PERFORMANCE ANALYSIS OF METAHEURISTICS-BASED UPLINK POWER CONTROL IN USER-CENTRIC CELL-FREE MASSIVE MIMO SYSTEMS

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ABSTRACT

User-centric cell-free massive MIMO is emerging as a key architecture for next-generation wireless systems, aiming to enhance fairness and spectral efficiency by eliminating cell boundaries and leveraging distributed access points (APs). To fully exploit its advantages in uplink communication, especially under dense user deployments, effective uplink power control (UPC) is essential to mitigate inter-user interference while ensuring fair resource allocation. This paper focuses on distributed optimization for the max-min fairness problem and compares three metaheuristic-based UPC algorithms: Particle Swarm Optimization (PSO), Bat Algorithm (BA), and Genetic Algorithm (GA). This evaluation is based on a composite objective function (F3) that captures both max-min fairness and sum spectral efficiency, enabling multi-objective optimization through a scalarized formulation. Simulation results across varying network scales demonstrate that PSO achieves the highest minimum spectral efficiency, reaching 3.1664 bit/s/Hz at the median user (CDF = 0.5), followed closely by BA (3.1563) and GA (3.1121). Under increasing user loads (from 8 to 15 UEs), PSO and BA maintain higher average minimum SE (down to 2.3441 and 2.3109, respectively), while GA declines more significantly (to 2.2223). In dense AP scenarios (up to 100 APs), PSO again leads with 4.9947 bit/s/Hz. Regarding convergence, PSO and BA reach near-optimal solutions rapidly, whereas GA converges more slowly and requires approximately 1.8 times the computation time. These findings position swarm-based methods as highly effective for real-time, fairness-oriented uplink power control in distributed cell-free massive MIMO systems.

Keywords: *User-centric cell-free massive MIMO; uplink power control; max-min fairness; Metaheuristic algorithm.*

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ABBREVIATIONS

AP	Access Point
PSO	Particle Swarm Optimization
BA	Bat Algorithm
GA	Genetic Algorithm
UC-CFmMIMO	User Centric Cell- Free Massive Multiple-Input Multiple-Output
SE	Spectral Efficiency
UE	User Equipment
UPC	Uplink Power Control

1. INTRODUCTION

The surge in demand for ultra-reliable, high-throughput, and low-latency communication is propelling the development of next-generation wireless networks. User-Centric Cell-Free Massive MIMO (UC-CFmMIMO) has emerged as a groundbreaking architecture capable of meeting these stringent requirements by eliminating conventional cell boundaries and enabling multiple distributed access points (APs) to collaboratively serve users. This architecture holds the potential to significantly enhance spectral efficiency (SE), user fairness, and total network capacity, particularly in densely populated scenarios [1-4].

A pivotal aspect of UC-CFmMIMO systems is uplink power control (UPC), which governs how user devices allocate their transmission power while sharing the wireless spectrum. The complexity of this task stems from the need to simultaneously enhance system-wide performance and promote equitable access across users. Traditionally, this challenge has been cast as a max-min fairness optimization problem, but such formulations often overlook the benefits of maximizing the overall spectral efficiency.

To bridge this gap, we redefine the optimization objective to incorporate a hybrid metric that combines max–min fairness SE with sum SE, thereby striking a practical balance between fairness and throughput. This composite objective enables more flexible trade-offs in diverse deployment scenarios and better reflects the dual goals of modern wireless systems [2, 5-9]. This formulation represents a multi-objective optimization approach that enables the system to jointly address fairness and throughput within a single scalarized function. As such, comparing different algorithms under this unified objective provides practical insight into their effectiveness in managing fairness-throughput trade-offs in real-world deployments.

Conventional UPC techniques - such as full power transmission, fractional power control, and fixed-point iterations targeting minimum SINR maximization - offer limited adaptability and may exhibit poor scalability or performance in large-scale heterogeneous environments [10-14]. Although metaheuristic algorithms are increasingly explored for wireless optimization, a systematic evaluation of their efficacy in addressing the trade-off between fairness and throughput in UC-CFmMIMO remains limited. Although some existing works examine fairness or system capacity independently, a joint formulation that reflects both objectives - evaluated through fairness-centric indicators such as minimum SE under a composite function - is still lacking. This limits informed algorithm selection for practical deployment settings [9, 15-17].

In this context, we explore the use of three well-known metaheuristic algorithms - Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bat Algorithm (BA) - to solve the uplink power control problem using our newly proposed composite objective function. These nature-inspired techniques are well-suited for navigating the high-dimensional, non-convex optimization landscape that typifies UC-CFmMIMO systems.

