QoS-Aware User Scheduling in Crowded XL-MIMO Systems Under Non-Stationary Multi-State LoS/NLoS Channels

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Abstract—Ensuring that the quality-of-service (QoS) requirements are satisfied in wireless communications systems with high user density is challenging due to the limitations on the transmit power budget and the number of resource blocks. In this paper, we propose a QoS-aware joint user scheduling and power allocation technique to enhance the number of served users in the downlink of crowded extra-large scale massive multiple-input multiple-output (XL-MIMO) with minimum QoS requirements guarantee. The proposed technique is constituted by two sequential procedures: the clique search-based scheduling (CBS) algorithm for user scheduling followed by optimal power allocation with transmit power budget and minimum achievable rate per user constraints. We propose a generalized non-stationary multi-state channel model based on spherical wave propagation assuming that users under line-of-sight (LoS) and non-LoS (NLoS) transmission coexist in the same communication cell. This is done to accurately evaluate the proposed technique in realistic XL-MIMO scenarios. Numerical results reveal that the proposed CBS algorithm provides fair coverage over the whole cell area, achieving remarkable numbers of scheduled users with satisfied QoS requirements when users under the LoS and NLoS channel states coexist in the communication cell.

Index Terms—Channel non-stationarities, resource allocation, user scheduling, XL-MIMO.

I. INTRODUCTION

EXTRA-LARGE scale massive multiple-input multiple-output (XL-MIMO) are the deployments of massive MIMO base stations (BSs) made of arrays of antennas with extreme physical dimensions, often with the size of thousands of wavelengths [1]. Such deployments are promising designs to address crowded communication scenarios, integrating the antenna elements with architectural structures of the environment, e.g., the ceiling, walls, and columns of a stadium, warehouse, or shopping mall [2]. For this reason, the distances between the users and the antenna elements are small compared with the co-located BS design, typically adopted in cellular systems.

Such small distances between the users in conjunction with the very large extent of the antenna array create spatial non-stationarities on the wireless channel, which drastically changes the signal propagation aspects compared with the conventional massive MIMO scenarios. We investigate two of these aspects. First, each antenna element experiences different average received power and phase from each user, suggesting the operation under the near-field propagation regime. Hence, the wireless channel is well-modeled by the spherical wavefront (SW) propagation model rather than the conventional plane wavefront propagation model [3]. Second, the closeness between the users and the antenna elements results in a predominantly line-of-sight (LoS) situation. However, due to the relief and presence of scatterers and obstacles in the environment, it is not accurate to assume that all the radio links experience LoS transmission. Hence, as is discussed in [4], it is reasonable to assume that part of the radio links are under the LoS regime, while the remaining links are under the non-line-of-sight (NLoS) one.

Under the near-field propagation regime considering the SW model, the array gain is limited [3]. This suggests that asymptotic favorable propagation, which results in the orthogonality between the channel vectors of different users, may also be compromised by the near-field propagation condition. However, further investigation is needed to support this claim. The looseness of the favorable propagation with the SW model increases the necessity of scheduling spatially compatible users to achieve reasonable DL performance while optimizing the expenditure of scarce radio resources, e.g., transmit power and resource blocks. In wireless systems with limited resources, resource allocation (RA) techniques are essential to assure that the target quality-of-service (QoS) levels are met for a higher number of served users. RA techniques for multi-user MIMO systems are surveyed in [5]. Despite that, further investigation is needed to assess the effectiveness of the conventional resource allocation strategies in crowded multi-user MIMO systems with physically large antenna arrays.

In this sense, in [6], [7] the authors propose methods for antenna selection aiming to maximize the energy efficiency and the spectral efficiency, respectively. The proposed methods...
use different approaches to compute the set of active antennas, including metaheuristic optimization, greedy strategies, and heuristic procedures deploying approximate expressions for the performance metrics. However, proposing solutions for different wireless propagation conditions while optimizing the expenditure of scarce radio resources, is still a need.

Generally, accurate channel state information (CSI) is required to perform efficient RA, precoding, and detection. Due to the near-field propagation and spatial non-stationarities of the XL-MIMO channel, new methods for CSI acquisition must be developed. Specifically, [8] proposed an efficient subarray-wise channel estimation method based on the orthogonal matching pursuit (OMP) algorithm. Such an algorithm is applied under the consideration that the channel is spatially stationary in the subarrays, so the subarray channel becomes sparse in the angular domain. Differently, in [9] is demonstrated that the SW channel is no longer sparse in the angular domain since the energy of each radio path spread towards multiple angles. In this sense, the authors demonstrate that the XL-MIMO channel is sparse in the polar domain, and exploit such a property in the polar-domain simultaneous OMP algorithm, an accurate and low-complexity approach for XL-MIMO channel estimation.

In [10], [11], user scheduling techniques for MIMO systems that employ zero-forcing beamforming as the spatial multiplexing strategy are proposed. Specifically, the semiorthogonal user selection (SUS) algorithm proposed in [11] can achieve the same asymptotic achievable sum-rate as that of dirty paper coding. However, the analysis is restricted to up to 4 antennas at the BS and Rayleigh fading channel, which not applies to physically large arrays. On the other hand, the problem of user scheduling for the XL-MIMO systems with the SW model is addressed in [12]. The authors propose a strategy based on the equivalent distance, a measure that combines the distance from the users to the BS and the interference level produced by the other scheduled users. The developed algorithm can outperform the performance of SUS with less computational complexity. Despite that, analyses of the individual achievable rates and the coverage reached by the algorithm are not provided. In [13], authors take advantage of the non-overlapping visibility regions (VR) across the array in a crowded XL-MIMO system to propose a joint random access and user scheduling protocol. Such a protocol explores the different VRs of the users to improve the access performance, besides seeking users with non-overlapping VRs to be scheduled in the same payload data pilot resource.

In [14], the problem of RA in the DL of user-centric cell-free MIMO networks is studied. The authors propose an iterative method to promote max-min fairness in the system by scheduling users, allocating power, and selecting the pilot length. In [15], the problem of DL precoding in millimeter-wave (mm-Wave) systems is examined. Exploiting the sparsity of the mm-Wave channel in the angular domain, three different algorithms for beam selection and user scheduling are proposed. Compared with the state-of-the-art, the proposed methods allow for increasing the number of users to be served, especially when there are fewer available DL beams.

The problem of user scheduling, via optimizing the configurations of a reconfigurable intelligent surface (RIS), and BS beamforming in multi-user networks assisted by RIS is analyzed in [16]. Specifically, a scheme with two graph neural networks is developed to schedule users and optimize the RIS configurations. The proposed scheme promotes fairness among the users, achieving better network utility.

