Optimizing UAV-IoT Network Integration: A Scalable Multi-Objective Communication Framework

Satnam Kaur
CSE Department, SGT University, Gurugram, India
satnam_fet@sgtuniveristy.org (corresponding author)

Nancy Arya
CSE Department, SGT University, Gurugram, India
nanarya1@gmail.com

Sugandha Singh
CSE Department, SGT University, Gurugram, India
sugandha77.cse@gmail.com

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ABSTRACT

In UAV-IoT systems, trajectory planning is crucial for maintaining effective communication, coordination, and energy efficiency. This challenge is further compounded when UAVs need to coordinate with IoT devices and maintain continuous communication. Existing approaches struggle with limited scalability and inefficient energy management in UAV-supported IoT networks, leading to increased latency and reduced data throughput as network size expands. This work introduces an energy-efficient framework using a multi-objective PathFinder algorithm designed to simultaneously handle transmission coordination between drones and IoT devices. The proposed approach facilitates collaborative decision-making for route planning and resource allocation by utilizing the Collaborative Index, which measures cooperative behavior among network nodes, emphasizing key node cooperativeness parameters. Furthermore, a multi-objective fitness function was constructed for effective path planning using the Collaboration Index of nodes in the path and the QoS of the path. To validate the efficacy of the proposed model, a series of simulations were conducted focusing on key performance indicators such as energy consumption, data delay, and task completion rates against existing state-of-the-art methods.

Keywords-UAV-IoT network; path planning; trajectory optimization

I. INTRODUCTION

Drones, also known as Unmanned Aerial Vehicles (UAVs), have revolutionized numerous sectors by providing enhanced capabilities for aerial surveillance, delivery services, environmental monitoring, and communication [1, 2]. When integrated with the Internet of Things (IoT) [3, 4], UAVs become part of a sophisticated network where devices communicate, share data, and perform tasks autonomously. The architecture of a UAV-IoT network is designed for robust communication and efficient data transfer [5]. The UAV-IoT network architectures integrate various communication technologies, including Wi-Fi/WiMax, 3G, 4G LTE, and 5G [6], each covering different clusters of IoT devices. The IoT devices are categorized into static and moving, facilitating diverse application scenarios. UAVs are positioned at different altitudes, low, medium, and high, each serving as a platform to relay and process data from ground-based IoT sensors to a central ground station and control center. The control center acts as the hub for data aggregation, processing, and command dispatch, ensuring optimized management of the entire network. This hierarchical UAV deployment allows for scalable coverage and enhanced communication capabilities across varied terrains and operational conditions [7].

Energy efficiency is one of the primary challenges in UAV-IoT networks [8, 9], as they are typically battery-powered, and their operational time is constrained by limited battery capacity. Efficient energy management is crucial to maximize flight time and ensure that UAVs can complete their missions without needing frequent recharges. This challenge is compounded when UAVs need to coordinate with IoT devices, as maintaining continuous communication and data transfer further drains the battery.

Trajectory planning for UAVs involves determining the optimal flight paths they should follow to complete their missions efficiently and safely [10, 11]. The trajectory planning process takes into account various factors, such as energy consumption, obstacles, weather conditions, communication requirements, and mission-specific objectives [10, 12]. Many existing trajectory planning methods are rigid and cannot dynamically adapt to unexpected changes in the environment, such as sudden weather changes or moving obstacles. This limitation can lead to failed missions or the need for manual intervention, reducing the autonomy of UAV operations. Current algorithms are often not optimized for the energy consumption of UAVs [13, 14], leading to suboptimal path planning that can drain battery life faster than necessary.

