
Update $\mathbf{D}\left[:, \mathcal{K}_{remov}\right] = \mathbf{0}_{\text{L}\times 1}$

Output: D

$\mathbf{C}$ is formulated. If the conditions defined in the previous section are unsatisfied, we sequentially remove the scheduled users based on the Perron-Forbenious eigenvalue properties. Considering $\mathbf{C}$ a square positive matrix, Perron-Forbenious eigenvalue satisfies the following inequality:

$$\min_i \sum_j \mathbf{C}_{ij} \leq r \leq \max_i \sum_j \mathbf{C}_{ij}. \tag{17}$$

Each element in $\mathbf{C}_{ki}$ refers to the interference to signal ratio, and removing the strongest interfering user will reduce the upper bound of Perron-Forbenious eigenvalue and improve the chance to meet the feasibility condition $r \leq 1$. We calculate the upper limit of the Perron-Forbenious eigenvalue, remove that i-th user, and check the feasibility conditions again; this process will be repeated until the conditions are met. A detailed description of the algorithm is presented in the Algo.1, where $\boldsymbol{\Gamma} \in \mathbb{R}^{K\times L}$ with each entry γ_{kl} calculated using (5), $\mathcal{K}_{\mathcal{G}}$, SE_{req} and $\mathcal{L}$ is given as input.

Power control algorithms often apply game theory methods with several essential properties such as cooperative behavior, flexibility in modeling dynamic environments, and enabling distributed decision-making. Considering the players as independent with the ability to observe and react, they can adjust their transmit powers based on local information and interactions with neighboring users, resulting in more scalable and efficient solutions for power control. Inspired by [10], we defined the problem $\mathcal{P}_2$ as a non-cooperative game $\mathcal{Z} = \left\{\mathcal{U}_{\text{schd}}, \{\mathcal{A}_k\}_{\forall k}, \left\{u_k\left(\eta_k, \boldsymbol{\eta}_{-k}\right)\right\}\right\}$, which has three critical components. Firstly, $\mathcal{U}_{\text{schd}}$ defines the set of scheduled user sets. Secondly, $\mathcal{A}_k = [\eta_{min}, \eta_{max}]$ defines the state space of actions available for each $k-$th user ranging between $\eta_{min} > 0$ and $\eta_k \leq \eta_{max}$. Finally, $u_k\left(\eta_k, \boldsymbol{\eta}_{-k}\right)$ is the utility function that measures each UE's ability to meet their respective goals with a given action, provided the knowledge of the other scheduled users, where $\boldsymbol{\eta}_{-k}$ denotes the power of all the users except k. Defining an appropriate utility function is important as it plays a significant role in choosing actions for each user to improve its chances of meeting the specified goal.

Considering the objective of $\mathcal{P}_2$, we define a utility function that balances reaching the targeted SINR requirement, and UL transmit power:

$$u_k\left(\eta_k, \boldsymbol{\eta}_{-k}\right) = \ln(\rho_k - \rho_{th}) - (\eta_k - \eta_{max})^2, \tag{18}$$

by solving $\frac{\partial u_k}{\partial \eta_k} = 0$, we can find the unique minimizer for UL transmit power η_k^* for k-th user, observing the current strategies of other users:

$$\eta_k^* = \begin{cases} \eta_k \frac{\rho_{th}}{\rho_k} + \frac{1}{2}\frac{1}{\eta_k - \eta_{max}}, & 0 < \eta_k < \eta_{max} \\ \eta_{max}, & \eta_k \geq \eta_{max} \end{cases} \tag{19}$$

A detailed description is mentioned in Algo.2.

Algorithm 2 Power Control Algorithm

Input:$\mathcal{U}_{\text{schd}}$, ρ_{th}, *nItr*

Initialization : $\boldsymbol{\eta}^0 \leftarrow$ Initialization
for $m = 0, 2, \ldots,$ *nItr* **do**
  Calculate $\rho_k, \forall k \in \mathcal{U}_{\text{schd}}$ using (3), (2) and $\boldsymbol{\eta}^m$
  Update $\eta_k^{m+1} \leftarrow \eta^*, \quad \forall k \in \mathcal{U}_{\text{schd}}$ using (19)
end for

Output:$\boldsymbol{\eta}$

V. Numerical Analysis

In this section, we evaluate the performance of the proposed algorithm, considering a small factory setup with a square geometry ($50m \times 50m$), where $L = 64$ single antenna APs, and $K = 40$ single antenna users ($N = 1$) are randomly and uniformly placed. We further adopt a dense clutter scenario with high AP (InF-DH) from the 3GPP Indoor Factory (InF) channel model [16] considering an industrial environment, where radio propagation is affected by the presence of a high clutter density. Table I captures the main simulation parameters. Results were generated using 2000 random setups, and each user can select up to $j = 20$ strongest APs. The proposed algorithm is compared with three benchmark schemes that adopt the DCC association algorithm [3], and the following approaches for power control benchmark schemes considering DCC as their choice of association algorithm:

TABLE I: Simulation Parameters

Parameter	**Value**
Bandwidth (BW)	20 MHz
Carrier frequency	3.5 GHz
max UL tx. power η_{max}	20 dBm
Noise Figure (nF)	7 dB
Noise Power	-174 + 10 * log_{10}(BW)[MHz] + nF
Factory size	small = $50m \times 50m$
InF-DH Clutter Prop.	Density[%]=80, height & size[m]=6 & 2
Height of AP & User	10m & 1.5m
UL Frame Prop.	τ_p = 5 & τ_f = 200
UL Combiner	P-MMSE (2)

- **Benchmark1: Game theory-based solution (BM1-GT)**: Authors in [10] formulated a non-cooperative game to calculate the UL transmit power by introducing a utility function for each user to lower data power levels while causing less interference to other users.
- **Benchmark2: Fractional Power control (BM2-FractPC)**: Using the LSF information fractional power control is proposed in [9] to minimize the variance of large-scale signal-to-interference ratio.
- **Benchmark3: Standard Power Control (BM3-SPC)**: Assuming P-MMSE precoder and perfect CSI knowledge, an iterative scheme is proposed using the standard interference function, based on instantaneous CSI [13].