In [17], the problem of maximizing energy efficiency under minimum throughput constraints in the DL channel of multi-cell massive MIMO schemes is studied. To increase the number of served users by each cell, a mini-slot-based transmit beamforming method is proposed, by scheduling the farther and nearer users into different time mini-slots. As a result, the BS can double the number of served users and reduce significantly the inter-cell interference, improving the performance of the border users.

Contributions: The contribution of this work is threefold.

i) We propose a QoS-aware joint user scheduling and power allocation algorithm based on the search in a graph for the DL channel of crowded XL-MIMO systems. Such an algorithm is designed to increase the number of served users with satisfied QoS requirements in XL-MIMO systems with high user density. The proposed graph-based technique can increase significantly not only the number of scheduled users, but the system achievable sum-rate, while providing fair coverage across the whole cell area.

ii) We propose a non-stationary multi-state channel model based on the SW propagation considering that users under LoS and NLoS transmission coexist in the same communication cell. In the proposed model, it is assumed that users under the LoS and NLoS states experience different propagation characteristics both in the multi-path fading and in the path loss rule. This is done aiming to capture the complexity of the propagation environment with physically large arrays of antennas.

iii) We extensively evaluate the performance of the proposed QoS-aware joint user scheduling and power allocation technique with numerical simulations. The performance of the proposed graph-based technique is evaluated in crowded XL-MIMO scenarios under different channel conditions and also compared with state-of-the-art techniques. As an outcome, a comprehensive analysis is obtained, including results on achievable sum-rate, number of scheduled users, computational complexity, and distribution of the scheduled users.

Notations. Boldface lowercase $\mathbf{a}$ and uppercase $\mathbf{A}$ letters represent vectors and matrices, respectively. Calligraphic letters $\mathcal{A}$ represent finite sets. $I_n$ denotes the identity matrix of size $n$. $\mathbf{0}_n$ denotes the zero column vector of length $n$. $\cdot^T$ and $\cdot^H$ denote, respectively, the transpose and the complex conjugate transpose operators. $\varphi(\cdot)$ denotes the power set operator.

II. SYSTEM MODEL

In the following, we describe the model of the communication system analyzed in this work. We consider the DL transmission of a narrowband XL-MIMO system with $K \in \mathbb{Z}_+$ users operating in the time-divisionduplexing (TDD) mode. The BS is equipped with $M \in \mathbb{Z}_+$ antennas organized as a uniform linear array (ULA) with elements spaced by the distance $d > 0$ meters.
Therefore, the array has an aperture of $D = (M - 1)d$ meters. A sketch of the crowded multi-user XL-MIMO communication scenario is depicted in Fig. 1. The BS antennas and the users are located at the $xy$-plane. Indeed, the ULA is oriented along the $x$-axis, and its center is at the origin of the coordinate system.

Adopting the representation in polar coordinates, the position of the user $k \in \{1, \ldots, K\}$ is described by the ordered pair $(r_k, \theta_k)$, where $r_k > 0$ is the distance from the user $k$ to the origin and $\theta_k \in [0, 2\pi)$ is the angle between the direction of user $k$ and the $x$-axis direction (see Fig. 1). Similarly, the position of the antenna $m$ is described by the pair $(r_m, \theta_m)$, whose coordinates are calculated by:

$$
r_m = \left|m - \frac{1}{2}\right|d, \quad \theta_m = \begin{cases} 0 & \text{if } m > 0 \\ \pi & \text{if } m < 0 \end{cases},
$$

$\forall m \in \left[-\frac{M}{2}, \frac{M}{2}\right], \ m \neq 0$.

### A. Channel Model

In this subsection, we formulate the channel model based on the SW model considering that users under LoS and NLoS channel states coexist in the same communication cell. For this reason, we define two channel vectors, one for the LoS channel model, and the other for the NLoS one. Then, we define a unified model capturing the multi-state aspect of the proposed channel model.

The LoS channel follows the SW model. Hence, the channel response between the antenna $m$ and the user $k$ can be expressed as [12]:

$$
a_{m,k} = \frac{\rho_{\text{LoS}}}{r_{m,k}} \exp\left(-\frac{2\pi}{\lambda} r_{m,k}\right),
$$

where $\rho_{\text{LoS}} > 0$ is the path loss attenuation at a reference distance, $\lambda > 0$ is the path loss exponent, $\lambda > 0$ is the carrier wavelength, and $r_{m,k} > 0$ is the distance from the antenna $m$ to the user $k$, calculated by:

$$
r_{m,k} = \sqrt{(r_k^m)^2 + (r_m)^2 - 2r_k^m r_m \cos (\theta_k^m - \theta_m^m)}. \tag{3}
$$

Considering (2), the channel vector $a_{k,\text{LoS}} \in \mathbb{C}^M$ for the LoS channel is equal to:

$$
a_{k,\text{LoS}} = [a_{1,k}, \ldots, a_{M,k}]^T. \tag{4}
$$

Differently, the NLoS channel follows the i.i.d. Rayleigh-fading model with the path loss computed independently for each antenna due to the variation of the average received power across the large-aperture XL-MIMO array [6]. The path loss of the NLoS radio link between the antenna $m$ and user $k$ is equal to:

$$
\beta_{m,k} = \frac{\rho_{\text{NLoS}}}{r_{m,k}^\gamma}, \quad \gamma > 1,
$$

where $\rho_{\text{NLoS}} > 0$ is the path loss attenuation at a reference distance and $\gamma_{\text{NLoS}} > 0$ is the path loss exponent, and $r_{m,k}$ is as in (3). Hence, the channel vector $a_{k,\text{NLoS}} \in \mathbb{C}^M$ for the NLoS channel is defined such that:

$$
a_{k,\text{NLoS}} \sim \mathcal{CN}(0_M, \Sigma_k), \quad \Sigma_k = \text{diag}(\beta_{1,k}, \ldots, \beta_{M,k})^T, \tag{7}
$$

Note that the uncorrelated channel assumption in (7) is justified since the antenna elements are separated by the distance $d \geq \lambda/2$.

Definition 1: Let $x_k \in \{0, 1\}$ be the channel state indicator associated with the user $k$, equal to 1 if the channel is under the LoS state, or 0 if it is under the NLoS state. To capture the influence of topographic features related to the communication cell on the channel state, e.g., the effect of relief, as well as the spatial configuration of scatterers and obstacles, the indicator is modeled as a random variable. Therefore, $x = f_{x_k}(r_k^m, \theta_k) \sim \mathbb{R}_+$ is the conditional probability mass function (pmf) that depends on the position of the user $k$ in the cell.

