

UAV Fleet Dimensioning for Continuous Aerial User-Centric Distributed Massive MIMO Networks

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Abstract—Distributed massive MIMO (D-mMIMO) systems, also known as cell-free networks, provide high and uniform spectral efficiency wireless networks. However, the high density of transmission-reception points (TRPs) in those networks is impractical in certain dynamic and emergency scenarios. This work investigates unmanned aerial vehicles (UAV) acting as TRPs in D-mMIMO systems, with a proposed fleet rotation framework for continuous service. It considers UAV mobility and energy consumption and recuperation, minimum battery threshold, flight time to changing station, and collision management based on potential fields. Numerical results show the impact of energy replenishment time on UAV availability and fleet size.

Keywords—Distributed massive MIMO, Cell-free networks, UAVs, Fleet rotation, Energy consumption and replenishment, Fleet size.

I. INTRODUCTION

User-centric (UC) distributed massive multiple-input multiple-output (D-mMIMO), otherwise known as cell-free massive MIMO, systems have emerged as one of the key technologies for sixth-generation (6G) systems due to their ability to provide high spectral efficiency, macro-diversity, and uniform service coverage [1], [2]. Unlike conventional cellular architectures, D-mMIMO systems deploy a large number of transmission and reception points (TRPs) distributed across the coverage area, which cooperatively serve user equipment (UE). This approach eliminates traditional cell boundaries, mitigates inter-cell interference, and provides high spectral efficiency (SE), as well as more uniform service coverage.

Despite these advantages, the deployment of a dense terrestrial infrastructure for D-mMIMO networks may be economically or geographically unfeasible in remote areas, complex terrains, scenarios with sporadic but high-demand events, or disaster-affected regions where conventional networks are unavailable. In this context, the integration of terrestrial and non-terrestrial networks has been envisioned as an important direction for 6G systems [3]. In particular, the use of unmanned aerial vehicles (UAVs) as aerial TRPs emerges as a promising alternative for the rapid and flexible deployment of wireless networks. Due to their high maneuverability, UAVs can be organized into cooperative swarms capable of dynamically adjusting their positions and trajectories according to UE mobility and varying traffic demands.

However, the operation of UAV swarms in communication systems faces challenges related to energy sustainability and

service continuity due to the limited capacity of lithium polymer (LiPo) batteries. Existing works have proposed energy replenishment strategies to support continuous UAV operation [4], [5]. In [4], continuous operation is analyzed for UAVs at fixed service locations, whereas the proposed framework dynamically repositions aerial TRPs according to the time-varying UE distribution and models their return-to-base trajectories. In contrast, [5] optimizes UAV trajectories to enhance coverage while assuming that fully charged replacement UAVs are always immediately available, without addressing the fleet size required to sustain operation. The present work builds on the mobility and communication framework of [6], which optimizes UAV trajectories assuming continuous availability. In contrast, we model return-to-base trajectories, replenishment downtime, standby replacement, and the fleet and battery inventory required for continuous operation. Consequently, although the literature addresses UAV positioning, communication performance, and energy management, these aspects are typically studied independently and often under idealized assumptions, limiting their applicability to realistic deployments.

Therefore, determining the number of UAVs required to sustain continuous operation remains an important open research problem. This fleet size depends on factors such as energy consumption, charging time, and mission duration, which directly influence the feasibility, scalability, and cost-effectiveness of UAV-based communication systems.

Furthermore, when multiple UAVs operate simultaneously, collision avoidance becomes essential to maintain fleet integrity and system reliability [7], [8]. For example, [7] employs an artificial potential field approach to guide UAV movement through attractive and repulsive forces, whereas [8] computes collision-free velocities. Nevertheless, collision avoidance remains largely overlooked in UAV-aided communication systems, where the primary focus has been on communication performance [5], [6].

In light of these challenges, this work proposes a unified framework for continuous UAV-enabled D-mMIMO operation by integrating UE-density-aware repositioning, energy-constrained fleet rotation, battery replenishment, and collision-aware navigation. Its main contribution is the joint dimensioning of the UAV fleet and battery inventory required to maintain a prescribed number of active aerial TRPs under finite-energy operation.