Given these challenges, there is a clear need for a more sophisticated approach. The proposed cooperative trajectory planning framework addresses these issues by leveraging collaboration among multiple UAVs. The main contributions of this work are:

- Proposes a novel collaborative framework designed to optimize the coordination of transmissions between UAVs and IoT devices, focusing on energy efficiency and resource allocation.
- Adapts the PathFinder optimization algorithm to enhance trajectory planning and resource allocation, ensuring optimal performance.
- Encourages collaborativeness between nodes within the network using a node ranking index, called Collaboration Index (CI), which takes into account node parameters including energy consumed, packet forwarding ratio, number of tasks completed, coordination overhead, and number of collisions.
- Develops a multi-objective fitness function for effective path planning using the CI of nodes in the path and the QoS of the path.
- Evaluates the framework using key performance metrics, including average delay, throughput, energy consumption, task completion rate, and packet loss rate, to determine its efficiency and reliability.

II. SYSTEM MODEL

The system model for UAV-IoT communication involves UAVs $\mathcal{U} = \{u_1, u_2, \ldots, u_U\}$ dispatched to collect data from ground-based IoT clusters $\mathcal{C} = \{c_1, c_2, \ldots, c_K\}$, with each cluster c_k composed of multiple IoT nodes $\mathcal{N} = \{\eta_1, \eta_2, \ldots, \eta_j\}$ and one designated as the Cluster Head (CH) n_{CH_k}. This model integrates several key components, outlined mathematically and functionally to ensure clarity and precision in understanding the UAV's mission, trajectory, and operational constraints. Each IoT node η_i and UAV u are assigned specific spatial coordinates. The nodes have fixed positions $p_{n_i} = (x_{n_i}, y_{n_i}, z_{n_i})$ while the UAV's position $p_u(t) = (x_u(t), y_u(t), z_u(t))$ changes over time as it flies. The UAV takes off from and returns to a Base Station (BS), represented by the point h_{BS} and follows a trajectory that includes hovering directly above each CH at designated points h_{CH_k}.

The UAV's trajectory is defined as a sequence of waypoints reflecting its path from the BS, through each cluster's CH, and back to the BS. This path is vital for optimizing the UAV's energy consumption and operational efficiency. The UAV does not account for acceleration or deceleration, simplifying the model to consider only direct flights from one point to another. The Euclidean distance between the UAV and any node is calculated as

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (1)$$

A. Multi-Objective Optimization Target

The UAV should consume the least amount of energy possible during its flight, which involves optimizing the path to reduce the distances flown over unnecessary areas or at suboptimal speeds. Reducing the time it takes to complete a mission is also crucial. In scenarios where predefined paths are optimal for regulatory or safety reasons, minimizing the deviation from these paths is essential.

B. Collaboration Index

The problem of trajectory planning can be divided into two parts, the first being the identification of the best path for communication and the second being selecting the best nodes for cooperation. The issue of the optimization target for the proposed communication consists of two main parts, which include node parameters, such as energy consumption, collision rate, and tasks completed, which are combined to create a node ranking index called CI. The CI can be defined as a metric that quantifies the degree to which nodes in the network actively engage in cooperative behaviors to achieve common objectives. It takes into account various aspects of collaboration, such as data sharing (packet forwarding ratio) and task coordination (completion time, coordination overhead). CI is formulated as

$$CI = w_1 \cdot \frac{1}{E} + w_2 \cdot \frac{1}{C} + w_3 \cdot T + w_4 \cdot P_{FR} + w_5 \cdot \frac{1}{CT} - w_6 \cdot \frac{1}{\Theta} \quad (2)$$

where E is the energy consumed, P_{FR} is the Packet Forwarding Ratio, T is the Completion Time for the tasks, Θ is the coordination overhead, and $w_1, \ldots, w_6$ are weights reflecting the relative importance of each component.

C. QoS Index

To construct a QoS index that effectively scores and identifies the best communication paths within a UAV-IoT network, several key performance metrics that affect QoS should be considered. The proposed QoS index integrates these metrics into a single comprehensive score. The QoS index is composed of QoS metrics such as average delay, E2E delay, throughput, and PDR of the path. Average delay (φ_{avg}) measures the average time taken for packets to travel across the network from the source to the destination. A lower average delay is indicative of a faster and more responsive network. End-to-End Delay ($E2E_{delay}$) captures the total transmission time from the source to the destination. This includes all delays incurred during packet processing, transmission, propagation, and queueing throughout the network path. Throughput ψ represents the rate at which successful message delivery occurs across a communication channel. Higher throughput values indicate more efficient data handling and network utilization. The ratio of the number of packets successfully delivered to the destination to the number of packets sent by the source is the PDR of the path. A higher PDR suggests a more reliable connection. The QoS index can be formulated as a weighted sum of these components, adjusting for the fact that delays should be minimized while throughput and PDR should be maximized.

