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Distributed Uplink Power Control in User-Centric Cell-Free Massive MIMO with Grey Wolf Optimization

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ABSTRACT: User-centric cell-free massive multiple-input multiple-output (UC-CFmMIMO) networks require efficient uplink power control to ensure both fairness and spectral efficiency (SE). However, existing schemes such as fractional power control (FPC) struggle to balance minimum SE and total SE, especially in large-scale deployments. To address this, we propose a grey wolf optimization (GWO)-based power control scheme, optimizing power allocation to maximize minimum SE while also improving total SE. Simulation results in a 1 km $\times$ 1 km UC-CFmMIMO network with 50 access points (APs) and 10 user equipments (UEs) show that our method outperforms FPC and fixed-point algorithm in both fairness and SE. Specifically, it achieves a minimum SE of 1.37 bit/s/Hz (vs. FPC: 0.13 bit/s/Hz) and a total SE of 39.17 bit/s/Hz at 100 APs (vs. FPC: 36.77 bit/s/Hz). The proposed approach scales effectively with AP and UE densities, making it a practical solution for future UC-CFmMIMO deployments.

1. INTRODUCTION

The advancement of wireless communication systems beyond 5G and 6G requires a fundamental rethinking of network architectures and technologies to accommodate increasing demands for higher data rates, lower latency, and improved connectivity. Within this context, cell-free massive multiple-input multiple-output (CFmMIMO) networks have emerged as a groundbreaking approach capable of reshaping the future of wireless communication networks [1–3]. By removing traditional cell boundaries, CFmMIMO fundamentally alters how users connect to the network, enabling a more uniform and efficient distribution of resources. The evolution of mobile networks has shifted from voice-centric to data-centric services, where network performance depends on data rates across coverage areas. Traditional cellular networks assign each user equipment (UE) to the access point (AP) with the strongest signal, leading to disparities in data rates despite advancements like massive MIMO [1–5]. This limitation motivates the need for a paradigm shift in network architecture, leading to the development of CFmMIMO.

CFmMIMO addresses these challenges by eliminating cell boundaries, allowing multiple APs to collaboratively serve UEs. These APs, connected via fronthaul links to a central processing unit (CPU), enable coordinated signal processing for improved coverage and data rate consistency. CFmMIMO integrates massive MIMO, ultra-dense networking, and coordinated multipoint techniques to optimize connectivity. Building upon this foundation, user-centric cell-free massive multiple-input multiple-output (UC-CFmMIMO) further refines the concept by dynamically associating UEs with their nearest APs, tailoring connectivity to individual user needs rather than enforcing a uniform network-wide policy. This approach enhances network efficiency, service stability, and user satisfaction [2, 4, 5].

A critical component of UC-CFmMIMO is uplink power control, which manages transmitting power to enhance spectral efficiency (SE) and reduce interference [6]. A simple approach assumes that UEs always transmit at maximum power, but this results in excessive interference and unnecessary power consumption [3, 7]. To overcome these inefficiencies, advanced power control algorithms are required to intelligently balance performance and computational complexity, ensuring both scalability and low latency in large-scale CFmMIMO deployments [8–10].

Various uplink power control methods have been proposed to enhance CFmMIMO network performance. When the power control problem exhibits convex or quasi-convex properties, optimal solutions can be obtained using Bisection search, convex optimization, geometric programming, or second-order cone programming [3, 6, 9, 11]. For example, power control techniques have been designed to optimize energy efficiency [12], maximize spectral efficiency under specific fading conditions [13], and balance fairness through advanced optimization strategies [14–16]. However, most existing studies rely on convex approximation techniques, such as geometric programming and sequential successive convex approximation, to transform power allocation problems into linear feasibility problems. These methods have inherent weaknesses [17, 18]. They depend on second-order cone programming, leading to high computational complexity, which limits their scalability in large-scale CFmMIMO networks [19]. Additionally, these approaches assume convexity, restricting their ability to explore global solutions in non-convex optimization problems. Consequently, traditional convex-based methods struggle to effectively handle the non-convex, multi-objective, and constrained

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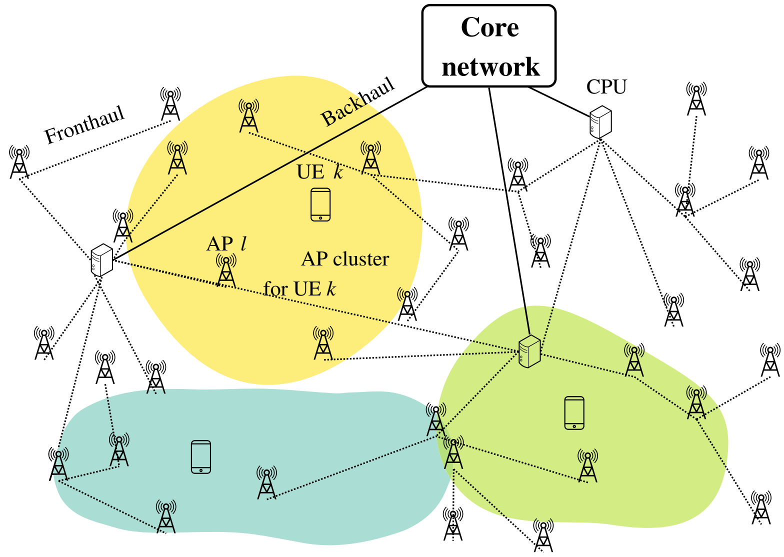

FIGURE 1. A UC-CFmMIMO network consists of L APs that jointly serve K UEs.

nature of uplink power control in CFmMIMO networks, necessitating alternative approaches.

