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Original Article

Enhancing Energy Efficiency in CF mMIMO Systems Using Hybrid Transmit Power Control and Optimal Power Allocation Algorithms

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Abstract *- As real-time access and high-capacity requirements in wireless communication networks increase rapidly, solutions must balance the complex relationship between Spectral Efficiency (SE), and Energy Efficiency (EE) metrics. The proposed approach emphasizes the importance of combining Transmit Power Control (TPC), and Optimal Power Allocation (OPA) methods to achieve optimal results. The basic premise is that the hybrid algorithm will boost EE while retaining an acceptable level of SE. The CF mMIMO technology is first tested in a controlled setting without TPC and OPA. A hybrid algorithm combining TPC (Max-min EE) and OPA (Sum SE maximization) is then created, and EE and SE are optimized in the hybrid algorithm. The mixed technique is found to outperform the individual TPC and OPA algorithms. With an unparalleled 33,263,040.4068 bits/Joule, the hybrid algorithm boosts average EE. The hybrid algorithm also exceeds the targeted SE of 21 bits/s/Hz, demonstrating its capacity to balance EE and SE. This study advances the theory of CF mMIMO systems and offers practical insight into energy-efficient wireless communication. Future research and development for sustainable and high-performing wireless networks can build on these insights.*

Keywords *- Cell-Free massive MIMO, Energy Efficiency, Optimal Power Allocation, Spectral Efficiency, Transmit Power Control.*

1. Introduction

Discussions on advancements in wireless communication, particularly in the context of 5G and beyond, have surged in the past decade. The bottlenecks with these networks encompass low energy efficiency, bandwidth efficiency limitation, and an increase in carbon impact, among others [1, 2].

Cell-Free massive Multiple Input Multiple Output (CF mMIMO) technology, depicted in Figure 1, plays a crucial role in these networks, involving collaborative Access Points (APs) serving users across a large region without cell boundaries [3-8].

The expanding wireless networks necessitate a balance between Spectral Efficiency (SE) and Energy Efficiency (EE). The primary challenge being addressed in this research is the urgent requirement to enhance EE in the downlink of CF mMIMO wireless communication systems. The CF mMIMO systems consume a significant amount of energy despite their potential for increased spectral efficiency and overall system effectiveness. This work focuses not only on improving EE but also on maintaining a respectable level of SE in CF mMIMO systems. This quest proves especially difficult in the face of rising demand and energy usage.

It is critical to recognize the complex link between EE and SE, as an increase in EE frequently results in a decrease in SE in CF mMIMO. Striking a careful balance between these two elements is an essential focus of this research. In response to these problems, a novel hybrid strategy that combines Transmit Power Control (TPC) and Optimal Power Allocation (OPA) is developed to maximize EE while preserving reasonable SE. This methodology improves CF mMIMO performance by systematically manipulating several parameters, resulting in a wide range of percentage increases. Prior research in 5G and beyond has explored various strategies to improve efficiency.

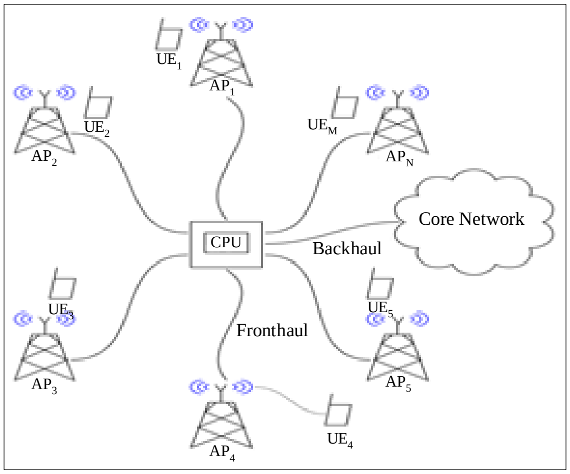


Fig. 1 Illustration of the Cell-Free massive Multiple Input Multiple Output (CF mMIMO) system architecture

In [8], Beamforming techniques are being studied to improve CF mMIMO system performance, particularly in higher frequency bands, to increase EE. To enhance both network capacity and data rates, Reconfigurable Intelligent Surface (RIS)-aided systems that are cost-effective and energy-efficient are used. This is done without hardware implementation and uses less power than typical CF mMIMO systems. However, energy efficiency increases in the study had some flaws. The effects of restricted fronthaul capacity on power regulation and data transmission in CF mMIMO systems must be addressed.

The study outlined in [9] introduces an innovative method to enhance EE in CF mMIMO networks, employing a low-complexity power control technique with a zero-forcing precoding design. Considering backhaul power usage and imperfections in channel state information, the method addresses the EE maximization problem, accommodating both perfect and imperfect channel estimation at Access Points (APs). By leveraging the convex nature of the objective function, the authors derive Optimal Power Control and precoding solutions to unlock the full potential of EE. However, the potential areas for further investigation of the proposed technique could include testing across diverse network and channel scenarios and exploring the impact of mobility and interference on energy efficiency in CF mMIMO networks.

In reference [3], EE and SE are enhanced through a variety of approaches. Specifically, the application of Weighted Minimum Mean Square Error (WMMSE) minimization, which is employed to optimize power allocation, aims for the maximization of the sum SE, along with the integration of an OPA algorithm. Through a quadratic transform, Fractional Programming (FP) dissociates signal and interference components to solve power allocation challenges. By using issue structure, the Alternating Direction Method of Multipliers (ADMM) solves convex subproblems quickly and efficiently for big problems. While FP requires fewer iterations, it may have a lower minimum SE at convergence than other approaches. The WMMSE algorithm's initialization may break stopping requirements, requiring more iterations for convergence, which makes it very complex, hence restricting scalability for large networks.

