AI-Centric Energy-Efficient Cell-Free MIMO Networks: Research Trends and Future Directions

Minji Lee†, Seungcheol Oh†, Joongheon Kim†, and Soohyun Park§
†Department of Electrical and Computer Engineering, Korea University, Seoul, Republic of Korea
§Division of Computer Science, Sookmyung Women's University, Seoul, Republic of Korea
E-mails: {lminji,seungoh,joongheon}@korea.ac.kr, soohyun.park@sookmyung.ac.kr

***Abstract*—Cell-free massive multiple-input multiple-output (CF-mMIMO) is considered a key technology for sixth-generation (6G) mobile networks. A large number of distributed antennas, called access points (APs), cooperate and serve users at the same time. This architecture provides almost uniform service quality over a wide area. As total power consumption increases rapidly, improving energy efficiency (EE) becomes a central design target. EE measures the ability of the system to maintain the same quality of service while reducing the consumed power. Recent research no longer relies solely on classical mathematical optimization. It also applies artificial intelligence (AI), including deep learning, deep reinforcement learning (DRL), and federated learning (FL), to automatically design power control, AP selection, and feedback bit allocation. Other studies use AI to control reconfigurable intelligent surfaces (RISs) to improve coverage and EE in CF-mMIMO networks. This paper explains these trends from an AI-centric viewpoint. It describes which EE-related problems appear in CF-mMIMO and how existing work defines and solves these problems in a simple and intuitive way. The paper also introduces recent research that combines CF-mMIMO with RIS, coordinated multi-point (CoMP), frequency-division-duplex (FDD) based CF systems, ultradense networks, integrated sensing and communication (ISAC), and FL. It then discusses open research directions for future 6G systems.**

***Index Terms*—Cell-free massive MIMO, Energy efficiency, Deep learning, Deep reinforcement learning, Federated learning, Reconfigurable intelligent surfaces**

I. Introduction

In fifth-generation (5G) and sixth-generation (6G) mobile communication, data traffic increases very rapidly. As traffic grows, the power that base stations (BSs) and user devices consume also increases. In this situation, it is not enough to focus only on higher spectral efficiency (SE). The system also needs to increase energy efficiency (EE), which measures how many useful bits it sends per unit of consumed power [1]. Cell-free massive multiple-input multiple-output (CF-mMIMO) uses many distributed access points (APs) that cooperate and act as one large antenna array. The distributed APs jointly serve all users on the same time–frequency resources. This structure reduces cell-edge problems and provides more uniform service quality across the coverage area [2]. In a traditional cellular network, each user is associated with one BS. In a CF-mMIMO system, a user receives service from several nearby APs at the same time. Because of this macro-diversity gain, the network can reduce the transmit power, or it can provide higher data rates with the same power. When the number of APs increases, the system consumes not only more transmit power but also more circuit power and more fronthaul and backhaul power. These components include baseband processing, data converters, and optical or wireless fronthaul links. Therefore, simply adding more APs does not always improve the global EE. The designer must answer questions such as how many APs should be active, which APs should serve which users, and how should the system set user transmit powers and beamforming vectors. Most EE studies formulate these questions as optimization problems. The objective is an EE metric. The constraints include power budgets and minimum rate or quality-of-service (QoS) targets [3].

The basic concepts and theory of CF-mMIMO are now well organized. Prior work clarifies channel models, user-centric clustering, pilot design, and power control, and it explains how these pieces form a scalable user-centric CF-mMIMO architecture. At the same time, ultradense CF-mMIMO for 6G raises new issues such as low-complexity architectures, scalable resource allocation, fronthaul limits, and massive access. In parallel, artificial intelligence (AI) centric designs appear for EE maximization, AP selection, user association, feedback optimization, and federated learning (FL) based resource management. These methods use deep neural networks (DNNs), deep reinforcement learning (DRL), and FL in order to replace or assist traditional optimization [4]. This paper organizes these research efforts under the common theme of AI-centric EE enhancement for CF-mMIMO. First, it introduces the basic CF-mMIMO system model and the mathematical definitions of SE and EE with simple equations. Next, it explains optimization-based work and AI-based work separately. Finally, it discusses future AI-centric CF-mMIMO that combines reconfigurable intelligent surface (RIS), integrated sensing and communication (ISAC), and FL and that aims at truly intelligent and energy-efficient 6G networks [5].