Given the definition of the channel state indicator, as well as the LoS and NLoS channel vectors, the multi-state channel vector $a_k \in \mathbb{C}^M$ can be defined as:

$$
a_k = x_k a_{k,\text{LoS}} + (1 - x_k) a_{k,\text{NLoS}}. \tag{8}
$$

Notice that, when $x_k = 1$, (8) is equal to the LoS channel vector. On the other hand, when $x_k = 0$, the channel vector of user $k$ is equal to the NLoS channel vector. Hence, users with different channel states may coexist in the same communication cell, depending on the definition of the state indicator pmf, $f_{x_k}(r_k^m, \theta_k)$.

In this sense, for the sake of simplicity and to enable the evaluation of the proposed techniques in a variety of channel scenarios, in the remainder of this work we consider that the channel state indicators follow a Bernoulli random distribution with parameter $0 \leq \rho \leq 1$, namely the LoS probability. Therefore, the conditional pmf results:

$$
f_{x_k}(r_k^m, \theta_k) = \rho^x (1 - \rho)^{1-x}, \quad \text{where } x \in \{0, 1\} \text{ and } \forall k \in \{1, \ldots, K\}. \tag{9}
$$
B. Signal Model

Now, we define the model for the signal received by the users. Let $\mathcal{K} \subseteq \{1, \ldots, K\}$ be the set of scheduled users. The transmitted signal by the BS is equal to:

$$ z = \sum_{k \in \mathcal{K}} \sqrt{p_k} s_k f_k, \quad (10) $$

where $p_k > 0$ is the power allocated for the user $k$, $s_k \in \mathbb{C}$ such that $\mathbb{E}[|s_k|^2] = 1$ is the signal intended for the user $k$, and $f_k \in \mathbb{C}^M$ such that $\|f_k\|_2 = 1$ is the precoding vector computed for the user $k$. The received signal by the user $k \in \mathcal{K}$ is equal to:

$$ y_k = \sqrt{p_k} s_k^H f_k + \sum_{i \in \mathcal{K} \setminus k} \sqrt{p_i} s_i^H f_i + w_k, \quad (11) $$

where $w_k \sim \mathcal{C}\mathcal{N}(0, \sigma^2_w)$ is the additive white Gaussian noise. Given the received signal in (11), the signal-to-interference-plus-noise ratio (SINR) calculated for the user $k \in \mathcal{K}$ is equal to [12]:

$$ \text{SINR}_k = \frac{p_k |a_k^H f_k|^2}{\sum_{i \in \mathcal{K} \setminus k} p_i |a_i^H f_i|^2 + \sigma^2_w}. \quad (12) $$

Without loss of generality, let $k \in \{1, \ldots, |\mathcal{K}|\}$ be the indices of the scheduled users. Then, the channel matrix with the channel vectors of all the scheduled users is defined as $A \in \mathbb{C}^{M \times |\mathcal{K}|}$ such that $A = [a_1 \cdots a_{|\mathcal{K}|}]$. For the sake of simplicity, we consider perfect CSI available at the transmitter,1 and that $|\mathcal{K}| \leq M$ and $\text{rank}(A) = |\mathcal{K}|$, then the BS can transmit the DL signal using the zero-forcing (ZF) precoder. Hence, the precoding vector for each user $k \in \mathcal{K}$ is equal to:

$$ f_k^{ZF} = A (A^H A)^{-1} e_k \left( (A^H A)^{-1} \right)_{k,k}^+, \quad (13) $$

where $e_k \in \{0, 1\}^{|\mathcal{K}|}$ is the $k$-th vector of the standard basis of the $|\mathcal{K}|$-dimensional Euclidean space.

Considering that the ZF precoder mitigates the inter-user interference (IUI), i.e., $a_i^H f_j = 0, \forall i, j \in \mathcal{K}, i \neq j$, substituting (13) in (12) results in the SINR calculated for user $k$ using the ZF precoder:

$$ \text{SINR}_{k}^{ZF} = \frac{p_k \sigma^2_w}{\left( (A^H A)^{-1} \right)_{k,k}^+}. \quad (14) $$

Using Shannon’s equation, the achievable rate of the user $k \in \mathcal{K}$ using the ZF precoder is equal to:

$$ R_{k}^{ZF} = \log_2 \left( 1 + \frac{p_k}{\sigma^2_w \left( (A^H A)^{-1} \right)_{k,k}^+} \right). \quad (15) $$

Observing (15), we note that the achievable rate of the user $k$ not only depends on its respective allocated power and the noise power, but also on the overall set of scheduled users and their respective channel vectors. For this reason, the user scheduling process is crucial for attaining reasonable performance levels.

Let $\overline{R}_k > 0, \forall k \in \mathcal{K}$ be the minimum achievable rate that the BS must serve to user $k$. Given the set of scheduled users $\mathcal{K}$, the maximum DL achievable sum-rate of the XL-MIMO system using the ZF precoder is succeeded with the allocated powers that solve the following optimization problem:

$$ \{p_k\}_{k \in \mathcal{K}} = \arg \max_{\{p_k\}_{k \in \mathcal{K}}} \sum_{k \in \mathcal{K}} R_{k}^{ZF}, \quad (16a) $$

subject to $R_{k}^{ZF} \geq \overline{R}_k, \forall k \in \mathcal{K}, \quad (16b)$

$$ \sum_{k \in \mathcal{K}} p_k \leq P_{\text{max}}, \quad (16c) $$

$$ p_k > 0, \forall k \in \mathcal{K}. \quad (16d) $$

where $P_{\text{max}} > 0$ is the maximum power available for DL transmission, and the achievable rates $R_{k}^{ZF}, \forall k \in \mathcal{K}$ are given by (15). Since (16) is equivalent to the optimization problem of allocating power on independent parallel Gaussian channels, the set of powers $\{p_k\}_{k \in \mathcal{K}}$ that solve it follows the water-filling distribution [18].

III. User Scheduling: Problem Formulation

In this section, we introduce the formulation of the studied user scheduling problem. The optimization problem of joint DL user scheduling and power allocation with individual minimum achievable rate constraints and transmit power budget can be defined as:

$$ P_0: \begin{align*}
\text{maximize}_{\{p_k\}_{k \in \mathcal{K}}} & \sum_{k \in \mathcal{K}} R_{k}^{ZF}, \\
\text{subject to} & R_{k}^{ZF} \geq \overline{R}_k, \forall k \in \mathcal{K}, \\
& \sum_{k \in \mathcal{K}} p_k \leq P_{\text{max}}, \\
& K \subseteq \{1, \ldots, K\}, \\
& p_k > 0, \forall k \in \mathcal{K}. \quad (17a)
\end{align*} $$

The constraints (17b) ensure that all the scheduled users are served with a minimum achievable rate. Moreover, the constraint (17c) ensures that the DL transmitted power does not exceed $P_{\text{max}}$. Finally, the constraints (17e) and (17d) define the domain of the optimization variables.

