QEEH: ADAPTIVE ENERGY-EFFICIENT HANDOVER FOR FANETS USING Q-LEARNING

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ABSTRACT

Flying Ad Hoc Networks (FANETs) are a critical component of UAV-based communication systems with applications in surveillance, disaster response, and defense. Their highly dynamic topology, high mobility and limited battery capacity makes reliable and energy-efficient communication challenging for them. Traditional handover mechanisms, often adapted from Vehicular Ad Hoc Networks (VANETs), rely on static thresholds and are not suited to the three-dimensional mobility and energy constraints of FANETs. This study proposes QEEH, a Q-learning–based Energy-Efficient Handover framework designed for FANET environments. QEEH employs reinforcement learning to make adaptive handover decisions by considering signal strength, node density, residual energy, and traffic load. It also integrates multiple energy states—active, sleep, hibernate, and wake-up—to reduce power consumption without compromising connectivity. NS3-based simulations show that QEEH consistently outperforms CLEA-AODV, LFEAR, and PARouting. Compared with CLEA-AODV, QEEH achieves up to 23% higher throughput, 20% higher packet delivery ratio, 30% lower end-to-end delay, and 28% lower energy consumption, while maintaining more than 90% node survivability at the end of simulation, exceeding other protocols by 15–21%. These results demonstrate that intelligent, energy-aware handover schemes can enhance FANET performance. However, the findings are limited to NS3 simulations with moderate UAV densities. Future work will focus on testbed validation, scalability to large UAV swarms, and extending QEEH with deep reinforcement and federated learning for decentralized training.

Keywords: FANET, VANET, Handover, Reinforcement Learning, Network Lifetime.

INTRODUCTION

Flying Ad Hoc Networks (FANETs) have been of growing interest because of their application in unmanned aerial vehicle (UAV) communication, which supports applications in disaster relief, military missions, surveillance, and smart city infrastructure. In contrast to conventional Mobile Ad Hoc Networks (MANETs) and Vehicular Ad Hoc Networks (VANETs), FANETs are in a three-dimensional (3D) dynamic environment, which introduces novel mobility, connectivity, and routing issues (Lakew et al., 2020). One of the most critical challenges in FANETs is handover management, wherein UAVs have to switch communication links seamlessly while keeping the network stable. Unlike networks on the ground, FANETs suffer from rapid topological changes, high-speed mobility, and interrupted connectivity, making conventional handover mechanisms inappropriate. Conventional Received Signal Strength (RSS)-based methods, typically employed in terrestrial networks, tend to result in frequent connectivity losses and latency increase because of their dependence on static thresholds (Albu-Salih & Khudhair, 2021). These limitations necessitate the development of adaptive, energy-

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efficient, and AI-driven handover mechanisms.

The dynamic nature of FANETs introduces several challenges for efficient handoverwhich are summarized due to the following reasons-UAVs experience high mobility and frequent topology changes unlike VANETs, where vehicles move in constrained paths, UAVs have unpredictable trajectories that lead to frequent link disruptions (Aruna & Sharma, 2019).For undisturbed communication it is necessary for the UAVs to maintain connectivity while moving in x, y, and z dimensions, impacting signal strength and link stability (Yang & Liu, 2019). While moving in 3d space there is numerous possibility of disruption in the network connecting the UAVs, which may be due to physical terrains, atmospheric variations over altitudes. Due to environmental interference and UAV dispersal, FANETs face frequent network partitions, making seamless handover management crucial (Malhotra & Kaur, 2024). UAVs operate on battery powerhaving limited energy resource therefore making energy-efficient routing and communication is essential for network longevity (Bharany et al., 2022). As they are operated on battery, there is a huge pressure on the battery energy to help in the motion of the UAV, its navigation system and also the network communication. Proper energy efficient algorithms would help in the saving a part of the batteries lifetime, which could be utilized towards other jobs of the UAV. At present the number of UAVs operating over a defined 3d space is limited in nature. But in the future as the UAV density increases, traditional handover mechanisms struggle with network congestion and inefficient bandwidth allocation (Albu-Slaih & Khudhair, 2021).

To overcome these challenges, researchers have explored AI-driven handover decision-making, and hybrid routing communication protocols AI-Based Handover Optimization. Recent studies have demonstrated the effectiveness of machine learning (ML) and reinforcement learning (RL) techniques in dynamically optimizing handover decisions. Q-learning-based approaches have been particularly effective in predicting UAV mobility patterns and optimizing handover timing to minimize latency and packet loss (Kumbhar & Shin, 2022). Given the limited battery life of UAVs, optimizing energy consumption is crucial. Cluster-based routing protocols have emerged as a viable solution, where UAVs are grouped into clusters to reduce routing overhead and improve energy efficiency (Gupta et al., 2024). Hybrid Radio Frequency (RF) and Light Fidelity (Li-Fi) communication models have been proposed to enhance handover success rates. RF provides long-range connectivity, while Li-Fi ensures high-speed, low-latency short-range communication, enabling seamless network transitions (Singh & Verma, 2015).

The functioning of FANETs is in a three-dimensional, dynamic, highly mobile environment. This specificity puts special parameters with challenges such as mobility management, routing stability, energy consumption, and particularly handover continuity. Under such dynamic contexts, handover from one node to another, is very difficult to perform. Most of the classical handover methodologies, such as those based on Received Signal Strength (RSS) do not work for FANETs because they rely on static parameters. These methods lead to handovers which are premature or too late, leading to higher packet loss and delays with lower communication quality. Secondly, most of these existing solutions are designed for VANETs operating on the ground, where mobility is two-dimensional and more or less predictable. On the other hand, FANETs experience wild topological changes and restricted energy reserves.One of the great research gaps exists in that there are no energy-efficient, intelligent-type of handover solutions designed specifically for FANET contexts. Existing solutions rarely accommodate energy constraints of UAVs or adapt to the erratic flight paths of the platforms. This gap thus calls for the development of a robust and adaptive handover mechanism that would intelligently manage energy usage while keeping on stable connectivity.

In this paper, QEEH (Q-Learning-based Energy-Efficient Handover) is proposed. It is a novel reinforcement learning framework used to improve handover decisions in FANETs. QEEH learns in real time to take actions optimally by observing parameters such as signal strength, node density, traffic load, and residual energy. Using Q-learning, it makes proactive decisions about whether a handover should be made or not, and if so, when and how it should be performed, to achieve a tradeoff between communication quality and energy efficiency.

The objective of this study is to design and evaluate an intelligent, energy-aware handover mechanism tailored for Flying Ad Hoc Networks, which operate under highly dynamic, three-dimensional mobility and face severe energy constraints. Most existing handover protocols either use static thresholds, rely solely on signal strength, or adapt solutions built for two-dimensional VANETs that do not perform optimally in FANET scenarios.