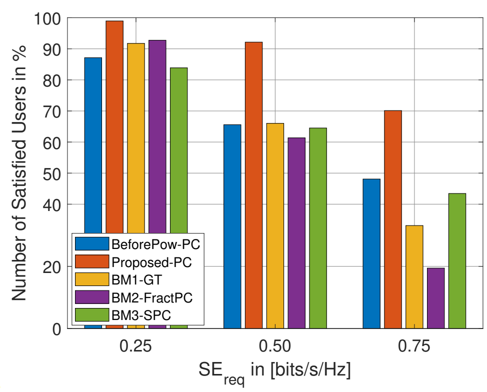

Fig. 2: Avg. no.of satisfied users in % for $\text{SE}_{\text{req}} = 0.25$, 0.50 and 0.75 bits/s/Hz

Fig. 2 displays the average number of satisfied users for different SE_{req} = 0.25, 0.50, and 0.75 bits/s/Hz. It is evident from the graph that, as the value of SE_{req} increases, the number of satisfied users decreases. While the benchmark solutions perform closely to the proposed solution at lower SE_{req} values, their performance degrades rapidly as SE_{req} increases, as can be seen in the case of BM1-GT and BM2-FractPC. However, BM3-SPC has the ability to adapt to different requirements. Our proposed solution improved performance by identifying and scheduling the best users. It also reduces interference through power control while maintaining the SE_{req} with minimum power. Table II captures the gain in % compared with all benchmarks at different SE_{req}.

In Fig. 3, we can see that the proposed algorithm has shown

TABLE II: Gain in % compared to benchmarks

SE_{req}	BM1-GT	BM2-FractPC	BM3-SPC
0.25	7%	6%	15%
0.50	26%	31%	28%
0.75	37%	50%	27%

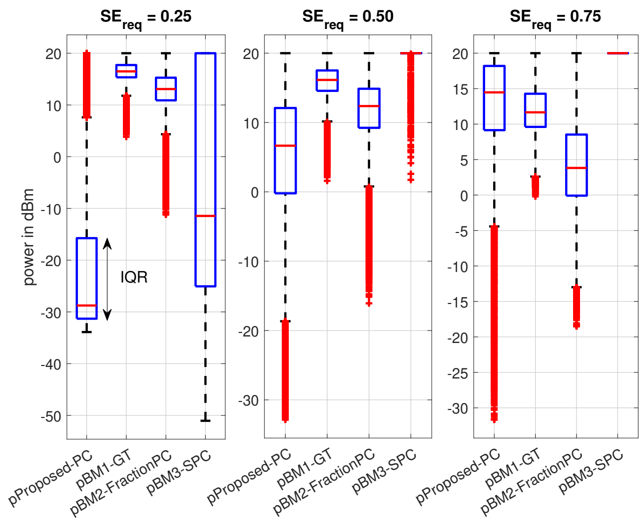

Fig. 3: UL transmission power required for $SE_{req} = 0.25$, 0.50 and 0.75 bits/s/Hz

variability in UL transmit power with respect to different SE_{req}. The plot displays the range of data with whiskers and identifies outliers with red points. The inter-quartile range (IQR), which is the range of values between the 25th and 75th percentiles ranges, is lower for $SE_{req} = 0.25$ ranging between -31 dBm to -15 dBm. This increases to the range 9-18 dBm as SE_{req} reached 0.75; such behavior is not observed in BM1-GT and BM1-FractionPC as they are not tailor-made for varying requirements. Even though BM3-SPC considered this, their algorithm works only when feasibility conditions are met. Our proposed solution is adaptable to varying SE_{req}, particularly at higher SE_{req}. Scheduling the best set of users while considering feasibility conditions and using a utility function to calculate the minimum power required based on SE_{req} improves overall user satisfaction.

VI. Conclusion

In this article, we have proposed a novel joint user association and power control algorithm for uplink cell-free massive MIMO to maximize the number of users meeting a minimum SE requirement (SE_{req}). We proposed a method to identify the best schedulable set of users based on large-scale fading values while meeting a power feasibility condition to ensure the potential achievement of SE_{req}. Upon obtaining the channel state information (CSI) on scheduled users and for serving access points (APs), a game theory-based power control is proposed to minimize the overall transmit power while guaranteeing SE_{req}. Simulation results have shown significant gains in terms of number of satisfied users. At lower $SE_{req} = 0.25$ bits/s/Hz, the proposed solution has observed a maximum gain of 15%, that increases to 50% for $SE_{req} = 0.75$ bits/s/Hz. The proposed solution has shown adaptability in finding minimum UL transmit power to various SE_{req}, compared to the state-of-art benchmark schemes.

Considering industrial scenarios with varied service requirements and priorities, future work will investigate distributed power control solutions based on the available computational resources and signaling overhead.

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