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FL-CARE: Federated Learning-Based Contention-Aware and Energy-Balanced Routing for Dense FANETs

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Abstract: In dense multi-drone FANET environments, routing efficiency is often reduced due to constant competition for a wireless channel, frequent changes in network topology, and uneven energy consumption between UAV nodes. These factors lead to a decrease in the packet delivery ratio, an increase in delays on the busiest or most unstable routes, and a reduction in the total network lifespan. Although many existing routing methods utilize mobility forecasting or reinforcement learning, most are based on independent decision-making by individual agents. As a result, such approaches may create a significant service load and insufficiently account for competition for the communication channel, as well as the fair distribution of energy consumption between network nodes. To overcome these integrated challenges, this paper proposes FL-CARE, a Federated Learning-based Contention-Aware and Energy-balanced Routing protocol. In FL-CARE, each UAV acts as a learning agent using a multidimensional state (predicted link stability, channel contention, queue occupancy, residual energy) and a tail-latency-sensitive reward function. A lightweight federated learning mechanism enables collaborative, swarm-level intelligence with bounded communication overhead. Extensive MATLAB simulations demonstrate that FL-CARE outperforms state-of-the-art protocols MP-QGRD and RL-MPEAOLSR, improving PDR by 12-18%, reducing average delay by 20–25% and tail latency (p99) by up to 30%. Additionally, FL-CARE yields a 15-22% energy consumption per bit delivered, and control overhead reduction of 35-45%, and advances network lifetime by approx. 25% in dense network deployments. The proposed framework maintains low computational and communication overhead through lightweight local learning and compact federated model updates, while adaptive aggregation intervals facilitate efficient collaborative learning and scalable operation under varying network conditions. These simulation results validate the holistic integration with federated multi-agent learning, with emphasis on contention awareness and energy balancing is essential for scalable and efficient routing in next-generation dense FANETs.

Keywords: Flying Ad Hoc Networks, Federated Learning, Contention-Aware Routing, Energy-Efficient Routing, Multi-UAV Networks

Introduction

Flying Ad Hoc Networks (FANETs) enable collaborative communication between among several Unmanned Aerial Vehicles (UAVs) or drones (UAVs) for applications like disaster response and environmental monitoring (Akmuratovich et al., 2021). Unlike terrestrial networks, FANETs operate in a dynamic 3D environment, characterized by rapid movement and constant topological change (Al-Bataineh et al., 2026). These inherent characteristics are a major difficulty in the development of effective and consistent routing protocols, which is especially true in cases where FANETs are deployed in densely populated region with a great number of UAVs which have a small geographical operating area (Almasoud, 2023; Baktayan et al., 2024). Several UAVs in high-density FANET nearly at the same time are sharing wireless medium, hence causing the continuous channel packets collisions, poor connectivity, and jammed network access (Bekal et al., 2024). The resulting contention does not only degrade throughput and Packet Delivery Ratio (PDR) but also makes performance appalling, end-to-end latency spikes, especially on the far right of the delay distribution (Cai et al., 2026). For many FANET instead, worst-case latency is more appropriate in applications, e.g. real-time surveillance or emergency response than average delay which defines success of a mission (Chu et al., 2025; Das et al., 2024). Simultaneously, UAVs are significantly constrained limited by the energy resources onboard the swarm, and asymmetrical power use within the swarm may cause collapsing of routing paths, node premature failures and fragmentation of the network (El-Basioni, 2025; Gharib et al., 2022). That is why, routing decisions in dense FANETs are required to combine the opportunities to deal with contention, energy efficiency, latency, and scalability as an objective, which has not been achieved by existing routing so far approaches (Das et al., 2024; El-Basioni, 2025; Gharib et al., 2022). Conventional MANET and VANET routing schemes do not fit well in FANET environment because they are based on relatively static topology assumptions and two-dimensional mobility models. Reactive routing algorithms have too much route discovery flooding which in dense FANETs is prohibitively expensive and makes channel congestion worse (Hao et al., 2024; Li et al., 2023). Even proactive routing protocols, although able to minimize route discovery delay, impose heavy control overhead since there is periodic update of topology, therefore, making them unproductive at low mobility and low energy budgets. Geographic routing protocols are based on the idea that routing involves multiple steps. This approach gained significant attention in FANET research because it requires minimal state information and scales efficiently, but they need to be dependent on periodic Hello messages and instant position information which frequently leads to dead knowledge of neighbors, results in a short lifetime of links, and routing failures which commonly occur in highly dynamic scenarios (Li and Sun, 2025; Maakar et al., 2025; Maleki et al., 2025). Subsequent studies (El-Basioni, 2025; Gharib et al., 2022; Prabha et al., 2025; Prakash et al., 2024; Prasad and Sasikumar, 2024; Slimani et al., 2025; Steinhoff, 2021; Tarif et al., 2025; Wang et al., 2008; 2025; Wijesekara and Gunawardena, 2023; Yang et al., 2024) have tried to solve these problems with the integration of mobility prediction and Reinforcement Learning (RL) to FANET routing. Mobility-prediction-based geographic routing schemes enhance stability of links by prediction of future node locations, hence controlling routing failures due to fast topology changes (El-Basioni, 2025; Gharib et al., 2022). RL-based routing methods also help in increasing flexibility as the nodes are able to acquire optimal forwarding strategies depending on network measurements. Nevertheless, in spite of such advances, there are still gaps, learning-based routing algorithms are generally created as single-agent systems where every UAV is an independent learner which studies local observations (Prakash et al., 2024; Prasad and Sasikumar, 2024). Isolated learning would not capture this as swarm-level behavior tends to make the wrong decisions in large networks where local optima actions possess the international outcomes. In addition, the majority of the available learning-based routing methods consider enhancing the average performance measures like mean delay or average energy consumption, without considering tail latency behavior and energy equality between nodes (Slimani et al., 2025; Steinhoff, 2021). In dense FANETs, a little segment of highly loaded UAVs also tends to turn into routers hotspots, quickly draining their energy sources and creating network instabilities. Although some protocols it reduces routing overhead by use of adaptive Hello intervals or by selection flooding, they seldom impose severe restrictions on control traffic. Consequently, routing overhead may continue to increase uncontrollably in the contention and annihilating the advantages of learning-based optimization (Tarif et al., 205). The other severe weakness of the existing FANET routing solutions is that they do not explicitly specify this contention awareness. Contention on channels is commonly regarded as an implicit side effect, not as a serious issue of a first-class routing metric. Nevertheless, in large FANETs, contest essentially influences performance in networks by affecting the packet loss, queue delay, retransmissions, energy and cost-per-bit delivered. Contention is ignored resulting in routing decisions that unwillingly direct traffic around overloaded areas of the network, aggravating delay and energy efficiency (Wang et al., 2025, 2008; Wijesekara et al., 2023; Yang et al., 2024). Hence, a good FANET routing protocol should actively have contention consciousness about its decision-making process.