This research proposes QEEH, a Q-learning-based Energy Efficient Handover framework, which integrates intelligent decision-making with energy-aware operational states (sleep, hibernate, wake-up). The framework aims to dynamically manage handover decisions by learning from the environment in real time.

The following research questions guide this investigation

- How can Q-learning be adapted to optimize handover decisions in FANETs characterized by high mobility and limited energy resources.
- To what extent does incorporating energy-aware operational modes (sleep, hibernate, wake-up) improve network lifetime and energy efficiency.
- How does the proposed QEEH framework perform in comparison with existing protocols in terms of throughput, packet delivery ratio, end-to-end delay, and energy consumption.

1. Literature Review

VANETs and FANETs have gained huge research attention over the last decade as a consequence of their major application in ITS and communication networks for UAVs. The frequent handovers, link breakage because of mobility, energy constraint, and time-varying topological variations are the predominant issues in VANETs and FANETs. Conventional handover methods based on received signal strength and static threshold-based mechanisms tend to fail in high-mobility environments, resulting in increased latency and packet loss. To overcome these challenges, machine learning-based handover methods, energy-efficient routing, and hybrid RF, Li-Fi solutions have been proposed as promising solutions. This chapter classifies and examines newer developments in handover schemes and routing protocols in VANETs and FANETs with comparative studies on various methodologies.

VANET based RSS driven handover approaches initiate handover whenever the strength of signals declines below a previously specified value. Premature as well as late handovers due to fixed values create adverse effects on latency as well as on connectivity. Malik and Sahu (2019) in their paper compared various VANET routing protocols, pointing out the disadvantages of RSS-based handover methods, which are plagued by indoor and outdoor frequent disconnections in urban scenarios. Nebbou et al. (2019) presented the Partial Backwards Routing Protocol (PBR), optimizing handover processes in terms of signal strength and distance measures. But this approach suffered from frequent link failures in high-speed traffic. Srivastava et al. (2020) suggested a location-based routing approach to enhance handover reliability, minimizing unnecessary handovers but demanding high GPS accuracy. Machine learning and reinforcement learning methods are being used more and more to optimize handover decisions by dynamically adjusting to real-time network conditions. Liu et al. (2020) presented the QMR protocol, combining Q-learning for multi-objective handover optimization, resulting in a 15% increase in network stability. Reinforcement learning-based routing protocols were discussed by (Bugarčić et al., 2022), highlighting their potential to minimize latency and optimize network resource allocation for VANET communication, suggesting an adaptive ML framework that enhanced routing efficiency. Frequent handovers in VANETs expose them to handover attacks, unauthorized access, and packet losses. Yadav et al. (2018) studied secure routing protocols, applying cryptographic methods to counter handover-based attacks in VANETs. Mahajan et al. (2021) performed a realistic study of reactive routing in urban VANETs, with an emphasis on security threats in high-density traffic.

FANETs introduce new challenges such as three-dimensional mobility, intermittent connectivity, and energy constraints, making traditional VANET handover techniques ineffective. Hassan et al. (2021) developed a hierarchical-based fish-eye state routing protocol, reducing handover overhead and energy consumption in FANETs. Lau et al. (2023) developed AQR-FANET, an anticipatory Q-learning routing protocol, which significantly improved handover success rates and network stability. Similarly, Xue et al. (2023) proposed QEHLR, a Q-learning empowered routing algorithm, which enhanced handover reliability in high-mobility UAV networks. Abdulhae et al. (2022) proposed a hierarchical clustering approach, reducing handover overhead while extending network lifetime. Additionally, nature-inspired IoT-based routing techniques, such as those proposed by Khan et al. (2020) have shown significant improvements in energy-aware handover decision-making.

Several routing protocols have been proposed to enhance communication efficiency in VANETs and FANETs. Each protocol offers distinct advantages while also facing certain limitations. Ad Hoc On-Demand Distance Vector (AODV) is an on-demand routing protocol that discovers routes only when needed, reducing routing overhead in sparse networks. Wang et al. (2023) introduced an Arithmetic Optimization AOMDV Routing Protocol, leveraging hybrid RF-Li-Fi technology to minimize handover latency. K. et al. (2024) in their work proposed Energy-Efficient AODV (EE-AODV) routing, which increased UAV network lifespan by 20%.The Optimized Link State Routing (OLSR) protocol, proposed by (Gangopadhyay & Jain, 2023), takes a proactive approach by maintaining updated routing tables to reduce control overhead. While OLSR performs well in structured environments, it becomes inefficient in highly dynamic networks due to the frequent need for topology updates. Another position-based routing protocol, Greedy Perimeter Stateless Routing (GPSR), was analyzed by (Kim et al., 2023) for its application in multi-UAV reconnaissance models. GPSR offers high scalability by using geographical information, but its performance degrades in low-density networks where greedy forwarding fails. Machine learning-based routing has also gained attention introducing the Q-learning-based Multi-Objective Routing (QMR) protocol, which dynamically optimizes handover decisions using real-time mobility and network conditions (Farithkhan et al., 2024). However, QMR has a high computational complexity, making it challenging to implement in resource-constrained FANETs. These approaches significantly improve handover success rates, but it requires dual transceivers, increasing hardware costs and system complexity as identified from the survey works of (Oubbati et al., 2019). Table 1 summarizes some of the hybrid and energy efficient routing protocols for FANET.

This analysis points out that although classical routing protocols like AODV and OLSR ensure base- line connectivity, machine learning-based and hybrid communication paradigms promise efficient handover and better network performance in highly mobile networks. Nevertheless, computational overhead, scalability, and hardware constraints continue to be deciding parameters for choosing a protocol for next-generation VANET and FANET networks. Over the past decade, considerable research has been dedicated to improving routing and handover techniques in both VANETs and FANETs. While VANET protocols have achieved relative maturity, FANETs continue to present critical challenges due to their three dimensional mobility, limited energy capacity, and high-speed dynamic topologies. Existing handover approaches, particularly those relying on static threshold-based RSS measurements, often result in premature or delayed handovers, leading to poor connectivity and increased energy usage.

Machine learning-based solutions, especially reinforcement learning approaches like Q-learning, have demonstrated potential in optimizing handover decisions dynamically. However, several limitations remain unaddressed in existing works:

- *Limited consideration of energy-awareness:* Most ML-based approaches focus solely on communication metrics such as signal strength or node density, ignoring critical energy constraints inherent in battery-operated UAVs.