II. SIMULATION FRAMEWORK AND NETWORK MODEL

A. Network Topology

We consider a UC D-mMIMO network composed of a central processing unit (CPU), a set of UAVs acting as

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aerial TRPs, and a set of UEs distributed over a predefined geographical area. Each aerial TRP is equipped with a compact N-antenna array, which avoids the large antenna payload associated with a conventional co-located massive MIMO base station. The aerial TRPs jointly serve the UEs through downlink Local Partial Minimum-Mean Squared Error (LP-MMSE) precoding, providing distributed beamforming and spatial macro-diversity gains.

The system evolution is modeled in discrete time steps. Let $n \in \mathbb{Z}^+$ denote the discrete-time index, obtained from the continuous-time variable $t \in \mathbb{R}^+$ with a sampling interval Δt . Thus, each simulation step represents a time interval of duration Δt , which is used to update UAV positions, UE locations, battery levels, and operational states throughout the mission.

Let $\mathcal{U} = \{1, \dots, U\}$ denote the set of UAVs and $\mathcal{K} = \{1, \dots, K\}$ the set of UEs. The position of each UAV $u \in \mathcal{U}$ at discrete time step n is defined as

$$\mathbf{q}_u[n] = [x_u[n], y_u[n], z_u[n]]^T, \quad (1)$$

while each UE $k \in \mathcal{K}$ is located at

$$\mathbf{w}_k[n] = [x_k[n], y_k[n]]^T. \quad (2)$$

The CPU forms a UC cluster of active aerial TRPs for each UE. Due to the dynamic nature of the scenario, UAV positions are updated over time according to UE distribution and system requirements. The UAV motion can be modeled as

$$\mathbf{q}_u[n+1] = \mathbf{q}_u[n] + \Delta \mathbf{q}_u[n], \quad (3)$$

where $\Delta \mathbf{q}_u[n]$ represents the displacement vector of UAV u at time step n . The UAV displacement is constrained by the adopted operational repositioning speed v_{op} as

$$\|\Delta \mathbf{q}_u[n]\| \leq v_{op} \Delta t, \quad (4)$$

where v_{op} denotes the operational speed adopted for controlled UAV repositioning within the service area, rather than the maximum physical speed supported by the platform. Moreover, $v_u[n] = \|\Delta \mathbf{q}_u[n]\|/\Delta t$ denotes the effective speed of UAV u at time step n . Following [6], the system operates in TDD mode with correlated Rician UAV-UE channels and uplink pilot-based LMMSE channel estimation. Only the downlink SE is evaluated, using distributed LP-MMSE precoding.

$$SE_k = \frac{\tau_d}{\tau_c} \log_2 \left(1 + \frac{DS_k}{IS_k + QN_k - DS_k + \sigma_{dl}^2} \right), \quad (5)$$

where τ_c is the coherence-block length, τ_d is the number of samples allocated to downlink data, and DS_k , IS_k , and QN_k denote the desired-signal, multiuser-interference, and fronthaul-quantization powers, respectively. Moreover, σ_{dl}^2 is the receiver-noise variance. For distributed LP-MMSE precoding, these terms and the resulting SE are evaluated through Monte Carlo simulations, since no closed-form expression is available.

B. Simulation Workflow and UAV Mobility Strategy

Fig. 1 summarizes the general workflow of the proposed UAV-enabled UC D-mMIMO simulation framework. The simulation starts with the definition of the network, UAV, mobility, and energy parameters, such as the number of UEs, the number of active UAVs, the coverage area, the mission duration, the

battery capacity, and the charging or battery replacement time. Then, the UE spatial distribution is generated and updated over time, representing the temporal variation of the traffic demand within the service area.