To overcome these limitations, we leverage the grey wolf optimization (GWO), which offers a promising alternative for addressing these challenges. Unlike convex approximation methods, GWO does not require convexity assumptions and efficiently explores complex, non-convex solution spaces using stochastic and population-based search strategies, reducing the risk of local optima [20]. GWO is well suited for global optimization, enabling a broader search beyond the limitations of convex methods. Additionally, GWO naturally handles multi-objective optimization by leveraging strategies like Pareto dominance and fitness sharing to achieve trade-off solutions. Its flexibility allows customization to accommodate various constraints and objectives, making it adaptable to different optimization scenarios [20–22]. This adaptability is particularly advantageous in CFmMIMO networks, where network conditions and performance objectives vary dynamically.

In centralized uplink operation, all channel estimation and data detection are handled at the CPU, causing high computational overhead and excessive fronthaul signaling. Distributed uplink operation in UC-CFmMIMO offloads processing to APs, reducing the CPU burden and enhancing scalability. This decentralized approach not only improves scalability but also facilitates seamless network expansion, as new APs can be integrated without requiring CPU upgrades. Since each AP has local processing capability, new APs can be added without CPU upgrades, enabling ultra-dense deployments. This approach also minimizes fronthaul signaling and quantization distortion, improving efficiency. Additionally, final data detection can be performed at an edge-cloud processor or a serving AP, reducing latency and making distributed processing ideal for large-scale networks [2].

Balancing SE and fairness is crucial in UC-CFmMIMO networks, as traditional methods focus either on max-min fairness or sum-SE maximization, often neglecting a trade-off between them. Thus, an effective power control solution must not only optimize SE but also maintain fairness across all UEs, ensuring a consistent user experience. To address this, we propose a distributed uplink power control scheme using GWO to optimize power allocation, ensuring fairness while enhancing SE. GWO efficiently explores the solution space, outperforming conventional methods in robustness and flexibility. Through numerical simulations, we demonstrate that GWO-based power control improves sum-rate and fairness, making it a practical solution for large-scale distributed networks.

The subsequent sections of this paper are structured as follows. Section 2 provides a comprehensive overview of the system model, elucidating the key components and their interactions. Section 3 delineates the formulated problems, offering insight into the specific optimization objectives and constraints. Section 4 details the proposed approach, explaining the methodology employed to address the formulated problems. Section 5 presents the numerical results obtained through simulations, providing empirical evidence of the effectiveness of the proposed approach. Finally, Section 6 encapsulates the conclusions drawn from this study, summarizing the contributions and implications of our work.

2. SYSTEM MODEL

We consider a UC-CFmMIMO network comprising K single-antenna UEs and L APs, each equipped with N antennas, as illustrated in Fig. 1. The wireless channel AP l and UE k within a given coherence block is denoted by $\mathbf{h}_{kl} \in \mathbb{C}^{N\times 1}$. This channel follows a block-fading model [2], where $\mathbf{h}_{kl}$ remains constant in time and flat in frequency within a coherence block containing τ_c symbols in time-division duplex protocol [7, 23]. τ_c is defined as $\tau_c = \tau_p + \tau_u + \tau_d$, where τ_p symbols are allocated uplink pilots, which allows channel estimation, $\hat{\mathbf{h}}_{kl}$, τ_u symbols for uplink data, and τ_d symbols for downlink data [8]. Within each coherence block, the channel undergoes independent realizations and is modeled using a correlated Rayleigh fading distribution, represented as $\mathbf{h}_{kl} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_N, \mathbf{R}_{kl})$, where $\mathbf{R}_{kl} \in \mathbb{C}^{N\times N}$ is the spatial correlation matrix between AP l and UE k. The impact of small-scale fading is represented using the Gaussian distribution, whereas large-scale fading, including elements like geometric path loss, shadowing, antenna gains, and spatial channel correlation, is described by a positive semi-definite correlation matrix $\mathbf{R}_{kl}$ [2].

