

Trajectory-Agnostic Charging Scheduling in 6G Mobile WRSNs Using Adaptive Charger Movement for Sensor Tracking

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Abstract—Future Sixth-Generation (6G) wireless networks are expected to support ultra-dense IoT deployments comprising large-scale mobile Wireless Rechargeable Sensor Networks (mWRSNs). In such environments, mobile chargers must sustain network operation by recharging energy-constrained sensors whose movement is continuous, dynamic, and often unpredictable. However, most existing charging scheduling approaches assume prior knowledge of sensor trajectories, limiting their applicability in practical mobile sensing systems. To address this challenge, this paper proposes a trajectory-agnostic reactive charging framework for mWRSNs that operates using only instantaneous sensor state information. The framework employs an adaptive pursuit mechanism to guide chargers towards moving sensors and a real-time synchronization mechanism to maintain charging engagement during sensor mobility. Charging requests are prioritized according to residual energy and spatial proximity, while a metaheuristic-based scheduling strategy is used to optimize charger travel cost and servicing efficiency. Extensive simulation results demonstrate that the proposed framework consistently outperforms representative reactive scheduling baselines in terms of sensor survivability, charging delay, charger travel distance, and energy utilization efficiency, while also revealing the trade-off between solution quality and computational overhead. The proposed framework provides a scalable and practical charging solution for future 6G-enabled dynamic sensing environments.

Index Terms—6G Networks, Internet of Things (IoT), mWRSNs, Mobile Charger Scheduling, Dynamic Sensor Networks, Trajectory-Agnostic Charging, Wireless Energy Transfer, Metaheuristic Optimization, Performance Analysis

I. INTRODUCTION

The emergence of 6G wireless networks is expected to significantly expand the scale and capability of Internet of Things (IoT) systems, enabling ultra-dense deployments with real-time connectivity and high-precision localization [1]. These advancements are expected to support a new generation of mobile sensing applications involving autonomous vehicles, mobile robots, wearable devices, smart logistics, and intelligent transportation systems. Consequently, traditional static Wireless Rechargeable Sensor Networks (WRSNs) are evolving into mobile WRSNs (mWRSNs), where sensors continuously move while performing sensing and communication tasks [2]. However, sensor mobility introduces significant challenges for charging scheduling, as mobile chargers must locate, track,

and recharge energy-critical sensors whose future trajectories may be unavailable or highly dynamic [3]. To sustain network operation in mWRSNs, a mobile charger dynamically determines which sensor to recharge, when to initiate charging, and how to intercept moving sensors under stringent energy and time constraints. This Charging Scheduling Problem (CSP) is known to be NP-hard [4].

Most existing charging schemes for mWRSNs are trajectory-dependent, assuming prior knowledge of sensor mobility or predefined movement models such as linear motion, Random Waypoint, and Gauss–Markov processes [5]–[7]. In a recent work, Tsuchida *et al* [8] have investigated charging scheduling for mobile sensors by optimizing charger trajectories based on predicted sensor mobility and charging utility models. These methods remain fundamentally trajectory-dependent and require future mobility information to guide charger navigation. However, mobility in practical 6G-enabled IoT systems is often stochastic, environment-driven, and continuously evolving, making accurate trajectory prediction difficult [9]. Consequently, predicted rendezvous points can quickly become obsolete, leading to missed charging opportunities, increased charger travel, higher scheduling overhead, and premature sensor failures. The real-time localization and communication capabilities envisioned in future 6G networks make trajectory-agnostic charging increasingly feasible. Nevertheless, existing studies have not fully leveraged these capabilities to develop reactive charging mechanisms that can intercept and recharge moving sensors without prior trajectory knowledge, particularly under multiple concurrent charging requests [1]. Further, selecting and sequencing charging requests in large-scale dynamic deployments remains an NP-hard optimization problem [4], motivating the use of metaheuristic techniques that can rapidly generate high-quality charging schedules [10].