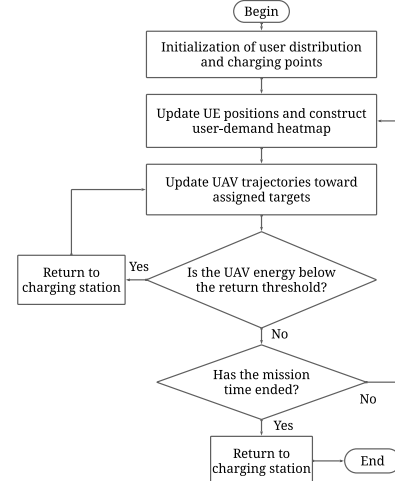


Fig. 1. General workflow of the proposed UAV-enabled D-mMIMO simulation framework.

In this work, a UE-density-aware mobility strategy is adopted through a two-dimensional density map that evolves in discrete time steps, where the active UAVs, acting as aerial TRPs, are dynamically driven toward regions with higher UE concentration.

During the simulation, UAVs move toward the selected target regions while respecting mobility, energy, and safety constraints, including the adopted operational speed, predefined altitude levels, battery availability, and collision-avoidance requirements [7], [8]. At each time step, the energy state of each UAV is evaluated. When the remaining energy is not sufficient to safely continue the mission, the UAV is redirected to a charging or battery replacement point, following the fleet rotation principle adopted in perpetual-flight UAV swarm systems [4].

After updating the UAV positions and operational states, the communication performance is evaluated using the resulting UAV-UE spatial configuration. In particular, the downlink spectral efficiency is computed using LP-MMSE precoding to assess the network performance. The relevant metrics, including UAV trajectories, energy consumption, fleet status, and spectral efficiency, are stored until the end of the simulation.

C. UE Density Map Creation

The UE distribution and mobility are modeled through a stochastic framework combining a birth-death continuous-time Markov chain (CTMC) with Markovian mobility dynamics. Initially, a finite number of UEs is randomly distributed over the considered coverage area, with associated moving state computed based on stopping (p_{stop}) and start moving (p_{start}) probabilities. The moving UEs update their movement directions according to the Markovian discrete angular mobility model proposed in [6]. The model introduces directional persistence by using angular movement steps (ϕ^{step}) and standard deviation (σ_ϕ) variables.

At each transition, UEs may appear or leave the system according to a birth-death CTMC, with exponentially distributed arrival (T_{arr}) and permanence (T_{stay}) times as in [9]. Sequential state transitions are simulated until a target operation time is reached. As a result, the framework generates a sequence of UE-distribution setups, each associated with a specific existence duration and UE population size.

Finally, the complete temporal evolution of the system, including UE births, departures, movement states, and mobility trajectories, is continuously stored and later discretized into time steps to generate spatial traffic-density and demand heatmaps representing the temporal evolution of UE demands.

III. FLEET ROTATION METHODOLOGY

A. UAV Operational States

To represent the UAV operation, each aerial TRP is modeled according to four operational states: active, return-to-charge, charging or battery replacement, and standby.

In the active state, the UAV operates as an aerial TRP, serving nearby UEs while moving toward the target position assigned according to the UE-demand distribution. Let U_{ac} denote the number of UAVs that must remain simultaneously active throughout the mission. The UAV remains in this state as long as its residual energy is sufficient to continue the mission and safely return to its assigned charging station.

When the residual energy falls below the return threshold, the UAV transitions to the return-to-charge state. In this state, the UAV stops following its assigned service target and proceeds toward its predefined charging station, referred to as its home base. Simultaneously, a standby UAV is activated and deployed to replace it, ensuring that the number of active UAVs remains constant. If no UAVs are available in the standby set, additional UAVs are instantiated. Consequently, the total fleet size increases, allowing the required fleet dimensioning to be determined.

When the return-to-charge UAV reaches its home station, it enters the charging (or battery replacement) state. The UAV remains unavailable for service until the charging counter satisfies $n_{\text{ch}}[u] \geq N_{\text{er}}$, where N_{er} denotes the energy replenishment time. At that point, the battery is assumed to be fully restored, and the UAV transitions to the standby state. Furthermore, let N_{bc} denote the battery charging time. If $N_{\text{er}} < N_{\text{bc}}$, the model represents a UAV battery replacement strategy; otherwise, it represents conventional charging.