Year	Approach Name	Objective	Identified Weaknesses
2022	CLEA-AODV (Mansour et al., 2022)	Improves FANET routing using a cross-layer approach with AODV, optimization-based clustering, and Cooperative MAC for better performance.	Higher computational complexity and increased overhead.
2023	UF-GPSR (Kumar et al., 2023)	Enhances GPSR routing to achieve stable and efficient data dissemination.	Lacks scalability and does not adapt the broadcasting interval for hello messages.
2023	ENSING (De Lucia et al., 2023)	Introduces an energy-efficient forwarding method to optimize network performance.	Struggles with network scalability, lacks adaptability to FANET due to UAV movement constraints, and fails to address routing holes.
2023	GPSR + (Hosseinzadeh et al., 2023)	Improves GPSR routing for more reliable data transmission.	Results in increased delay in data transfer and suffers from limited network scalability.
2023	PARouting (Liu et al., 2023)	Enhances FANET routing using deep reinforcement learning and UAV mobility prediction to reduce routing overhead and improve efficiency.	Computational complexity and reliance on accurate mobility prediction.
2024	EARVRT (Hosseinzadeh et al., 2024a)	Minimizes unnecessary control messages to optimize routing efficiency.	Has low network scalability.
2024	GPSR+AODV (Hosseinzadeh et al., 2024b)	Enhances data reliability within the GPSR routing framework.	Leads to high routing overhead.
2024	LFEAR (Hosseinzadeh et al., 2024c)	Enhances FANET routing using a cross-layer approach with AODV, Glow Swarm Optimization for cluster head selection, and Cooperative MAC to improve performance.	Potentially higher computational complexity, increased overhead from cross-layer interactions, and dependency on environmental conditions.

Table 1. Different FANET Approaches for Handover Mechanism

- *High algorithmic complexity:* Solutions involving deep RL or multi-objective optimization often incur high computational overhead, making them impractical for deployment on lightweight, resource-constrained UAVs.
- *Lack of operational mode integration:* Few protocols incorporate adaptive operational states (such as sleep, hibernate, and wake-up) that are essential for energy conservation without sacrificing connectivity.
- *Scalability in 3D aerial space:* Most handover solutions are adapted from terrestrial VANET models and fail to scale efficiently in FANETs where mobility is highly unpredictable in x, y, and z dimensions.

While recent works like AQR-FANET, QEHLR, and PARouting have applied RL for improving link reliability or routing stability, they fall short in integrating energy conservation mechanisms and dynamic power states, particularly in real-time learning scenarios. To address these gaps, this study proposes QEEH (Q-learning-based Energy Efficient Handover), a lightweight, scalable, and energy-conscious framework specifically designed for FANETs. QEEH introduces:

- A distributed Q-learning mechanism that learns handover decisions based on real-time input of residual energy, traffic load, and node density.
- Multi-mode operation (active, sleep, hibernate, wake-up) to reduce unnecessary energy drain and extend network lifetime.
- A performance evaluation setup using NS3 that benchmarks QEEH against existing state-of-the-art protocols across throughput, delay, energy metrics, and network lifetime.

The work here proposes a Q-Learning-based Energy-Efficient Handover handover process which addresses this issue by integrating energy conservation into the handover decision process. By taking into account the energy levels of devices (vehicles or drones), the algorithm tunes the frequency and circumstances upon which handovers take place. The emphasis of this model is placed on the optimization of energy-efficient handovers through the implementation of an altered Q-based algorithm, specifically developed for VANETs (Liu et al., 2022), to fit the dynamic characteristics of FANETs. The handover decision process is optimized based on key factors like battery life remaining and signal strength. These devices enable communication with base stations with Active Antenna Systems (AAS), which ensures seamless connectivity and guaranteed data transmission (Kalita & Barooah, 2020). Utilizing the hardware and Q-based handover mechanism presented in this paper, the system designed here supports seamless handover of communication and network operation with energy conservation in densely dynamic UAVs.

This novel combination of energy-awareness, learning-based adaptation, and 3D scalability makes QEEH a significant step toward practical, real-world deployment of intelligent FANET handover strategies.

2. Methodology

This study adopts a simulation-based modeling approach to evaluate the effectiveness of an energy-efficient, intelligent handover framework for FANETs using Q-learning. The methodology comprises system modeling, reinforcement learning integration, power-state transitions, and performance evaluation through simulations. The design and evaluation were executed in the NS3 simulator under varying network and mobility conditions.

FANETs are confronted with critical problems of 3D high-speed mobility, dynamic network topology, and stringent energy constraints. To resolve these challenges, we introduce the QEEH framework. This framework is made to facilitate seamless and energy-efficient handovers by utilizing reinforcement learning and local environmental perception. As opposed to conventional RSS-based or static threshold methods, QEEH learns to optimally adopt handover policies with time by taking into account various parameters: signal intensity, remaining energy, network density, and traffic. The model is capable of adapting to dynamic network environments and facilitating decision-making for putting nodes into suitable operational modes (active, sleep, hibernate, or wake-up), thus achieving maximum energy efficiency and link stability.

The system model given in this section covers an entire network of UAVs, which communicate amongst themselves and with other endpoints that fall within a circular region. The below section summarizes the detailed sub models for better understanding.

3. Network Model

FANET is modeled in 3D space comprising of UAVs which are believed to be communicating with multiple endpoints through a number of communication models in the system. There are four communication systems as established in this work.

- *Satellite-UAV Communication:* The UAVs communicate with satellites to obtain live GPS data during Beyond Line-of-Sight (BLOS) as shown in Figure 1. It offers secure flight, especially over areas where there is no established infrastructure. The satellite communication link provides huge bandwidth and extended-range communication.
- *UAV-to-Cellular Communication:* UAVs can be employed to establish a stable communication network over rural or urban areas, providing extensive coverage and supporting communication with ground users as shown in Figure 2. UAVs can function as either User Equipment (UEs) or Base Stations (BSs), which allow direct communication with cellular networks. This model broadens the range of communication and minimizes dependence on ground networks.
- *UAV-to-Ground Control Station Communication:* UAVs are linked to the ground control stations over terrestrial or satellite networks as depicted in Figure 3. This facilitates the UAVs to communicate for purposes like cargo transport, surveillance and video streaming. Aerial relays serve as gateways linking UAVs with the cellular network, providing persistent data transmission.
- *UAV-to-UAV Communication:* In the case of UAV swarms, UAVs interact with each other for data

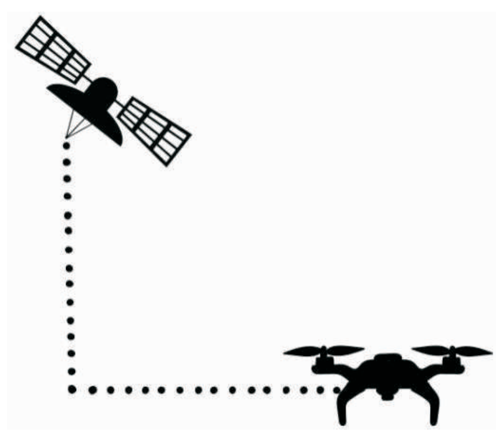

Figure 1. Satellite-UAV Communication

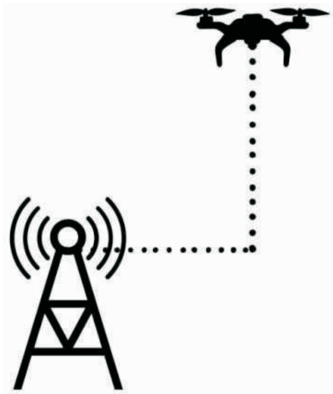

Figure 2. UAV-to-Cellular Communication

exchange, autonomous flight coordination, and system-wide functions as depicted in Figure 4. UAV-to-UAV communication enhances spectrum efficiency, energy efficiency, and lessens transmission delay by offloading traffic from backhaul links.