The study presented in [10] proposes a new way to boost massive MIMO systems' EE. The Energy-Efficient Power Allocation (PA) algorithm considers each user's minimum power needs to ensure QoS. The algorithm determines EE maximization by comparing minimum power requirements to maximum transmission power. Optimization of EE occurs if the aggregate is less than the total transmission power; otherwise, the technique maximizes cluster user admission. Simulation findings show that the suggested technique outperforms similar methods. Since Spectral Efficiency is not addressed, more analysis is needed to understand the algorithm's limit.

The research discussed in [11] explores diverse strategies for enhancing EE, with a notable focus on the investigation of Optimal Power Allocation algorithms. These algorithms are currently under thorough examination to improve resource allocation within Device-to-Device (D2D) communication systems. The primary objective of these algorithms is to optimize the distribution of power among users, with the goal of maximizing the cumulative transmission rate, thereby promoting more efficient utilization of resources, including energy.

Researchers have investigated the utilization of TPC algorithms with various strategies to enhance multiple metrics. Paper [12] optimizes power allocation using transmission power control algorithms to save energy and resources. The study also investigates using Minimum Mean-Square Error (MMSE) combining to reduce interference from surrounding User Equipments (Ues) and improve SE. Concentrated deployments perform better in SE due to channel hardening and propagation, while semi-distributed deployments perform better in average UE and downtime. Semi-distributed setups should have fewer APs to match fully distributed deployments and improve EE. The paper focuses on specifically combining precoding schemes and transmit power control algorithms; therefore, exploring other methods or algorithms may provide different EE and SE results.

Lastly, the research in [13] examines CF mMIMO EE and SE in the uplink. EE is affected by TPC algorithms, the quantity and layout of APs and UEs, and their propagation channels. The research analyzes three TPC algorithms: max-power, max-min SE, and max-min EE while preserving a target SE. A variety of antenna and UE configurations are examined. The max-min EE TPC method improves uplink EE, especially when no UE in a group of served UEs has bad channel conditions, and the base station antennas are fully spread. However, it is essential to acknowledge that the paper concentrates on a specific scenario of CF mMIMO systems with measured propagation channels at 3.5 GHz. It evaluates a limited number of transmit power control algorithms and antenna arrangements and may not encompass all possible scenarios and configurations.

Examining various research patterns in the literature review, TPC and OPA are used to improve EE and SE. Additionally, there is a mix of techniques involving either TPC or OPA and not necessarily a combination of both, despite their everyday use to enhance EE and SE. This study investigates the integration of TPC and OPA to optimize CF mMIMO systems for both energy and spectral efficiency. The promising results from simulations contribute significantly to future research, showcasing the efficacy of this hybrid approach.

Moreover, the study addresses a literature gap by providing baseline EE and SE values for CF mMIMO systems without optimization techniques. This foundational insight enables a nuanced exploration of the impact of optimization methods on CF mMIMO's energy and spectral efficiency, bridging a knowledge gap and establishing the groundwork for a deeper understanding of system efficiency dynamics.

2. Power Control and Power Allocation in CF mMIMO for Energy Efficiency

In the pursuit of optimizing EE in CF mMIMO systems, this research explores the collaboration of power control and power allocation, which are TPC and OPA. Building on [14], which introduces an implicit iterative algorithm for optimal power allocation in the downlink of CF mMIMO, the study advances this concept by proposing a novel hybrid approach.

This hybridization combines a max-min EE TPC method with a specialized OPA strategy, explicitly targeting the maximization of sum-SE. Seeking to balance EE with a predetermined SE objective, the hybrid approach represents a pioneering effort for superior efficiency gains in CF mMIMO, distinct from previous research that focused on individual TPC and OPA techniques.

The study, parallel to [15], discusses the benefits and limitations of TPC and OPA methods for optimizing EE in CF mMIMO systems. TPC, known for its simplicity and real-time adaptability to channel conditions, prioritizes minimal EE and shows improvements in low SNR or high user density settings [16]. However, TPC has a limited scope, may involve SE trade-offs, and faces coordination challenges across multiple APs [13, 17].

On the other hand, OPA is praised for its system-level optimization and simultaneous optimization of power allocation for EE and SE [15]. Yet, OPA encounters challenges such as high computational complexity, reliance on accurate CSI, and dynamic adaptability to real-time channel circumstances [16].

The suggested hybrid approach, which uses max-min EE TPC for individual users and OPA for sum-SE optimization, overcomes these strengths and weaknesses [14]. Leveraging TPC and OPA adaptability, the hybrid method aims to balance system-level EE and SE under unique channel conditions, maximizing resource allocation and overcoming each method's limitations. The mixed solution, according to the study, has the potential to improve EE performance in CF mMIMO systems while retaining SE, thus increasing wireless network resource efficiency and sustainability.

2.1. Applications

This research will lead to more energy-efficient CF mMIMO deployments in 5G and future networks, lowering network operator costs and improving environmental sustainability. Consumer energy bills and mobile communication infrastructure carbon footprint may drop [18].

The project aims to enhance wireless consumers' Quality of Service (QoS) by improving EE and maintaining appropriate SE, ensuring consistent data throughput and dependable connectivity from demanding or remote places. For video conferencing, streaming, and online gaming, this can improve customer satisfaction.

By optimizing resource use and power distribution, [16] showed that denser deployments of CF mMIMO base stations can increase network capacity and coverage, meeting the increased demand for mobile data traffic. This can improve underserved areas and increase digital access. The findings could help create future wireless systems like 6G by providing insights into optimizing resource sustainability in network operations. This could promote low-latency communication, huge IoT installations, and holographic networking allocation and attainment [14-16].

3. Optimization of Wireless Communication Systems

The optimization of wireless communication systems encompasses several subjects, such as SE and EE maximization, convergence analysis, and Access Point selection. These subjects are frequently examined within the framework of maximizing the efficiency of wireless resources, minimizing energy usage, and optimizing the overall performance of wireless networks.