The optimization problem $P_0$ is concave in the variables $\{p_k\}_{k \in \mathcal{K}}$, but not in the variable $K$. For this reason, it isn’t possible to solve $P_0$ optimally with standard convex optimization tools. An alternative path to reach a sub-optimal solution is to split $P_0$ into two sub-problems in which each variable is optimized independently. We discuss this strategy in the sequel.

Let $g : \varphi(\{a_k\}_{k=1}^{K}) \rightarrow \mathbb{R}_+$ be a function that measures the spatial compatibility between users from their channel vectors. The spatial compatibility quantifies how efficiently these channel vectors can be separated in space. Examples of spatial compatibility metrics are the condition number and the null-space projection of the channel matrix. Since there exists a

1Further, in Subsection V-D, the impact of inaccurate CSI at the transmitter on the performance of the user scheduling techniques is numerically evaluated.
correspondence between spatial compatible users and the preceding performance, optimizing a spatial compatibility metric is a promising path to obtain a good set of scheduled users [5]. The generic user scheduling problem solved by maximizing a spatial compatibility metric is called user grouping and can be formulated as:

\[ P_1 : \quad K^* = \arg\max_{K} g(\{a_k\}_{k \in K}), \quad (18a) \]

subject to \( K \subseteq \{1, \ldots, K\}. \quad (18b) \]

The optimization problem \( P_1 \) is an NP-complete combinatorial problem solved only by exhaustive search. Since, in crowded XL-MIMO systems, the number of users in the communication cell is high, the size of the solution space of \( P_1 \) scales quickly. Hence, in such a case, it is impractical to solve the user grouping problem in a feasible time. For this reason, Section IV develops an effective, quasi-optimal, and computationally efficient method to carry out user scheduling in crowded XL-MIMO scenarios.

Given the set of scheduled users \( K^* \), the optimal set of allocated powers \( \{P_k^*\}_{k \in K^*} \) can be calculated by solving the following optimization sub-problem:

\[ P_2 : \quad \{p_k^*\}_{k \in K^*} = \arg\max_{\{p_k\}_{k \in K^*}} \sum_{k \in K^*} R_{k}^{ZF}, \quad (19a) \]

subject to \( R_{k}^{ZF} \geq \overline{P}_k, \forall k \in K^* \), \( (19b) \)

\[ \sum_{k \in K^*} p_k \leq P_{\max}, \quad (19c) \]

\[ p_k > 0, \forall k \in K^*. \quad (19d) \]

The optimization problem \( P_2 \) is identical to (16) and, if feasible, it can be solved optimally by the water-filling solution [18]. A simple way to check the feasibility of \( P_2 \) is presented in the following.

Remark 1: The optimization problem \( P_2 \) is feasible if and only if the sum of the minimum allocated powers necessary to serve each user with its respective minimum achievable rate does not exceed \( P_{\max} \), i.e.,

\[ \sum_{k \in K^*} \overline{p}_k = \sigma_w^2 \sum_{k \in K^*} \left( 2\overline{P}_k - 1 \right) \left[ (A^H A)^{-1} \right]_{k,k} \leq P_{\max}, \quad (20) \]

where \( \overline{p}_k > 0 \) is the minimum power required to serve user \( k \) with the achievable rate in (15) equal to the minimum achievable rate \( \overline{R}_k \).

Considering that the feasibility criterion in (20) is satisfied, the solution of \( P_2 \) is given by:

\[ p_k^* = \max \left( \overline{p}_k, \mu - \sigma_w^2 \left[ (A^H A)^{-1} \right]_{k,k} \right), \quad (21) \]

\( \forall k \in K, \) where \( \mu \in \mathbb{R} \) is a constant called water-level. Moreover, to meet the constraint (19c) with equality, the optimal water-level can be obtained by satisfying:

\[ \sum_{k \in K^*} \max \left( \overline{p}_k, \mu - \sigma_w^2 \left[ (A^H A)^{-1} \right]_{k,k} \right) - P_{\max} = 0, \quad (22) \]

which can be easily solved by a root-finding algorithm [18].

A. \( P_2 \) Infeasibility Test

In this subsection, we present an efficient method to check the infeasibility of the optimization problem (19) without needing to
calculate the inverse matrix \((A^H A)^{-1}\). This method motivates the development of the graph representation used in the proposed scheduling algorithm and reduces significantly the number of operations required to test the feasibility of the set of scheduled users.

Let \(R_k^\text{SU} > 0\) be the single-user capacity of the user \(k\) calculated by:

\[
P_k^\text{SU} = \log_2 \left( 1 + \frac{p_k \|a_k\|^2_\Sigma}{\sigma_w^2} \right).
\]

The single-user capacity is the achievable rate if, during the DL, the BS transmits only the signal of user \(k\). Following this definition, the minimum required power \(P_k^\text{SU} > 0\) for the user \(k\) to experience its minimum achievable rate \(R_k\) is equal to:

\[
P_k^\text{SU} = \frac{\sigma_w^2}{\|a_k\|^2_\Sigma} \left( 2^R_k - 1 \right).
\]

**Lemma 1:** For any set of scheduled users \(K \subseteq \{1, \ldots, K\}\), if the sum of the minimum powers required to equal the single-user capacity of each scheduled user to its minimum achievable rate is equal to or greater than \(P_{\text{max}}\), i.e., \(\sum_{k \in K} P_k^\text{SU} \geq P_{\text{max}}\), the optimization problem (19) is infeasible. Such a condition is sufficient but not necessary to confirm the infeasibility of \(P_2\). If \(\sum_{k \in K} P_k^\text{SU} < P_{\text{max}}\), the feasibility or infeasibility of \(P_2\) can only be proved by checking whether (20) holds.

**Proof:** The effective channel gain obtained by user \(k\) with the ZF precoder is upper-bounded by [19]:

\[
\|a_k\|^2_\Sigma \geq \left( A^H A \right)^{-1}_{k,k} = \|a_k\|^2_\Sigma - a_k^H \bar{A}_k \left( \bar{A}_k^H \bar{A}_k \right)^{-1} \bar{A}_k^H a_k,
\]

where \(\bar{A}_k \in \mathbb{C}^{M \times |K|^{-1}}\) is the channel matrix with the channel vectors of all the scheduled users, except for \(k\), i.e.,

\[
\bar{A}_k = \begin{bmatrix} a_1 & \cdots & a_{k-1} & a_{k+1} & \cdots & a_K \end{bmatrix}.
\]

Since \(A\) has full rank, \((\bar{A}_k^H \bar{A}_k)^{-1}\) is positive definite and, consequently, the equality in (25) is obtained if and only if \(\bar{A}_k^H a_k = 0\), i.e., the channel vector of user \(k\) is orthogonal to the channel vectors of all the other users. Therefore, we obtain the following relationship between the sum of the minimum allocated powers required to attain the minimum achievable rates of the scheduled users:

\[
\sum_{k \in K} P_k \geq \sum_{k \in K} P_k^\text{SU}.
\]

Accordingly, noticing that it is impossible to get perfectly orthogonal channel vectors in practice, if \(\sum_{k \in K} P_k^\text{SU} \geq P_{\text{max}}\) we have that \(\sum_{k \in K} P_k > P_{\text{max}}\), indicating that \(K\) is an infeasible set of scheduled users for the optimization problem \(P_2\). Conversely, in the ideal case where the scheduled users have all mutually orthogonal channel vectors, (27) attains equality.