$$QoS\ Index\ = \varpi_1 \cdot \frac{1}{AD} + \varpi_2 \cdot \frac{1}{E2ED} + \varpi_3 \cdot \psi + \varpi_4 \cdot PDR \quad (3)$$

where ϖ are the weights assigned to each metric according to their relative importance in the specific application. These weights are adjusted by optimizing the operational priorities or specific network performance targets. Creating a function that combines QoS and CI allows for a more holistic approach to managing UAV-IoT networks, ensuring that both technical performance and collaborative effectiveness are optimized. The combined fitness function aims to balance these indices, recognizing that the network's ultimate goal is to optimize both communication quality and collaborative efficiency. These indices are combined using a weighted sum approach.

$$Fitness\ = maximize\ \ (\lambda \cdot\ QoS\ Index\ + (1 - \lambda) \cdot\ Collaboration\ Index) \quad (4)$$

where λ is the weight that reflects the relative importance of QoS versus collaboration in the specific application scenario, and the goal of the optimization algorithm is to maximize the fitness function return.

D. PathFinder Algorithm

The Pathfinder algorithm [15] in the context of optimization is a relatively recent nature-inspired metaheuristic designed to solve complex optimization problems. The Pathfinder algorithm operates using a population of candidate solutions, called pathfinders. Each pathfinder explores the search space, and its movements are influenced by the best solution found in the population. Pathfinder dynamically adapts its search strategy based on the fitness landscape of the problem.

Pathfinder optimization, when applied to UAV trajectory planning in the context of energy-efficient transmission coordination for cooperative UAV-IoT networks, can offer significant advantages [15, 16]. Pathfinder's ability to effectively balance the exploration of new paths and the exploitation of known good paths can significantly optimize UAV routes, ensuring comprehensive coverage and efficient path planning. UAVs operating in dynamic environments, such as changing weather conditions or variable IoT signal requirements, can benefit from Pathfinder's adaptive search mechanisms that respond to real-time data. By optimizing the UAV's flight path for energy efficiency and time management, Pathfinder can help prolong UAV operational times and reduce the need for frequent recharging or maintenance. Optimized trajectories mean less wear and tear on UAVs and less fuel or battery usage, which collectively reduce the operational costs associated with UAV fleets.

Since UAVs operate in a 3D space (latitude, longitude, altitude), the algorithm's position vector and the swarm members are defined in a 3D space. This includes adapting all force vectors and movement calculations to incorporate the three dimensions. The leader, or the Pathfinder, is selected based on its position relative to a defined objective, such as the most energy-efficient route or the quickest path considering no-fly zones and weather conditions. Leader selection criteria can include factors such as battery level, proximity to the final destination, or even UAV's current network connectivity status, ensuring the leader is best suited for leading the swarm under current conditions.

1) PathFinder Algorithm For UAV Trajectory Planning

- P_i^{t+1}: New position of UAV i at time $t+1$.
- P_i^t: Current position of UAV i at time t.
- P_j^t: Current position of another UAV j in the swarm.
- P_l^t: Current position of the leader or pathfinder UAV at time t.
- V_1, V_2: Random vectors with components in the range $[-1, 1]$.
- S_{ij}: Euclidean distance between UAV i and UAV j.
- N: Current iteration number.
- $N_{\max}$: Maximum number of iterations allowed.
- Ω: Random vibration or perturbation term.
- Λ: Fluctuation factor affecting the leader's trajectory.