3.1. EE and SE Maximization

In the realm of wireless communication systems, energy efficiency is commonly described as the ratio of information sent to power consumed, typically measured in bits per Joule [19]. This is crucial for assessing the sustainability and effectiveness of wireless networks. According to [19, 20], EE is commonly characterized as:

$$\text{EE (bits/J)} = \frac{\text{data rate (bits/s)}}{\text{Energy consumption (Joules/s)}} \qquad (1)$$

EE maximizing requires the implementation of advanced techniques such as resource allocation algorithms, modulation schemes, and transmission power management mechanisms [21]. These strategies are designed to optimize data transmission efficiency while decreasing energy consumption during communication. Maximizing energy EE is especially important given the increasing need for wireless connectivity, the widespread use of Internet of Things (IoT) devices, and the growing dependence on battery-powered communication devices. Optimizing the trade-off between spectral efficiency and energy consumption is a complex challenge that necessitates careful examination of system factors and network dynamics. Different objectives, constraints, and algorithms are applied while the EE maximization is done.

Spectral efficiency quantifies the amount of data that can be carried per unit of bandwidth in a specific communication channel [22]. The parameter measures the net throughput, omitting error correction codes. It is commonly expressed in bits per second per Hertz (bit/s/Hz). According to [23], the general formula is given below:

$$SE\ (bits/s/Hz) = \frac{capacity\ (bits/s)}{bandwidth\ (Hz)} \qquad (2)$$

The performance evaluation of the proposed algorithms is based on the utilization of EE and SE as critical metrics. These metrics are used as benchmarks to evaluate the effectiveness of the algorithms, especially in dealing with the challenges related to spectral and energy efficiency discussed in the chapters to follow.

Algorithms 1 and 2 use Equations 1 and 2 customized to the optimization problems being solved. The optimization objectives focus on enhancing the overall performance of the CF mMIMO system by maximizing the minimum EE and maximizing the sum SE.

Several factors, including power, frequency, noise power, and bandwidth, influence the optimization processes for EE and SE. It is worth mentioning that in the hybrid scenario, the algorithm incorporates certain conditions to adjust power allocation. This adaptation is motivated by the difference between the average EE and SE, aiming to achieve a solution that is harmonized and balanced.

Further details will be provided in the upcoming chapters to bring about a clear picture of these concepts and their practical implications. These details will help shed light on the complexities of the algorithms, giving a better understanding of how they affect system performance and efficiency.

3.2. Convergence Analysis

Convergence analysis involves a thorough examination and discussion of the inherent convergence properties in the algorithms being used. This examination explores the complex mechanisms by which the proposed approaches attain stability and optimal solutions during their iterative processes [24]. Every algorithm used in this research has its unique convergence characteristics when applied to find optimal solutions. In power adjustment, TPC demonstrates convergence once it reaches the maximum number of iterations.

The OPA algorithm distributes power based on the weight of each AP. Convergence is achieved once power is assigned. The integration of TPC and OPA involves a complex convergence process that requires careful consideration of weights and a set threshold to balance the performance indicators EE and SE.

The hybrid of the two has a maximum iteration value of 50,000. The initial iterations bring about significant changes, while the subsequent iterations aim to find a balance between the EE and SE objectives. The forthcoming results section provides a comprehensive explanation of these convergence behaviors and their implications.

3.3. Access Point Selection

Choosing the right access point is crucial in wireless communication systems as it dramatically affects network performance and user satisfaction. In order to make the communication process more relatable, it is essential to have a good AP selection. This involves considering important factors such as signal strength, channel conditions, and load balancing [25].

This careful selection guarantees efficient use of resources and effortless connectivity for users. The choice of access points in wireless communication systems greatly influences network performance and user experience. Although the current work primarily focuses on optimizing EE and SE in CF mMIMO, it is crucial to recognize the influence of access point selection on these metrics. Efficient AP selection schemes strive to improve the scalability of communication systems, ensuring optimal resource utilization and connectivity for end-users.

In a recent paper [26], a novel joint optimization strategy that makes use of the Accelerated Projected Gradient (APG) method was introduced. This approach prioritizes the protection of legitimate users' quality of service while minimizing the signal-to-interference-plus-noise ratio for potential eavesdroppers.

The research presents a comprehensive optimization framework that emphasizes the importance of collaboration between AP selection and power optimization in enhancing resource efficiency. The combination of AP selection and power optimization plays a vital role in creating a wireless communication network that is both efficient and dependable. The existing literature [27-31] offers valuable insights into different AP selection strategies, with a focus on enhancing SE and EE. Although the current study does not explicitly address access point selection algorithms, the discussion highlights their importance in optimizing wireless communication. Future research could investigate the integration of dynamic AP selection mechanisms to improve the performance metrics discussed in this study further.

4. System Model

The CF mMIMO system is carefully analyzed in the sense of how it operates in Time Division Duplex (TDD) mode. TDD enhances the ability to switch between uplink and downlink transmissions in the same time/frequency block, improving communication flexibility and efficiency [4]. Figure 1 from the first chapter illustrates the system architecture, which consists of N randomly placed APs.

Each AP is equipped with K antennas and can serve single-antenna UEs simultaneously. The essential fronthaul network connects all APs, creating a crucial connection to a Central Processing Unit (CPU). This network facilitates the flow of important network information between APs, promoting a synchronized and effective operation of the CF mMIMO system [32].