II. Fundamentals of Energy Efficiency in Cell-Free Massive MIMO

A. Cell-Free Massive MIMO System Model

In a CF-mMIMO network, M APs and K user equipments (UEs) share the same time–frequency resources. Each AP has N antennas. Each UE usually has one antenna. For simplicity, this subsection considers uplink transmission from UEs to APs.

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (RS-2025-00561377). *(Corresponding authors: Soohyun Park, Joongheon Kim)*

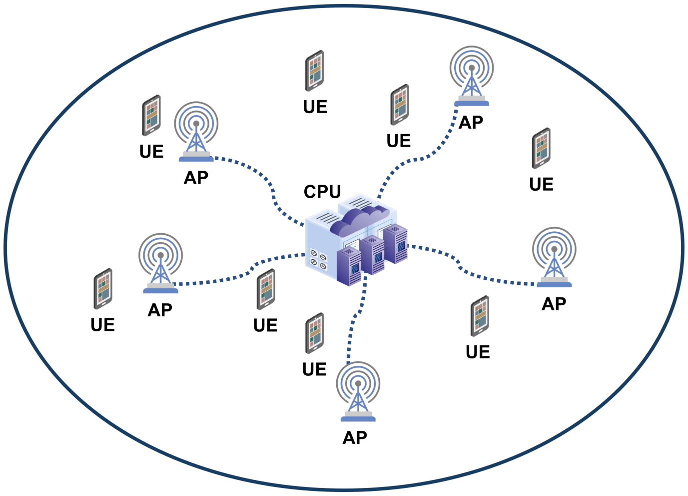

Fig. 1: Illustration of a cell-free massive MIMO network, where a CPU coordinates distributed APs that jointly serve UEs.

Fig. 1 illustrates a CF-mMIMO network. A central processing unit (CPU) connects to distributed APs through fronthaul links and coordinates their operation. The APs jointly serve multiple single-antenna UEs that are scattered over the coverage area on the same time–frequency resources. This user-centric architecture provides macro-diversity and enables more uniform service quality compared with conventional cellular systems.

The received signal at the mth AP is expressed as in (1):

$$y_m = \sum_{k=1}^{K} \sqrt{p_k}\, g_{m,k} s_k + n_m \tag{1}$$

where p_k is the transmit power of UE k, $g_{m,k}$ is the complex channel coefficient between AP m and UE k (including path loss and small-scale fading), s_k is the transmit symbol of UE k with unit power, and n_m is receiver noise at AP m [2].

In a CF-mMIMO architecture, a CPU, or a set of distributed processing nodes, collects all received signals y_m. The CPU then jointly detects all user symbols by linear or non-linear processing. As a result, even if one user is far from some APs, other nearby APs can still provide strong signal power. This joint processing creates almost uniform signal-to-noise ratio (SNR) and data rate over the service area [6].

B. SINR and Spectral Efficiency

For each user, the receiver can separate the received signal in practical scenarios into desired-signal power, interference power, and noise power. The signal-to-interference-plus-noise ratio (SINR) of UE k is expressed as in (2):

$$\gamma_k = \frac{S_k}{I_k + \sigma^2}, \tag{2}$$

where S_k is the desired-signal power, I_k is the total interference power from other users or cells, and σ^2 is the noise power. The exact expressions of S_k and I_k depend on the receiver, for example maximum-ratio, zero-forcing, or minimum mean square error (MMSE), but the basic interpretation useful signal divided by interference plus noise does not change.