Our key contribution lies in a comparative analysis of PSO, GA, and BA when optimizing the fairness-throughput trade-off. We assess each algorithm based primarily on minimum spectral efficiency resulting from the composite fairness-throughput objective, along with convergence behavior and computational complexity. This focus allows us to evaluate how well each method balances equity and efficiency within a unified framework.

The rest of the paper is structured as follows: Section 2 outlines the UC-CFmMIMO network model. Section 3 defines the uplink power control optimization problem. Section 4 details the metaheuristic algorithms used - PSO, GA, and BA. Section 5 covers the simulation results and performance evaluation. Section 6 wraps up the paper and suggests directions for future work.

2. SYSTEM MODEL

We examine a UC-CF mMIMO network composed of K single-antenna user equipments (UEs) and L access points (APs), each equipped with N antennas. The channel between AP l and UE k in any given coherence block is represented by $\mathbf{h}_{kl} \in \mathbb{C}^N$. The channel is modeled using block fading, where $\mathbf{h}_{kl}$ is assumed to remain constant over time and flat in frequency within a coherence block of τ_c symbols under a TDD protocol. The coherence interval τ_c is divided into τ_p pilot symbols for uplink channel estimation (producing $\hat{\mathbf{h}}_{kl}$), τ_u symbols for uplink data, and τ_d symbols for downlink data [2, 19, 20]; uplink data symbols, and τ_c downlink data symbols. Within each block, channels are modeled independently and follow a correlated Rayleigh fading distribution $\mathbf{h}_{kl} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_N, \mathbf{R}_{kl})$, while $\mathbf{R}_{kl} \in \mathbb{C}^{N\times N}$ is the spatial correlation matrix between AP l and UE k. The Gaussian distribution captures small-scale fading, while the positive semi-definite correlation matrix $\mathbf{R}_{kt}$ accounts for large-scale fading, including geometric path loss, shadowing, antenna gains, and spatial channel correlation [4, 8].

The uplink transmit powers are represented as a vector $\mathbf{p} = [p_1, \ldots, p_K]^T$, which affects the entire network. The uplink SE for a given UE k is determined by its SINR, which depend on $\mathbf{p}$. Specifically, the SINR numerator is influenced by the desired UE's transmit power p_k while the denominator includes interference from all UEs' power levels in $\mathbf{p}$. The effective SINR for UE k, applicable to centralized uplink operations, is expressed in a generalized form as [4, 8]:

$$\mathrm{SINR}_k(\mathbf{p}) = \frac{b_k p_k}{\mathbf{c}_k^T \mathbf{p} + \sigma_k^2} \tag{1}$$

where:

$$b_k = \left|\mathbb{E}\left\{\mathbf{v}_k^H \mathbf{D}_k \mathbf{h}_k\right\}\right|^2 \quad \forall k, \tag{2}$$

$$c_{kk} = \mathbb{E}\left\{\left|\mathbf{v}_k^H \mathbf{D}_k \mathbf{h}_k\right|^2\right\} - b_k \ \ \forall k, \tag{3}$$

$$c_{ki} = \mathbb{E}\left\{\left|\mathbf{v}_k^H \mathbf{D}_k \mathbf{h}_i\right|^2\right\} - b_k \ \ \forall k, \forall i \neq k, \tag{4}$$

$$\sigma_k^2 = \sigma^2 \mathbb{E}\left\{\left\|\mathbf{D}_k \mathbf{v}_k\right\|^2\right\}. \tag{5}$$

with $\mathbf{v}_k = \left[\mathbf{v}_{k1}^T, \ldots, \mathbf{v}_{kL}^T\right]^T \in \mathbb{C}^{LN}$ is combining vector centralized at the CPU. $\mathbf{h}_i : i = \{1, \ldots, K\}$ is the channel vectors from all K UEs. $\mathbf{D}_k = \mathrm{diag}\{\mathbf{D}_{k1}, \cdots, \mathbf{D}_{kL}\}0.5$ is a block-diagonal matrix. As the result, the uplink SE of UE k depends on **p** and it is given by [2]:

$$SE_k(\mathbf{p}) = \frac{\tau_u}{\tau_c} \log_2\left(1 + SINR_k(\mathbf{p})\right) \tag{6}$$

3. PROBLEM FORMULATION

UPC involves selecting suitable transmit power levels for the UEs to optimize a specific utility function, most commonly tied to SE. In this work, we focus on two main power control objectives: maximizing the total SE and ensuring fairness through max-min SE optimization.