To address these issues, this research paper has come up with a new routing framework integrating contention awareness, energy balancing and federated learning into one single design that is tailored on dense and highly dynamic FANETs. Federated learning provides a potential paradigm of swarming the use of intelligence by providing sensing swarms with the ability to train collaborative models without the requirement of central exchange of control or raw data. The approach of sharing miniature model demands that UAVs share federated learning greatly diminishes updates instead of detailed state information overheads communication-wise and it maintains scalability. More to the point, it allows swarm level learning, routing policies to develop in accordance with the experience of the entire network, not only local observations in isolation. The proposed system is routing and reinforcement-learning-optimized link-state protocols proposes a federated multi agent-based learning system where the UAVs learn locally. Multidimensional network acts on observation-based routing policy. These observations include predictable channel link stability, degree of channel contention, queue buffer, and remaining energy. The process of learning is operated with the tail-latency-sensitive and contention-conscious reward function making sure that the routing decisions do not increase worst-case delay and energy spending achieved bit delivery with high PDR. In addition, the suggested framework imposes determined limits on routing control overhead by budget and event-based signaling mechanisms, inhibiting the uncontrolled expansion of the control traffic at high density of nodes.

The routing framework suggested has practical FANET constraints in mind, such as onboard limited computing, energy deficiency and lack of centralization coordination. Wide simulators testify that the offered strategy contributes much is superior to state-of-the-art mobility-prediction-based and reinforcement-learning-based dense FANET routing protocols. Through a combined optimization on contention awareness, energy balance and tail latency by means of federated learning, the model in question provides a powerful one and next-generation scalable UAV networks solution.