To address the aforementioned challenge, this paper proposes a trajectory-agnostic reactive charging framework for dynamic mWRSNs. The framework integrates Reactive Position-Bearing Pursuit (RPBP) for real-time sensor interception, Real-Time State Synchronization (RTSS) for charging-while-moving, and a metaheuristic-based scheduling layer that

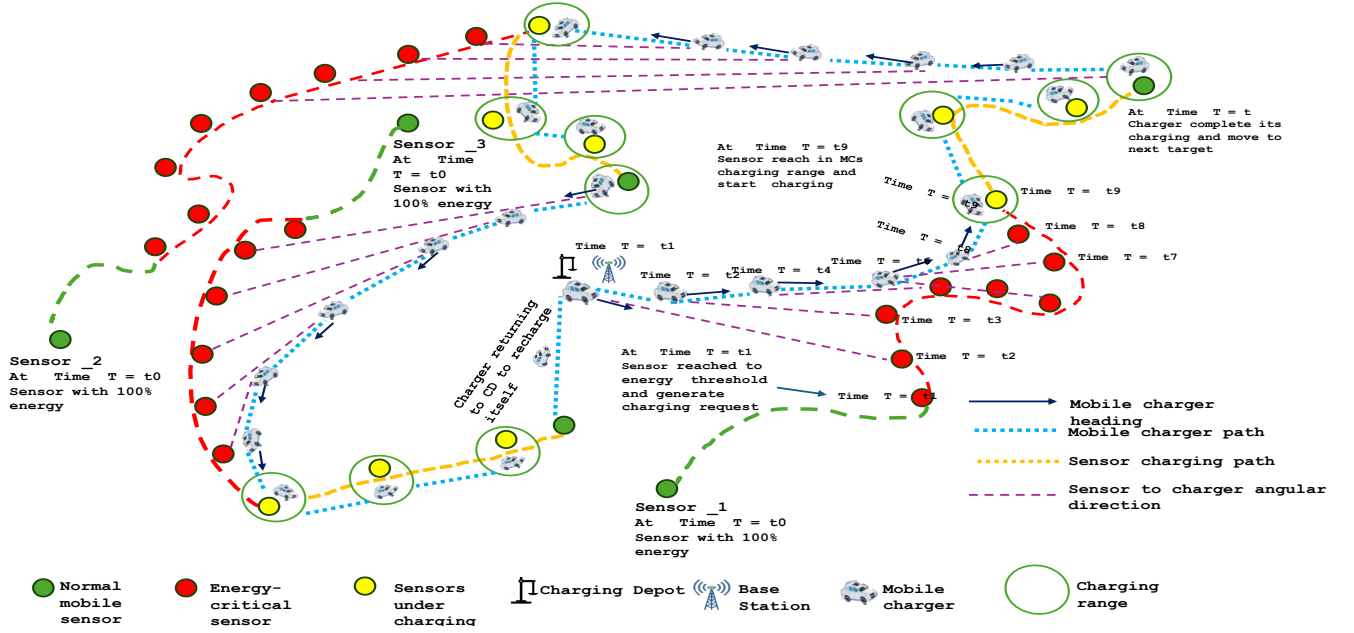


Fig. 1: Explanation of the proposed trajectory-agnostic charging framework

prioritizes charging requests according to residual energy and spatial proximity. The major contributions of the paper are summarized as follows:

- A trajectory-agnostic reactive charging framework for dynamic mWRSNs that operates without prior trajectory information.
- RBPB and RTSS mechanisms for real-time sensor interception and charging-while-moving under dynamic mobility.
- A priority-aware metaheuristic scheduling strategy for efficient servicing of multiple concurrent charging requests.
- Extensive performance evaluation using six metaheuristics against First Come First Serve (FCFS) and Nearest Job Next (NJN) baselines across multiple network scales.

The remainder of this paper is organized as follows. Section II presents the system model and problem formulation. Section III describes the proposed trajectory-agnostic charging framework and scheduling methodology. Section IV presents the simulation setup and performance evaluation results. The last Section V contains conclusion and outlines future research directions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section presents the network model, energy dynamics, mobility assumptions, and the formal problem statement.

A. Network and Mobility Model

As illustrated in Fig. 1, the considered mWRSN consists of a set of mobile sensors $S = \{S_1, S_2, \dots, S_n\}$ deployed in a two-dimensional region $\mathbb{R}^2$, a Base Station (BS), a Charging Depot (CD), and a Mobile Charger (MC). The BS collects periodic state reports from sensors and coordinates charging decisions. The MC is initially stationed at the CD, possesses

a battery capacity M_b , and must maintain a minimum reserve energy $M_{b\min}$ to safely return to the depot. The MC travels with speed $\omega \in [\omega_{\min}, \omega_{\max}]$ and consumes energy at a rate ψ per unit distance.