**IV. USER SCHEDULING BASED ON CLIQUE SEARCH**

In this section, first, we introduce the concept of the undirected vertex-weighted graph (UWG) model for modeling the interference between the users in the proposed user scheduling XL-MIMO operating under non-stationary multi-state LoS and NLoS channels. Then, we formulate a clique search problem on the UWG to solve the user scheduling and power allocation sub-problems \(P_1\) and \(P_2\) proposed in Section III.

**A. Undirected Vertex-Weighted Graph Model**

Let \(\mathcal{G} = (\mathcal{V}, \mathcal{E})\) be a UWG, where \(\mathcal{V} = \{v_1, \ldots, v_{|\mathcal{V}|}\}\) is the set with the graph vertices such that \(|\mathcal{V}| = |\mathcal{V}|\), and \(\mathcal{E} \subseteq \{\{v_i, v_j\} | v_i, v_j \in \mathcal{V}, v_i \neq v_j\}\) is the set with the graph edges. Let \(\mathcal{E} \in \{0, 1\}^{|\mathcal{V}| \times |\mathcal{V}|}\) be the adjacency matrix of the graph \(\mathcal{G}\) such that:

\[
[\mathcal{E}]_{i,j} = \begin{cases} 1, & \text{if } \{v_i, v_j\} \in \mathcal{E} \\ 0, & \text{otherwise} \end{cases}
\]

The vertex weight function \(\omega : \mathcal{V} \rightarrow \mathbb{R}\) characterizes the weight of each vertex \(v_i \in \mathcal{V}\).

In our work, the UWG \(\mathcal{G}\) represents the users in the communication cell and the orthogonality relationship between their respective channel vectors. Each user \(k \in \{1, \ldots, K\}\) is represented by a vertex \(v_k\). Moreover, the edges \(\mathcal{E}\) are described by the adjacency matrix constructed from the channel vectors according to the \(\epsilon\)-orthogonality rule,

\[
[\mathcal{E}]_{i,j} = \begin{cases} 0, & \text{if } i = j \\ I_{\epsilon \in [0,1]}(|\mathcal{A}_v| \geq \frac{|a_i^H a_j|}{\|a_i\|^2_\Sigma}, & \text{otherwise} \end{cases}
\]

\forall i, j \in \{1, \ldots, K\}\), where \(I_{\epsilon}(\cdot)\) denotes the indicator function and \(0 \leq \epsilon \leq 1\) represents the admissibility for channel orthogonality. Such a method for defining the graph edges will make only those vertices representing users with quasi-orthogonal channel vectors to be connected. Finally, the weight of vertex \(k\) is defined as the minimum power required for user \(k\) to achieve a single-user capacity equal to its minimum achievable rate, i.e.,

\[
\omega(v_k) = P_k^\text{SU} = \frac{\sigma_w^2}{\|a_k\|^2_\Sigma} \left( 2^R_k - 1 \right), \forall k \in \{1, \ldots, K\}.
\]

Fig. 3 depicts a diagram of a UWG representation of a hypothetical XL-MIMO system with \(K = 7\) users and its equivalent adjacency matrix.

**Definition 2:** The subgraph \(\mathcal{G}' = (\mathcal{V}', \mathcal{E}')\) is called a clique if the vertices in \(\mathcal{V}'\) are mutually adjacent to one another, i.e., \(\mathcal{E}' = \{\{v_i, v_j\} | v_i, v_j \in \mathcal{V}', v_i \neq v_j\}\). Moreover, the number of vertices in the clique is called the clique number [20].

**B. User Scheduling Based on Clique Search**

Now, we formulate the user scheduling process as a clique search problem in the UWG \(\mathcal{G}\) that represents the XL-MIMO system. Let \(\mathcal{C}_g\) be the set of all the cliques of the graph \(\mathcal{G}\). We aim to find the clique with the largest clique number and with the sum of the weights less than \(P_{\text{max}}\). This clique search problem can be written in the form:

\[
P_1 : \quad \mathcal{G}' = \arg\max_{\mathcal{G}'} |\mathcal{V}|,
\]

subject to \(\sum_{v_k \in \mathcal{V}} \omega(v_k) < P_{\text{max}}\).
Algorithm 1: CBS – Greedy Algorithm to Solve the Clique Search Problem \( P_3 \).

\[ \begin{align*}
\text{Input:} & \quad \text{The set of graph vertices, } V \\
\text{Output:} & \quad \text{The set of clique vertices, } \mathcal{V}' \\
\text{1} & \quad \mathcal{V}_0 \leftarrow \text{arg min}_{v \in V} \omega(v); \\
\text{2} & \quad \mathcal{V}'(0) \leftarrow \{v_0\}; \\
\text{3} & \quad \mathcal{N}'(0) \leftarrow \text{neighbors}(v_0); \\
\text{4} & \quad \omega(v) \leftarrow \omega(v); \\
\text{5} & \quad n \leftarrow 0; \\
\text{6} & \quad \text{repeat} \quad \text{\{} \\
\text{7} & \quad \mathcal{V}_n \leftarrow \text{arg min}_{V \in \mathcal{N}'(n)} \omega(v); \\
\text{8} & \quad \mathcal{V}'(n+1) \leftarrow \mathcal{V}'(n) \cup \{v_n\}; \\
\text{9} & \quad \mathcal{N}'(n+1) \leftarrow \mathcal{N}'(n) \cap \text{neighbors}(v_n); \\
\text{10} & \quad \mathcal{V}'(n+1) \leftarrow \mathcal{V}'(n) + \omega(v_n); \\
\text{11} & \quad \text{if } \mathcal{V}'(n+1) \geq P_{\text{max}} \text{ then} \\
\text{12} & \quad \text{\} exit \ loop; \\
\text{13} & \quad n \leftarrow n + 1; \\
\text{14} & \quad \text{until } \mathcal{N}'(n) = \emptyset; \\
\text{15} & \quad \mathcal{V}' \leftarrow \mathcal{V}'(n); \\
\end{align*} \]

The constraint \( \mathcal{G}' = (\mathcal{V}', \mathcal{E}') \subseteq \mathcal{G} \).