This case scenario's focus hinges on the downlink, which is the communication from APs to UEs facilitated by the fronthaul link. The assumption is that all N APs can concurrently serve all M users within the same time-frequency resource. The complex channel gains h_{nm} capture the wireless channel characteristics between the n^{th} AP and the m^{th} UE. The channel model is defined by:

$$\mathrm{h_{nm}} = \beta_{\mathrm{nm}}{}^{1/2} \cdot \mathrm{g_{nm}} \quad (3)$$

This formula captures the essence of wireless communication, where large-scale fading, β_{nm} and small-scale fading g_{nm} intricately shape the link between the n^{th} AP and the m^{th} UE. The small-scale fading is typically modeled as a Rayleigh fading distribution, which assumes that the real and imaginary parts of the channel gain are independently and identically distributed with a zero mean and unit variance.

This model is frequently employed to capture the wireless channel characteristics in cases where there is no prominent line-of-sight component and the signal experiences unpredictable multipath fading, symbolizing large-scale fading, thereby representing the deterministic attenuation of the signal over distance and environmental obstacles. Below are the details of the two algorithms which have been incorporated in this research:

4.1. Transmit Power Control (Max-Min EE)

TPC is a technique used to adjust the transmit power levels of APs based on the channel conditions. The goal of the Max-Min EE approach is to maximize the minimum EE among all APs. The algorithm iteratively adjusts transmit powers to achieve a balance between maximizing EE and maintaining acceptable SE [13].

Algorithm 1: Transmit Power Control - Max-Min EE Approach

Input:

- Maximum number of iterations (max_iter)
- Initial transmit powers (P) for APs
- Number of APs (N) and Mobile Stations (M)
- Channel gains (g) representing the wireless channel

Steps:

1. Initialize transmit powers for TPC
2. Perform iterations from 1 to max_iter
   a. Calculate EE for the current power allocation:

$$\mathrm{EEi} = \log_2\left(1 + \frac{\mathrm{P\_with\_TPC}*\mathrm{g}}{N_0 * B}\right) \quad (4)$$

   Where:
   - EEi is the Energy Efficiency for the i^{th} AP-UE pair.
   - P_with_TPC is the Transmit power after applying the TPC algorithm.
   - G is the Complex channel gain between the AP and UE.
   - N_0 is the noise power.
   - B is the channel bandwidth.

   b. Find the minimum EE values for each AP:
   c. Update transmit powers based on the Max - Min EE approach:
   for i = 1 to N
      i. Find the positions with minimum EE for AP i:
      ii. If min_positions is not empty, update powers: - P_with_TPC (i, min_position) = 2 * P_with_TPC (i, min_position)
      iii. Else, display a message:
         - No minimum position found for AP
3. End for loop
4. Finish iterations

Output:

- Updated transmit powers (P_with_TPC) based on the Max-Min EE approach
- SE and EE with TPC

4.2. Optimal Power Allocation (OPA) - Sum SE Maximization

Sum-SE maximizing power allocation refers to the power allocation strategy in CF mMIMO systems that aims to maximize the sum SE of all users. In this approach, the objective is to prioritize users with good channel conditions and allocate power in a way that maximizes the overall data throughput [3].

Algorithm 2: Optimal Power Allocation - Sum SE Maximization

Input:

- Number of Access Points (N) and Mobile Stations (M)
- Transmit Power (P) for each AP
- Channel Gains (g) representing the wireless channel
- Channel Bandwidth (B)
- Noise power (N0) in Watts/Hz

Steps:

1. Initialize weight W equally for each access point:
2. Allocate power P_i to each access point based on calculated weights:
3. Calculate SE with OPA after the power allocation:

$$\text{SE\_with\_OPA} = \log_2\left(1 + \frac{\sum_{m=1}^{M} P_{with\_OPA,m} * g_{nm}}{N_0 * B}\right) \quad (5)$$

4. Calculate EE with OPA:

$$EE\_with\_OPA = \frac{\log_2\left(1+\frac{\sum_{m=1}^{M} P_{with\_OPA,m} * g_{nm}}{N_0 * B}\right)}{\sum_{m=1}^{M} P_{with\_OPA,m} + N_0} \quad (6)$$

   For Equations 3 and 4:
   - EE_with_OPA is the Energy Efficiency with OPA.
   - SE_with_OPA is the Spectral Efficiency with OPA.
   - $P_{with\_OPA,m}$ is the allocated power for the *mth* UE under the OPA scheme.
   - g_{nm} is the complex channel gain between the n^{th} AP and the m^{th} UE.
   - N_0 is the noise power.
   - B is the channel bandwidth.
5. End

Output:

- Power allocation matrix (P_with_OPA) based on the Sum SE Maximization approach
- SE and EE with OPA

5. Materials and Methods

The simulations conducted in this study explore the performance of TPC, OPA, and a hybrid model combining both algorithms within the context of the CF mMIMO systems. The objective is to enhance the energy efficiency of the system while ensuring a satisfactory level of spectral efficiency. The results demonstrate the effectiveness of these algorithms in achieving a balance between energy and spectral efficiency in the TDD-operated CF mMIMO setup.

The simulation models a CF mMIMO system operating in TDD mode. The system involves N randomly deployed APs, each equipped with K antennas and M single-antenna UEs. The simulation parameters are shown in Table 1.

Utilizing MATLAB for simulation, the study was initiated with a straightforward approach involving the generation of random complex channel gains through the Rayleigh fading model. The system's performance was assessed by computing both SE and EE. Following this, a TPC mechanism was implemented using the Max-Min EE approach, dynamically adjusting transmit powers for balanced system performance. The simulation also integrated OPA for Sum SE Maximization, distributing power based on assigned weights to each AP.