B. Target Assignment Strategy

Target locations are periodically selected from the UE density map. The highest-intensity point is selected first, while subsequent targets are required to be at least r_{target} meters apart from previously selected targets. This prevents multiple UAVs from being assigned to nearby locations. The selected targets are assigned to active UAVs by solving a linear assignment problem that minimizes the swarm travel distance. Let $\mathbf{q}_u$ denote the position of UAV u and $\mathbf{p}_\ell$ the position of target ℓ . The assignment problem is formulated as

$$\begin{aligned} \min_{\{x_{u,\ell}\}} \quad & \sum_u \sum_\ell \|\mathbf{q}_u - \mathbf{p}_\ell\| x_{u,\ell} \\ \text{s.t.} \quad & \sum_\ell x_{u,\ell} = 1 \quad \forall u, \quad \sum_u x_{u,\ell} = 1 \quad \forall \ell, \quad x_{u,\ell} \in \{0, 1\}, \end{aligned} \quad (6)$$

where $x_{u,\ell} = 1$ if target ℓ is assigned to UAV u , and $x_{u,\ell} = 0$ otherwise.

C. Fleet Rotation Strategy

To ensure continuous system operation, a fleet rotation strategy is adopted, in which UAVs dynamically transition between operational states according to their energy levels.

Let $E_u[n]$ denote the residual energy of UAV u at time step n , with $0 \leq E_u[n] \leq E_{\text{max}}$. The energy evolution depends on the UAV operation and is given by

$$E_u[n+1] = E_u[n] - P_u[n]\Delta t, \quad (7)$$

where $P_u[n]$ denotes the propulsion power at speed $v_u[n]$ [6], [10]. Each UAV $u \in \mathcal{U}$ is associated with a predefined charging station, referred to as its home base. Consequently, when a return-to-charge procedure is triggered, the UAV travels to its assigned charging station. The decision to initiate the return-to-charge procedure is based on the following conditions:

$$E_u[n] < E_{\text{req},u}[n] \quad \text{or} \quad E_u[n] < \lambda E_{\text{max}}, \quad (8)$$

where $E_{\text{req},u}[n]$ denotes the energy required for UAV u to travel from its current position to its home base. The first condition ensures that the UAV can safely reach its assigned charging station. The second condition corresponds to a safety threshold, defined as a fraction of the maximum battery capacity, where $0 < \lambda < 1$ is a design parameter specifying the minimum allowable energy level. This technique ensures that UAVs avoid energy depletion during operation by maintaining a safety margin. Once a UAV enters the return-to-charge state, a replacement UAV from the standby set can be deployed to maintain service continuity.

D. Safety Constraints

In addition to energy constraints, safe navigation is a critical aspect of multi-UAV operation. Let $d_{u,v}[n]$ denote the Euclidean distance between UAVs u and v at time step n . To mitigate collision risks, a desired minimum separation between UAVs is considered, although it is not strictly guaranteed, as

$$d_{u,v}[n] \geq d_{\min}, \quad \forall u \neq v, \quad (9)$$

where $d_{\min}$ represents the minimum safe distance.

To support collision-aware motion, UAV interactions are modeled through a repulsive artificial potential field [7]. The resulting repulsive field is analogous to Coulomb's law, where the force magnitude increases rapidly as two UAVs approach one another. Let $\mathbf{r}_{u,j}[n] = \mathbf{q}_u[n] - \mathbf{q}_j[n]$ be the relative displacement between UAVs u and j , and let $d_{u,j}[n] = \|\mathbf{r}_{u,j}[n]\|$ be the corresponding three-dimensional distance. The repulsive force vector acting on UAV u is computed as

$$\mathbf{F}_u^{\text{rep}}[n] = \sum_{\substack{j \in \mathcal{U} \\ j \neq u, d_{u,j}[n] < d_{\text{rep}}}} k_{\text{rep}} \frac{\mathbf{r}_{u,j}[n]}{d_{u,j}^3[n]}, \quad (10)$$

where k_{rep} controls the repulsion intensity and d_{rep} defines the interaction radius.