The goal of max-min SE fairness is to improve equity by maximizing the minimum SE across all UEs, ensuring that the UE with the worst performance is still adequately served. This approach, known as max-min fairness, adjusts the transmit power allocations to balance performance among users. The corresponding optimization problem is defined mathematically as follows:

$$\begin{aligned} (\mathbf{P1}): \ & \max_{\mathbf{p}} \ \min_{k \in \{1,\ldots,K\}} SE_k(\mathbf{p}) \\ & \text{s.t.} \quad 0 < p_k \leq p_{max}, \quad k = 1, \ldots, K. \end{aligned} \tag{7}$$

While max-min SE fairness prioritizes fairness for UEs with poor channel conditions, it may not fully exploit the potential for higher spectral efficiencies in large networks. In contrast, the sum SE maximization problem focuses on maximizing the total number of transmitted bits, irrespective of their distribution among UEs. This approach is particularly suitable for scenarios where each UE only interferes with a small subset of neighboring UEs. The sum SE maximization problem can be described by:

$$\begin{aligned} (\mathbf{P2}): \ & \max_{\mathbf{p}} \ \sum_{k=1}^{K} SE_k(\mathbf{p}) \\ & \text{s.t.} \quad 0 < p_k \leq p_{max}, \ \ k = 1, \ldots, K. \end{aligned} \tag{8}$$

To overcome the trade-off between fairness and throughput posed by the individual objectives in (P1) and (P2), we introduce a joint optimization problem that simultaneously considers both the minimum and the total SE across users. This hybrid objective, denoted as (P3), aims to strike a balance between improving the SE of the weakest user and maximizing overall system throughput. The problem is formulated as:

$$\begin{aligned} (\mathrm{P3}): \ & \max_{\mathbf{p}} \ \left\{\min_{k \in \{1,\ldots,K\}} SE_k(\mathbf{p}), \sum_{k=1}^{K} SE_k(\mathbf{p})\right\} \\ & \text{s.t.} \quad 0 < p_k \leq p_{max}, \quad k = 1, \ldots, K. \end{aligned} \tag{9}$$

4. UPLINK POWER CONTROL SCHEMES

4.1. Genetic Algorithm

The Genetic Algorithm (GA) is a population-based metaheuristic inspired by the principles of Darwinian natural selection. Candidate solutions are encoded as fixed-length binary or real-valued chromosomes, which evolve over successive generations to approximate optimal outcomes. The standard GA framework consists of (1) encoding the objective or cost function, (2) defining a fitness function to quantify solution quality, (3) initializing a population of individuals, and (4) iteratively applying genetic operators - selection, crossover, and mutation - to generate new generations of solutions.

Selection mechanisms prioritize individuals with higher fitness, promoting convergence toward optimal regions. Crossover recombines genetic material from parent chromosomes, typically via single-point or multi-point crossover, producing offspring that inherit traits from both parents. Mutation introduces stochastic variation by randomly altering genes (e.g., bit-flipping), helping maintain genetic diversity and prevent premature convergence. This evolutionary process, driven by fitness-based reproduction, enables GA to effectively explore and exploit complex search spaces.

Strengths: GA is gradient-free and highly adaptable, making it well-suited for solving discrete, nonlinear, and multi-modal optimization problems. Its population-based structure facilitates broad exploration of the search space.

Limitations: GA may converge slowly and is sensitive to the configuration of key parameters such as crossover and mutation rates. Its effectiveness also depends heavily on the choice of encoding scheme and fitness function design.

4.2. Particle Swarm Optimization

PSO is a stochastic, population-based optimization technique inspired by the collective behavior observed in bird flocks and fish schools. In this framework, each particle represents a potential solution and navigates the search space by updating its position and velocity based on two components: its own best-known position (personal experience) and the global best position discovered by the swarm. This cooperative information-sharing mechanism enables particles to balance exploration and exploitation as they converge toward optimal or near-optimal solution.

At each iteration t, the velocity v_i and position x_i of particle i are updated as:

$$v_i(t+1)=wv_i(t)+c_1r_1(p_i-x_i(t))+c_2r_2(g-x_i(t)) \quad (10)$$

$$x_i(t+1)=x_i(t)+v_i(t+1) \quad (11)$$

where w is the inertia weight; c_1, c_2 are cognitive and social acceleration coefficients; $r_1,r_2 \sim U(0,1)$, p_i is the best previous position of particle i, and g is the global best position in the swarm.

Strength: PSO offers rapid convergence, straightforward implementation, and requires minimal parameter tuning. It is particularly effective in solving continuous, high-dimensional optimization problems.