In this study, channel estimation is performed using the partial minimum mean squared error scheme in conjunction with Rayleigh fading channels. The most intricate uplink configuration in CFmMIMO involves a fully distributed operation, where APs handle most processing tasks independently. These tasks include channel estimation, receiving combining, data detection, and power control. The APs transmit their received baseband signals to the CPU for further processing, reducing reliance on a central CPU and enhancing system flexibility and resilience. Once the signals are received by the APs, the serving APs send the extracted information to the CPU, where large-scale fading decoding is applied to jointly process the received uplink signals [14]. The signal-to-interference-plus-noise ratio (SINR) for UE k is computed based on the locally estimated channel state information and distributed signal processing at each AP.

We compute the SE for each UE k based on the effective SINR in the network. The uplink transmit powers of the UEs are gathered in a vector $\mathbf{p} = [p_1, \ldots, p_K]^T$, where p_k represents the uplink power of UE k. The effective SINR for UE k depends on the power p_k of its desired signal and the interference term in the denominator, which depends on all power coefficients in $\mathbf{p}$. The generic expression for SINR is:

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

where:

$$b_k = \left|\mathbf{a}_k^H \mathbb{E}\left\{\mathbf{g}_{kk}\right\}\right|^2, \quad \forall k, \tag{2}$$

$$c_{kk} = \mathbb{E}\left\{\left|\mathbf{a}_k^H \mathbf{g}_{kk}\right|^2\right\} - b_k, \quad \forall k, \tag{3}$$

$$c_{ki} = \mathbb{E}\left\{\left|\mathbf{a}_k^H \mathbf{g}_{ki}\right|^2\right\}, \quad \forall k, \forall i \neq k, \tag{4}$$

b_k is the average channel gain for the desired signal of UE k; $\mathbf{c}_k$ is the vector of average channel gains for the interfering signals; σ_k^2 is the effective noise variance for UE k. For a detailed derivation of the SINR expression, please refer to [2].

The difference between the centralized and distributed uplink operations lies in the values of the parameters b_k, $\mathbf{c}_k$, σ_k^2, which are computed as functions of the local channel state information and the distributed signal processing at each AP. Based on the effective SINR for UE k, the SE for UE k can be expressed as:

$$\mathrm{SE}_k(\mathbf{p}) = \frac{\tau_u}{\tau_c}\log_2\left(1 + \mathrm{SINR}_k(\mathbf{p})\right). \tag{5}$$

The SE serves as the primary performance metric in our analysis, reflecting the effectiveness of uplink power control in UC-CFmMIMO systems. It directly influences network performance and user fairness. In the following section, we formulate the optimization problems based on SE to achieve both max-min fairness and total SE maximization.

3. PROBLEM FORMULATION

The process of uplink power control involves determining the optimal power levels for UEs to maximize a specific utility function, typically associated with SE. This study addresses two key challenges: achieving max-min SE fairness and balancing minimum SE fairness with total SE. To tackle the first challenge, we formulate the following optimization problem (P1) to maximize the minimum SE, ensuring fairness among UEs. This approach adheres to the concept of max-min fairness by optimizing power coefficients to promote an equitable SE distribution across all UEs. Mathematically, it is expressed as follows:

$$\begin{aligned} \text{(P1):} \quad & \max_{\mathbf{p}} \min_{k\in\{1,\ldots,K\}} \mathrm{SE}_k(\mathbf{p}) \\ & \text{s.t.} \quad 0 < p_k \leq p_{\max}, \quad k = 1, \ldots, K. \end{aligned} \tag{6}$$

Although max-min SE fairness benefits users with weaker channel conditions, it may limit the overall spectral efficiency in large-scale networks. Conversely, the total SE maximization problem focuses on maximizing total transmitted bits without considering their allocation across UEs. While this approach enhances network capacity, in an uplink scenario, achieving maximum total SE can be straightforward by setting the transmitting power of all UEs to their maximum values $p_k = p_{\max}$. As a result, this study does not focus solely on optimizing total SE. Instead, it considers a dual optimization approach that balances the minimum SE and total SE. The goal is to ensure fairness by improving the SE of the weakest users while also maximizing the overall system efficiency. This challenge, referred to as the joint maximization of minimum SE fairness and total SE, seeks to achieve an optimal trade-off between these two objectives. To achieve this balance, we formulate the joint optimization of minimum SE and total SE. This approach ensures that the weakest user achieves an acceptable SE while maximizing the network's total SE. The problem is formulated as follows:

$$\begin{aligned} \text{(P2):} \quad & \max_{\mathbf{p}} \left\{ \min_{k\in\{1,\ldots,K\}} \mathrm{SE}_k(\mathbf{p}), \sum_{k=1}^{K} \mathrm{SE}_k(\mathbf{p}) \right\} \\ & \text{s.t.} \quad 0 < p_k \leq p_{\max}, \quad k = 1, \ldots, K. \end{aligned} \tag{7}$$

Addressing max-min SE fairness and the joint optimization of minimum SE fairness and total SE is crucial for optimizing UC-CFmMIMO performance. While max-min SE fairness ensures equitable SE distribution, balancing minimum SE fairness with total SE enhances both fairness and efficiency. To tackle these challenges, we propose a robust power control strategy. The next section introduces our approach to achieving optimal power allocation for improved network performance.