Table 1. Simulation parameters and values

Parameters	Values
Number of Access Points (N)	64
Number of Mobile Stations (M)	128
Number of Antennas per Access Point (K)	8
Transmit Power of Each AP (P)	1 Watt
Frequency of Sub-6 GHz Frequency Band (f)	2.4 GHz
Channel Bandwidth	10 MHz
Noise Power Spectral Density (N0-dBmHz)	-174 dBm/Hz
Threshold	0.001

The innovative solution introduces a hybrid model that intelligently combines TPC and OPA by iteratively adjusting power allocations to effectively address the challenge of achieving a balanced trade-off between EE and SE. A threshold mechanism was incorporated to prevent oscillations and ensure convergence to a stable state.

The results are visually represented using MATLAB plots, which are Cumulative Distribution Functions (CDF) plots that depict the distribution of EE and SE over all investigated techniques. Furthermore, a Pareto front value graphic dynamically captures and revises the EE and SE values during the iterative process of the hybrid model. The pareto graphical representation provides a clear view of the intricate balance between energy efficiency and spectral efficiency, offering valuable insights into how these two important objectives interact.

During the simulations, several challenges were encountered that added complexity to the study. One significant challenge was the complicated balancing act required in optimizing the hybrid model. Achieving equilibrium between TPC and OPA to strike an optimal balance between EE and SE posed difficulties. The iterative nature of the hybrid model introduced potential oscillations in power allocations, requiring the implementation of a threshold mechanism to ensure stability and convergence to a consistent state.

Another challenge stemmed from the dynamic and unpredictable nature of wireless communication channels, modeled using the Rayleigh fading. The randomness inherent in channel gains added variability to the simulations, making it crucial to devise robust algorithms that could adapt to changing channel conditions. This necessitated the implementation of sophisticated control mechanisms to mitigate the impact of channel fluctuations on the overall system performance.

Furthermore, the process of combining TPC and OPA in the hybrid model posed difficulties in terms of algorithmic complexity and parameter adjustment. Careful consideration was given to balancing the weights assigned to each AP in the OPA scheme and determining the appropriate weight for TPC in order to achieve optimal performance. Addressing these challenges involved a combination of algorithmic refinement, robust control strategies, and careful parameter tuning to enhance the resilience and effectiveness of the proposed hybrid model in real-world scenarios.

Several assumptions were made to streamline the model and focus on specific aspects of Cell-Free massive MIMO systems. These assumptions include but are not limited to, perfect synchronization, ideal backhaul and front haul links, and static user locations. The assumptions were made to simplify the simulation process and to isolate particular facets of the problem for a more targeted analysis. Each assumption introduced in this simulation model serves a specific purpose and is grounded in a well-defined rationale.

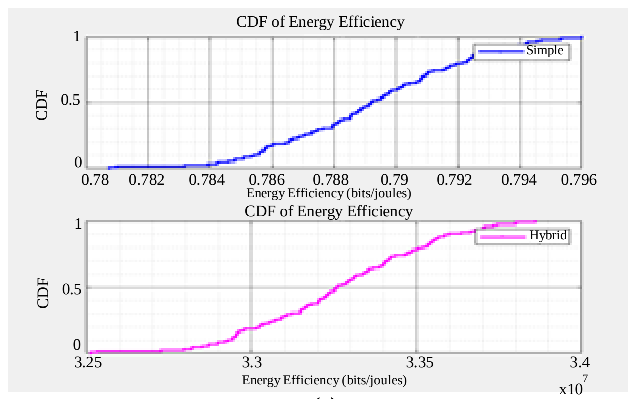
For instance, ensuring perfect synchronization is essential for isolating the impact of particular algorithms on energy efficiency. Although dealing with real-world synchronization can be challenging, this assumption allows for a more targeted examination of the effectiveness of the proposed techniques, free from the complications of synchronization problems.

It is imperative to discuss the potential impact of these assumptions on the outcomes of the simulation study. Take into consideration that assuming static user locations oversimplifies the complex reality of user mobility. Although this simplification allows for a more straightforward analysis of the proposed algorithms, it might result in overly optimistic performance estimates in situations where users' movements are constantly changing. Understanding these assumptions is crucial for a comprehensive interpretation of the results.

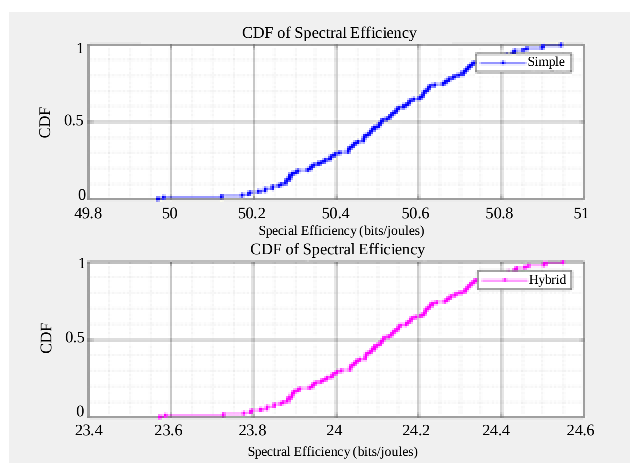
6. Results and Discussion

Figures 2(a), and 2(b) depict EE and SE values, respectively, through CDF plots. These plots illustrate the performance of both the baseline, represented by the simple approach, and the proposed hybrid approach in the simulation. Notably, the hybrid approach demonstrates a remarkable 99.99% improvement in EE but incurs a 52.26% reduction in SE. The trade-off between EE and SE was carefully managed by setting a threshold, ensuring a balance between the two metrics. Upon convergence, the average EE and SE values for both approaches are as follows: In the simple approach, the average EE is 0.78924 bits/J, while the average SE is 50.5112 bits/s/Hz. In contrast, the hybrid approach yields an average EE of 33,263,040.4068 bits/J and an average SE of 24.1157 bits/s/Hz. These outcomes align with the primary objectives of the simulation, aiming for an EE target equal to or greater than 10 Mbit/J and SE similar to or greater than 21 bits/s/Hz.