Limitations: Despite its simplicity, PSO is prone to premature convergence and may stagnate in complex multimodal search spaces, especially when swarm diversity is not adequately preserved.

4.3. Bat Algorithm

The BA is a bio-inspired optimization technique that mimics the echolocation mechanism of microbats. In nature, bats emit ultrasonic pulses and interpret the returning echoes to estimate the location of prey, subsequently adjusting their movement accordingly. This natural behavior is modeled computationally using a population of virtual bats, where each individual represents a candidate solution navigating the search space.

At each iteration t, bat i updates its frequency, velocity, and position as follows:

$$f_i=f_{min}+(f_{max}-f_{min})\cdot\beta, \quad \beta\sim U(0,1) \quad (12)$$

$$v_i^{(t+1)}=v_i^{(t)}+\left(x_i^{(t)}-x^*\right)\cdot f_i \quad (13)$$

$$x_i^{(t+1)}=x_i^{(t)}+v_i^{(t+1)} \quad (14)$$

where:

- f_i is the frequency for bat i
- x_i, v_i are the position and velocity of bat iii
- x^* is the current global best solution
- β is a is a random number controlling exploration in [0,1] .

For local exploitation, a new solution is generated near the best current solution using:

$$x_{new}=x_{old}+\sigma\cdot\epsilon_t\cdot A(t), \quad \epsilon_t\sim N(0,1) \quad (15)$$

where A(t) is the current average loudness and σ is a scaling factor.

Additionally, bats adjust their loudness A_i and pulse emission rate r_i over time:

$$A_i^{(t+1)}=\alpha A_i^{(t)}, \quad r_i^{(t+1)}=r_i^{(0)}\cdot[1-\exp(-\gamma t)] \quad (16)$$

where $\alpha\in(0,1)$ controls loudness decay and $\gamma > 0$ adjusts pulse rate growth.

The BA combines global exploration through frequency-tuned motion with local exploitation guided by adaptive pulse loudness and emission rates. This hybrid mechanism allows BA to handle complex, multimodal, and nonlinear optimization tasks effectively. However, its performance is notably influenced by the choice of algorithmic parameters, and it lacks rigorous theoretical convergence guarantees.

Strength: BA offers a balanced approach between global search and local refinement by leveraging frequency modulation and adaptive loudness dynamics, making it effective for diverse optimization landscapes.

Limitations: The algorithm is highly sensitive to parameter tuning, and in contrast to more mature methods, it does not benefit from well-established theoretical convergence frameworks.

5. NUMERICAL RESULTS

5.1. Simulation Setup

To assess the performance of the proposed UPC algorithms in a UC-CFmMIMO environment, we simulate a network deployed over a 1km × 1km area comprising 50 randomly distributed access points (APs) and 10 randomly placed user equipments (UEs). Each AP is equipped with a single antenna, resulting in a total of 100 antennas across the system. To ensure statistical reliability, the simulation includes 500 distinct network topologies, with 50 random realizations for each topology.

The system operates within a 20MHz bandwidth, with receiver noise incorporating both thermal noise and a 7 dB noise figure. Each UE is subject to a practical maximum uplink power p_{max} = 100mW. Channel coherence is characterized by a 2ms coherence time and 100kHz coherence bandwidth, suitable for sub-6 GHz scenarios involving both indoor and outdoor mobility. Large-scale fading follows the 3GPP Urban Microcell path loss model, while small-scale Rayleigh fading incorporates spatial correlation using a local scattering model.

For the metaheuristic algorithms, PSO and BA are executed with a population size of 300 particles or bats and a maximum of 100 iterations. The GA algorithm is configured with a population of 300 individuals evolved over 100 generations. For each simulation setup, the minimum spectral efficiency is calculated and averaged over all realizations to evaluate both user fairness and the overall effectiveness of each algorithm.

5.2. Performance Metrics

The key performance indicator in this study is the minimum SE among all UEs, measured in bit/s/Hz. This metric serves as a direct indicator of fairness, as it captures the performance of the worst-case user under a given power control strategy. Maximizing this value - aligned with the max-min fairness principle - is particularly important in cell-free massive MIMO systems, where consistent service quality and user-centric coverage are prioritized. However, in this study, the minimum SE is not optimized in isolation. It is derived from a composite objective function (F3) that combines both max–min fairness and sum SE. This scalarized formulation enables simultaneous evaluation of fairness and throughput performance, aligning with the multi-objective nature of practical deployments. To evaluate algorithmic performance under realistic network conditions, the minimum SE is computed over multiple independent network topologies and averaged across all realizations. The statistical distribution of minimum SE values is further visualized through cumulative distribution function (CDF) plots, offering a deeper understanding of both average and edge-case user experiences. In addition to communication performance, computational complexity is considered as a secondary metric to assess the practical applicability of each optimization method. While GA relies on computationally intensive evolutionary processes, PSO and BA utilize simpler, arithmetic-driven update rules. This leads to distinct differences in execution time, which are quantified through average runtime per simulation setup. Evaluating these trade-offs between fairness and computational efficiency provides a well-rounded assessment of each algorithm's suitability for large-scale, real-time UC-CFmMIMO deployments.