Let τ_p be the pilot length and τ_c be the coherence length. The SE of UE k in bit/s/Hz, overhead, is expressed as in (3):

$$R_k = \left(1 - \frac{\tau_p}{\tau_c}\right) \log_2\big(1 + \gamma_k\big). \tag{3}$$

In (3), the factor $\left(1 - \frac{\tau_p}{\tau_c}\right)$ represents the fraction of symbols that carry data instead of pilots. The function $\log_2(1 + \gamma_k)$ comes from the Shannon capacity formula for a Gaussian channel and expresses the data rate per unit bandwidth. Let B denote the system bandwidth. In many papers, the total rate in bit/s is BR_k, and the analysis uses average SE values over fading, which are called ergodic rates [1].

C. Definition of Energy Efficiency

EE measures the number of successfully transmitted bits per unit of consumed energy. Consider the total rate $B\sum_{k=1}^{K} R_k$ in bit/s for K users and the consumed power P_{tot}. The total power includes transmit power, circuit power, and fronthaul and backhaul power. The network EE in bit/J is defined as in (4):

$$\text{EE} = \frac{B\sum_{k=1}^{K} R_k}{P_{\text{tot}}} \quad [\text{bit/J}]. \tag{4}$$

The numerator $B\sum_{k=1}^{K} R_k$ expresses how much useful data rate the network delivers (in bit/s), while the denominator P_{tot} expresses how much power the network uses to deliver this rate. A larger ratio in (4) means a more energy-efficient system [7].

An analysis of CF-mMIMO with random AP locations examines how system parameters affect EE. The analysis adjusts the number of users, the transmit powers, and the pilot length in order to maximize EE as in (4). Studies on ultradense CF-mMIMO show that very dense AP deployments create trade-offs between SE and EE. In summary, EE analysis in CF-mMIMO usually considers optimization of the EE definition in (4) under realistic constraints. The next section explains representative optimization-based approaches.

III. Optimization-Based Approaches for Energy Efficient Design

This section analyzes optimization-based methods that enhance EE in CF-mMIMO networks. It presents representative problem formulations for power control and AP selection and also describes cooperative transmission mechanisms based on CoMP operation. It further outlines optimization approaches that use RIS and ISAC functions. These topics show how optimization methods define system behavior and reveal factors that affect EE under practical constraints.

A. Power Control and AP Selection

A way to improve EE is to control the transmit power of each user and to decide which APs remain active. Many works define optimization problems that follow the form in (5):

$$\begin{aligned} \max_{\mathbf{p},\boldsymbol{\alpha}} \quad & \text{EE}(\mathbf{p},\boldsymbol{\alpha}) \\ \text{s.t.} \quad & R_k(\mathbf{p},\boldsymbol{\alpha}) \geq R_k^{\min}, \quad k = 1,\dots,K, \\ & 0 \leq p_k \leq p_k^{\max}, \quad k = 1,\dots,K. \end{aligned} \tag{5}$$

where $\mathbf{p} = [p_1, \ldots, p_K]$ is the user-power vector and $\boldsymbol{\alpha}$ denotes design variables such as AP–user association or beamforming weights. The constraint $R_k^{\min}$ represents the minimum rate requirement of UE k [3]. In general, the problem in (5) is non-convex. The numerator and denominator of $\mathrm{EE}(\mathbf{p}, \boldsymbol{\alpha})$ have coupled variables, and the rate constraints also have non-linear forms. Many works therefore use fractional programming, successive convex approximation, or iterative algorithms in order to find good local optima [1].

Joint multi-user grouping and AP switch on/off for EE maximization in CF-mMIMO is considered. The method selects a set of APs and assigns the APs to user groups. It then turns off APs that provide little benefit, thereby reducing circuit power. At the same time, it satisfies rate constraints of all users by keeping APs that are important for user performance. A network-assisted full-duplex CF-mMIMO system is analyzed. In this scenario, each AP sends downlink data and receives uplink data at the same time. The design must handle self-interference at APs and cross-link interference between uplink and downlink. The analysis defines optimization problems that jointly set uplink and downlink powers and that select receiver and precoder structures. The results show that well-designed full-duplex CF-mMIMO can improve both SE and EE under realistic interference and hardware constraints [8].