The adapted UAV trajectory planning algorithm uses a modified PathFinder optimization framework to effectively manage UAVs in a three-dimensional environment. The algorithm commences by initializing the positions of all UAVs P_i^0 in 3D space and selecting an initial pathfinder or leader based on specific criteria, such as battery status or proximity to the final destination. Each UAV i updates its position according to

$$P_i^{t+1} = P_i^t + C_1 \cdot \left(P_j^t - P_i^t\right) + C_2 \cdot (P_l^t - P_i^t) + \Omega \quad (5)$$

where P_j^t is the position of another UAV j in the swarm, P_l^t is the position of the pathfinder, and Ω represents a random vibration or noise factor, defined as

$$\Omega = \left(1 - \frac{N}{N_{\max}}\right) \cdot V_1 \cdot S_{ij} \quad (6)$$

with V_1 being a random vector in the range $[-1, 1]$ and S_{ij} denoting the distance between UAVs i and j. This term introduces variability and adapts to dynamic changes in the environment, simulating real-world uncertainties. The pathfinder's position is updated using

$$P_l^{t+1} = P_l^t + \Delta P + \Lambda \quad (7)$$

with ΔP being the movement vector, and Λ being the fluctuation factor calculated by:

$$\Lambda = V_2 \, e^{-\frac{2N}{N_{\max}}} \quad (8)$$

where V_2 is another random vector. As iterations proceed, N increments until it reaches the maximum allowed iterations $N_{\max}$ or until the UAVs converge sufficiently to the optimal path. After updating positions, the multi-objective fitness function is evaluated for each pathfinder to assess the current configuration's effectiveness in achieving objectives, and if $Fitness_{new}$ is better than global fitness $Fitness_{global}$, the PathFinder algorithm updates $Fitness_{global}$ with $Fitness_{new}$. If N reaches $N_{\max}$ or if the UAVs have sufficiently converged to the optimal path, the algorithm is stopped.

Figure 1 describes a UAV trajectory planning model using the Pathfinder algorithm, which begins with the initialization phase, where drones are deployed at random positions in a 3D space. After initialization, each drone receives target positions from a BS, setting the stage for trajectory planning. Within the Pathfinder process, each drone and its target point are grouped into clusters, and potential paths are generated. These paths are evaluated based on a CI and a QoS index to ensure optimal routing and cooperation between drones.