To model the distribution of UAVs and other nodes, it is assumed that the UAVs, which are commonly referred to as nodes that are distributed within a circular region, defined by α which denotes node density per unit area as shown in Figure 5. This distribution aids in the study of the density of UAVs and other nodes in various parts of the network, which is essential for resource allocation, handover control, and reducing failures. The total number of nodes Narea in a circular area with communication range (cR) is calculated through Equation 1.

$$N_{area} = \alpha\pi(cR)^2 \quad (1)$$

If a portion of the circular region, i.e. quarter of the circular

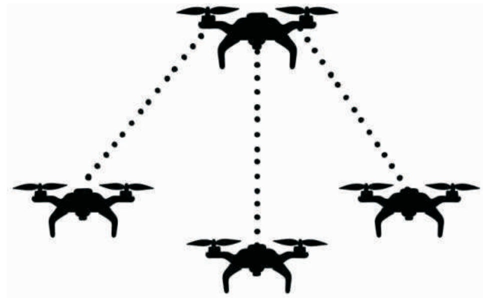

Figure 4. UAV-to-UAV Communication

region if considered then Narea is modified as given in Equation 2, which gives the number of nodes (N) in space.

$$N = \alpha\pi(cR)^2/4 \quad (2)$$

The node distribution is assumed to be homogeneous, and the nodes are randomly placed in the area. The cR of each node determines the coverage area and the ability of nodes to communicate with each other. A larger cR increases coverage but may require more energy.

3.1 System Architecture

In the QEEH system, every UAV node operates independently within a distributed FANET network while adding to the overall efficiency and stability of the network. UAVs, at regular intervals, broadcast a beacon signal to keep track of their surroundings, encompassing an estimate of the signal strength (SStr) from adjacent nodes, a determination of the network occupancy(NetO) within the range of their communication, a measure of their residual battery energy (Res.E), and an observation of the present traffic load intensity (TFI) from queue

Figure 3. UAV-to-Ground Control Station Communication

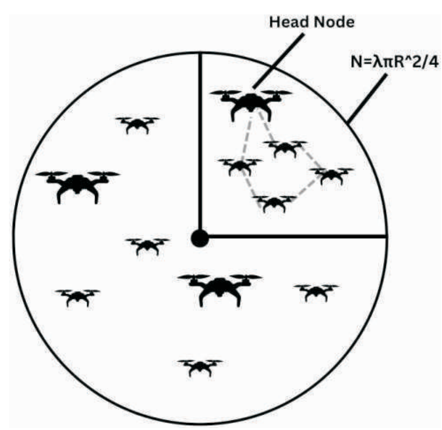

Figure 5. Distribution of UAVs in space

utilization. With these, nodes transition among four working modes dynamically: active, sleep, hibernate, and wake-up. Active nodes fully participate in communication and data transmission. A node may enter sleep mode if it determines it has adequate neighboring coverage and its own signal is low, therefore conserving energy but remaining partially awake. Under heavy traffic load conditions, where keeping communication would consume high energy or lead to packet congestion, the node goes into hibernate mode—a lower power-saving regime. Nodes can, on the other hand, return to active mode using a wake-up process initiated either by scheduled timers or by pressing communication needs in their surroundings. A central role in this design is filled by the Head Node (H_no), which is chosen dynamically according to maximum signal intensity and minimum priority number (Pr_no). The Head Node oversees local communications, coordinates energy-conserving role changes within its group, and ensures connectivity of the network as node roles change over time. The different modes and the process to determine them are detailed in the below section.

3.2 Mode Transition

The parameters guiding the transition of nodes from one mode to another are dependent on two factors.

3.2.1 Sleep mode factor (SMF)

SMF is calculated through Equation (3) which is given as follows:

$$SMF = \frac{N}{\mathrm{SStr} \times \mathrm{cR}} \qquad (3)$$

If a node possesses weak signal strength but has numerous neighbor nodes at the vicinity range of one-hop, it can put itself into sleep mode without any issues because other nearby nodes are capable of forwarding packets on its behalf. All such candidate nodes are determined and as long as the count does not surpass the number considered advisable in the region, they are listed according to their Sleep Mode Factor (SMF) in descending order and then put into sleep mode.

3.2.2 Traffic Load Intensity

TFI is defined as the ratio between the traffic load and the maximum allowable queue size (q_{max}) which is holding the packets for transmission is considered constant (Equation 4).

$$TFI = \frac{Traffic\ load}{q_{max}} \qquad (4)$$

The traffic load is dependent on average queue size (q_{avg}) and N (Equation 5).

$$\text{Traffic load} = q_{avg} \times N \qquad (5)$$

Depending on its TFI, a node may be suspended into hibernation mode to save power if the traffic is heavy. A node with a TFI higher than some predetermined threshold enters the hibernation and is placed in the queue. However, this queue stores only one-third of the number of nodes in the cluster as per Equation 2. When the queue size is exceeded, some of the sleeping nodes in the area are activated to help deal with the traffic.

In conventional wireless networks, decisions for entering sleep or hibernation are typically autonomous to the node and not directly tied to routing or handover mechanisms. In QEEH, however, these decisions are context-aware, a node only transitions into low-power states when neighbor density and routing load indicate that connectivity will not be compromised. In this way, energy saving behavior is synchronized with routing and handover processes, ensuring that local node actions do not negatively affect network-wide stability.

A wake-up mechanism is initiated either on a regular basis : time-based using a cross-ladder wake-up scheme (Keshavarzian et al., 2006) or forcibly, in the event that there are too many nodes sleeping or hibernating , to continue communication. The effective wake up period for nodes in sleep mode ($N_{s\text{-}mode}$) is dependent on the threshold value of the nodes entering the hibernation modes ($N_{h\text{-}mode}$) within its one hop distance. The forced wake up time (T_{ws})can be mathematically correlated as (Equation 6):

$$T_{ws} = \int_{i=1}^{N} (N_{h-mode}) \qquad (6)$$

Effectively, the nodes in the network distribute the data load and alternate between active and power save states. However, being a distributed algorithm, it does not interrupt the ongoing data flow between the data generators and the base station.

