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Learning-Based Access Point Selection for Scalable Cell-Free Massive MIMO

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Abstract

Cell-free Massive MIMO has emerged as a promising wireless architecture capable of providing uniformly high spectral efficiency for the next wireless communication generation [1-2]. This can be done by coherently serving users through a large number of distributed access points (APs). Recent results have shown that centralized minimum mean-square error (MMSE) processing enables cell-free systems to compete with conventional cellular Massive MIMO [3], such performance gains rely on the assumption of full cooperation among all APs. In such architectures, all APs are connected to a central processing unit (CPU) via fronthaul links, where joint signal detection and processing are performed. In practice, this assumption leads to prohibitive fronthaul requirements and computational complexity, motivating the need for scalable user-centric transmission strategies in which only a subset of APs serves each user [4]. In this work, we investigate online user-centric AP selection in a cell-free Massive MIMO uplink system under correlated shadow fading and pilot reuse.

The scenario considered follows a standard and widely accepted cell-free deployment, with 100 single-antenna APs distributed over a coverage area and 40 User Equipment (UEs) randomly located according to a uniform spatial distribution (see Figure 1). Large-scale fading incorporates distance-dependent path loss and spatially correlated log-normal shadowing, while pilots are reused across users according to a fixed reuse factor. Importantly, the physical channel model, network geometry, and signal processing architecture are kept unchanged (published code in [3]) with respect to established benchmarks, ensuring a fair and meaningful comparison.

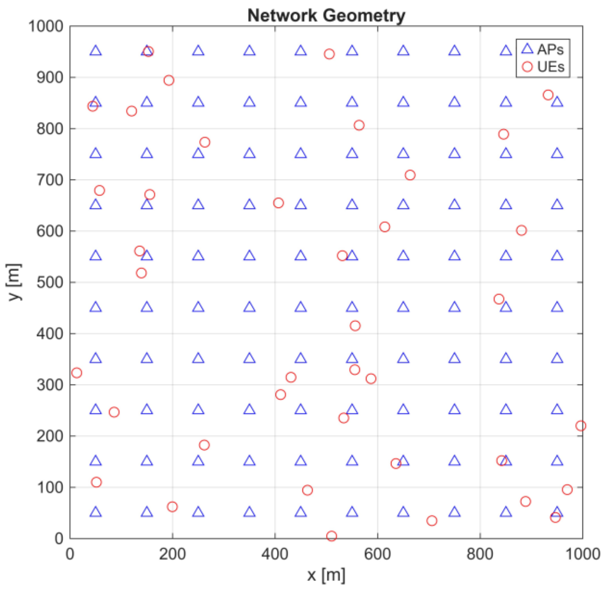

Figure 1. Cell-free network geometry with 100 single-antenna APs and 40 UEs.

To illustrate the intrinsic structure of the considered network and motivate user-centric AP selection, Fig. 2 depicts the average received signal power as a function of the number of serving APs per user, based solely on large-scale fading. For a given user k**,** the average received signal power when served by S Aps can be approximated as:

$$P_k(S) \approx \sum_{m \in A_{k(S)}} \beta_{m,k} \quad (1)$$

Where $\beta_{m,k}$ denotes the large-scale fading coefficient between AP m and user k, and $m \in A_{k(S)}$ is the set of the S strongest APs. The results reveal that only a small subset of APs (between 10 and 15) contributes significantly to the received power, while the performance gain rapidly saturates as additional APs are included. The observed behavior is a direct consequence of distance-dependent path loss and spatially correlated shadow fading, which create highly uneven large-scale channel conditions across the distributed APs. Consequently, full cooperation among all APs yields marginal performance improvements at the cost of excessive fronthaul usage, underscoring the need for efficient AP selection mechanisms. Selecting an appropriate subset of serving APs for each user constitutes a combinatorial optimization problem whose complexity grows rapidly with the network size.

The AP selection decisions are inherently coupled across users due to inter-user interference and pilot reuse, which results in a non-convex and generally NP-hard problem. Therefore, obtaining globally optimal solutions in real time using classical optimization methods becomes impractical for large-scale deployments. Existing heuristic strategies, such as selecting APs solely based on large-scale fading strength, do not adapt to dynamic pilot reuse patterns or spatially correlated shadowing, and may therefore lead to suboptimal performance in dense cell-free networks.