The benchmark was established based on insights gleaned from relevant literature [3, 12, 13, 33], where EE and SE were pivotal performance indicators, often involving TPC or OPA algorithms. While the achieved EE exceeded expectations, SE needed to be improved to meet the stated objective, highlighting the importance of the proposed solution improvements over the baseline method.



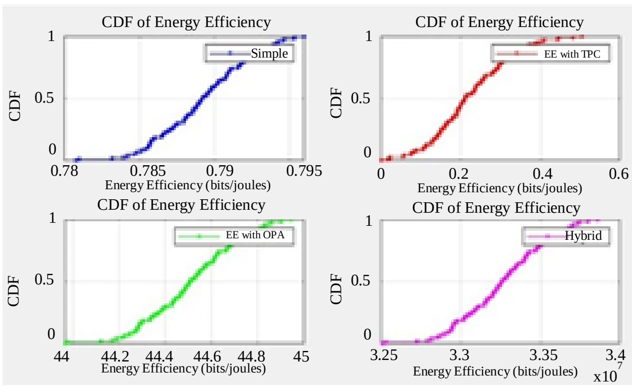
(a)



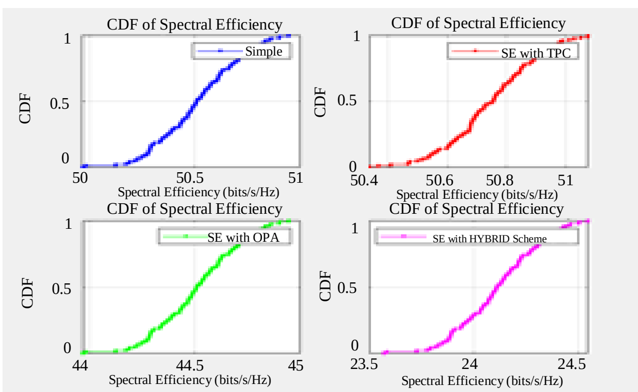
(b)

Fig. 2 Comparison of (a) EE, and (b) SE between the simple and hybrid approaches.

In Figures 3(a), and 3(b), a comprehensive portrayal of EE and SE values, respectively, are presented, utilizing CDF plots.



(a)



(b)

Fig. 3 Comprehensive comparison of (a) EE, and (b) SE across all four explored scenarios.

These visuals encapsulate the performance of four distinct approaches: the baseline, OPA, TPC, and the hybrid model. The average metrics derived from the plots are shown in Table 2. These outcomes emphasize the evolution from a basic scenario, where the simple approach established a reference point. Implementing TPC maintained a commendable SE of 50.7459 bits/s/Hz but at the cost of a substantial EE reduction to an average of 0.2241 bits/J.

On the other hand, OPA showcased an improvement in EE to an average of 44.5112 bits/J, coupled with a reduction in SE to 44.5112 bits/s/Hz, illustrating a distinct trade-off between energy and spectral efficiency. Notably, the hybrid approach emerged as a standout performer, achieving an exceptional average EE of 33,263,040.4068 bits/J, which is a 99.99% improvement over the simple approach. Despite a decrease in SE to 24.1157 bits/s/Hz, the hybrid strategy struck a commendable balance, surpassing literature standards and meeting predefined thresholds.

The SE and EE in the study exhibit a clear trade-off connection. An exciting tendency was discovered, as shown in Table 2, where a decrease in SE of at least one led to a considerable surge in EE (almost double the initial value of EE right before the drop), showing an inherent feature of wireless communication networks. The incorporation of a threshold mechanism in the hybrid algorithm was pivotal in effectively managing a gradual reduction in SE, ensuring that it did not drop below the predetermined threshold of 21 bits/s/Hz. This strategic implementation adds a greater level of complexity to enhance the hybrid method. It ensures that the reduction in SE is intentional and regulated, in line with the overall goal of maximizing EE while still maintaining a satisfactory level of SE.

Table 2. The averages of EE and SE for all four scenarios

Type of Approach	Average EE in Bits/J	Average SE in Bits/s/Hz
Simple	0.78924	50.5112
TPC	0.2241	50.7459
OPA	44.5112	44.5112
Hybrid	33,263,040.4068	24.1157

The deliberate distribution of weights, specifically the giving of a greater weight of 0.725 to the OPA algorithm compared to TPC, which was 0.275, demonstrates an intentional choice to emphasize the improvement of EE. This technique, which takes into account the relative importance of different factors, shows a deep awareness of the complexities of the system.

The weight allocation mechanism significantly contributes to the higher performance of the hybrid algorithm in comparison to individual scenarios, such as the simple approach, TPC, and OPA. In addition, the evaluation of the threshold, allocation of weight, and gradual decrease in SE inside the hybrid model all contribute to the surpassing outcomes achieved by the conventional state-of-the-art method. The effectiveness of the suggested hybrid approach is supported by the careful adjustment of parameters and the repeated experimentation involved in completing a delicate balance.

In summary, the hybrid approach presents a promising solution, demonstrating a substantial increase in EE without disproportionately compromising SE. These results align with established literature goals and fulfill specific thresholds set for the study, highlighting the practical applicability of the hybrid strategy in real-world scenarios. The findings emphasize the critical importance of striking a delicate balance between energy and spectral efficiency for optimal system performance in CF mMIMO configurations.

Figure 4 presents a pareto front plot, visually capturing the intricate trade-off dynamics between EE and SE values. The plot unveils a linear relationship, portraying the inherent challenge of enhancing one metric at the expense of the other, as clarified previously.