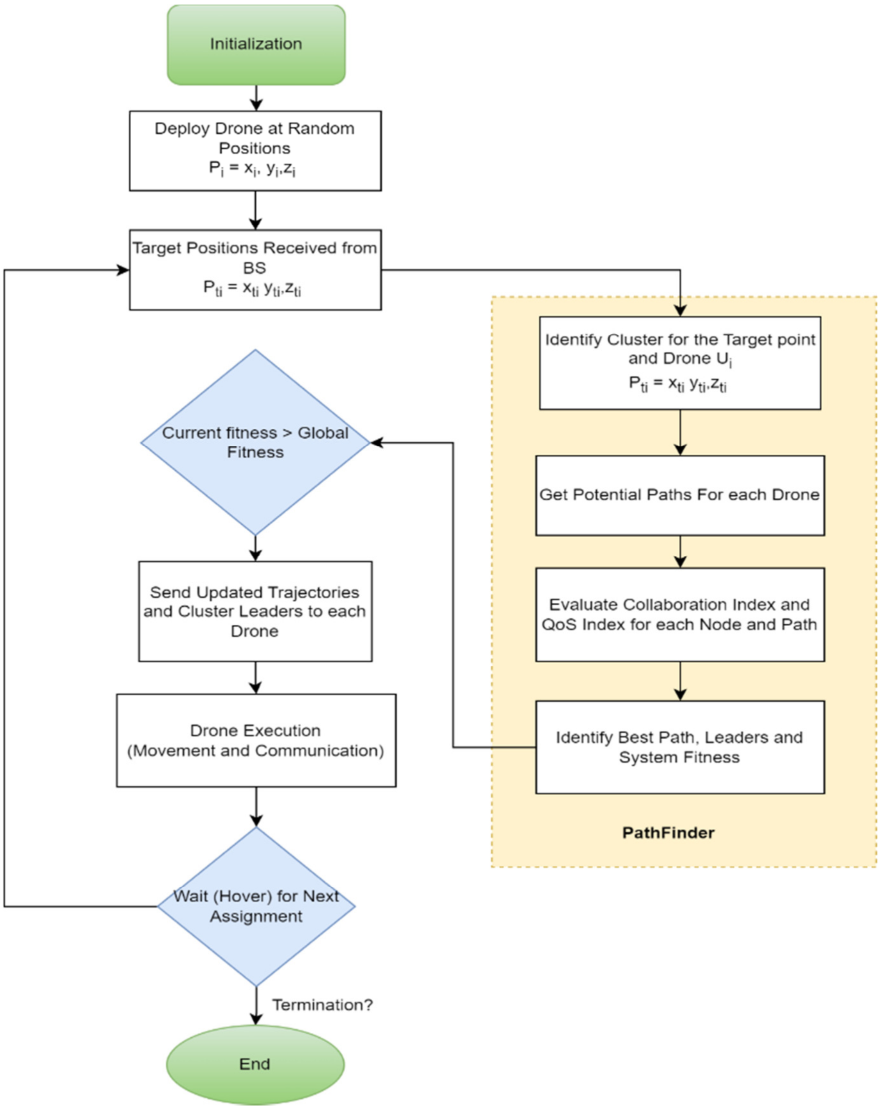

Fig. 1. Trajectory planning using the pathfinder algorithm for collaborative UAV-IoT network.

If the current system's fitness, assessed through these indices, surpasses a predefined global fitness standard, the improved trajectories and cluster leader information are communicated to each drone. Subsequently, the drones execute these updated plans, involving movement and communication as specified. Post-execution, drones wait in a hover state for further instructions or the next assignment. The process continuously checks for a termination condition, which could be based on task completion, time elapsed, or other criteria. The operation ends when these conditions are satisfied, terminating the process. This structured approach allows for dynamic and efficient management of UAV trajectories, ensuring high performance and adaptability in UAV operations.

III. EXPERIMENTAL ANALYSIS

The experimental setup to evaluate UAV trajectory optimization protocols used MATLAB [17] on an Intel i5 CPU with 16GB RAM, simulating a dynamic environment with parameters such as a 300×300 m coverage area and UAV speeds set to 20 m/s. Table I shows the parameter settings used to remain consistent with state-of-the-art methods.

TABLE I. PARAMETERS FOR THE EXPERIMENTAL SETUP FOR EVALUATING COLLABORATIVE UAV-IOT

Parameter	Value
Channel gain	-20 dB
Coverage Area	300×300 m
Hovering altitude of UAV	6 m
Max Elevation	20 m
Max Iterations	10
Noise power	-50 dBm
Number of IoT devices	100- 900
Number of UAVs	1-10
Propagation Model	Two-ray
Radio Interface	IEEE 802.11p
Transmission bandwidth	150 KHz
UAV speed	20 m/s

Simulations involve 1-10 UAVs and 100-900 IoT devices, evaluating protocols such as Queuing Delay and Transmission Delay (QDTD) [18], Drone-enabled Data Communication for IoT (DDCIoT) [1], Comprehensive Energy Consumption (CEC) [19], Propulsive Energy Minimization (PEM) [20], and Age of Information-based strategy planning (AoI-IP) [21] across metrics including data delay, throughput, task execution delay, task completion rates, and energy consumption of both IoT devices and UAVs. The objective is to compare these protocols in terms of scalability, energy efficiency, responsiveness, and reliability under varying network densities and operational demands. This setup allows for a detailed analysis of each protocol's performance, emphasizing the efficiency and effectiveness of UAV operations within a large-scale IoT environment. By varying the number of IoT devices and UAVs, the experiments can test how well each trajectory planning protocol scales and performs under different network densities and operational demands. The key focus is on how each protocol manages and minimizes energy consumption, which is crucial for practical deployment where battery life and operational costs are critical. This setup is designed to provide a comprehensive assessment of the proposed Pathfinder performance optimization against state-of-the-art techniques in UAV trajectory planning, especially concerning energy management and operational efficiency in dynamic and potentially dense IoT environments.