The repulsive force is incorporated into the UAV motion by modifying its displacement vector according to

$$\Delta \mathbf{q}_u[n] = \Delta \mathbf{q}_u^{\text{nom}}[n] + \alpha_{\text{rep}} \mathbf{F}_u^{\text{rep}}[n], \quad (11)$$

where $\Delta \mathbf{q}_u^{\text{nom}}[n]$ denotes the nominal displacement generated by the trajectory planning algorithm, $\Delta \mathbf{q}_u[n]$ is the resulting displacement after applying collision-avoidance corrections, and α_{rep} is a scaling factor that determines the influence of the repulsive force on the UAV motion.

IV. NUMERICAL RESULTS

A. Case Study

The simulations assess the impact of mission duration, energy-replenishment strategy, and the number of simultaneously active UAVs on fleet size and battery requirements. Two replenishment strategies are considered: conventional battery charging, in which the UAV remains unavailable during N_{bc} , and battery replacement, in which the depleted battery is replaced within a shorter replenishment time N_{er} and recharged offline. An additional comparison between different UAV configurations is presented in Fig. 4. The remaining simulation parameters are given in Table IV-A. The adopted value $v_{\text{op}} = 0.9$ m/s is an operational repositioning speed rather than the platform's physical maximum speed.

TABLE I
SIMULATION PARAMETERS.

Parameter	Value
Area; K	500×500 m ² ; 200
Charging points; U_{ac}	15; 25–200
Mission duration	Up to 240 min
Baseline UAV configuration	DJI Mini Plus
Antennas per aerial TRP, N	4
v_{op} ; Δt	0.9 m/s; 5 s
E_{max} ; λ	102286.8 J; 0.3
N_{bc} ; N_{er}	90 min; 5 or 90 min
T_{arr} ; T_{stay}	3600 s; 10000 s
ϕ^{step} ; σ_{ϕ}	10°; 30°
p_{stop} ; p_{start}	0.05; 0.10
UE speed	0.9 m/s
k_{rep} ; d_{rep}	10; 18 m
α_{rep} ; d_{min}	1/9; 1 m

B. UAV Fleet and Battery Inventory Dimensioning

Fig. 2 shows the required number of UAVs and batteries as a function of the mission duration, with 25 active UAVs. The results compare 5-minute battery replacement ($N_{\text{er}} = 5$ min) and 90-minute conventional charging ($N_{\text{er}} = N_{\text{bc}} = 90$ min). For short missions, both replenishment strategies require a similar number of UAVs, since the number of rotation cycles is still limited.

With 5-minute battery replacement, the required number of UAVs remains nearly constant after 30 minutes, staying close to 50 UAVs up to 240 minutes. This occurs because the short replacement time allows UAVs to return quickly to service, reducing the need for additional standby UAVs. However, this advantage requires a larger battery inventory, since depleted batteries must still be recharged before being reused.

In contrast, the 90-minute charging strategy requires a larger UAV fleet as the mission duration increases. Since UAVs remain unavailable for a longer period during charging, additional UAVs are needed to maintain continuous operation. As a result, the required fleet reaches approximately 100 UAVs at 120 minutes and around 125 UAVs for longer missions. In this case, the number of required batteries follows approximately the same trend as the number of UAVs.

The perpetual-flight baseline from [4] is used as a reference for the required UAV fleet size. Two mission radii (R) are

considered, representing the minimum and maximum distances traveled by a UAV from its charging station to the target location. For longer missions, the baseline estimates a minimum fleet size of 100 UAVs and a maximum of 150 UAVs. This difference arises because the fixed-location baseline does not capture the dynamic service and return-to-base trajectories modeled by the proposed fleet-rotation framework.