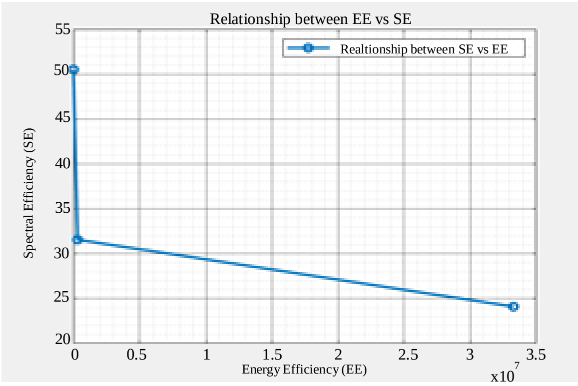


Fig. 4 Visualization of the trade-off between Energy Efficiency and Spectral Efficiency through pareto front plot

The graph pattern shows that as EE experienced improvements, there was a concurrent reduction in SE values, which is characteristic of the delicate equilibrium required in optimizing CF mMIMO systems. Commencing from the initial position of the plot's starting point, one comes across the SE and EE values that come before the first iteration of the hybrid model.

This initial representation serves as a starting point, capturing the current state of SE and EE before the optimization process begins. Subsequently, the second point on the graph encapsulates the outcomes following the first iteration. This stage demonstrated a significant reduction of 37.5% in SE, contrasted with a 0.95% gain in EE. Throughout subsequent iterations, guided by a carefully chosen threshold to balance EE and SE, the plot unveils gradual improvements.

The approach used resulted in reduced SE levels and significant improvements in EE. This iterative refinement process played a crucial role in achieving excellent EE performance while also maintaining a harmonious balance with SE metrics. The Pareto front plot provides a dynamic record of the optimization process, showcasing the convoluted balance between EE and SE and the strategic trade-offs made to reach an optimal equilibrium. Table 3 presents a comprehensive overview of this work's results in relation to other notable works in the domain.

This comparative analysis underscores the diversity of approaches employed by different studies to optimize EE and SE in CF mMIMO systems. While each work may have distinct objectives, the performance indicators extracted from CDF plots against SE and EE provide a standardized basis for comparison. This work, employing the Hybrid TPC & OPA algorithm in a downlink scenario, has a reasonable EE range of 32.5-33.9*10^6 bits/J, showcasing a substantial improvement over some other algorithms. Furthermore, the SE range of 23.6-24.5 bits/s/Hz signifies a commendable balance between achieving high EE and maintaining competitive SE.

It is important to note that the observed ranges in EE and SE are context-specific and may vary based on the unique goals and scenarios targeted by each algorithm. This comprehensive overview serves as a valuable reference for researchers and practitioners in the field of CF mMIMO, offering insights into the diverse landscape of algorithmic approaches and their corresponding performance outcomes.

Table 3. Comparative analysis of CF mMIMO algorithms for improved Energy and Spectral Efficiency

Reference	Type of Algorithm	Link Type	EE Range Bits/J	SE Range Bits/s/Hz
[10]	EE Power Allocation	Downlink	4.6 * 10^6	N/A
[13]	TPC (Optimized) Experimental	Uplink	1.2-2.7 * 10^9	6-16
[3]	Hybrid OPA & FP	Downlink	N/A	1-4.5
[12]	TPC & MRC	Downlink	0.2-1.4 * 10^6	1-3
[7]	Max-Min Power Control	Downlink	7.5-9.5 * 10^6	2.5-3.5
This Work	Hybrid TPC & OPA	Downlink	32.5-33.9 * 10^6	23.6-24.5

7. Conclusion

In conclusion, the model provides substantial insights, and the findings achieved the target of attaining higher EE with a balanced level of SE. Although the model provides valuable insights, it is essentially a representation of CF mMIMO systems that simplify certain complexities found in the real world. Future studies should include realistic factors like dynamic user mobility and non-uniform user distributions. These changes aim to improve comprehension of CF mMIMO systems in practical circumstances, placing this work's findings in a more realistic context. The model must be refined to make this research applicable and relevant in the dynamic telecom industry. Despite the acknowledged simplifications, the proposed algorithm has demonstrated effectiveness. It solves simulation issues, advancing CF mMIMO system optimization. The proposed method's efficacy and attention to real-world considerations make it a worthwhile contribution to the area.