Figure 2 shows the relationship between data throughput in Mbps and the channel busyness ratio for QDTD, DDCIoT, and the proposed method. The channel busyness ratio, ranging from 1 to 10, represents the proportion of time the channel is active (not idle).

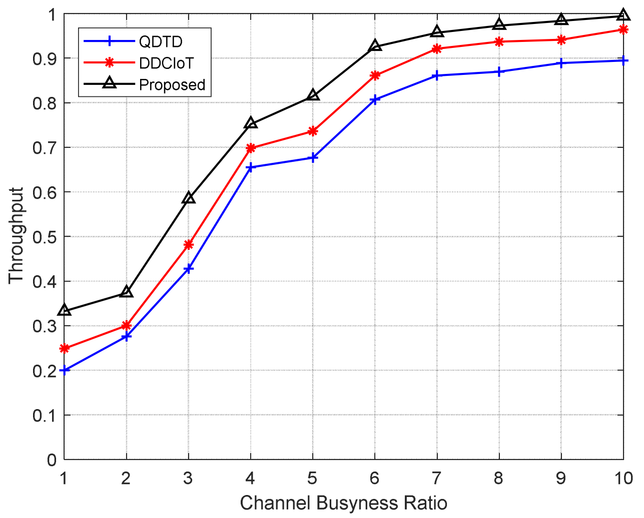

Fig. 2. Throughput vs channel busyness of the proposed collaborative UAV-IoT network.

Figure 2 shows that as the channel busyness ratio increases, the throughput for all methods also increases, indicating that more active channel usage allows higher data transmission rates. Initially, all three methods start with relatively low throughput at a channel busyness ratio of 1. As the ratio increases, each method's throughput improves significantly, with the proposed method and QDTD showing a steeper increase compared to DDCIoT. At lower busyness ratios (1 to 5), the proposed method outperforms both QDTD and DDCIoT, demonstrating its efficiency in managing higher throughput even when the channel is less occupied. As the ratio continues to increase, the performance differences between the methods become less pronounced, but the proposed method consistently maintains the highest throughput, followed closely by QDTD, with DDCIoT consistently trailing. The proposed method achieved the highest throughput, suggesting that it is more effective in optimizing data transfer rates across varying channel activities.

Figure 3 shows the data delay in seconds as a function of the channel busyness ratio for QDTD, DDCIoT, and the proposed method. From the data, it can be observed that the proposed method consistently demonstrates the lowest delay across all channel busyness ratios, indicating its superior performance in managing communication latency in busy channels. The proposed method is the most effective in minimizing delay, which makes it potentially more suitable for real-time applications where low latency is crucial.

Figure 4 shows the energy consumption in mJ for various methods across different network sizes, ranging from 100 to 900 IoT nodes. The methods compared are CEC, PEM, AoI-IP, EETO-GA, and the proposed. This figure shows that as the network size increases, the energy consumption generally increases for all methods. However, the rate of increase and the absolute values differ significantly between them. The proposed method shows a relatively consistent and moderate increase in energy consumption as the network size increases, suggesting that it effectively manages energy efficiency across different scales. The proposed method appears to offer a favorable balance of energy efficiency across varying network sizes, suggesting its potential utility for large-scale UAV-IoT deployments where energy conservation is crucial, making it a compelling choice for energy-sensitive UAV-IoT applications.

