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Uplink scheduling evaluation in D-MIMO networks

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***Abstract*— Distributed multiple-input multiple-output (D-MIMO) networks have been studied and developed due their ability to increase the coverage area and provide more uniform data rates. The scheduling algorithms are crucial for managing radio resources efficiently and ensuring a higher quality of service. This work then investigates the performance of three scheduling algorithms, each one with different selection criteria. The numerical results indicate that the enhanced subset greedy performs better than the other algorithms in terms of average sum rate for most access point arrangements; however, it has lower fairness than the other schedulers.**

***Keywords*— D-MIMO, user scheduling, fairness.**

I. INTRODUCTION

Wireless communication systems have been developed to address the massive rise in services and number of actives users that requires higher data rates and reduced latency [1]. Fifth generation (5G) and beyond systems have been designed to expand the system capacity, to support the high density of user equipment (UE), and also the diversification of services [2]. However, the scarcity of radio resources persists as a limiting factor to attend such demands [3].

One solution to this is the use of scheduling algorithms, which control users' access to system resources. Such strategies are essential for the resource management to be done efficiently for different flow types and applications [1], since the orthogonalization of the channels helps mitigate a large part of the inter-user interference problem [3].

Associated to the strategies mentioned above, some technological solutions have been studied and proposed to increase the networks' spectral efficiency [4]. In this context, the distributed multiple-input multiple-output (D-MIMO) architecture appears as an appealing solution. It comprises a number of access points (APs) distributed in a given area, connected to a central processing unit (CPU) by a backhaul network, and simultaneously serving users [4], [5], possibly through coherence transmission and distributed signal processing.

The contribution of this work then lies in the analysis of different UE scheduling strategies deployed in D-MIMO networks. The random and the maximal performance class (MPC) schedulers described in [6] are adapted for the D-MIMO scenario. In addition, the enhanced subset greedy (ESG) scheduler, proposed in [7], is considered as the state-of-art. The three scheduling strategies are evaluated in terms of the sum-rate and fairness. As a key finding, the ESG tends to perform better than the other approaches, but with lower fairness as less UEs are usually scheduled.

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II. SYSTEM MODEL

In this work, we present a D-MIMO system for uplink transmissions that is composed of L single-antenna APs equally distributed in a coverage area. All APs are connected to a single CPU, which synchronizes the APs and provides services to UEs simultaneously by jointly and coherently processing their received signals. All K single-antenna UEs are randomly dropped within the coverage area.

A key assumption of this work is that $K > L$, which implies that the degrees of freedom are not enough to properly receive UEs' signals. This motivates the network to schedule only a subset of UEs at a time. In this context, let $\mathcal{U}_s$ be the set of scheduled UEs with cardinality $n_s = |\mathcal{U}_s|$. Thus, the constraint $n_s \leq L$ is imposed on the UE scheduler.

Regarding the channel model, the channel coefficient $g_{k,l} \in \mathbb{R}$ between the UE k and the AP l is given by:

$$g_{k,l} = \sqrt{10^{-\frac{\beta_{k,l}}{10}}}\,, \tag{1}$$

where $\beta_{k,l}$ is the large-scale fading modeled as $\beta_{k,l} = \mathrm{PL}(d_{k,l})+\sigma_{sh}$, with $\sigma_{sh} \sim N\left(0, \sigma^2\right)$ denoting the shadowing fading generated as a normally distributed random variable, $\mathrm{PL}(d_{k,l}) = 30.5 + 36.7 \log_{10}(d_{k,l})$ is the path loss component [5], and $d_{k,l} > 1$ m is the distance between the UE k and the AP l. Vector $\mathbf{g}_k = [g_{k,1}, \cdots, g_{k,L}]^T$ contains the channel coefficients of UE k to all APs, and $(\cdot)^T$ is the transpose operator. All channel coefficients are assumed to be known at the CPU.

As for key performance indicators (KPIs), the uplink signal-to-interference-noise-ratio (SINR) γ_k of UE k is defined as [5]:

$$\gamma_k = p\mathbf{g}_k^T \left(p \sum_{i \neq k}^{K} \mathbf{g}_i \mathbf{g}_i^T + \nu \mathbf{I}_L \right)^{-1} \mathbf{g}_k\,, \tag{2}$$

where p and ν stand for the UE transmit power and noise power, respectively, and $\mathbf{I}_L$ is an $L \times L$ identity matrix. The channel capacity of UE k is given as [3]:

$$C_k = B \log_2(1 + \gamma_k)\,, \tag{3}$$

in which B is the system bandwidth. At last, the sum-rate is then $C = \sum_{k \in \mathcal{U}_s} C_k$. The SINR expression in Eq. (2) can be obtained after a minimum mean square error (MMSE)-based signal combining at the CPU, while the rate in Eq. (3) is an upper-bound assuming Gaussian signaling.

III. UE SCHEDULING SCHEMES

In this section, we briefly explain three UE scheduling algorithms, namely: i) *Random*; ii) *Maximal performance class (MPC)*; and iii) *Enhanced subset greedy (ESG)*. As a general rule, these schedulers aim at selecting $n_s \leq L$ UEs and allocate them to the set $\mathcal{U}_s$.

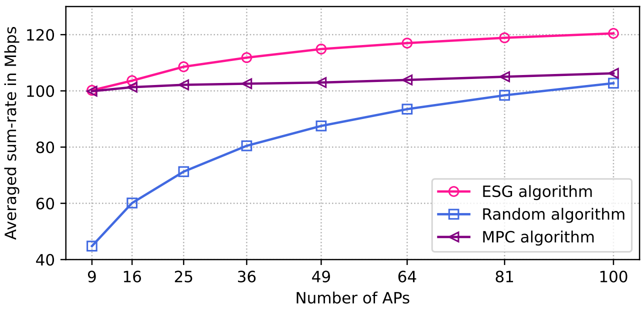

Fig. 1. A comparison of all schedulers in terms of sum-rate.