B. CoMP-Based Cooperative Transmission and Energy Efficiency

CF-mMIMO is closely related to coordinated multi-point (CoMP) systems, where several BSs cooperate in order to serve users near cell edges. CoMP is an important historical step toward fully cell-free operation. A CoMP-integrated cellular network is studied. The study designs cooperative caching and transmission strategies with reinforcement learning (RL). The goal is to improve cell-edge performance and to reduce backhaul load at the same time. In this system, multiple BSs form a CoMP joint-transmission cluster. A RL agent decides which content to cache at each BS and which BSs jointly serve each user. This dynamic policy improves user rates and reduces unnecessary data transfers over backhaul [9]. An energy-efficient resource allocation problem in a multi-cell CoMP heterogeneous network is analyzed. The analysis considers a multi-cell cooperation antenna (MSCA) scheme and optimizes transmit powers and serving-BS sets under EE criteria. Although the network is not fully cell-free, many ideas transfer to CF-mMIMO. In both cases, several spatially separated transmitters cooperate, and the designer must decide which nodes actually serve each user in order to satisfy rate constraints with minimal power [10].

C. RIS and ISAC in Cell-Free Architectures

A RIS uses many passive reflecting elements with tunable phase shifts. It shapes the propagation environment and changes both signal power and interference patterns without active RF chains. An energy-efficient RIS-aided CF-MIMO architecture is proposed [5]. The analysis shows that proper RIS design focuses energy toward intended users and reduces interference toward others. As a result, the network can achieve higher rates for the same transmit power or can reduce power while it keeps the same rates. An overview of energy-efficient RIS-aided CF-mMIMO systems is provided. The overview discusses use cases, design opportunities, and important challenges such as RIS placement, joint optimization of active and passive beamforming, and the combination of RIS with AI and FL. The work does not give a single closed-form solution. Instead, it provides a conceptual framework and highlights the need for scalable EE-focused algorithms in RIS-aided CF-mMIMO [11]. An RIS-enabled multi-user ISAC system is studied. The study designs location sensing and beamforming together. In this model, the RIS helps both communication and sensing. It improves user localization accuracy and data rates through joint transmit and reflection-beam design. This idea suggests that when ISAC and CF-mMIMO combine with RIS, the network can support sensing and communication simultaneously with high EE [12].

IV. AI-Centric for Energy Efficient CF-mMIMO

The previous section focuses on optimization based mainly on analytical models. This section explains how AI-based methods such as deep learning, DRL, and FL help EE-centric design in CF-mMIMO.

A. Deep Learning for Processing, Fronthaul, and Feedback

One main AI-centric line of work replaces or assists complex channel estimation and detection with deep learning. This is especially useful in systems with limited fronthaul or feedback capacity. An uplink CF-mMIMO system with limited fronthaul capacity is considered. The study compares two schemes. In quantize-and-forward (QF), each AP quantizes its received signal and its local channel estimates and forwards the quantized data to the CPU. In combine-quantize-and-forward (CQF), each AP first combines its signals, then quantizes and forwards the resulting data. The formulation defines a sum-rate maximization problem under fronthaul constraints and solves it with geometric programming. The approach then trains a deep convolutional neural network that maps large-scale fading coefficients to near-optimal power control solutions. This network allows fast power control without solving the optimization at every coherence interval [4]. Deep-learning-aided channel training and precoding for frequency-division-duplex (FDD) massive MIMO is studied. The method uses channel statistics such as covariance matrices to design downlink pilots and precoders jointly. The system achieves high sum rate even when the number of pilot symbols and feedback bits is small. This idea is important for FDD CF-mMIMO, where feedback links are often the main bottleneck [13].