3.2.3 Network Lifetime

The goal is to optimize Network Lifetime (NL) as the time when dead node percentage (DNP) crosses a threshold value where packet generation rate follows poisons exponential law (Shirazi & Mirabedini, 2016). Dead nodes are those in which total energy expenditure crosses their initial energy. The total energy consumed (TE_{com}) during sleep and hibernation mode is given as (Equation 7).

$$\boldsymbol{TE_{con}} = \boldsymbol{E_{con\,[sleep\,mode]}} + \boldsymbol{E_{con\,[hibernation\,mode]}} \quad (7)$$

The amount of time until nodes run out of total energy present at any instant of time (T_{total})is given by the time period (p) is given as Equation 8.

$$T_{total} = \sum_i^p [(TE_{con} + C_E) - I_E] \quad (8)$$

Where C_E is energy the consumed during packet transmission and I_E is initial energy. The node having the min (T_{total}) would have greater chances of being a dead node and max(T_{total}) represents the alive nodes with a greater probability to be involved in successive routing schemes. The dead nodes is represented by dead node percentage (DNP) as Equation 9.

$$DNP = \frac{\sum_{i=1}^{n} T_{total} - \sum_{i=1}^{n} \max(T_{total})}{N} \times 100 \quad (9)$$

NL can be estimated as the max time (T) till the DNP crosses the threshold dead node percentage (Td) over subsequent network phases (K) given as Equation 10.

$$NL = K.\int_0^T \frac{1}{DNP - Td} \quad (10)$$

To ensure uninterrupted connectivity and efficient communication, an intelligent handover mechanism is employed,where active nodes dynamically reassign roles and maintain link stability before transitioning into energy saving modes.

Although the proposed multi-variable energy model improves accuracy, it also introduces computational overhead due to additional monitoring and state-transition logic. In real UAV deployments, flight controllers and onboard processors may have limited resources, making it challenging to run complex calculations in real time. To address this, future implementations of QEEH could employ lightweight approximations of the energy model, parameter pruning, or offload computation to ground control stations or edge servers, ensuring practical deployment feasibility.

3.3 Q-Learning Framework

In the Q-learning framework for handover, the state of a node is defined by parameters such as NetO and SStr. The objective is to decide the best action, such as placing the node in different energy saving modes, based on the state of the system and the Q-value, which estimates the long-term benefit of an action in a particular state. The Equation 11 for Q learning rule is as shown below using (Watkins, 1989).

$$Q(S, A) + \alpha (R + \gamma Q(S', A') - Q(S, A)) \rightarrow Q(S, A) \quad (11)$$

For implementation the Q-learning the learning rate (α) of 0.1, discount factor (γ) of 0.9, and exploration probability (ε) were initialized at 0.2 with exponential decay over time. These values were selected based on prior reinforcement learning studies in ad hoc networks [Oubbati et al (2019), Bugarčić et al. (2022)] and tuned empirically to balance convergence speed and stability. A higher γ was used to prioritize long-term network stability over short-term energy savings, while a moderate ε ensured sufficient exploration in the highly dynamic FANET environment.

The term(S', A') in Equation (11) defines next state and action and the reward given by the agent is defined by R. The action is taken using $\in$ −greedy policy, when the probability is (1− $\in$), then the action will be taken as per the value in the Q-table. If the handover request is agreed and the action is yes, then it will select a network accordingly. The algorithms described below shows the process of using reinforcement learning and integrating it with the energy saving modes thereby facilitating successful handover mechanism.

3.3.1 Algorithm

Input: States (S) = (NetO, Nm, SStr), initialize Q table with action values set to 0, Vehicle (V) requesting for handover

Output: Action (A), selecting next operational mode (Sleep mode , Hibernate mode Wake-up)

- Initialize Q-table with all values set to 0 for all state-action pairs Initialize the state S (NetO, N_m, SStr):
- Calculate the SStr for each node, and assign a Pr_no to each node
- For each step:

Step 1: Apply $\in$ -greedy policy to obtain the Q-value from the Q-table Select action based on the Q-value for the current state

Step 2: Perform the selected action, A = (Sleep Mode, Hibernate Mode, Wake-Up Mode) based on Q (S,A)

Step 3: Compute the reward based on the success of the action and the current state

If the action results in power savings without affecting connectivity, reward is positive

If the action causes network failure, the reward is negative

Step 4: Determine the next state (S') after the action is performed

Step 5: Update the Q-table using Equation (11).

- Repeat steps 1–5 for each node handover decision in the network.

The simulation varies UAV counts between 5 and 40 to keep computational complexity manageable in NS3 while ensuring meaningful comparisons across protocols. This range reflects a moderate scale FANET, but does not fully capture the scalability demands of future dense aerial networks, which may involve hundreds of UAVs. Thus, the current evaluation should be viewed as proof of concept, with large scale validation left as future work.

4. Simulation Set-up

The performance of the suggested QEEH method for FANET is explained by utilizing NS3 as the simulator. The network is simulated in a 3D environment of size 10000 × 10000 × 10000 m^3, which is a large area where UAVs (Unmanned Aerial Vehicles) can move and communicate. The simulation changes the UAV number between 20 to 100 nodes in order to investigate the effects of varying node density on network performance. The UAVs have an IE supply of 100 Joules and speeds that are between 10 to 110 m/s to simulate various flying conditions which can be faced by real UAV missions. The communication area of every UAV is established at 250 meters so that there can be local communication between other UAVs nearby. Table 2 presents the simulation parameters.

The UAVs employ the Random Waypoint Mobility Model (RWP) to model their mobility patterns, and they broadcast their status every now and then with a 1-second beacon interval. The transmission power is 10 dBm. The MAC layer protocol used is IEEE 802.11g, which provides efficient data transmission in wireless networks. The data communication traffic model applied is Constant Bit Rate (CBR), and for each packet, the size is 512 bytes while the traffic rate is fixed at 2 Mbps to emulate steady data transmission common in UAV networks. Five main performance evaluation metrics are emphasized in simulation: energy expenditure, data delivery rate, network lifetime, routing overhead, and delay. These metrics enable us to evaluate the performance of the network as a whole, considering the energy efficiency of the UAVs, data delivery effectiveness, and network lifetime according to energy consumption. QEEH algorithm is contrasted with CLEA-AODV (Mansour et al., 2022), PARouting (Liu et al., 2023), LFEAR (Hosseinzadeh et al., 2024c). The protocols are simulated to determine the optimal one with regard to minimizing energy

Parameter	Value
Simulation Software	Ns3
Simulation Environment	10000 × 10000 × 10000 m^3 (3D space)
Number of UAVs	5 to 40 nodes
Maximum UAV Energy	100 Joules
UAV Speed	10 m/s to 110 m/s
Communication Range	250 meters
Beacon Period	1 second
Mobility Model	Random Waypoint Mobility Model (RWP)
Transmission Power	10 dBm
MAC Standard	IEEE 802.11g
Traffic Model	Constant Bit Rate (CBR)
Packet Size	512 bytes
Traffic Rate	2 Mbps
Antenna Type	Omni-Antenna
Simulation Duration	150 seconds

Table 2. Simulation Parameters

consumption and achieving effective communication between UAVs.