5.3. Key Findings

5.3.1. Computational Time

This section compares the computational efficiency of the FPA and the FPC method in determining the optimal transmit powers under varying network scales. Tables 1 and 2 present the average execution time (in milliseconds) for each method when changing the number of users (K) and APs (L), respectively. All simulations were conducted using MATLAB R2021b on an Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz, providing a consistent computational environment for performance comparison.

Table 1 summarizes the average computation time of the evaluated algorithms. PSO exhibits the fastest performance, completing its run in 289.73 milliseconds, followed closely by BA at 298.45 milliseconds. In comparison, GA incurs a notably higher computational overhead, taking 532.08 milliseconds - approximately 1.8 times longer than PSO. These findings underscore the computational efficiency of swarm intelligence approaches (PSO and BA), which outperform the more resource-intensive evolutionary strategy used by GA.

Table 1. Average computational time (in milliseconds) for BA, GA and PSO with fixed L = 10 and K = 50

Algorithm	BA	GA	PSO
Computation time (miliseconds)	**298.45**	**532.08**	**289.73**

5.3.2. Fitness Convergence Performance of PSO, BA, and GA

When examining the convergence behavior, as illustrated in Figure 1, all three algorithms demonstrate effective performance, yet differ in their convergence speed and stability. PSO reaches a fitness value of 0.9999 within only 3 iterations and achieves perfect fitness (1.0) at iteration 20, showcasing exceptionally fast and stable convergence.

BA performs comparably well, attaining a fitness value above 0.9999 as early as iteration 2 and reaching 1.0 by iteration 21. Its curve closely mirrors PSO's after the early iterations, suggesting similar optimization efficiency with only a marginal delay.

In contrast, GA exhibits a more gradual convergence trajectory. It begins with a lower initial fitness of 0.92597, and despite improving steadily, it only reaches 0.98624 after 25 iterations and does not converge to 1.0 within the first 100 iterations. This reflects a slower rate of fitness improvement, indicating GA's reliance on more incremental evolutionary progress and potential sensitivity to local optima.

Overall, PSO clearly leads in convergence speed, followed closely by BA, while GA lags significantly behind. These findings suggest that swarm-based algorithms (PSO and BA) are more suitable for real-time or large-scale deployments, where rapid convergence is crucial.

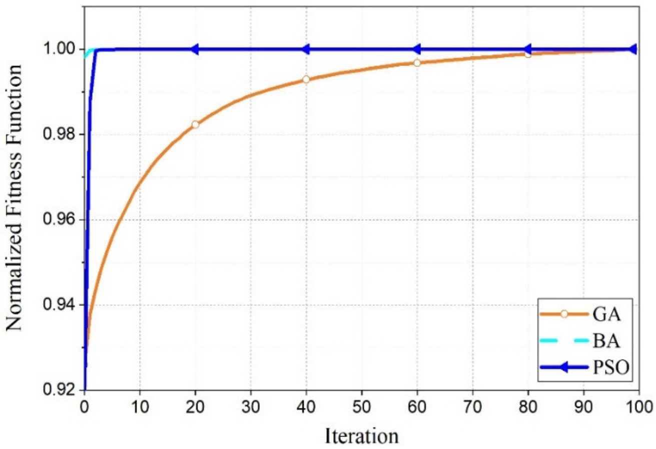

Figure 1. Normalized fitness convergence curves for PSO, BA, and GA

5.3.3. Effectiveness of the Schemes

To evaluate how different metaheuristic algorithms handle the trade-off between user fairness and overall system efficiency, we adopt a composite utility function (F3) that jointly accounts for both max-min fairness and throughput considerations. Rather than assessing sum spectral efficiency directly, we focus on the minimum SE obtained after optimizing F3. This approach enables a fairness-centered evaluation while implicitly reflecting system-wide performance through the structure of the objective function.