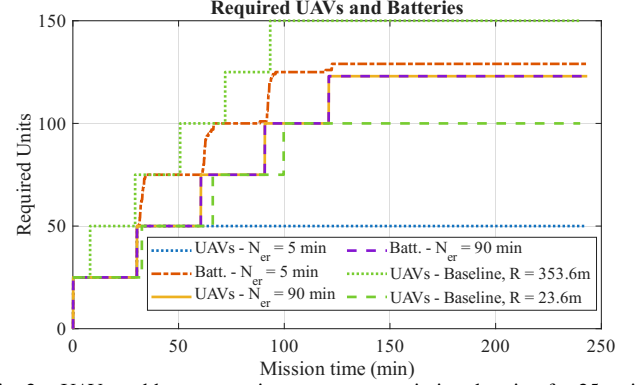


Fig. 2. UAVs and battery requirements versus mission duration for 25 active UAVs under battery replacement and charging strategies.

C. Effect of Swarm Size and UAV Type on Fleet Dimensioning

The impact of UAV swarm group size and energy replenishment strategy on continuous UAV-enabled D-mMIMO operation is analyzed in Fig. 3. The results compare the number of UAVs required under conventional 90-minute charging with the number of batteries required under the 5-minute battery replacement strategy. The required infrastructure increases with both the number of active UAVs (U_{ac}) and the mission duration. As expected, the 90-minute charging strategy requires a larger UAV fleet because UAVs remain unavailable for longer periods while charging. In contrast, the 5-minute battery replacement strategy reduces UAV downtime but shifts the infrastructure demand to spare batteries needed to sustain continuous operation. A key observation is that the required fleet size is approximately five times the number of active UAVs (U_{ac}). However, this scaling factor depends strongly on the UAV characteristics, particularly flight endurance and battery charging time.

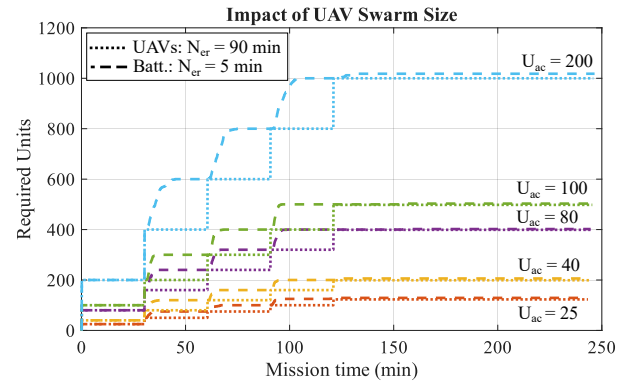


Fig. 3. Required UAVs and batteries versus mission time for different numbers of active UAVs (U_{ac}).

Fig. 4 shows the required fleet size for different UAV configurations with 25 active UAVs, 200 UEs, and a mission duration of 240 minutes. The standard DJI Mini Plus configuration requires 123 UAVs (fleet-to-active-UAV ratio ≈ 5),

whereas the configuration with additional batteries reduces this requirement to 100 UAVs (ratio ≈ 4). In contrast, the small UAV model from [10] requires 261 UAVs (factor ≈ 10). These results show that low-endurance UAVs substantially increase UAV fleet requirements. Similar trends are observed for the battery inventory, which remains higher than the UAV count due to the need for spare batteries for the replacement process.

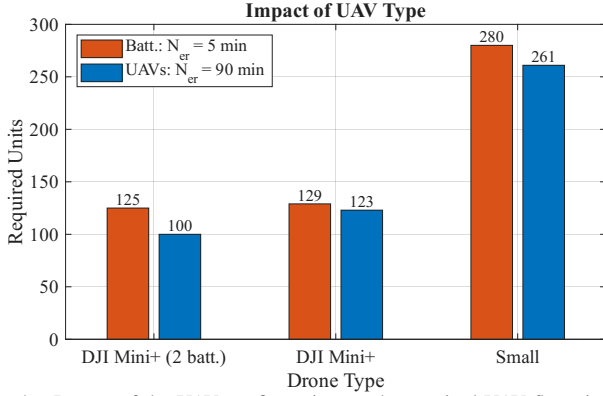


Fig. 4. Impact of the UAV configuration on the required UAV fleet size and batteries for 25 active UAVs, 200 UEs, and 240-minute mission duration.