4. PROPOSED SCHEME

We propose an effective uplink power control scheme using GWO to tackle optimization challenges in UC-CFmMIMO systems. GWO excels in solving nonlinear, high-dimensional problems by efficiently exploring vast solution spaces, overcoming limitations of conventional techniques. Its global search capability prevents convergence to local optima, ensuring high-quality solutions even in complex wireless environments [20]. Notably, the formulated optimization problems (P1) and (P2) are non-convex due to the fractional and logarithmic structure of SE. Traditional convex optimization techniques, such as dual decomposition or water-filling approaches, fail to provide globally optimal solutions. Heuristic and metaheuristic approaches are, therefore, more suitable for handling such challenges. Given this, our GWO-based approach serves as a promising and efficient alternative, capable of navigating complex solution landscapes while maintaining computational simplicity.

4.1. Fitness Function Formulation

To effectively apply GWO for uplink power control, well-defined fitness functions are essential to represent optimization objectives and constraints. These functions evaluate candidate solutions, guiding the search for optimal power control strategies. For max-min SE fairness and the balance between fairness and total SE maximization, tailored fitness functions ensure alignment with UC-CFmMIMO system constraints. The constraint functions regulate user power within a feasible range $[0, p_{\max}]$, ensuring compliance with power limits. For problem (P1), a single-objective fitness function ($F1$) is designed to maximize performance while adhering to system constraints.

$$F1\left(\mathbf{p}\right) = \min_{k \in \{1,\ldots,K\}} \mathrm{SE}_k\left(\mathbf{p}\right). \tag{8}$$

The inherent non-convexity of (P1) prevents direct solutions using conventional optimization tools such as convex relaxation or gradient-based methods. Instead, our approach leverages GWO's efficient global search capability, which is particularly well suited for handling complex, non-convex search spaces in UC-CFmMIMO networks. For uplink power optimization in CF-mMIMO networks, we also propose a joint optimization model that simultaneously regulates power for max-min SE fairness and total SE maximization, ensuring both user fairness and system throughput enhancement. To efficiently solve this multi-objective problem, we adopt the product method, which reformulates the joint optimization as a single-objective problem. Unlike the weighted sum method, which relies on subjective weighting coefficients and may not fully capture the multi-objective nature, the product method ensures a more balanced treatment of all objectives. The formulation for ($F2$), used in this approach, is given in the following equation:

$$F2\left(\mathbf{p}\right) = \min_{k \in \{1,\ldots,K\}} \mathrm{SE}_k\left(\mathbf{p}\right) \frac{1}{K} \sum_{k=1}^{K} \mathrm{SE}_k\left(\mathbf{p}\right). \tag{9}$$

Similarly, problem (P2) is also non-convex due to its joint max-min SE and total SE objectives. Standard optimization techniques fail to provide efficient solutions due to the lack of convexity and differentiability in certain cases. GWO, by contrast, excels at navigating such complex search spaces, striking a balance between convergence speed and solution quality. Given the complexity and nonlinearity of the formulated fitness functions, GWO provides an effective optimization approach by efficiently exploring the solution space while ensuring SE maximization under constraints. The following sections detail its application in developing a robust uplink power control scheme for UC-CFmMIMO systems.

4.2. Proposed Algorithm

GWO is a metaheuristic algorithm inspired by the leadership hierarchy and cooperative hunting strategies of grey wolves. It classifies wolves into four roles — alpha, beta, delta, and omega — where the alpha guides the search process by adjusting positions based on leading individuals. A key advantage of GWO is its ability to explore the entire solution space, avoiding local optima and efficiently navigating complex environments [20]. By balancing exploration and exploitation, it enhances convergence toward optimal solutions. Leveraging these strengths, we propose a GWO-based optimization algorithm to solve the formulated uplink power control problems for UC-CFmMIMO systems, detailed in Algorithm 1. The algorithm is structured into two stages:

Initialize:

- Specific parameters to UC-CFmMIMO systems are defined, encompassing aspects such as the number of APs, UEs, antennas per AP and UE, the number of channel realizations, and the maximum uplink transmit power of each UE.
- Specific parameters for the grey wolf algorithm are also set up, including the number of iterations N_{iter}, population size N_{pop}, lower and upper bounds lb, ub for the search space.
- Fitness functions $(F1, F2)$ corresponding to the two defined optimization problems are formulated.
- The initial positions $\mathbf{p}_i$ of the wolves are randomly initialized using uniformly distributed random numbers $\mathcal{U}(0,1)_{1\times K}$, ensuring diversity in the population for effective exploration within the problem's search domain.