As shown in Figure 1, all three algorithms - GA, PSO, and BA - demonstrate comparable results in terms of fairness. At the median point (CDF = 0.5), GA achieves the highest minium SE at 2.8521 bit/s/Hz, slightly ahead of PSO (2.8217) and BA (2.8210). Despite the narrow margins, this suggests that GA is marginally more effective in navigating the fairness-throughput balance embedded in the F3 formulation.

At CDF = 0.1 - representing worst-case user scenarios - GA again leads with 2.1355 bit/s/Hz, followed by PSO (2.1196) and BA (2.1186). This consistent performance across both typical and adverse conditions confirms GA's slight advantage under fairness-driven optimization. While all algorithms optimize the same composite objective, their performance reflects different multi-objective behaviors. GA tends to prioritize fairness more effectively, consistently achieving higher minimum SE values across various CDF levels. In contrast, PSO demonstrates better throughput scalability in large-scale AP deployments. BA offers consistent performance, indicating its robustness in balancing fairness and efficiency.

In summary, although the differences are small, all three algorithms perform robustly when optimizing the F3 objective. The results validate their ability to support fairness under practical constraints, with GA maintaining a modest but consistent edge in minimum SE across the distribution.

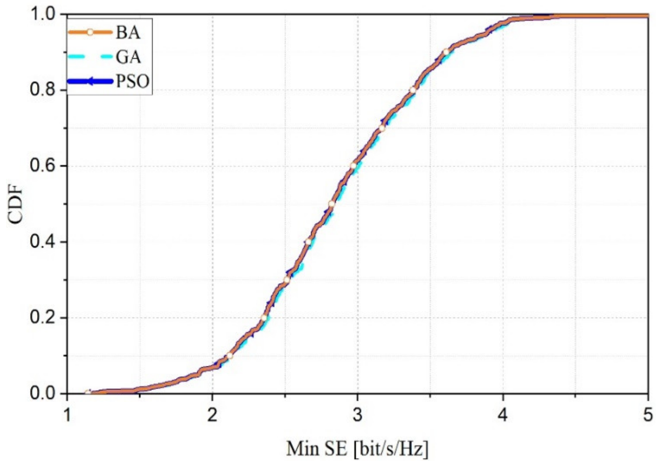

Figure 2. Comparison of UPC schemes in term of minium SE

5.3.4. Impact of Number of APs and UEs

This section evaluates the effect of increasing the number of APs and UEs on system performance, focusing on average minimum SE, which is crucial for assessing user fairness and network coverage in dense deployments.

Figure 3 reveal that increasing the number of APs consistently improves the minimum SE across all metaheuristic schemes - BA, GA and (PSO). At 30 APs, the average minimum SE remains below 1.63 bit/s/Hz for all methods, indicating limited coverage and strong inter-user interference in sparse deployments. Among them, GA achieves the highest value of 1.62534 bit/s/Hz, slightly outperforming BA (1.60819) and PSO (1.60796). As the number of APs increases to 50, a significant jump in performance is observed, with all algorithms exceeding 2.84 bit/s/Hz. The trend stabilizes between 50 and 70 APs, where average minimum SE shows minimal variation, suggesting a temporary saturation region. At 100 APs, all three algorithms show a marked improvement, exceeding 4.72 bit/s/Hz. GA again leads with the highest performance of 4.76075 bit/s/Hz, followed closely by BA

(4.72332) and PSO (4.72317). These results confirm that denser AP deployments significantly enhance user fairness, particularly benefiting users at the network edge by reducing path loss and improving signal reliability.

Figure 4 illustrates the impact of increasing the number of users on the average minimum SE for the BA, GA, and PSO algorithms. As the number of users grows from 8 to 15, all three schemes experience a consistent decline in minimum SE due to increased inter-user interference and more constrained power allocation. At 8 users, GA achieves the highest minimum SE of 3.14486 bit/s/Hz, slightly outperforming BA (3.12467) and PSO (3.12466). As user count increases to 10 and 12, GA continues to lead marginally, with minimum SE values of 2.86939 and 2.54829 bit/s/Hz, respectively. BA and PSO follow closely, showing near-identical performance across all user densities. At 15 users, the performance gap remains narrow, with all three methods converging to around 2.08 bit/s/Hz. GA again slightly outperforms the others at 2.0823 bit/s/Hz, followed by PSO (2.08494) and BA (2.08651). These trends indicate that while increasing the number of users degrades minimum SE, all metaheuristic schemes maintain stable and comparable performance under heavier user loads.