D. Spectral Efficiency Analysis

The downlink communication performance is evaluated using [6]. Fig. 5 shows the SE cumulative distribution function (CDF) for 200 UEs, a 240-minute mission, and different fleet sizes and energy-replenishment strategies. While fleet dimensioning is driven by UAV availability, the cell-free architecture affects the SE through user-centric cooperation and the spatial distribution of the active aerial TRPs. The comparison uses approximately the same total fleet sizes for both energy-replenishment strategies. However, due to the shorter UAV downtime, battery replacement supports a larger number of simultaneously active aerial TRPs than conventional charging.

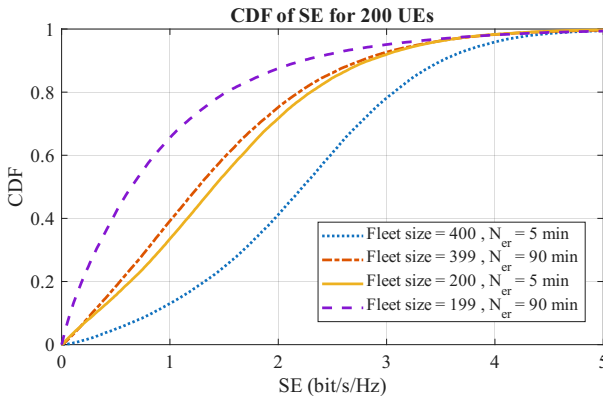


Fig. 5. Downlink SE CDF for 200 UEs using LP-MMSE precoding under different energy-replenishment strategies.

For total fleet sizes close to 200 UAVs, conventional charging maintains $U_{ac} = 40$ active UAVs with a fleet size of 199, whereas battery replacement maintains $U_{ac} = 100$ active UAVs with a fleet size of 200. Similarly, for fleet sizes close to 400, conventional charging maintains $U_{ac} = 80$ active UAVs with a fleet size of 399, while battery replacement maintains $U_{ac} = 200$ active UAVs with a fleet size of 400.

Fig. 5 shows that the median SE (50th percentile) ranges from 0.64 to 1.40 bit/s/Hz for a fleet of 200 UAVs, and

from 1.26 to 2.20 bit/s/Hz for a fleet of 400 UAVs. The conventional battery charging approach ($N_{er} = 90$ min) yields lower SE values than the battery replacement strategy ($N_{er} = 5$ min). The SE gain achieved by battery replacement is approximately 54.3% and 44.0% for fleets of 200 and 400 UAVs, respectively. This improvement arises because battery replacement supports approximately 2.5 times as many active UAVs as conventional charging while maintaining the same UAV-fleet size. For example, with a fleet of 400 UAVs, the battery replacement strategy can support up to 200 active UAVs acting as TRPs, whereas the charging approach supports only 80. While this suggests that battery replacement is more beneficial, it is important to note that battery-replacement infrastructure is more complex, and a battery inventory is necessary. Nevertheless, this strategy allows significantly more UAVs to remain operational simultaneously.

V. CONCLUSION

This work investigated a UAV-enabled D-mMIMO framework for continuous wireless service provision, jointly considering UAV mobility, energy consumption, fleet rotation, battery replenishment, and safety-oriented navigation. The results showed that the battery replacement strategy reduces UAV downtime and the required fleet size compared with conventional charging, although it requires additional batteries. For the evaluated scenarios, the required fleet size ranges from approximately four to 10 times the number of active UAVs, although this factor strongly depends on UAV flight endurance and charging characteristics.

Regarding communication performance, the battery replacement strategy provides higher SE than conventional charging for the same fleet size, since it allows more UAVs to remain available as active aerial TRPs. Overall, the results indicate that continuous UAV-enabled D-mMIMO networks are feasible, but their practical deployment requires joint dimensioning of the fleet, battery inventory, charging infrastructure, and communication performance.

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