Find the best solution:

- Each wolf in the initial population is evaluated to determine the current optimal transmit powers $\mathbf{p}^*$.
- The algorithm then enters the main loop, where it iteratively updates the positions of the wolves.
- The leadership hierarchy is established, where the best three wolves, α (alpha), β (beta), and δ (delta), guide the search process.
- A position of each wolf is updated based on the influence of the three best wolves, using adaptive coefficients A and C that simulate encircling and attacking prey.
- The coefficient vector A determines the movement behavior of the wolves:
  - If $A \geq 1$, the wolves explore the search space more broadly, looking for potential better solutions.
  - If $A < 2$, the wolves narrow their search range and begin approaching the best-known solutions.

Algorithm 1 Proposed Uplink Power Control Algorithm

Initialize:

- Parameters for UC-CFmMIMO Systems
- $N_{pop}; N_{iter}; lb \leftarrow 0; ub \leftarrow p_{\max}$
- $F(\mathbf{p}), \mathbf{p} = [p_1, \ldots, p_K]^T$
- $\mathbf{p}_1 \leftarrow p_{\max, 1\times K}$
- $\mathbf{p}_i \leftarrow lb + (ub - lb)\,\mathcal{U}(0,1)_{1\times K}$, **if** $i \neq 1$, $i = 1, \ldots, N_{pop}$

for $i \leftarrow 1$ **to** N_{pop} **do**
    Evaluate $F(\mathbf{p}_i)$
    Update $\mathbf{p}^{\alpha}, \mathbf{p}^{\beta}, \mathbf{p}^{\delta}$
end for
$\mathbf{p}^* \leftarrow \mathbf{p}^{\alpha}$
for $t \leftarrow 1$ **to** N_{iter} **do**
    $a \leftarrow 2 - t\left(\frac{2}{N_{iter}}\right)$
    for $i \leftarrow 1$ **to** N_{pop} do
        $A_1 \leftarrow 2a\mathcal{U}(0,1) - a$; $\quad C_1 \leftarrow 2\mathcal{U}(0,1)$
        $D_1 \leftarrow |C_1\mathbf{p}^{\alpha} - \mathbf{p}_i|$; $\quad X_1 \leftarrow \mathbf{p}^{\alpha} - A_1 D_1$
        $A_2 \leftarrow 2a\mathcal{U}(0,1) - a$; $\quad C_2 \leftarrow 2\mathcal{U}(0,1)$
        $D_2 \leftarrow |C_2\mathbf{p}^{\beta} - \mathbf{p}_i|$; $\quad X_2 \leftarrow \mathbf{p}^{\beta} - A_2 D_2$
        $A_3 \leftarrow 2a\mathcal{U}(0,1) - a$; $\quad C_3 \leftarrow 2\mathcal{U}(0,1)$
        $D_3 \leftarrow |C_3\mathbf{p}^{\delta} - \mathbf{p}_i|$; $\quad X_3 \leftarrow \mathbf{p}^{\delta} - A_3 D_3$
        $\mathbf{p}_i \leftarrow \frac{X_1 + X_2 + X_3}{3}$
        Evaluate $F(\mathbf{p}_i)$
        Update $\mathbf{p}^{\alpha}, \mathbf{p}^{\beta}, \mathbf{p}^{\delta}$
    end for
end for
end while
return $\mathbf{p}^{\alpha}$

Output: Optimal transmit powers: $\mathbf{p}^* \leftarrow \mathbf{p}^{\alpha}$

  - If $A > 1$, the wolves aggressively attack the optimal solution found so far by moving closer to α, β, and δ, refining the search through local exploitation.
- A random exploration factor is introduced to enhance diversity in the search, allowing wolves to escape local optima.
- The fitness function $F(\mathbf{p}_i)$ is evaluated for the new position of each wolf.
- If the fitness function value for the new position is better than the best solution found so far, the position of the alpha wolf $\mathbf{p}^{\alpha}$ is updated accordingly.
- The algorithm iterates until reaching the maximum number of iterations.
- Finally, the algorithm outputs the optimal transmitting power $\mathbf{p}^*$, which corresponds to the optimal transmitting power allocation for the uplink power optimization problem.

5. NUMERICAL RESULTS AND DISCUSSION

5.1. Parameter Setup

In Section 4, we introduced a GWO-based uplink power control scheme for UC-CFmMIMO systems, aiming to maximize minimum SE fairness and balance minimum SE fairness with total SE. Leveraging GWO's efficiency, our approach effectively addresses massive MIMO's optimization challenges.

To evaluate its performance, we simulate a 1 km $\times$ 1 km UC-CFmMIMO network with 50 randomly placed APs and 10 UEs. Each AP has one antenna, totaling 50 antennas across the network. The system operates over a 20 MHz bandwidth, with receiver noise power set at -94 dBm, including a 7 dB noise figure. Each UE transmits at a maximum of 100 mW, while APs are positioned 10 meters above the UE plane. The coherence block consists of 200 samples, aligning with a 2 ms coherence time and a 100 kHz coherence bandwidth.