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References

[1] Hien Quoc Ngo et al., "Cell-Free Massive MIMO versus Small Cells," *IEEE Tranactions on Wireless Communications*, vol. 16, no. 3, pp. 1834-1850, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] Xiaofei Wang et al., "A Survey of Green Mobile Networks: Opportunities and Challenges," *Mobile Networks and Appications*, vol. 17, pp. 4-20, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[3] Sucharita Chakraborty et al., "Efficient Downlink Power Allocation Algorithms for Cell-Free Massive MIMO Systems," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 168-186, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Hien Quoc Ngo et al., "On the Total Energy Efficiency of Cell-Free Massive MIMO," *IEEE Transactions on Green Communications and Networking*, vol. 2, no. 1, pp. 25-39, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[5] Emil Björnson, and Luca Sanguinetti, "Scalable Cell-Free Massive MIMO Systems," *IEEE Transactions on Communications*, vol. 68, no. 7, pp. 4247-4261, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Trang C. Mai, Hien Quoc Ngo, and Trung Q. Duong, "Downlink Spectral Efficiency of Cell-Free Massive MIMO Systems with Multi-Antenna Users," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 4803-4815, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jiayi Zhang et al., "Cell-Free Massive MIMO : A New Next-Generation Paradigm," *IEEE Access*, vol. 7, pp. 99878-99888, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Joumana Kassam et al., "A Review on Cell-Free Massive MIMO Systems," *Electronics*, vol. 12, no. 10, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Long D. Nguyen et al., "Energy Efficiency in Cell-Free Massive MIMO with Zero-Forcing Precoding Design," *IEEE Communications Letters*, vol. 21, no. 8, pp. 1871-1874, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[10] Abdolrasoul Sakhaei Gharagezlou et al., "Energy Efficient Power Allocation in Massive MIMO Systems with Power Limited Users," *Proceedings of the 4th International Conference on Telecommunications and Communication Engineering*, pp. 35-46, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] A. Gupta, and R.K. Jha, "A Survey of 5G Network : Architecture and Emerging Technologies," *IEEE Access*, vol. 3, pp. 1206-1232, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[12] Masaaki Ito et al., "Impact of Antenna Distribution on Spectral and Energy Efficiency of Cell-Free Massive MIMO with Transmit Power Control Algorithms," *IEEE Open Journal of the Communications Society*, vol. 3, pp. 1615-1629, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Thomas Choi et al., "Energy Efficiency of Uplink Cell-Free Massive MIMO with Transmit Power Control in Measured Propagation Channel," *IEEE Open Journal of Circuits and Systems*, vol. 2, pp. 792-804, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Elina Nayebi et al., "Precoding and Power Optimization in Cell-Free Massive MIMO Systems," *IEEE Transactions on Wireless Communications*, vol. 16, no. 7, pp. 4445-4459, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[15] Ayman Younis, Tuyen X. Tran, and Dario Pompili, "Energy-Efficient Resource Allocation in C-RANs with Capacity-Limited Fronthaul," *IEEE Transactions on Mobile Computing*, vol. 20, no. 2, pp. 1536-1233, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Adeeb Salh et al., "Energy-Efficient Power Allocation and Joint User Association in Multiuser-Downlink Massive MIMO System," *IEEE Access*, vol. 8, pp. 1314-1326, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Shengrong Bu, F. Richard Yu, and Halim Yanikomeroglu, "Interference-Aware Energy-Efficient Resource Allocation for OFDMA-Based Heterogeneous Networks with Incomplete Channel State Information," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 3, pp. 1036-1050, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[18] Manijeh Bashar et al., "On the Uplink Max-Min SINR of Cell-Free Massive MIMO Systems," *IEEE Transactions on Wireless Communications*, vol. 18, no. 4, pp. 2021-2036, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[19] Emil Björnson, and Erik G. Larsson, "How Energy-Efficient Can a Wireless Communication System Become?," *2018 52nd Asilomar Conference on Signals, Systems, and Computers*, Pacific Grove, USA, pp. 1252-1256, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[20] Emil Björnson, Jakob Hoydis, and Luca Sanguinetti, "Massive MIMO Networks: Spectral, Energy, and Hardware Efficiency," *Foundations and Trends in Signal Processing*, vol. 11, no. 3-4, pp. 154-655, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[21] Xianghua Liu, and Jianlin Mo, "Spectral-Energy Efficiency Maximization for Wireless Powered Low-Latency NOMA Systems with Full-Duplex Relaying," *EURASIP Journal on Wireless Communications and Networking*, vol. 2019, pp. 1-11, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[22] Zaki Masood, Sokhee P. Jung, and Yonghoon Choi, "Energy-Efficiency Performance Analysis and Maximization Using Wireless Energy Harvesting in Wireless Sensor Networks," *Energies*, vol. 11, no. 11, pp. 1-15, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[23] Anyi Girón, Eliana Rivera, and Gustavo Gómez, "Measurement of the Spectral Efficiency of a Heterogeneous Network Architecture of the NG-PON Type for a Quasilinear Propagation Regime," *Entropy*, vol. 24, no. 4, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Atiquzzaman Mondal et al., "Spectrum and Energy-Efficiency Maximization in RIS-Aided IoT Networks," *IEEE Access*, vol. 10, pp. 103538-103551, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[25] Na Li, Yuanyuan Gao, and Kui Xu, "On the Optimal Energy Efficiency and Spectral Efficiency Trade - Off of CF Massive MIMO SWIPT System," *EURASIP Journal on Wireless Communications and Networking*, vol. 2021, pp. 1-22, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[26] Yasseen Sadoon Atiya et al., "Joint Power Optimization and AP Selection for Secure Cell-Free Massive MIMO," *arXiv*, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[27] Chongzheng Hao et al., "User Association and Power Control in Cell-Free Massive MIMO with the APG Method," *2023 31st European Signal Processing Conference (EUSIPCO)*, Helsinki, Finland, pp. 1469-1473, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[28] Shuaifei Chen et al., "Structured Massive Access for Scalable Cell-Free Massive MIMO Systems," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1086-1100, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[29] Stefano Buzzi et al., "User-Centric 5G Cellular Networks : Resource Allocation and Comparison with the Cell-Free Massive MIMO Approach," *IEEE Transactions on Wireless Communications*, vol. 19, no. 2, pp. 1250-1264, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[30] Hussein A. Ammar, and Raviraj Adve, "Power Delay Profile in Coordinated Distributed Networks: User-Centric v/s Disjoint Clustering," *2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Ottawa, Canada, pp. 1-5, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[31] Hien Quoc Ngo et al., "On the Performance of Cell-Free Massive MIMO in Ricean Fading," *2018 52nd Asilomar Conference on Signals, Systems, and Computers*, Pacific Grove, USA, pp. 980-984, 2018. [CrossRef] [Google Scholar] [Publisher Link]
[32] Trang C. Mai, Hien Quoc Ngo, and Le-Nam Tran, "Energy-Efficient Power Allocation in Cell-Free Massive MIMO with Zero-Forcing : First Order Methods," *Physical Communication*, vol. 51, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[33] Sucharita Chakraborty, Emil Björnson, and Luca Sanguinetti, "Centralized and Distributed Power Allocation for Max-Min Fairness in Cell-Free Massive MIMO," *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, Pacific Grove, USA, pp. 576-580, 2019. [CrossRef] [Google Scholar] [Publisher Link]