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Algorithm 1 presents a method to find a near-optimal solution for the clique search problem \( P_3 \). We call this algorithm as clique search-based scheduling (CBS). In this pseudocode, the operator \( \mathcal{G} \rightarrow \omega(\mathcal{V}) \) returns the set of vertices that have edges with the input vertex \( v_k \), i.e., \( \text{neighbors}(v_k) = \{ v_i \mid \{ v_k, v_i \} \in \mathcal{E} \} \).

The greedy algorithm starts by finding the vertex that requires the least weight and adding it to the clique. The neighboring vertices of the first vertex constitute the clique neighborhood, computed in line 3. In the loop beginning at line 6, the vertex of the clique neighborhood with the least weight is added to the clique. Next, in line 9, the clique neighborhood is updated with the vertices that are simultaneously neighbors of all the clique vertices. This loop repeats until the sum of the weights in the clique is less than or equal to \( P_{\text{max}} \), or if there are no more vertices in the clique neighborhood. When the first stop criterion is met, the algorithm outputs the set of vertices obtained during the previous iteration, satisfying the constraint \( \mathcal{G}' \). Hence, the set of scheduled users is calculated from the output of the Algorithm 1 by \( \mathcal{K} = \{ k \in \{ 1, \ldots, K \} \mid v_k \in \mathcal{V}' \} \). It is worth mentioning that the scheduling criterion used in CBS results in a set of users possibly feasible w.r.t. \( P_2 \), without guaranteeing that the users in \( \mathcal{K} \) can be scheduled satisfying the power budget and minimum achievable rate constraints simultaneously. For this reason, we need a procedure to verify the feasibility of \( \mathcal{K} \) w.r.t. the problem \( P_2 \) and remove users from the set if the power allocation is infeasible. We describe the adopted approach in the following.

C. Obtaining a Feasible Set of Scheduled Users

When the set of scheduled users produced by the CBS algorithm is infeasible, a user removal procedure must be adopted to get a feasible one. The proposed user removal algorithm is based on the \( P_2 \) feasibility criterion in \( (20) \) and described in Algorithm 2. In this procedure, the user with the lowest channel power, namely the user with the worst channel condition, is removed from the set of scheduled users until the power allocation problem \( P_2 \) becomes feasible. Accordingly, in lines 4-7, the user with the lowest channel power is removed, then the minimum powers necessary to serve the users in the reduced set are calculated. These steps repeat until the power allocation feasibility is confirmed according to the condition in \( (20) \), as evaluated in line 8.

Finally, with a feasible set of scheduled users, power allocation can be carried out satisfying both the transmit power budget and the minimum achievable rate constraints. Fig. 4 sketches out the whole proposed technique for joint user scheduling and power allocation problems in crowded XL-MIMO systems.

D. Scheduling Users Analyzing Their Channel Powers

Now, we describe a simple but effective approach to schedule users based on the powers of the channel vectors. Let \( P_k > 0 \) be

Constraint \( \mathcal{G}' = (\mathcal{V}', \mathcal{E}') \subseteq \mathcal{G} \) is a necessary condition for ensuring the power feasibility of the solution, but not a sufficient condition. This occurs since the simplified feasibility test in constraint \( \mathcal{G}' \) assumes perfect orthogonality between scheduled users. If there exists a certain interference level between them, more transmit power is required, and therefore a more accurate, time-consuming procedure to verify the feasibility of the solution has to be performed.
the power of the channel vector of user $k$, calculated from the multi-state channel vector in (8) by:

$$P_k = \|a_k\|^2_2. \quad (32)$$

The power of the channel vector is a suitable measure of the channel quality for a given user, resulting from its distance w.r.t. the BS array and its channel state. Moreover, by inspecting (20) and (25), one can see that the minimum allocated power necessary to serve user $k \in \mathcal{K}$ with its respective minimum achievable rate is inversely proportional to $P_k$.

$$\bar{p}_k = \frac{\sigma_w^2 \left( 2\pi k - 1 \right)}{P_k - a_k H \hat{A}_k \left( \hat{A}_k^H \hat{A}_k \right)^{-1} \hat{A}_k^H a_k}. \quad (33)$$

Therefore, we use the channel powers to develop a user scheduling technique named channel power-based scheduling (CPBS).

Let $n \in Z_+^*$ be the number of the iteration of the CPBS algorithm. During each iteration, the CPBS schedules the user with the largest channel power, solving the following optimization problem until a stop criterion is met:

$$k^* = \arg \max_k P_k, \quad (34a)$$

subject to $k \in \{1, \ldots, K\} \setminus \mathcal{K}^{(n-1)}. \quad (34b)$

The pseudocode of the CPBS algorithms is given in Algorithm 3. The CPBS algorithm operates with the procedure described in the following. In lines 5 and 6, the algorithm schedules the user with the largest channel power by solving problem (34).

The algorithm repeats this procedure until the set of scheduled users results in an infeasible power allocation problem according to the criterion described in Remark 1, or if all the users in the communication cell are scheduled. Similarly to the CBS algorithm, the set of scheduled users calculated by the CPBS generates an infeasible power allocation problem. Therefore, the procedure derived in Section IV-C must be applied to $\mathcal{K}$ to generate the final set of scheduled users.

V. NUMERICAL RESULTS

In this section, we present numerical results to demonstrate the effective performance of the introduced user scheduling methods operating in crowded XL-MIMO systems. In the Monte-Carlo simulations, we consider $K = 10^3$ users located inside a cell such that $r_k^{UE} \in [0.03, 1]$ km and $\theta_k^{UE} \in [-\pi, \pi]$, $\forall k \in \{1, \ldots, K\}$. The users are uniformly distributed in the cell area. Hence, the angles $\theta_k^{UE}$ follow a uniform distribution, while the distances $r_k^{UE}$ follow the probability density function [21]:

$$f_{r_k^{UE}}(r) = \begin{cases} 2(r_{max}^2 - r_{min}^2)^{-1}, & \text{if } r_{min} \leq r \leq r_{max}, \\ 0, & \text{otherwise} \end{cases}, \quad (35)$$

where $0 < r_{min} < r_{max}$ are respectively the possible minimum and maximum distances from the array center to any user in the communication cell. The BS is equipped with $M = 10^3$ antennas. The minimum achievable rate per user is set to $R_k \in [5, 15]$ bps/Hz, $\forall k \in \{1, \ldots, K\}$. We choose the minimum value of 5 bps/Hz to meet the ITU-R experienced data rate requirement of 100 Mbps for the dense urban eMBB scenario [22]. On the matter of the channel model, the path loss attenuation and coefficients are defined according to the ITU-R urban micro-cell environment [23].