The simulation lasts 150 seconds and delivers a precise assessment of the behavior of the network over time. This configuration permits an exhaustive testing of the protocols' performance under a FANET environment with regard to energy management, data delivery effectiveness, and network reliability under different operation conditions.

The baselines selected in this study (CLEA-AODV, LFEAR, and PARouting) represent widely adopted and state-of-the-art protocols reported in recent FANET literature for energy-efficient routing and handover evaluation. These provide a strong comparative foundation; however, it is acknowledged that emerging deep reinforcement learning and federated learning based schemes are gaining attention in UAV networks. Such approaches often require higher computational capacity, dual transceivers, and distributed learning infrastructures, which are not easily replicated in NS3 under lightweight UAV assumptions

The effectiveness of the proposed method is measured in terms of network parameters such as throughput, PDR, end to end delay, energy consumption, standard deviation of energy (SDE) with a special emphasis on routing overhead and handover efficiency. The subsequent sections present an in-depth discussion of each metric accompanied by respective graphs and tables.

5. Results and Analysis

5.1 Throughput Analysis

Throughput is a key performance measure of the rate of successful delivery of data. From the visualization as depicted in Figure 6 and results summarized from Table 3, it can be seen that QEEH performs the highest throughout in all the mobility conditions with varying node speeds from 121.37 Mbps at 10 m/s to 604.23 Mbps at 110 m/s. This indicates the capacity of QEEH to sustain data transmission with effectiveness even at high node speeds.

The throughput performance of CLEA-AODV, LFEAR, and PARouting badly degrades with mobility. From table the throughput of CLEA-AODV is 523.54 Mbps at 110 m/s, which is substantially less than QEEH. This indicates QEEH's better capability to achieve high rates of data delivery under evolving network conditions, providing guaranteed communication in FANETs indicates QEEH's capability to provide data transmission at efficiency even during high node velocities.The throughput performance of PARouting, LFEAR, and CLEA-AODV degrades considerably with mobility. For example, the throughput of CLEA-AODV at 110 m/s is 523.54 Mbps, which is much less than that of QEEH. This indicates QEEH's enhanced capability to provide high data delivery rates under dynamic network conditions, providing guaranteed communication in FANETs.

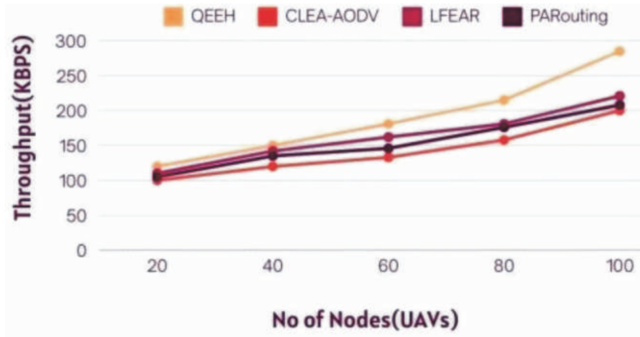

Figure 6. Throughput Vs. Number of Nodes

Parameter	Mobility	QEEH	PARouting	LFEAR	CLEA- AODV
Throughput (Mbps)	10	121.37	113.22	107.49	101.88
	30	243.68	228.91	216.45	202.56
	60	362.74	342.17	325.83	309.32
	90	482.59	454.43	431.71	417.19
	110	604.23	568.89	539.67	523.54
PDR (%)	10	99.12	95.87	91.43	87.34
	30	94.67	91.35	86.92	82.59
	60	89.34	85.91	81.47	77.36
	90	83.98	80.53	76.19	72.43
	110	78.54	75.23	71.56	67.84
End-to-End Delay (ms)	10	15.78	18.95	20.83	24.68
	30	23.62	27.49	30.91	36.79
	60	31.45	36.03	40.99	48.89
	90	39.28	44.56	51.07	60.98
	110	47.12	53.1	61.15	72.45
Energy Consumption (J)	10	7.86	9.37	10.82	12.79
	30	15.67	18.73	21.65	24.56
	60	23.98	27.81	31.22	36.78
	90	32.17	36.97	41.29	48.14
	110	40.23	46.34	51.49	60.27

Table 3. Performance Parameters of Various Parameters in Terms of Mobility of Nodes

5.2 Packet Delivery Ratio

Packet Delivery Ratio calculates data packet delivery efficiency from source to destination. The PDR results are shown in Figure 7 and validated by the numerical results in Table 3, which shows QEEH performing with higher PDR values in all speed scenarios, ranging from 99.12% at 10 m/s to 78.54% at 110 m/s. The reduction in PDR with rising speed is anticipated because there are more link breakages in highly mobile networks.

Nevertheless, QEEH possesses a much larger PDR compared to the rest of the protocols. For example, when at 110 m/s, the PDR of CLEA-AODV is 67.84% while it is 10.7% lower compared to QEEH. This implies that QEEH is better at maintaining packet reduction and data integrity, leading to its robust communication reliability for FANETs.

5.3 End-to-End Delay

End-to-End Delay is a measure of the amount of time, on average, that a data packet takes to travel from source to destination. The end-to-end delay as measured by the analysis is found invariably to be smallest for QEEH in comparison with the other protocols considered as presented in Figure 8 and Table 3. While at 10 m/s delay for QEEH is found to be 15.78 ms, it is 24.68 ms for CLEA-AODV. As node speed raises, end-to-end delay increases for every protocol as a result of numerous link breakages and route flapping. Nonetheless, QEEH incurs the slowest increasing rate and, at 110 m/s, attains a delay of 47.12 ms versus CLEA-AODV at 72.45 ms. This clearly reflects the ability of QEEH to conserve latency levels with real-time