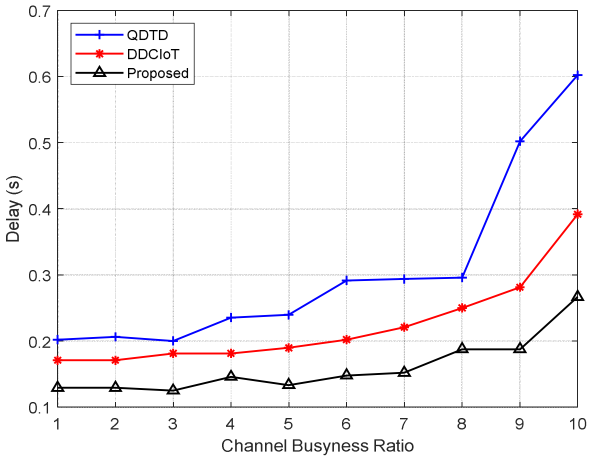

Fig. 3. Communication delay vs channel busyness of the proposed collaborative UAV-IoT network.

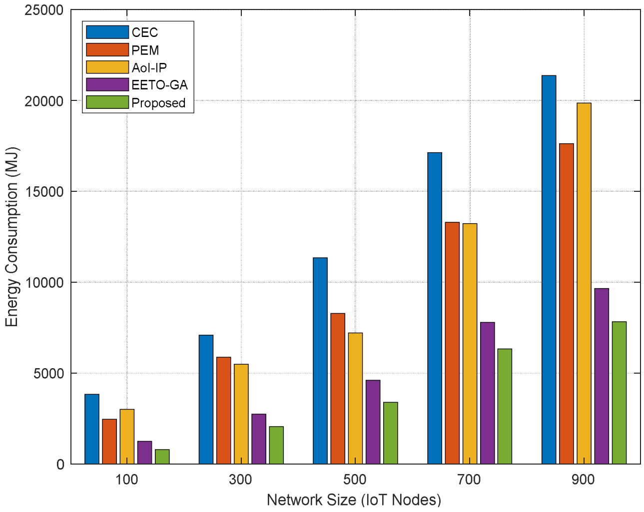

Fig. 4. UAV energy consumption compared to state-of-the-art methods.

Figure 5 compares the energy consumption of IoT devices across various network management methods as the network size increases from 100 to 900 IoT nodes. Energy consumption for all methods increases with network size, reflecting the greater demand for resources as more devices are connected. Notably, the proposed method consistently exhibits the lowest energy consumption across all network sizes. The proposed method is at least 70% better compared to the other state-of-the-art methods in terms of IoT device energy consumption.

Figure 6 illustrates the task completion percentages for various SOTA methods across different network sizes and the improvements each method achieved. The proposed method significantly outperformed the others across all network sizes, as it was 12.4%, 13.9%, 11.5%, and 3.2% better in terms of Task Completion Rate (%) compared to CEC, PEM, AoI-IP, and EETO-GA, respectively.

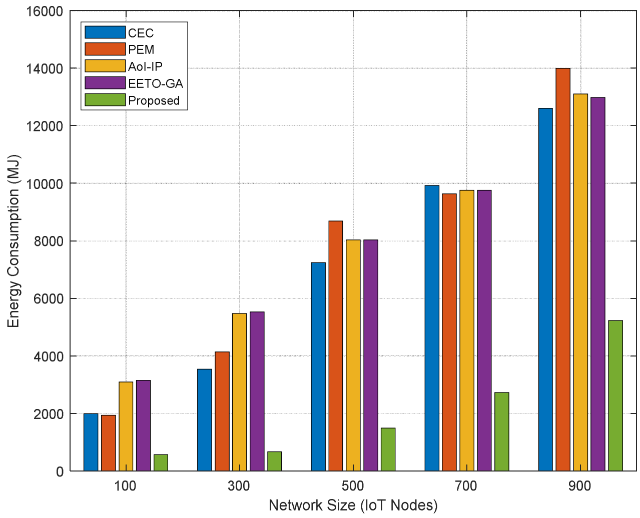

Fig. 5. IoT Device energy consumption comparison.