Pathloss is modeled using the 3GPP Urban Microcell model, with a pathloss exponent of 3.67. A wraparound topology ensures interference from all directions, and spatial correlation is modeled with Rayleigh fading. Pilot assignment and AP selection follow the strategy in [2]. SE is the primary performance metric, analyzed using cumulative distribution function (CDF) curves generated from 500 network setups, each with 50 channel realizations. The GWO algorithm uses a population size of 300 and runs for 50 iterations per setup, by default.

5.2. Evaluation of the Proposed Uplink Power Control Scheme

Figure 2 illustrates the convergence of the fitness functions $F1$ and $F2$ over multiple iterations, demonstrating the effectiveness of the proposed GWO-based power control scheme. The results show that both functions steadily improve, with $F1$ approaching convergence within 6 iterations, whereas $F2$ takes 60 iterations to reach a near-stable value. This difference is due to $F1$ focusing solely on maximizing the minimum SE, while $F2$ balances minimum SE fairness and total SE. Consequently, $F2$ achieves a higher total SE at the cost of slightly lower minimum SE than $F1$.

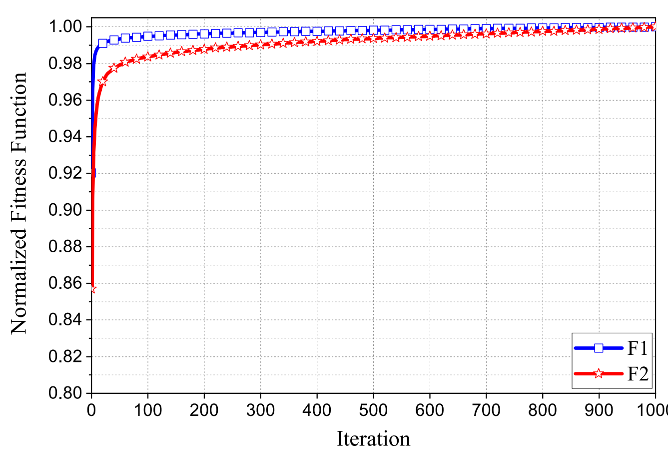

FIGURE 2. Normalized fitness functions versus number of iterations.

Computational efficiency was analyzed by measuring execution time using MATLAB 2021b on a laptop with an Intel Core i7-9750H CPU (2.6 GHz, 12 cores) and 32 GB RAM. At convergence, $F1$ completed in 4.81 milliseconds at iteration 6,

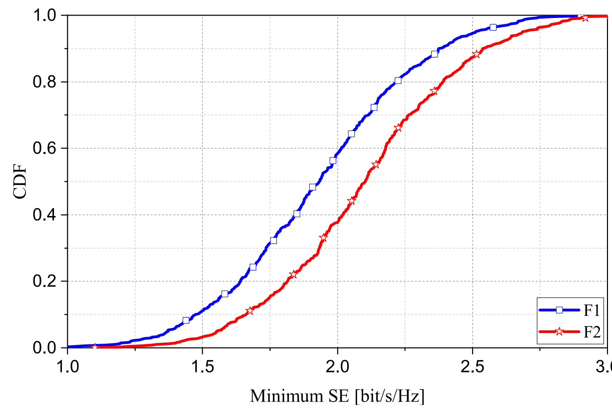

FIGURE 3. CDFs versus minimum SE in the network.

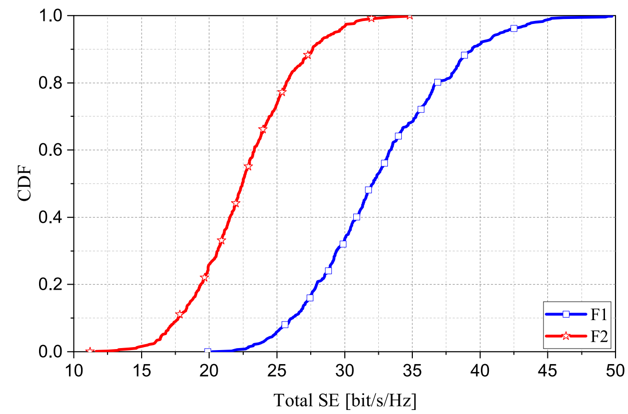

FIGURE 4. CDFs versus total SE in the network.

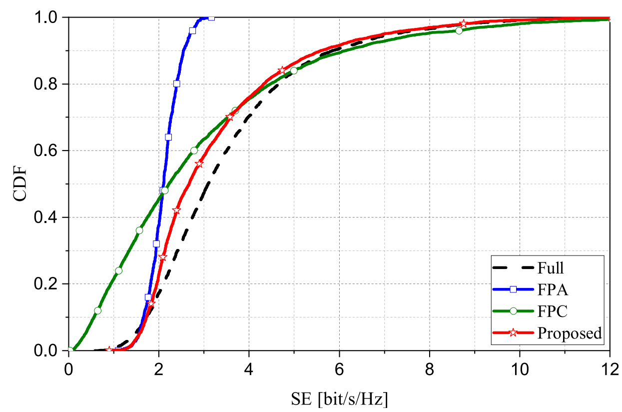

FIGURE 5. Comparison of uplink power control schemes in terms of SE per user.