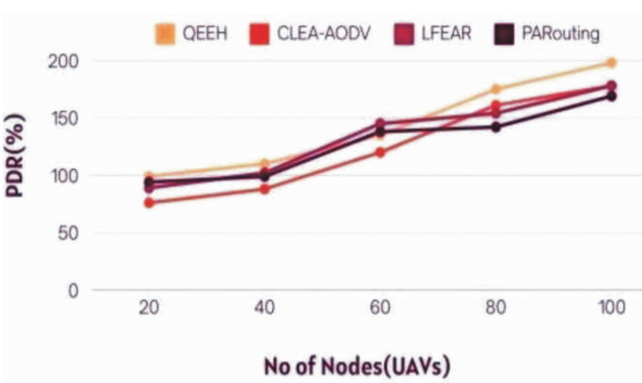

Figure 7. PDR Vs Number of Nodes

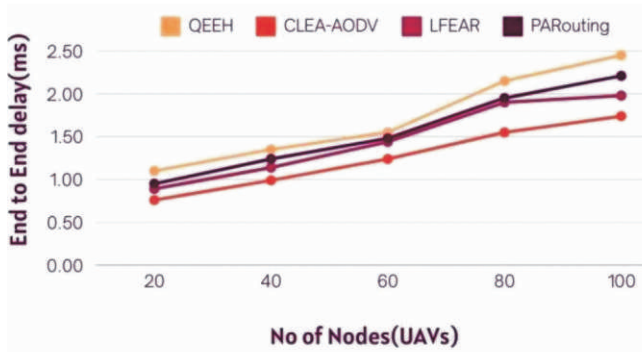

Figure 8. End to End Delay Vs. Number of Nodes

delivery of data in scenarios involving high-mobility FANET environments.

5.4 Energy Consumption

Energy Consumption is essential in FANETs since UAVs are usually battery-powered. The findings are depicted in Figure 9 and detailed in Table 3, which shows that QEEH has the lowest energy consumption for all speed scenarios. At 10 m/s, QEEH consumes 7.86 Joules, whereas CLEA-AODV consumes 12.79 Joules.The energy conservation in QEEH is also visible at higher velocities, with 40.23 Joules being consumed at 110 m/s as opposed to CLEA-AODV's 60.27 Joules. This indicates that QEEH conserves energy effectively, greatly increasing the operational life of UAV nodes. The lower energy consumption also helps to ensure network connectivity by keeping more nodes active for longer periods.

5.5 Standard Deviation of Energy

Standard Deviation of Energy is used to determine the variation in energy usage by all nodes, which reflects energy balance and network stability. The fairness of

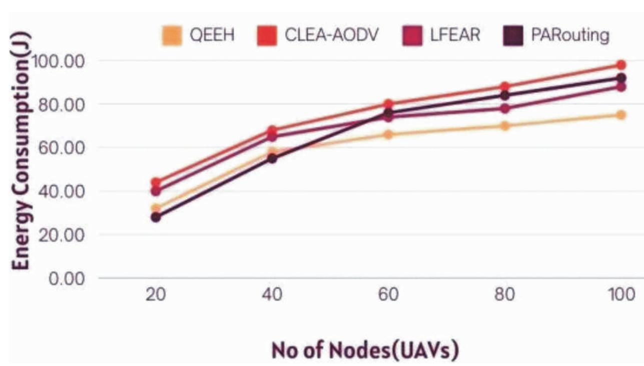

Figure 9. Energy Consumption Vs. Number of Nodes

energy utilization among UAVs is evaluated using the standard deviation of energy consumption, as shown in Figure 10. A lower deviation indicates that energy use is more evenly distributed across nodes, thereby delaying premature failures. QEEH consistently achieves the lowest deviation compared to CLEA-AODV, LFEAR, and PARouting. For example, at a mobility speed of 10 m/s, QEEH records a deviation of 0.82 J, compared to 1.47 J for CLEA-AODV, 1.32 J for LFEAR, and 1.21 J for PARouting. At higher mobility of 110 m/s, QEEH maintains a deviation of 2.63 J, while CLEA-AODV, LFEAR, and PARouting rise to 4.12 J, 3.85 J, and 3.54 J, respectively. These results clearly show that QEEH balances node-level energy consumption more effectively than competing protocols. Although Table 3 does not explicitly list deviation values, the balanced consumption observed in Figure 10 is consistent with the improved network lifetime shown in Figure 11 and reported in Table 3, since uniform energy utilization directly contributes to longer survivability.

5.6 Network Lifetime and Node Longevity

Network Lifetime Vs. Dead Node Percentage graph shows that QEEH keeps the most nodes alive throughout the simulation period. QEEH achieves the longest network lifetime, with more nodes remaining operational over extended simulation time. For example, QEEH maintains 90% alive nodes beyond 700 seconds, whereas CLEA-AODV falls below the same threshold by 500 seconds. The correlation between Figure 11 and Table 3 confirms that QEEH's energy-aware handover mechanism prolongs network survival. The table below shows the comparison

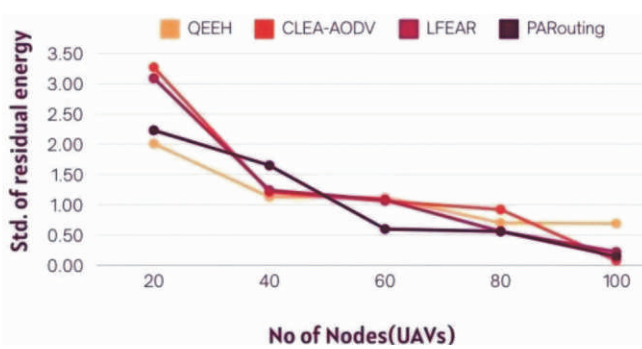

Figure 10. Standard Deviation of Residual Energy Vs. Number of Nodes

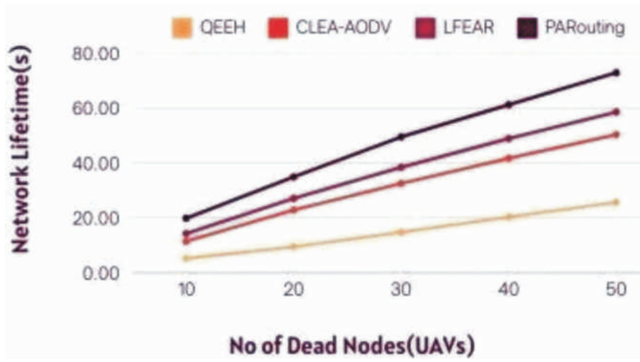

Figure 11. Network Lifetime Vs. Number of Dead Nodes

between different state of art approaches in terms of network performance parameters.

5.7 Routing Overhead Analysis

For FANETs, in which UAVs are extremely mobile, routing overhead has a profound effect on network performance. The experiments show that QEEH results in significantly lower routing overhead than PARouting, LFEAR, and CLEA-AODV for all mobility conditions. This is mainly because of QEEH's proactive routing mechanism, which reduces the number of route discoveries and repairs.

QEEH utilizes an optimal routing table updating mechanism that does not propagate control packets unless the need arises, thereby saving network bandwidth and traffic congestion. CLEA-AODV and PARouting, with their reactive route discovery schemes incur higher routing overhead via constant route rediscovery with higher node velocities. Moreover, the localized broadcast property of QEEH

keeps routing updates from spreading past the impacted neighborhood, curbing further control packet flooding unnecessary in the entire network. This effective routing overhead control enables QEEH to allocate additional bandwidth to data packets, which helps it in its enhanced throughput and minimized end-to-end delay.