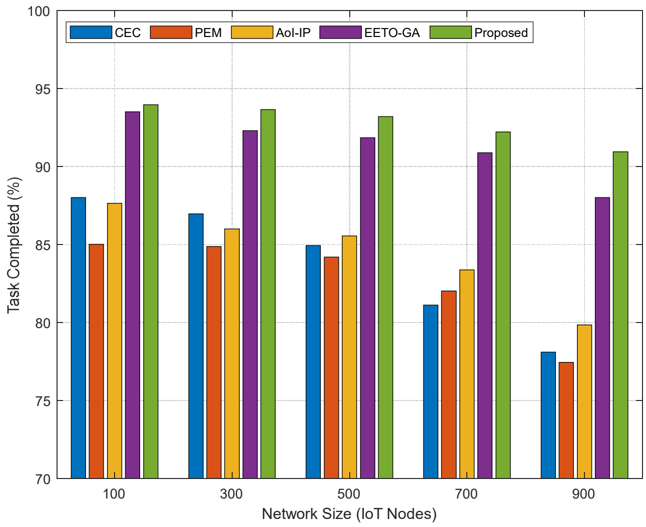

Fig. 6. Task completion percentage compared to existing methods.

Figure 7 shows that the proposed method significantly reduced the delay across all network sizes compared to the other methods. The average delay for the proposed method remained markedly lower, particularly in larger network sizes, highlighting its efficiency and optimized performance in handling larger and more complex networks. The other methods show an increasing trend in delay as the network size increases, with CEC and PEM experiencing a particularly sharp increase in delays at larger network sizes. AoI-IP and EETO-GA also show increasing delays, but their increase is less steep compared to CEC and PEM. The proposed method substantially reduced delay compared to the others, achieving the most significant improvement over CEC (62.0%), followed by PEM (56.1%), AoI-IP (54.7%), and EETO-GA (26.8%).

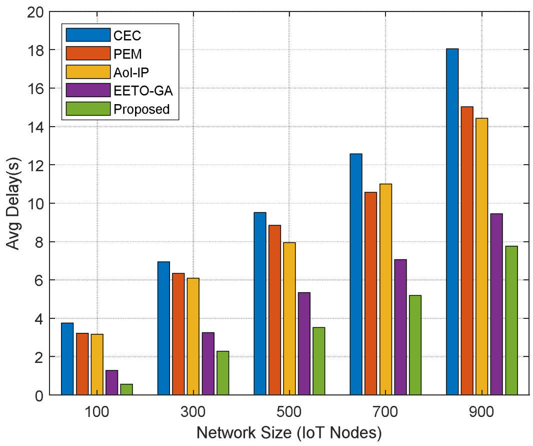

Fig. 7. Average delay (s) compared to existing methods.

IV. CONCLUSION

This study proposed an energy-efficient transmission coordination framework for cooperative UAV-IoT networks using the PathFinder optimization algorithm. The framework was designed to simultaneously handle transmission coordination between UAVs and IoT devices, aiming to optimize trajectory planning and resource allocation while considering network parameters. The comprehensive evaluation and analysis demonstrated promising results compared to existing methods for optimizing the performance and efficiency of cooperative UAV-IoT networks. The novelty of the proposed method is the introduction of the Collaboration Index (CI), which serves as a key metric to assess the cooperativeness and collaborative efficiency of the nodes within a UAV-IoT network. This index is calculated based on several factors, including the frequency and reliability of data exchanges between nodes, the successful completion of shared tasks, and the synchronization accuracy in communication protocols among UAVs and IoT devices. The proposed method consistently outperformed other UAV-IoT network methods (QDTD, DDCIoT, CEC, PEM, AoI-IP, EETO-GA) across various metrics and network sizes. It exhibited the highest data throughput and task completion rates, significantly lower energy consumption, and markedly reduced delay times, even as network sizes scaled up to 1000 nodes. Its performance indicates superior scalability and efficiency, particularly in larger networks. The improvements in delay reduction and energy efficiency are substantial compared to previous state-of-the-art methods, confirming its potential suitability for large-scale UAV-IoT deployments where minimizing delay and energy consumption is crucial for optimal performance. Looking forward, the potential for expanding this architecture includes incorporating machine learning algorithms, especially deep learning models, to dynamically predict and adapt to network demands. Additionally, implementing more comprehensive security protocols to protect data in transit between UAVs and ground stations in this increasingly complex network would be crucial to address.

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