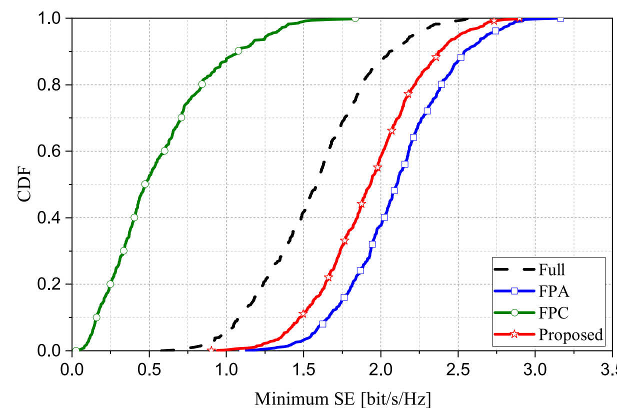

FIGURE 6. Comparison of uplink power control schemes in terms of minimum SE.

while $F2$ took 5.02 milliseconds at iteration 58. Although $F2$ required more iterations, its overall execution time remained comparable due to the efficiency of the GWO algorithm. The longer convergence of $F2$ is attributed to its additional objective of optimizing total SE, which requires a broader search space exploration.

Figure 3 presents the CDFs of minimum SE under both fitness functions. The results indicate that $F1$ provides higher minimum SE for a larger percentage of users, but $F2$ offers a more balanced performance across all users. Although $F2$ slightly sacrifices minimum SE, it significantly enhances total SE, as shown in Fig. 4. Under $F2$, total SE increases from 19.90 to 57.21, whereas $F1$ only achieves a range from 11.20 to 34.81. This confirms that $F1$ prioritizes fairness, while $F2$ provides a more practical trade-off between fairness and overall network performance.

These findings highlight the impact of the fitness function choice: $F1$ maximizes fairness but limits total SE, whereas $F2$ effectively balances both objectives, making it a more robust approach for real-world deployment.

5.3. Comparison of the Proposed Scheme with Other Schemes

The performance comparison in Figs. 5, 6, and 7 highlights the effectiveness of the proposed scheme, which optimizes both fairness and total SE using the fitness function $F2$. For

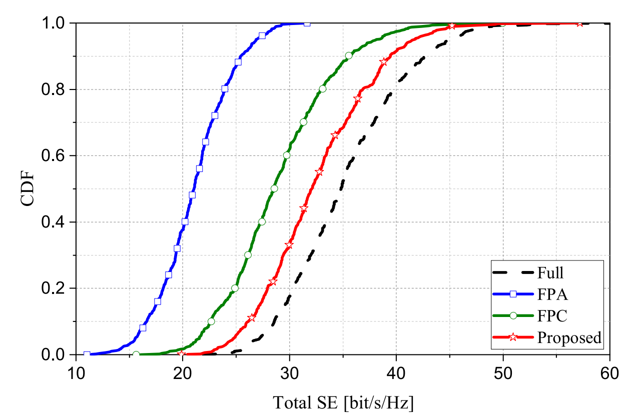

FIGURE 7. Comparison of uplink power control schemes in terms of total SE.

SE across all UEs (Fig. 5), the proposed scheme consistently achieves higher SE than both the fixed-point algorithm (FPA) and fractional power control (FPC), though it remains slightly lower than full power control (Full). At a CDF of 0.1, it attains 1.7222, outperforming FPA (1.66) and FPC (0.56), but slightly below Full (1.7195). At a CDF of 0.5, it reaches 2.67, surpassing FPA (2.10) and FPC (2.22) while still trailing Full (3.09).

Regarding minimum SE (Fig. 6), the proposed scheme proves more effective than both Full and FPC but is slightly outperformed by FPA. At a CDF of 0.05, it achieves 1.37, significantly exceeding Full (0.97) and FPC (0.13). Similarly, at a CDF of 0.5, it reaches 1.93, higher than Full (1.59) and FPC (0.47), but slightly lower than FPA (2.10).

When considering total SE (Fig. 7), the proposed scheme demonstrates a clear advantage over FPA and FPC. At a CDF of 0.1, it attains 26.16, outperforming FPA (16.63) and FPC (22.65). While Full achieves the highest total SE, the proposed scheme effectively balances total SE and fairness, making it a strong alternative.

Importantly, although FPC is designed to balance fairness and total SE, the proposed scheme consistently delivers superior results across all key metrics: SE for all UEs, minimum SE, and total SE. This confirms the effectiveness of the GWO-based optimization approach in achieving a well-balanced and efficient power control strategy.