A user-centric association and feedback-bit allocation method for FDD CF-mMIMO is presented. The method uses a Saleh–Valenzuela multi-path model and identifies which path-gain parameters are important for beamforming. The scheme jointly decides which APs serve which UEs and how many feedback bits each UE sends for each path. As a result, the system can achieve high SE under strict feedback budgets.

This work shows that intelligent feedback management is a key tool for energy-efficient FDD CF-mMIMO [14]. These methods improve EE in an indirect but important way. By reducing fronthaul and feedback requirements, the system can use simpler hardware and shorter training phases. The same physical infrastructure then supports higher rates per unit energy.

B. Deep Learning for Joint Pilot and Data Power Control

Another AI-centric line of work focuses on power control and pilot allocation. The goal is to replace repeated heavy optimization with a trained DNN. A deep-learning-based scheme for joint pilot and data power control in CF-mMIMO networks is proposed. The DNN takes channel and large-scale fading information as input and outputs power levels for both pilot and data symbols. After an offline training phase, the DNN produces near-optimal power vectors for new channel realizations with very low complexity. This allows fast adaptation even in fast-fading environments [15].

Energy-efficient AP selection in CF-mMIMO with DRL is studied. The study models the AP-selection problem as a Markov decision process. The agent observes user and AP positions and learns which APs should serve which users in order to maximize an EE reward. The evaluation tests DRL algorithms such as DDPG and soft actor–critic variants and shows that the learned policies outperform heuristic AP-selection rules. The result is higher EE for network topologies.

C. RL for CoMP, Caching, and Resource Management

RL is also useful for CoMP-style cooperative networks that are closely related to CF-mMIMO. The framework uses RL to control both caching and CoMP transmission policies. The agent observes content popularity and user positions and selects which content to cache at which BS and which BSs should cooperate for each user. The results show that the learned policy improves cell-edge throughput and reduces backhaul traffic. These improvements indirectly increase EE because the network dispenses with unnecessary data transfers [9].

An energy-efficient resource-allocation framework for MSCA-enabled CoMP in heterogeneous networks is presented. The approach optimizes power allocation and BS selection under rate and power constraints, and the results show that cooperative transmission increases EE when the cooperation sets are chosen carefully. These insights are also useful for CF-mMIMO system design, which faces similar trade-offs between cooperation gain and overhead [10].

D. Federated Learning Over RIS Assisted CF-mMIMO

A new research direction considers the EE of AI itself when it runs on CF-mMIMO networks. In FL, many UEs train local models and send updates to a central server over wireless links. FL over RIS-assisted CF-mMIMO networks is studied. The setting considers a scenario where each UE trains a local model and uploads parameters to a server through a CF-mMIMO network with RIS. The formulation defines an EE optimization problem that includes both communication energy and training energy. The decision variables include RIS phase shifts and transmit powers. The results show that proper joint optimization significantly reduces the total energy needed for FL while maintaining model accuracy [16]. This line of work shows that CF-mMIMO can serve not only as a data-delivery platform but also as an energy-aware computation and learning platform. In future networks, designers may need to optimize EE from the physical layer up to the AI applications.

E. Foundations of User Centric CF-mMIMO and Links to AI

A detailed monograph on the foundations of user-centric CF-mMIMO is provided. The monograph defines user-centric dynamic cooperation clustering (DCC), channel estimation, uplink and downlink transmission schemes, and power optimization algorithms. The monograph also analyzes channel hardening, favorable propagation, and scalability issues such as fronthaul load and computational complexity. It shows that CF-mMIMO can provide more uniform SE than cellular networks and that user-centric clustering is a key mechanism for scalability [2]. A survey of ultradense CF-mMIMO for 6G is presented. The survey discusses challenges such as dense AP deployment, synchronization, channel acquisition, and scalable resource allocation. Many of these challenges require data-driven or learning-based solutions. For example, scheduling, distributed precoding, and dynamic user selection in very dense networks naturally fit DRL or graph neural network formulations. Thus, the theoretical foundations in these works provide a base on which AI-centric resource allocation methods can build [6].