Further comparison based on the baseline protocols are summarized in Table 4.

5.8 Handover Mechanism Effectiveness

The handover mechanism is essential in FANETs to ensure continuous communication since UAVs traverse the

Metric	QEEH	CLEA-AODV	LFEAR	PARouting	QEEH vs Best Baseline
Throughput (Mbps)	2.1	1.7	1.78	1.82	23% over CLEA-AODV
Packet Delivery Ratio (%)	91.4%	76.2%	78.3%	79.4%	20% over CLEA-AODV
End-to-End Delay (ms)	58 ms	84 ms	76 ms	69 ms	30% vs LFEAR
Energy Consumption (J)	57 J	79 J	75 J	71 J	28% vs CLEA-AODV
Residual Energy (J)	43 J	33.4 J	36.2 J	38 J	22% vs CLEA-AODV
Alive Nodes (at 150s)	92%	71%	74%	77%	21% vs CLEA-AODV
Network Lifetime (secs)	206 s	147 s	154 s	161 s	40% over CLEA-AODV

Table 4. Performance Comparison of QEEH with Different Baseline Protocols for 100 Nodes at 110 m/s Simulation Scenario

network very fast. The suggested QEEH protocol has an extremely efficient handover mechanism that minimizes packet loss and ensures minimal disturbance during node transfer. QEEH does this by anticipating handover nodes in advance before the current link fails. It analyzes node mobility behavior and residual energy to choose the most appropriate next-hop node to guarantee route stability and continuity of communication.

Conversely, PARouting and CLEA-AODV experience route failures frequently with their reactive handover processes, thereby causing higher routing overhead and packet loss. The protocols only initiate a rediscovery of routes after the detection of a link break, thereby creating delayed data delivery and longer end-to-end delays. LFEAR, despite outperforming CLEA-AODV in terms of link preservation, is still plagued by less than optimal handover efficiency due to its failure in proactive node selection.

QEEH's handover process also avoids network partitions via smooth handovers in high-mobility scenarios. This is supported by dynamic power control of transmission and adaptive beaconing processes, which constantly inform neighboring nodes of potential handovers without flooding the network with control packets. Therefore, QEEH not only keeps routing overhead at a minimum, but it also ensures high PDR and low end-to-end delay, thus enhancing general network performance.

The comparison clearly demonstrates that QEEH is superior to PARouting, LFEAR, and CLEA- AODV in terms of all performance metrics uniformly, i.e., throughput, PDR , end-to-end delay, energy consumption, SDE, and network lifetime. QEEH achieves this by optimized routing and power consumption strategically, with a high delivery rate of data, low latency, energy usage balance, and enhanced network lifetime, followed by QEEH being superior to other algorithms in handling routing overhead by pre-routing and neighbor broadcasting, limiting the transmission of control packets and network loading.Its smooth handover policy ensures uninterrupted connectivity between the nodes by pre-selecting the best next-hop nodes in advance, with low packet loss and high route stability even during massive mobility. All these are good reasons why QEEH is the best option for effective and reliable communication in dynamic FANET scenarios.

It should be noted that the results presented here are constrained by the simulated UAV density (up to 40 nodes). While QEEH consistently outperforms baselines in this range, its performance in high density networks (100+ UAVs) remains unexplored. Larger networks may introduce new challenges such as higher control overhead, increased interference, and potential Q-table explosion in reinforcement learning. These aspects form an important direction for future scalability studies.

6. Limitations and Real World Validation

While this study employs NS3-based simulations to evaluate the proposed QEEH framework, real world deployment is recognized as a critical next step. Simulation enables controlled experimentation under varying mobility, density, and energy configurations, offering an effective platform for proof of concept validation. However, it cannot fully account for environmental noise, hardware limitations, or unexpected interference in physical deployments.

To enhance the credibility and applicability of this research, future work will involve:

- Implementing QEEH in UAV testbeds equipped with programmable flight controllers and wireless transceivers.

- For measuring the computational complexity the multi-variable energy model and reinforcement learning operations may be demanding for resource constrained UAVs. While feasible in simulation, future work will focus on developing lightweight approximations and distributed/edge assisted learning to make QEEH deployable on low power UAV hardware.

Moreover, QEEH, in its current form, assumes all UAV nodes are trusted and does not incorporate explicit mechanisms for detecting malicious nodes or spoofing attacks during handover. In practice, adversarial UAVs could exploit handover events to launch denial-of-service or route manipulation attacks. While these threats are beyond the present scope, security-aware extensions of QEEH such as integrating anomaly detection into the reward function or coupling with lightweight cryptographic authentication during handover represent an important area for future work.

Conclusion

This paper presents QEEH, a Q-learning–based Energy Efficient Handover mechanism specifically designed for the high-mobility and energy-constrained environment of FANETs. QEEH introduces a distributed reinforcement learning framework that optimizes handover decisions by considering dynamic factors such as signal strength, node density, residual energy, and traffic load. The framework also integrates multi-state energy control modes-including active, sleep, hibernate, and wake-up-to extend the operational lifetime of UAV networks. The key contributions of this work include the development of a reinforcement learning framework tailored for 3D FANET mobility and constrained energy environments, the integration of adaptive power-saving modes within the handover decision process, and the implementation of NS3-based simulations benchmarking QEEH against state-of-the-art protocols such as CLEA-AODV, LFEAR, and PARouting under varying mobility and density conditions.

Simulation results demonstrate that QEEH achieves up to 23% higher throughput and a 20% improvement in packet delivery ratio compared to CLEA-AODV. It also reduces end-to-end delay by 30% and energy consumption by 28%, thereby enhancing network lifetime. Moreover, QEEH maintains 92% node survivability at the end of simulations, outperforming other protocols by 15–21%. These findings indicate that reinforcement learning can provide reliable, delay-tolerant, and energy-efficient communication within UAV swarms under dynamic conditions. However, the results should be interpreted as indicative rather than definitive, as the study is limited to NS3 simulations with moderate UAV densities (5–40 nodes). Real-world complexities such as hardware processing constraints, security threats (e.g., spoofing or malicious UAVs), and large-scale scalability were not addressed. In addition, Q-learning parameters were tuned empirically without exhaustive optimization, and the multi-variable energy model may be computationally intensive for lightweight UAVs.

Future work will focus on validating QEEH in UAV testbeds and outdoor field trials, refining reward functions through deep reinforcement learning, incorporating adaptive parameter tuning, and extending the framework to support federated learning for decentralized training across multiple UAV networks. These efforts will establish the robustness and deployment readiness of QEEH in real-world FANET environments.

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