A. Random scheduling algorithm

This approach preserves the fairness of the network as it selects $n_s = L$ UEs at random, i.e., without using any criterion in favor of some UE.

B. Maximal performance scheduling algorithm

This algorithm, an adaptation of MPC described in [6], also schedules $n_s = L$ UEs, as in the random approach. However, it has a selection criterion of scheduling the n_s UEs with the highest channel gains $\mathbf{g}_k^T \mathbf{g}_k$ without considering the potential interference.

C. ESG multiuser scheduling algorithm

This algorithm is described in detail in [7]. Differently from the random and MPC approaches, it schedules $n_s \leq L$. It has two stages. Firstly, it sequentially picks the UEs with the highest channel gains in descending order until the sum-rate is no longer increased. Then, it exhaustively searches UEs, from those not picked in the first stage, that can replace the last-picked UE in the first stage and still improve the sum-rate. The second stage then tries to indirectly cope with interference. Clearly, the two stages restrict the value of n_s.

IV. Simulation Results

In this section, the performance of the three UE schedulers, namely random, MPC and ESG, will be evaluated and compared in terms of the sum-rate C and the number of scheduled UE n_s, both averaged over a total of 1000 Monte Carlo runs. The simulated D-MIMO system comprises $K = 128$ UE and L drawn from the subset of perfect square numbers $\{9, 16, \ldots, 81, 100\}$ to keep a regular grid of APs within a coverage area of 400×400 square meters. The difference in height between APs and UEs is 10 m. APs and UEs are equipped with a single omnidirectional antenna. UE transmit power $p = 10$ dBm and noise power $\nu = -96$ dBm, both in dB scale, and system bandwidth $B = 10$ MHz.

Fig. 1 presents the average sum-rate against L. As expected, the random approach is beaten by the other two algorithms for any value of L, approaching them, but mostly the MPC, as L tends to K. Interestingly, for small L, e.g., 9 and 16, the ESG has a sum-rate performance similar to the MPC. The reason is that in this cases the interference levels are small; thus, the

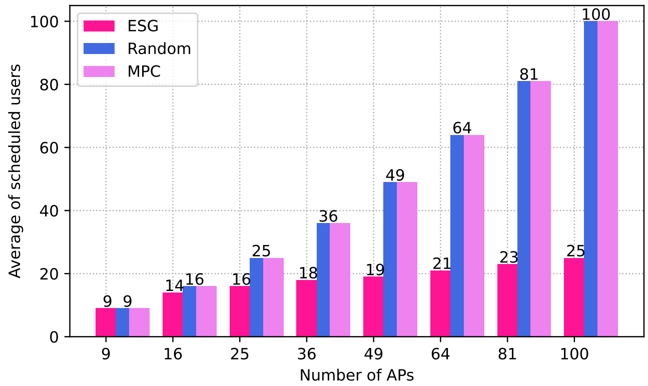

Fig. 2. Average number of scheduled UEs vs AP number.

MPC's scheduling criterion becomes as good as that of ESG. However, as L increases, so do the interference levels, and the ESG's scheduling criterion consequently becomes better as it indirectly copes with the interference.

Furthermore, in Fig. 2 the fairness aspect of the schedulers is investigated. The obtained results show that both the random and the MPC schedulers present the same fairness as L increases because they always schedule $n_s = L$ UEs. On the other hand, as ESG tries to find the subset of UEs that maximizes the sum-rate, the number UEs it schedules is usually less than L. It is worth noting that although the random and MPC schedulers always select the same number of UEs, MPC scheduler has a criterion for their selection, so it becomes more unfair compared to the random scheduler.

V. Conclusions

This work analyzed three scheduling strategies, namely MPC, random, and ESG algorithms, adapted for D-MIMO scenarios with a large number of active UEs when compared to the number of APs. From the simulation results, it is possible to conclude that MPC and random schedulers have higher fairness in the selection of the UEs than ESG. However, ESG presents the highest sum-rate for the system by selecting only a small group of UEs towards the sum-rate maximization.

References

[1] A. Mamane, M. Fattah, M. E. Ghazi, M. E. Bekkali, Y. Balboul, and S. Mazer, "Scheduling algorithms for 5G networks and beyond: Classification and survey," *IEEE Access*, vol. 10, pp. 51 643–51 661, 2022.

[2] A. Dogra, R. K. Jha, and S. Jain, "A survey on beyond 5G network with the advent of 6G: Architecture and emerging technologies," *IEEE Access*, vol. 9, pp. 67 512–67 547, 2021.

[3] F. Cavalcanti, T. Maciel, W. Freitas, and Y. Silva, *Comunicação móvel celular*. Elsevier, 2018, ISBN: 9788535280432.

[4] J. Denis and M. Assaad, "Improving cell-free massive MIMO networks performance: A user scheduling approach," *IEEE Transactions on Wireless Communications*, vol. 20, no. 11, pp. 7360–7374, 2021.

[5] Ö. T. Demir, E. Björnson, and L. Sanguinetti, *Foundations of User-Centric Cell-Free Massive MIMO*. 2021.

[6] Z. Han and K. J. R. Liu, *Resource Allocation for Wireless Networks: Basics, Techniques, and Applications*. Cambridge University Press, 2008.

[7] S. Mashdour, R. C. De Lamare, A. Schmeink, and J. P. S. H. Lima, "Sequential multiuser scheduling and power allocation for clustered cell-free massive MIMO networks," in *2023 31st European Signal Processing Conference (EUSIPCO)*, 2023, pp. 1484–1488.