No mobility model or trajectory information is assumed in this work. Each sensor S_i moves with speed ω_s and an arbitrary time-varying heading $\theta_i(t) \in [0, 2\pi]$. The position of sensor S_i at time t is represented as

$$P_i(t) = (x_i(t), y_i(t)) \quad (1)$$

with instantaneous velocity

$$\vec{v}_i(t) = (\omega_s \cos \theta_i(t), \omega_s \sin \theta_i(t)). \quad (2)$$

Accordingly, the sensor position evolves as

$$P_i(t + \Delta t) = P_i(t) + \vec{v}_i(t)\Delta t. \quad (3)$$

The BS receives only the instantaneous position $P_i(t)$ at each reporting interval Δt . Velocity, heading information, future waypoints, and mobility models are unavailable to both the BS and the MC. A charging request is generated when the residual energy of a sensor falls below a threshold $S_{b\min}$. Each request is associated with a charging deadline

$$t_{dead}^i = t_{start}^i + \frac{S_{br}(t_{start}^i)}{\psi_s} \quad (4)$$

where $S_{br}(t_{start})$ denotes the residual sensor energy at request generation and ψ_s is the sensor energy consumption rate. The MC must initiate charging before t_{dead}^i to avoid sensor failure.

The MC dynamically adjusts its speed and heading while moving. Let its position at time t be denoted by

$$\mathbf{c}(t) = (x_c(t), y_c(t)). \quad (5)$$

For a target sensor located at $\mathbf{s}(t) = P_i(t)$, the relative distance between the MC and the sensor is

$$d(t) = \|\mathbf{s}(t) - \mathbf{c}(t)\|. \quad (6)$$

The MC operates in two modes. When $d(t) > R_c$ i.e. the sensor is outside the MC charging range R_c , a reactive interception mechanism guides the MC towards the sensor. Once the sensor enters the charging range, a charging-while-moving mechanism is activated to maintain continuous wireless power transfer. The non-linear wireless charging model of [11], which employs Wireless Power Transfer (WPT) for energy replenishment, is adopted in this work.

B. Problem Formulation

At a scheduling epoch t , let $\mathcal{Q}(t) = \{S_1, S_2, \dots, S_m\}$, where $m \leq n$, denote the set of sensors that have generated charging requests. The objective is to determine a subset of sensors $\mathcal{R} \subseteq \mathcal{Q}(t)$ and an associated service sequence $\pi = (S_1, S_2, \dots, S_{|\mathcal{R}|})$ that minimizes the charging cost while maximizing the number of serviced requests. The optimization objective then is formulated as

$$\min_{\pi} J(\pi) = D_{\text{total}}(\pi) + \lambda(|\mathcal{Q}| - |\mathcal{R}|) \quad (7)$$

where $D_{\text{total}}(\pi)$ denotes the total charger travel distance and λ is a penalty associated with each unserved request. The total travel distance is computed using the instantaneous sensor locations at the scheduling epoch as

$$D_{\text{total}}(\pi) = \|\mathbf{s}_{\pi_1}(t) - \mathbf{c}_0\| + \sum_{k=2}^{|\mathcal{R}|} \|\mathbf{s}_{\pi_k}(t) - \mathbf{s}_{\pi_{k-1}}(t)\| + \|\mathbf{c}_{\text{depot}} - \mathbf{s}_{\pi_{|\mathcal{R}|}}(t)\|. \quad (8)$$

Where $\mathbf{c}_0$ is the initial position of the MC. The charging schedule must satisfy the following constraints:

(i) Deadline Constraint

$$t_i^* \leq t_{\text{dead}}^i, \quad \forall i \in \mathcal{R} \quad (9)$$

where t_i^* is the time when MC approaches the sensor and recharging begins.

(ii) MC Energy Constraint

$$M_{br}(t) \geq \psi_c D_{\text{total}}(\pi) + \sum_{j \in \mathcal{R}} E_{t,j} + M_{b_{\min}} \quad (10)$$

(iii) Speed Constraint

$$0 \leq \omega(t) \leq \omega_{\max} \quad (11)$$

(iv) Charging Range Constraint

$$d(t) \leq R_c, \quad \forall t \in [t_i^*, t_{\text{full},i}] \quad (12)$$

(v) **Permutation Constraint:** The sequence π must contain each selected sensor exactly once.