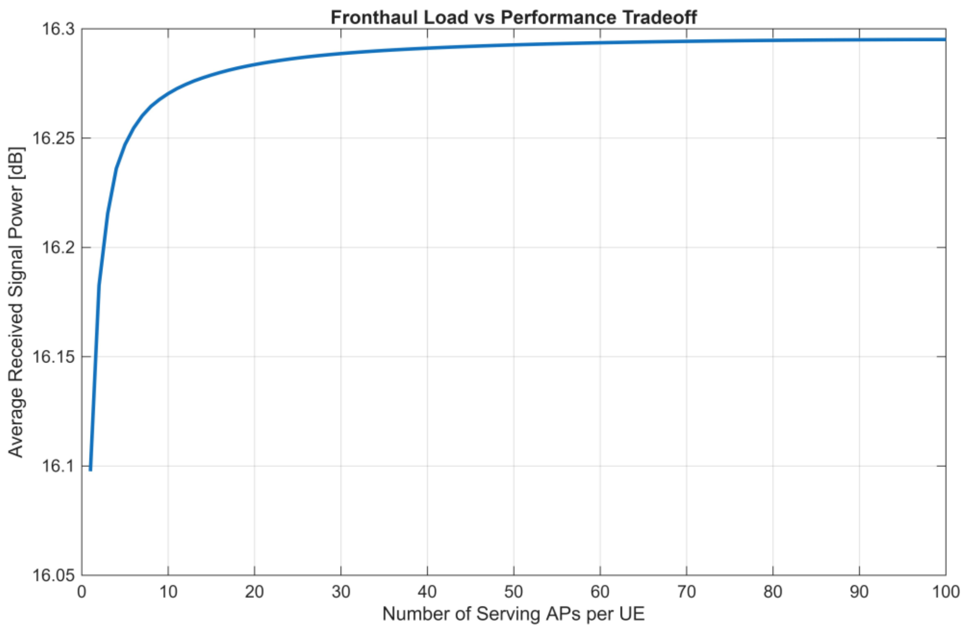

Figure 2. Average received signal power vs. number of serving Aps per UE.

To address this challenge, we formulate online AP selection as a contextual learning problem operated at the central processing unit. A centralized agent observes only slowly varying large-scale information, including AP–UE large-scale fading coefficients, pilot reuse relationships, and coarse user distribution indicators. Based on this context, the agent selects a user-centric subset of APs for each user at every large-scale coherence interval. The action space is inherently combinatorial, corresponding to AP subset selection, while the reward captures the achieved spectral efficiency penalized by fronthaul usage and pilot-induced interference. This formulation explicitly captures the trade-off between performance, scalability, and robustness.

The proposed framework leverages online learning techniques using Reinforcement learning that do not require prior channel statistics or offline training. By adapting AP selection decisions to the current propagation and pilot conditions, the learning-based approach is able to exploit macro-diversity while significantly reducing fronthaul signaling and computational burden. Unlike end-to-end learning approaches, the proposed method preserves the model-based structure of Massive MIMO systems and operates purely on large-scale statistics, ensuring interpretability and stability.

We evaluate the proposed online AP selection strategy through numerical simulations under realistic propagation conditions. The idea of using online selection has shown incredible results in adapting to realistic environmental conditions [5]. Performance is compared against full cooperation, strongest-AP heuristics, distance-based selection, and random AP selection. Results demonstrate that online learning achieves near-optimal spectral efficiency with a small fraction of active APs per user, while substantially improving worst-user performance and robustness to shadow fading. Moreover, the learning-based approach effectively mitigates pilot contamination by implicitly avoiding APs that amplify interference from pilot-sharing users.

This study shows that online learning provides an effective and principled tool for tackling NP-hard resource allocation problems in cell-free Massive MIMO without modifying the underlying physical-layer model. By embedding intelligence at the decision-making level rather than the signal-processing level, the proposed framework enables scalable and adaptive cell-free deployments suitable for beyond-5G and 6G networks.

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