V. Future Research Directions for AI-Centric CF-mMIMO

This section summarizes promising research directions for AI-centric energy-efficient CF-mMIMO networks. First, there is a strong need for integrated AI design that spans the physical, medium-access control, and network layers. Many current works focus on local problems such as power control, AP selection, or pilot design [7]. In practice, however, decisions at different layers interact. Scheduling, handover, fronthaul capacity management, caching, and ISAC resource splitting influence each other. Multi-layer DRL or graph-based methods that jointly learn scheduling, power control, and AP selection in ultradense CF-mMIMO constitute an important research direction. Second, RIS-assisted CF-mMIMO requires more detailed EE-aware models. Existing work mainly demonstrates conceptual gains or uses small-scale examples. Future studies should answer practical questions such as where to deploy how many RIS panels, how often to update the configurations, and how to balance the power consumed by RIS control circuits against the EE gain in communication. Prior studies demonstrate the potential of RIS in ISAC contexts, which motivates joint optimization of RIS control, sensing accuracy, and EE in CF-mMIMO [12].

Third, FDD-based CF-mMIMO still poses many open challenges for feedback and user association. A joint user-centric association and feedback-bit allocation framework for FDD CF-mMIMO is presented under limited feedback budgets, and a deep-learning-based FDD training and precoding approach is introduced to enhance downlink performance [13]. Future work may consider deep-learning-based feedback compression, unsupervised feature extraction for channel representation, and RL-based adaptive feedback policies that react to traffic load and mobility. These methods need to optimize both feedback overhead and EE at the same time [14].

Fourth, FL and distributed AI on top of CF-mMIMO create new cross-layer EE trade-offs. It is shown that RIS-assisted CF-mMIMO can reduce the energy required for FL by proper joint optimization of communication and learning parameters [16]. Future studies should analyze the three-way trade-off between model accuracy, communication resource usage, and energy consumption. Future studies should also quantify how user-centric CF-mMIMO structures help FL by providing robust connectivity to many devices [11]. Finally, a combination of model-based and data-driven approaches is likely to be crucial. Analytical models and optimization tools for CF-mMIMO are provided in prior work, and practical constraints for ultra-dense deployments are detailed in existing studies. Model-aided learning can use these analytical results to shape neural network architectures, constrain action spaces, or generate high-quality training data. This can improve the reliability and interpretability of AI-centric EE designs and reduce the risk of unstable or suboptimal policies.

VI. Conclusion

This paper surveys research on energy-efficient CF-mMIMO networks from an AI-centric perspective. It first introduces the basic CF-mMIMO architecture, the uplink system model, and the definitions of SINR, SE, and EE with simple equations. These explanations help beginners understand how CF-mMIMO differs from cellular systems and why it has strong potential for high and uniform SE and EE. The paper then reviews optimization-based studies that design power control, AP selection, CoMP-style cooperation, and RIS configurations under EE objectives. It also summarizes AI-based methods that apply deep learning, DRL, and FL to power control, AP selection, fronthaul and feedback constraints, and energy-aware FL over RIS-assisted CF-mMIMO.

Overall, CF-mMIMO shows high potential to provide user-centric, uniform service quality and high EE. It does so by using many distributed APs that cooperate in a flexible way. When combined with AI techniques, CF-mMIMO can learn complex resource-allocation policies, adapt to network dynamics, and exploit structures such as RIS, ISAC, FDD operation, CoMP cooperation, and FL in an energy-aware manner. Future research needs to consider end-to-end EE optimization from the physical layer up to AI applications. It should integrate model-based and data-driven tools, use realistic large-scale simulations and testbeds, and explore standardization and implementation aspects. Through such efforts, CF-mMIMO can move from theory to practice and become a core infrastructure for 6G networks that are both intelligent and energy efficient.

Acknowledgement

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (RS-2025-00561377). (Corresponding author: Joongheon Kim).

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