The above formulation highlights three key challenges: trajectory-free sensor mobility, deadline-constrained charging requests, and the combinatorial complexity of scheduling multiple concurrent requests. The proposed framework addresses

TABLE I: Finite State Machine of the Mobile Charger

State	Condition	Action
IDLE	No active target	Await / trigger scheduler
INTERCEPT	$d(t) > R_c$	Execute RPBP
CHARGE	$d(t) \leq R_c$	Execute RTSS + WPT
RETURN	$M_{br}(t) \leq M_{b_{\min}}$	Return to depot

these challenges through a reactive interception mechanism, a charging-while-moving strategy, and a metaheuristic-based scheduling layer described in the next section.

III. PROPOSED TRAJECTORY-AGNOSTIC CHARGING FRAMEWORK

To address the trajectory-agnostic charging scheduling problem, a hybrid framework combining reactive motion control and metaheuristic scheduling is proposed. The framework operates in three sequential stages:

- 1) Priority-based request selection and scheduling,
- 2) RPBP for sensor interception,
- 3) RTSS for charging-while-moving.

The MC operates as a finite-state machine consisting of four states: IDLE, INTERCEPT, CHARGE, and RETURN, as summarized in Table I. At every update interval Δt , the BS receives fresh sensor position reports and updates charger decisions using only instantaneous network information. No trajectory prediction, mobility model, or future waypoint information is utilized.

A. Priority-Based Scheduling

Each request in $\mathcal{Q}(t)$ is assigned a priority score based on energy urgency and spatial proximity as

$$f(i) = \frac{1}{\|\mathbf{s}_i(t) - \mathbf{c}(t)\|} + \frac{1}{\tau_i} \quad (13)$$

where τ_i represents the remaining survival time of sensor S_i . Sensors are then ranked in descending order of $f(i)$ and the most critical requests are forwarded to the scheduling stage. Before dispatching the MC, feasibility is verified through

$$\frac{\|\mathbf{s}_{\pi_1}(t) - \mathbf{c}(t)\|}{\omega_{\max} - \omega_s} \leq \tau_i \quad (14)$$

together with the energy feasibility constraint (10). The resulting service sequence π is obtained using metaheuristic optimization of the objective function (7). Since the underlying scheduling problem is NP-hard, six representative metaheuristics PSO, GA, ACO, JAYA, Mayfly, and SA are evaluated against base line FCFS and NJN baselines to demonstrate that the proposed RPBP-RTSS framework is independent of the specific optimization engine used.

B. RPBP: Reactive Position-Bearing Pursuit

After a target sensor is selected, the MC enters the interception phase and activates RPBP. Unlike trajectory-dependent approaches that compute future rendezvous locations, RPBP continuously steers the MC towards the sensor's latest reported position. Consequently, interception decisions rely only on

Algorithm 1 Trajectory-Agnostic Charging Framework

Require: Charging request queue $Q(t)$, Sensor states $\{P_i(t), S_{br,i}(t), \omega_s\}$, charger state $\{c(t), M_{br}(t), \omega_{\max}\}$, charging range R_c , time step Δt

Ensure: Charging schedule π

- 1: Update $Q(t)$ and compute priority scores using (13)
- 2: Optimize schedule π for the top $Q_{\max}$ requests using (7)
- 3: **for** each sensor $S_{\pi_k} \in \pi$ **do**
- 4: **if** constraints (9)–(10) are satisfied **then**
- 5: Execute RBPB using (15), (16) until $d(t) \leq R_c$
- 6: Activate RTSS using (20), (21) and perform co-motion charging
- 7: **end if**
- 8: **if** $M_{br}(t) \leq M_{b_{\min}}$ **then**
- 9: Return MC to depot
- 10: **end if**
- 11: **end for**
- 12: Terminate when $Q(t) = \emptyset$

instantaneous sensor locations and remain independent of any mobility model. The instantaneous line-of-sight (LOS) bearing is given by

$$\theta_c(t) = \text{atan2}(y_s(t) - y_c(t), x_s(t) - x_c(t)). \quad (15)$$

The MC aligns its heading with the LOS direction and moves at maximum speed

$$\dot{\mathbf{c}}(t) = \omega_{\max} \hat{\mathbf{e}}(t), \quad (16)$$

where

$$\hat{\mathbf{e}}(t) = \frac{\mathbf{s}(t) - \mathbf{c}(t)}{\|\mathbf{s}(t) - \mathbf{c}(t)\|} \quad (17)$$

is the LOS unit vector. The discrete position update is

$$\mathbf{c}(t + \Delta t) = \mathbf{c}(t) + \omega_{\max} \hat{\mathbf{e}}(t) \Delta t \quad (18)$$

The interception phase continues until the charger enters the wireless charging range i.e.

$$d(t) = \|\mathbf{s}(t) - \mathbf{c}(t)\| \leq R_c \quad (19)$$

at which point control is transferred to RTSS.