The complete list of the simulation parameters is organized in Table I. The evaluation metrics are calculated by averaging the results obtained from $S = 10^3$ realizations. During each realization, the users’ positions and the channels are generated by sampling random distributions following the definitions provided in Section II.

A. Evaluation Metrics

The metrics used to evaluate the user scheduling techniques are $a)$ the achievable sum-rate; $b)$ the average achievable rate; and $c)$ the number of scheduled users. Moreover, we have defined metrics to analyze the $d)$ distribution of the scheduled users.
across the cell, and e) the probability of a user being scheduled given its channel state.

From the achievable rate of the user $k$ defined in (15), the system achievable sum-rate is calculated by:

$$ R = \sum_{k \in \mathcal{K}} \log_2 \left( 1 + \frac{P_k}{\sigma_w^2} \left( A^H A \right)^{-1} \right). $$

Using (36), the average achievable rate can be expressed by dividing the sum-rate by the number of scheduled users:

$$ \overline{R} = \frac{R}{|\mathcal{K}|}. $$

To measure the distribution of the scheduled users across the cell, we determine the complementary cumulative distribution function (CCDF) of the $2D$ distance between the scheduled users and the array center. The CCDF for a distance $r\geq 0$ is calculated by:

$$ \hat{F}(r) = \Pr \left( k \in \mathcal{K} \mid r^\text{UE}_k > r \right). $$

From a numerical perspective, the CCDF in (38) can be approximated by deploying the result of a Monte-Carlo simulation as:

$$ \hat{F}(r) = \frac{\sum_{k \in \mathcal{S}} \sum_{k' \in \mathcal{K}} I_{\{r' \in \mathbb{R} \mid r' > r\}} (r^\text{UE}_k)}{\sum_{k \in \mathcal{K}} |\mathcal{K}|}, $$

where $\mathcal{S} = \{ \mathcal{K}_1, \ldots, \mathcal{K}_S \}$ is the set containing all the sets of scheduled users obtained in each of the $S = |\mathcal{S}|$ Monte-Carlo realizations.

A complementary metric to evaluate the distribution of the scheduled users is the probability of a user being scheduled given its channel state. These probabilities w.r.t. a user under the LoS or NLoS channel state are respectively given by:

$$ P_{\text{LOS}} = \Pr \left( k \in \mathcal{K} \mid x_k = 0 \right), $$

Similarly to (38), these two probabilities can be estimated from the result of a Monte-Carlo simulation by calculating:

$$ \hat{P}_{\text{LOS}} = \frac{\sum_{k \in \mathcal{S}} \sum_{k' \in \mathcal{K}} I_{\{1\}} (x_k)}{\sum_{k \in \mathcal{K}} |\mathcal{K}|}, $$

$$ \hat{P}_{\text{NLOS}} = \frac{\sum_{k \in \mathcal{S}} \sum_{k' \in \mathcal{K}} I_{\{0\}} (x_k)}{\sum_{k \in \mathcal{K}} |\mathcal{K}|}. $$

### B. Baseline Techniques

The baseline user scheduling techniques for XL-MIMO systems adopted for comparison with the proposed CBS and CPBS algorithms include the greedy weighted clique (GWC) search algorithm [10], the distance-based scheduling (DBS), and the simplified DBS (DBS-s), both latter proposed in [12].

In GWC, the users in the communication cell are represented by a UWG. The edges are drawn according to the $\epsilon$-orthogonal rule as described in Section IV, while the vertices weights are the single-user capacities considering uniform power allocation. The GWC algorithm of [10] implements a greedy algorithm to search the maximum weighted clique in the graph aiming to obtain a set of scheduled users that have simultaneously high channel powers and quasi-orthogonal channel vectors.

Differently, the DBS algorithm performs user scheduling using a metric named equivalent distance, defined in eq. (7) of [12]. The equivalent distance of a given user during an iteration of the DBS algorithm essentially depends on its distance to the center of the BS array and the sum of the inner products between its channel vector and the precoding vectors of the currently scheduled users. Hence, users with lower equivalent distance values have higher scheduling priority. The algorithm proceeds by selecting the users with the lowest equivalent distance until there is a reduction in the achievable sum-rate. Alternatively, also in [12] is proposed the DBS-s algorithm, a version of the DBS with lower computational complexity. In this algorithm, the equivalent distance metric is substituted by the distance between the user and the center of the BS array, reducing the complexity of the algorithm at the cost of performance degradation.

For a fair comparison between the proposed and baseline scheduling techniques, we have included one additional stop criterion on the GWC, DBS, and DBS-s algorithms. During the end of each iteration of the baseline algorithms, the feasibility of the power allocation problem is evaluated by applying (20). If this criterion is violated, the last scheduled user is removed from the set and the algorithm stops. After the user scheduling procedure, the power allocation is carried out by calculating the solution of optimization problem $P_2$.

### C. User Scheduling Performance

Fig. 5 depicts the achievable sum-rate and the number of scheduled users obtained by the proposed CBS algorithm depending on the parameter of admissibility for channel orthogonality. This analysis is paramount to tune the CBS $\epsilon$ parameter for the performance comparison carried out in the following. From Fig. 5, one can see that both the sum-rate and the number
CBS algorithm is the one that achieves the best performance. The DBS and DBS-s algorithms achieve almost the same performance for all the evaluated cases, outperforming only the random scheduling. Indeed, it is worth mentioning that, except for the random scheduling, all the evaluated techniques achieve similar performance for $\rho = 0$. The random scheduling achieves the poorest performance because its scheduling criterion does not take into account the quality of the users’ channel vectors. Such a behavior repeats for all the numerical results in the sequel.

Fig. 7 depicts the number of scheduled users as a function of the transmit power considering different values of LoS probability. One can see that the number of scheduled users increases with the transmit power and LoS probability. Specifically for $\rho = 0$, all the evaluated techniques, except for the random scheduling, achieve almost the same number of users. For $\rho > 0$, the CBS algorithm achieves the best performance in terms of the number of scheduled users, followed by GWC. It is worth mentioning that, despite the GWC attaining a higher sum-rate than the CBS for $P_{\text{max}} > 15$ dBm and $\rho \in [0; 0.75]$, the CBS consistently schedules a higher number of users. Finally, similarly to what occurs with the sum-rate metric, the number of scheduled users achieved by all the scheduling techniques treated herein, except for the random scheduling, are nearly the same for $\rho = 0$.

Fig. 8 depicts the average achievable rate depending on the transmit power considering different values of LoS probability. For all the evaluated techniques, except for the random scheduling, the average rate is inversely proportional to the number of scheduled users. Specifically, for $\rho < 1$, the CBS algorithm obtains achievable rate values close to the minimum achievable rate of 5 bps/Hz. For $\rho \geq 0.75$, the best techniques in terms of the average rate are the DBS and DBS-s. On the other hand, for $\rho \leq 0.25$, the random scheduling achieves the best performance in terms of average rate. However, it is important to mention that this high average rate is obtained at the cost of scheduling an extremely low number of users, as demonstrated in Fig. 7.