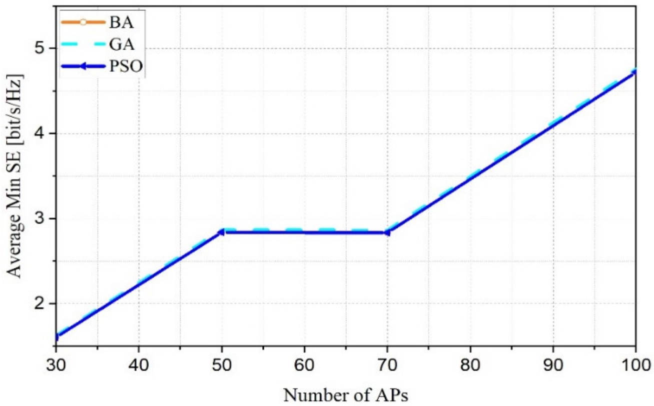

Figure 3. Average minium SE versus number of APs

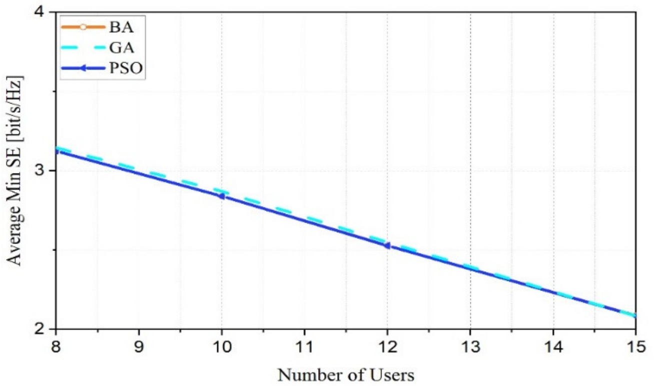

Figure 4. Average minium SE versus number of Ues

In summary, increasing the number of APs improves minimum SE across all algorithms, with GA consistently achieving the highest values. As the number of users increases, minimum SE declines for all methods, though GA maintains a slight advantage. Overall, all three metaheuristic algorithms exhibit stable and comparable performance across varying network conditions.

6. CONCLUSION

This work presents a comprehensive evaluation of three metaheuristic-based uplink power control (UPC) strategies - PSO, BA and GA - within the context of user-centric cell-free massive MIMO (UC-CFmMIMO) systems. By adopting a hybrid utility function that balances max–min fairness and throughput (F3), this study provides valuable insights into the trade-offs between fairness, scalability, and computational efficiency.

Our findings reveal that GA consistently delivers the highest fairness, achieving a minimum spectral efficiency (SE) of 2.8521 bit/s/Hz at the median user (CDF = 0.5), and 2.1355 bit/s/Hz under worst-case conditions (CDF = 0.1). However, GA's performance declines more significantly as user load increases, with minimum SE dropping to 2.2223 bit/s/Hz at 15 UEs. In contrast, PSO demonstrates superior scalability, achieving the highest minimum SE of 4.9947 bit/s/Hz at 100 APs, and maintaining strong performance under heavier user loads (2.3441 bit/s/Hz at 15 UEs). BA performs comparably across all scenarios, with slight deviations from PSO.

In terms of computational efficiency, PSO is the fastest, requiring only 289.73ms, closely followed by BA (298.45ms), while GA lags behind at 532.08ms, nearly 1.8× slower. These results indicate that swarm-based algorithms (PSO and BA) are highly suitable for real-time and large-scale deployments, whereas GA may be preferred in fairness-critical systems with moderate user density. Although each algorithm is evaluated under the same fairness-throughput objective (F3), their optimization tendencies diverge. GA proves more effective for fairness-oriented goals, making it suitable for service-equality-critical scenarios. PSO, by contrast, offers superior scalability and runtime efficiency, positioning it as a strong candidate for systems emphasizing both performance and responsiveness. BA maintains steady behavior across all scenarios, making it a balanced and reliable option in general-purpose settings.

In summary, GA is well-suited for fairness-oriented designs, PSO offers the best balance between speed and scalability, and BA serves as a reliable middle ground with consistent results. This work offers practical guidance for selecting UPC strategies in next-generation wireless networks.

Future research directions include extending this framework to optimize the trade-off parameter λ adaptively, incorporating realistic constraints such as imperfect CSI and latency, and exploring downlink scenarios involving beamforming, precoding, and joint user scheduling. Additionally, the integration of energy-efficiency models and hardware impairments would further bridge the gap between theory and practical deployment.

REFERENCES

[1]. Wei Jiang, Fa-Long Luo, *6G key technologies: A comprehensive guide*. New Jersey, NJ, USA: Wiley-IEEE Press, 447-463, 2023.