C. RTSS: Real-Time State Synchronization

The idea of RTSS is inspired by leader-follower synchronization and consensus-based cooperative control, where the charger continuously adjusts its velocity using real-time observations of the sensor state [12]. Once the charger enters the charging range, RTSS is activated to maintain charging while both the sensor and charger remain in motion. Since future sensor motion is unknown, the instantaneous sensor velocity is estimated from consecutive position reports as

$$\hat{\mathbf{v}}_s(t) = \frac{\mathbf{s}(t) - \mathbf{s}(t - \Delta t)}{\Delta t}. \quad (20)$$

The corresponding unit direction is $\mathbf{u}_t^s(t) = \hat{\mathbf{v}}_s(t) / \|\hat{\mathbf{v}}_s(t)\|$.

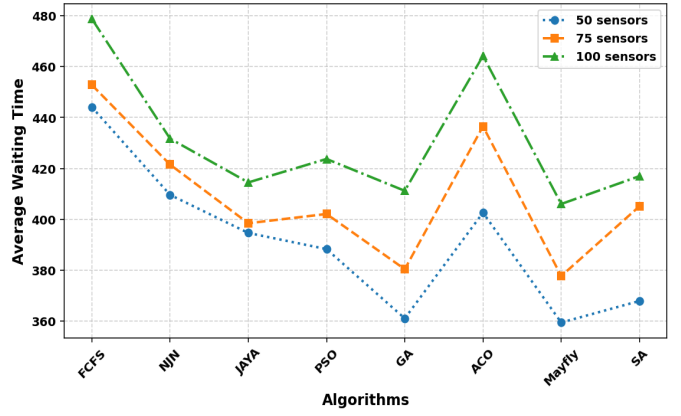


Fig. 2: Comparison of average waiting time across different algorithms for varying network sizes

RTSS combines velocity synchronization and distance regulation through

$$\dot{\mathbf{c}}(t) = \hat{\mathbf{v}}_s(t) + k_r(d(t) - d_{ref})\hat{\mathbf{e}}(t) \quad (21)$$

where k_r is the regulation gain and d_{ref} denotes the desired charging distance. The first term synchronizes charger motion with the sensor, while the second regulates the charger-sensor separation toward d_{ref} . The corresponding speed and heading are

$$\omega_c(t) = \omega_s + k_r(d(t) - d_{ref}) \quad (22)$$

$$\theta_c(t) = \text{atan2}(u_{t,y}^s, u_{t,x}^s) \quad (23)$$

RTSS continuously updates charger motion using real-time sensor observations, enabling stable charging without trajectory prediction.

The present work focuses on the charging framework and its performance evaluation. Formal convergence and stability analysis of RBPB and RTSS are an area of future work.

D. Framework Summary

The proposed framework is summarized in Algorithm 1. The framework decouples scheduling from motion control. The scheduling layer determines the charging sequence using instantaneous sensor states, while RBPB and RTSS provide the low-level motion control required for interception and charging, respectively. By combining reactive pursuit, real-time synchronization, and metaheuristic scheduling, the framework provides a scalable trajectory-agnostic charging solution for dynamic mWRSNs operating in future 6G-enabled IoT environments.