5.4. Scalability Analysis: Impact of AP and UE Density on SE Performance

The proposed power control scheme effectively optimizes power allocation as the network scales, ensuring a balance between fairness and total SE. Compared to Full, FPA, and FPC, it consistently outperforms FPC in all key SE metrics, while also maintaining a competitive balance between efficiency and fairness.

As shown in Tables 1 and 2, increasing the number of APs enhances both minimum SE and total SE. The proposed scheme achieves a minimum SE of 1.17 bit/s/Hz at 30 APs, higher than FPC (0.23 bit/s/Hz) and close to FPA (1.31 bit/s/Hz). At 100 APs, it reaches 3.14 bit/s/Hz, surpassing FPC (1.42 bit/s/Hz) and approaching FPA (3.35 bit/s/Hz), while Full remains slightly higher (2.76 bit/s/Hz). For total SE, the proposed method consistently outperforms FPA and FPC. At 100 APs, it achieves 39.17, higher than FPC (36.77) and FPA (24.45), but lower than Full (47.23), which prioritizes SE at the cost of fairness.

TABLE 1. Average minimum SE versus number of APs.

Number of APs	Full	FPA	FPC	**Proposed**
30	0.88	1.31	0.23	**1.17**
50	1.57	2.09	0.60	**1.91**
70	2.12	2.68	0.90	**2.49**
100	2.76	3.35	1.42	**3.14**

TABLE 2. Average total SE versus number of APs.

Number of APs	Full	FPA	FPC	**Proposed**
30	13.09	23.99	21.52	**26.69**
50	20.90	32.51	29.16	**35.02**
70	26.82	38.77	34.43	**41.16**
100	33.47	45.10	40.56	**47.23**

The impact of UE density is analyzed in Tables 3 and 4. As the number of UEs increases, minimum SE decreases, but the proposed scheme remains superior to FPC and comparable to FPA. At 8 UEs, it achieves 2.17 bit/s/Hz, higher than FPC (0.81 bit/s/Hz) and close to FPA (2.36 bit/s/Hz). When UEs increase to 15, it maintains 1.47 bit/s/Hz, significantly better than FPC (0.31 bit/s/Hz), while Full drops to 0.98 bit/s/Hz. For total SE, the proposed scheme consistently outperforms FPA and FPC, reaching 39.17 at 15 UEs, while FPC and FPA achieve 36.77 and 24.45, respectively.

TABLE 3. Average minimum SE versus number of UEs.

Number of UEs	Full	FPA	FPC	**Proposed**
8	1.90	2.36	0.810	**2.17**
10	1.59	2.12	0.610	**1.95**
12	1.29	1.87	0.400	**1.71**
15	0.98	1.63	0.310	**1.47**

TABLE 4. Average total SE versus number of UEs.

Number of UEs	Full	FPA	FPC	**Proposed**
30	26.69	18.86	25.01	**28.43**
50	35.02	21.18	27.66	**31.28**
70	41.16	22.45	32.25	**35.69**
100	47.23	24.45	36.77	**39.17**

Overall, the proposed method scales efficiently with AP and UE density, ensuring a strong balance between SE performance and fairness. While Full achieves the highest total SE, it lacks fairness, whereas FPA and FPC prioritize fairness but sacrifice SE performance. The proposed scheme achieves the best tradeoff, consistently outperforming FPC while remaining competitive with Full and FPA.

6. CONCLUSION

In this paper, we proposed a GWO-based uplink power control scheme for UC-CFmMIMO systems, addressing the critical challenge of balancing minimum SE fairness and total SE. Our approach demonstrated significant improvements over existing methods, such as FPC, by achieving a minimum SE of 1.37 bit/s/Hz (compared to FPC's 0.13 bit/s/Hz) and a total SE of 39.17 bit/s/Hz (compared to FPC's 36.77 bit/s/Hz) in a 100-AP network setup. The proposed scheme not only outperforms traditional algorithms in terms of fairness and network performance, but also scales effectively with the density of APs and UEs, ensuring optimal power control even in large-scale deployments. These results make the proposed scheme highly applicable to future UC-CFmMIMO networks, which are expected to become more prevalent in 5G and beyond wireless systems. The key contribution of this work lies in providing a practical and efficient solution for uplink power control that optimizes both fairness and total SE, making it a promising direction for future research. Further exploration could focus on adaptive optimization techniques, heterogeneous network environments, and real-time implementation, all of which hold potential for enhancing the performance of UC-CFmMIMO systems in real-world applications. In addition to the conducted simulations under idealized conditions, it is important to further assess the proposed algorithm's robustness in more practical UC-CFmMIMO deployments. Real-world factors such as imperfect CSI acquisition, limited-capacity fronthaul links, and hardware impairments could impact system performance. As such, future work will focus on extending the proposed scheme to account for these non-ideal conditions and validating its effectiveness through both theoretical analysis and more comprehensive simulations. This would further reinforce the proposed scheme's applicability to real-world 5G and beyond wireless systems.

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