Fig. 9 depicts the achievable sum-rate as a function of the minimum achievable rate considering different values of LoS probability. For all the techniques, except for the CBS, the achievable sum-rate decreases by increasing the minimum
Fig. 8. Average rate of the scheduled users vs. the transmit power under scenarios with different LoS probabilities. Simulation parameters are detailed in Table I.

Fig. 9. Achievable sum-rate vs. minimum achievable rate per user under scenarios with different LoS probabilities. $P_{\text{max}} = 30$ dBm.

achievable rate. This behavior is expected since increasing the minimum achievable rate constraint implies allocating more power per user to satisfy this requirement. Especially, the GWC for $\rho \in \{0.25, 0.75\}$ reaches achievable sum-rate values that increase with the minimum achievable rate, up to a point where this behavior reverses. As we will see in the result in the sequel, this maximum point of achievable sum-rate occurs due to a reduction in the number of scheduled users slower than the increase in the minimum achievable rate.

Fig. 10 depicts the number of scheduled users depending on the minimum achievable rate considering different values of LoS probability. As expected, the stricter minimum achievable rate constraints with a fixed transmit power budget results in a reduction on the number of scheduled users. Specifically, we see that the CBS and GWC algorithms present a slow rate of decrease in the number of scheduled users for $\rho = 0.75$ and $R_k \leq 11$ bps/Hz, $\forall k$. This is the cause of the partially increasing behavior of the achievable sum-rate obtained by these algorithms identified in Fig. 9 for $\rho \in \{0.25, 0.75\}$.

D. User Scheduling Performance With Inaccurate CSI

Since the proposed and benchmark scheduling algorithms rely on CSI, it is important to evaluate their performance in the case when inaccurately estimated channel vectors are available at the BS. Let $\hat{a}_k \in \mathbb{C}^M$ denotes the estimated channel vectors that follow the model below:

$$\hat{a}_k = \sqrt{1 - \alpha^2}a_k + \alpha \nu_k, \forall k \in \{1, \ldots, K\},$$ (44)

where $0 \leq \alpha < 1$, and $\nu_k \sim \mathcal{CN}(0, I_M, \|a_k\|_2^2 I_M)$ denotes the estimation error. Therefore, the NMSE of the estimate is:

$$\mathbb{E}\left[\frac{\|a_k - \hat{a}_k\|_2^2}{\|a_k\|_2^4}\right] = 2 \left(1 - \sqrt{1 - \alpha^2}\right),$$ (45)

where the expectation is taken over $\nu_k$. In this sense, Fig. 11 depicts the achievable sum-rate and the number of scheduled users vs. the normalized mean-squared error (NMSE) of the estimated channel vectors. The NMSE values are in accordance with recent results for channel estimation in XL-MIMO systems [9]. Analyzing Fig. 11, one can notice that the achievable sum-rate decreases with the channel estimate NMSE, once the mismatch between the channel vectors and their estimates produces IUI, preventing the users from reaching their required QoS levels. Moreover, the channel estimation error has a significant impact on the number of scheduled users by the CBS and GWC algorithms when the NMSE is above $-20$ dB, and when it is above $-10$ dB for the others. In the worst case, the methods cannot carry out user scheduling when the NMSE is greater or equal to $-5$ dB for the graph-based techniques and $-10$ dB for the others. Therefore, even though the CBS algorithm is affected by inaccurate CSI as the other scheduling techniques, it can achieve remarkable performance in crowded XL-MIMO
scenarios, scheduling around 560 users with a channel estimate NMSE of $-20$ dB.

E. Computational Complexity

Table II shows the running time of the evaluated scheduling algorithms for $\rho \in \{0, 0.25, 0.75, 1\}$. With this result, the performance-complexity trade-off obtained by the algorithms can be compared by the ratio between the running time and the number of scheduled users (Fig. 7). For $\rho = 1$, the CBS algorithm has the best trade-off, achieving the highest number of scheduled users at the expense of a running time 3.7 times lower than DBS and 79 times lower than GWC. On the other hand, for $\rho = 0$, the CPBS algorithm achieves the best trade-off, since all the evaluated techniques schedule approximately the same number of users, except for the random scheduling. For $\rho \in \{0.25, 0.75\}$, the DBS-s algorithm achieves the best trade-off. Whereas, it is worth noticing that the CBS algorithm can schedule up to 5 times more users than DBS-s with a similar trade-off. Therefore, the benefits of the proposed CBS algorithm are achieved in realistic scenarios where users under the LoS and NLoS channel states coexist, i.e., $\rho > 0$. 

F. Distribution of the Scheduled Users

Fig. 12 depicts the CCDF of the 2D distance between the scheduled users and the array center under scenarios with different LoS probabilities. $P_{\max} = 30$ dBm, $\overline{R}_k = 5$ bps/Hz.

Fig. 13. Probability of a user being scheduled given its channel state under scenarios with different LoS probabilities. $P_{\max} = 30$ dBm, $\overline{R}_k = 5$ bps/Hz.

VI. CONCLUSION

In this paper, we study the problem of user scheduling in crowded XL-MIMO systems with per-user QoS requirements. To increase the number of served users in the DL channel of XL-MIMO systems with high user density, we propose the CBS algorithm, a QoS-aware joint user scheduling and power allocation algorithm based on the search in a graph. Moreover, to capture the complexity of the propagation environment with physically
large arrays, we propose a non-stationary multi-state channel model that accounts for the co-existence of users under LoS and NLoS transmission in the same communication cell. The user scheduling performance of the developed CBS algorithm is evaluated and compared with the state-of-the-art, considering the proposed channel model under different conditions. As a result, the CBS algorithm demonstrates superiority over state-of-the-art techniques in crowded XL-MIMO scenarios, scheduling up to 5 times more users with satisfied QoS requirements than the DBS algorithm [12] when users under both LoS and NLoS channel states coexist ($0 < \rho < 1$). Still, this improved performance is reached even when inaccurate CSI is available at the BS. Besides, the CBS algorithm achieves fair coverage over the whole cell area, providing a more uniform communication experience for all users, including the ones located at the cell border. Finally, the computational complexity analysis demonstrates that the CBS algorithm presents a good performance-complexity trade-off, scheduling more users than the graph-based GWC algorithm [10] in a running time up to 79 times lower. Future research directions include incorporating strategies to schedule the non-scheduled users on subsequent frames, improving the users’ average achievable rates, and thereby promoting fairness among them.

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