IV. PERFORMANCE EVALUATION

This section evaluates the proposed trajectory-agnostic charging framework through extensive simulations and compares FCFS, NJN, with JAYA, PSO, GA, ACO, Mayfly, and SA under network sizes ranging from 50 to 100 sensors. The algorithms are evaluated using average waiting time, dead sensor count, MC travel distance, Energy Utilization Efficiency

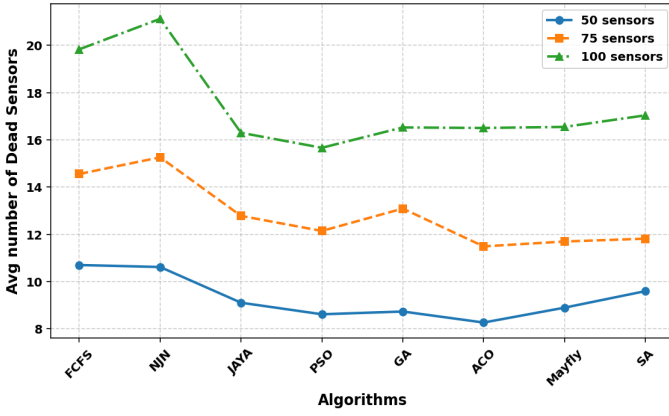


Fig. 3: Comparison of number of dead sensors across different algorithms for varying network sizes

(EUE), and optimization time. Each metaheuristic was executed using an identical population size, iteration budget, and termination criterion to ensure a fair comparison. The objective is to analyze how different scheduling strategies influence charging effectiveness and charger mobility in dynamic mWRSNs. It is worth highlighting that the existing learning-based charging methods generally assume access to trajectory information or future mobility estimates, which is inconsistent with the trajectory-agnostic assumptions considered in this work. Therefore, FCFS and NJN are selected as baseline schemes for performance evaluation.

The average waiting time experienced by charging requests is presented in Fig. 2. As the number of sensors increases, waiting time rises for all methods due to increased charging demand and scheduling contention. FCFS and NJN consistently exhibit the highest delays because they make scheduling decisions using only temporal arrival order or spatial proximity, respectively. In contrast, the metaheuristic approaches jointly consider multiple charging requests and explore a larger solution space, leading to more efficient service sequences. Among them, GA and Mayfly achieve the lowest waiting times, reducing delays by up to 20% compared with the baseline methods. The results indicate that intelligent sequencing of charging requests becomes increasingly important as network density grows.

Fig. 3 shows the number of dead sensors under different scheduling strategies. Sensor failures increase with network size as the MC must serve a larger number of energy-constrained nodes. However, the proposed metaheuristic-based scheduling significantly improves sensor survivability by prioritizing critical requests more effectively. PSO achieves the lowest dead sensor count, reducing failures by up to 26% relative to FCFS and NJN. ACO and Mayfly provide comparable performance, yielding reductions of approximately 22–25%. These results demonstrate that high-quality scheduling decisions directly translate into improved network sustainability.

Fig. 4 presents the comparison of total distance traveled by the MC. Excessive travel distance not only increases charging

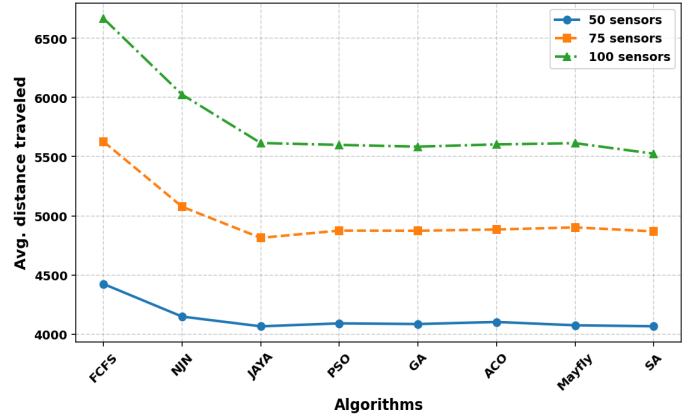


Fig. 4: Comparison of distance traveled by MC across different algorithms for varying network sizes

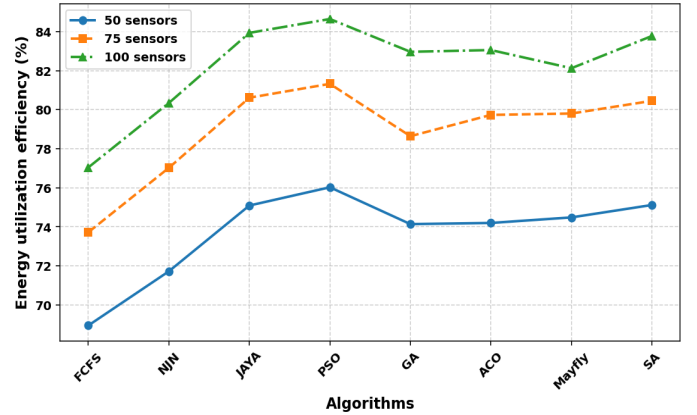


Fig. 5: Comparison of EUE% across different algorithms for varying network sizes

latency but also depletes charger energy, thereby reducing overall network efficiency. SA achieves the shortest travel distance, providing up to 17% reduction compared with FCFS. GA and PSO closely follow with reductions of 15–16%. The improvement arises because the metaheuristic algorithms optimize the charging sequence globally, avoiding inefficient charger movements that frequently occur in greedy scheduling approaches.