[2]. T.V. Luyen, N.V. Cuong, P.D. Hung, "Convex optimization-based linear and planar array pattern nulling," *Progress in Electromagnetics Research M*, 128, 21-30, 2024.

[3]. Ö. T. Demir, et al., "Foundations of user-centric cell-free massive MIMO," *Foundations and Trends® in Signal Processing*, 14, 3-4, 162-472, 2021.

[4]. T.V. Luyen, N.V. Cuong, T.V.B. Giang, "Convex optimization-based sidelobe control for planar arrays," in *2023 IEEE Statistical Signal Processing Workshop (SSP), Hanoi, Vietnam*, 304-308, 2023.

[5]. E. Nayebi, A. Ashikhmin, T. L. Marzetta, H. Yang, B. D. Rao, "Precoding and power optimization in cell-free massive MIMO systems," *IEEE Trans. Wireless Commun.*, 16, 7, 4445-4459, 2017.

[6]. S. Chen, J. Zhang, E. Björnson, J. Zhang, B. Ai, "Structured massive access for scalable cell-free massive MIMO systems," *IEEE J. Sel. Areas Commun.,* 39, 4, 1086-1100, 2021.

[7]. R. Nikbakht, R. Mosayebi, A. Lozano, "Uplink fractional power control and downlink power allocation for cell-free networks," *IEEE Wireless Commun. Lett.,* 9, 6, 774-777, 2020.

[8]. T.V. Luyen, N.V. Cuong, "Metaheuristics-based uplink power control scheme for user-centric cell-free massive MIMO systems," *IEEE Access,* 12, 96603-96616, 2024.

[9]. E. Björnson, J. Hoydis, L. Sanguinetti, "Massive MIMO networks: Spectral, energy, and hardware efficiency," *Foundations and Trends® in Signal Processing,* 11, 3-4, 154-655, 2017.

[10]. M. Bashar, K. Cumanan, A. G. Burr, M. Debbah, H. Q. Ngo, "On the uplink max-min SINR of cell-free Massive MIMO systems," *IEEE Trans. Wireless Commun.,* 18, 4, 2019, 2021-2036, 2019.

[11]. E. Björnson, L. Sanguinetti, "Making cell-free massive MIMO competitive with MMSE processing and centralized implementation," *IEEE Trans. Wireless Commun.,* 19, 1, 182-186, 2020.

[12]. E. Björnson, L. Sanguinetti, "Scalable cell-free massive MIMO systems," *IEEE Trans. Commun.,* 68, 7, 4247-4261, 2020.

[13]. S. Buzzi, C. D'Andrea, A. Zappone, C. D'Elia, "User-centric 5G cellular networks: Resource allocation and comparison with the cell-free massive MIMO approach," *IEEE Trans. Wireless Commun.,* 19, 2, 1250-1264, 2020.

[14]. Y. Zhang, M. Zhou, H. Cao, L. Yang, H. Zhu, "On the performance of cell-free massive MIMO with mixed-ADC under Rician fading channels," *IEEE Commun. Lett.,* 24, 1, 43-47, 2020.

[15]. O. T. Demir, E. Bjoernson, L. Sanguinetti, "Cell-free massive mimo with large-scale fading decoding and dynamic cooperation clustering," in *25th International ITG Workshop on Smart Antennas,* 1-6, 2021.

[16]. G. Interdonato, E. Björnson, H. Q. Ngo, P. Frenger, E. G. Larsson, "Ubiquitous cell-free massive MIMO communications," *EURASIP J. Wirel. Commun. Netw.,* 2019, 197, 2019.

[17]. M. Alonzo, S. Buzzi, A. Zappone, C. D'Elia, "Energy-efficient power control in cell-free and user-centric massive MIMO at millimeter wave," *IEEE Trans. Green Commun. Net.,* 3, 3, 651-663, 2019.

[18]. Xin-She Yang, *Nature-Inspired Optimization Algorithms*, 1st ed., Elsevier, 2014. ISBN: 978-0-12-416743-8.

[19]. K.X. Thuc, H.M. Kha, N.V. Cuong, T.V. Luyen, "A metaheuristics-based hyperparameter optimization approach to beamforming design," *IEEE Access,* 11, 52250-52259, 2023.

[20]. J. Zhang, S. Chen, Y. Lin, J. Zheng, B. Ai, L. Hanzo, "Cellfree massive MIMO: A new next-generation paradigm," *IEEE Access*, 7, 99878-99888, 2019.