The Energy Utilization Efficiency (EUE) results are presented in Fig. 5. EUE measures how effectively the charger's energy expenditure is converted into useful charging service. The baseline methods exhibit the lowest efficiency because a significant portion of charger energy is consumed in travel rather than energy transfer. Metaheuristic scheduling improves this balance by reducing unnecessary movement and servicing critical sensors more effectively. Among all algorithms, PSO achieves the highest EUE of 84.64%, corresponding to an improvement of approximately 10% over FCFS and NJN. JAYA and SA also demonstrate strong performance, achieving gains of 8–9%.

Table II summarizes the optimization time required by

TABLE II: Optimization Time in seconds

Algorithm	50 Sensors	75 Sensors	100 Sensors
FCFS	0.0000287	0.0000298	0.0000564
NJN	0.0022016	0.0036285	0.0124757
JAYA	0.5674	0.9425	3.0116
PSO	1.0606	0.9234	2.9291
GA	1.2229	2.5289	4.8562
ACO	11.2667	15.8904	21.3095
Mayfly	1.6980	2.1536	2.5566
SA	0.6942	2.2688	3.5503

each scheduling algorithm. As expected, FCFS and NJN incur negligible computational overhead since they rely on simple deterministic rules. Metaheuristic approaches require additional processing time due to their iterative search procedures. Among them, ACO exhibits the highest computational cost, while JAYA, PSO, and Mayfly achieve significantly lower execution times. Despite the additional overhead, all metaheuristic algorithms complete within a few seconds, making them practical for near-real-time charging decisions in dynamic mWRSNs.

Overall, the results demonstrate that integrating trajectory-agnostic motion control with metaheuristic scheduling substantially improves charging performance compared with conventional scheduling strategies. The proposed framework reduces waiting time, lowers sensor failures, decreases charger travel distance, and improves energy utilization efficiency while maintaining acceptable computational overhead. These benefits become increasingly pronounced as network size grows, highlighting the suitability of the framework for future large-scale 6G-enabled mWRSNs.

V. CONCLUSION

This paper presented a trajectory-agnostic reactive charging framework for dynamic mWRSNs operating in future 6G-enabled IoT environments. Unlike existing trajectory-dependent approaches, the proposed framework relies solely on instantaneous sensor state information and does not require prior knowledge of sensor mobility patterns or future trajectories. The framework combines RBPB for real-time sensor interception, RTSS for charging-while-moving, and a priority-aware metaheuristic scheduling layer for handling multiple concurrent charging requests. Extensive simulations involving networks of 50–100 mobile sensors demonstrate that the proposed approach significantly improves charging performance under dynamic mobility conditions. Compared with conventional FCFS and NJN scheduling strategies, the metaheuristic-based framework reduces sensor failures by up to 26%, lowers charging waiting time by up to 20%, and decreases charger travel distance by up to 17%, while achieving an Energy Utilization Efficiency (EUE) of up to 84.64%. The results further highlight the trade-off between scheduling quality and computational cost, showing that algorithms such

as PSO, GA, and Mayfly provide an effective balance between performance improvement and execution time.

The proposed trajectory-agnostic framework is particularly relevant to emerging 6G-enabled mobile sensing applications where sensor mobility is inherently dynamic and future trajectories are unavailable or difficult to predict. Examples include autonomous robotic fleets, intelligent transportation systems, wearable sensing platforms, and mobile edge sensing applications, where devices continuously adapt their movement according to environmental conditions and operational objectives [1], [3]. In such scenarios, charging decisions must be made using real-time state information, making trajectory-agnostic operation a practical requirement for sustainable network operation.

Future work can be directed to investigate multi-charger coordination, obstacle-aware charging strategies, charging under localization uncertainty and communication delays, and learning-assisted scheduling techniques for large-scale autonomous sensing systems.

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