Motivation

This study has been motivated by the fact that dense swarms of UAVs have increasingly been deployed in practice and have to communicate reliably, with low latency with low energy consumption (Das et al., 2024; El-Basioni, 2025; Gharib et al., 2022). Although recent routing protocols have shown encouraging progress with the use of either mobility prediction or RL, their effectiveness deteriorates with time as the network density grows (Maakar et al., 2025; Maleki et al., 2025; Prabha et al., 2025; Prakash et al., 2024). Pervasive FANETs suffer critical packet collisions, retransmission and uncertain delay burst because of persistent wireless contention that is the main performance bottleneck in the dense FANETs. The majority of routing systems do not take this issue into consideration as contention is viewed as a by-product as opposed to a design consideration (Prasad and Sasikumar, 2024; Slimani et al., 2025; Steinhoff, 2021). In addition to this, the majority of routing protocols implemented through learning are independent and every UAV makes routing decisions on an adaptive basis, based on local observations only. This type of single-agent learning does not make use of the collective intelligence of the swarm and leads to routing of hotspots (Yang et al., 2025; Yue et al., 2024; Zhang et al., 2025; Zhao et al., 2025). This causes an imbalanced energy consumption and consequently, the life span of the network is lessened.

As illustrated in Fig. 1, the dense deployment of multiple UAVs leads to frequent shared-medium contention and requires multi-hop communication, which together exacerbate these challenges.

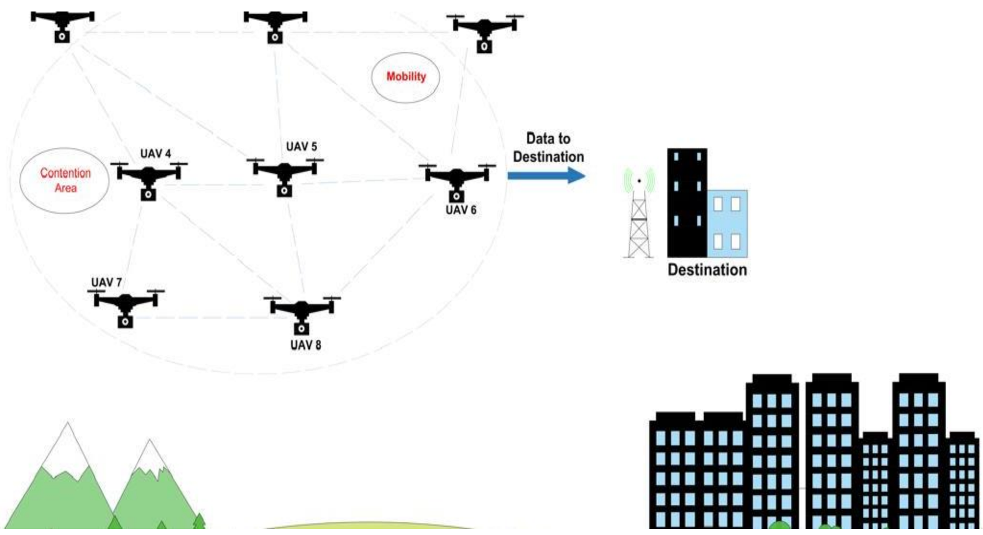

Fig. 1: Dense FANET topology illustrating multi-UAV communication, shared wireless medium contention and multi-hop

The other important gap is in the absence of strict control over routing overhead. Adaptive mechanisms can help to decrease the overhead on average; however, they are not able to avert the rise of overhead in poor conditions. These limitations highlight the need of a completely new routing approach combining collaborative learning with clear contention awareness, energy fairness, and bounded control overhead. Centralized learning is often unsuitable for dense FANET environments because it requires continuous transmission of network-state information from UAVs to a central controller, leading to increased communication overhead, higher latency, scalability limitations, and potential single-point-of-failure issues. In contrast, federated learning enables UAVs to perform local training and exchange only compact model updates, thereby reducing communication burden while maintaining distributed operation and improving adaptability to rapidly changing network conditions. These advantages make federated learning particularly suitable for dense and highly dynamic FANET deployments Such solution can be naturally achieved through Federated Learning which allows distributed, privacy preserving, and communication efficient collaboration between UAVs (Zheng et al., 2024; Zhou and Liu, 2025). This research work aims to bridge the gap between advances in learning-driven networking theory and the practical demands of dense FANET deployments.

The primary objectives of this research are:

- To analyze the limitations of existing FANET routing protocols in dense multi-UAV environments
- To design a federated learning-based routing framework capable of collaborative swarm-level intelligence
- To incorporate explicit channel contention awareness and energy balancing into routing decisions
- To minimize packet loss, delay, tail latency, and energy consumption in dense FANET deployments

Scientific Contributions

The key scientific contributions of this work are summarized as follows:

a. A federated multi-agent learning–based routing framework for dense FANETs that enables collaborative swarm-level intelligence while strictly bounding routing control and learning overhead
b. A contention-aware and energy-balanced routing decision mechanism that explicitly incorporates channel contention, predicted link stability, and energy fairness to minimize energy per delivered bit and tail end-to-end latency
c. A tail-latency-sensitive reward formulation and bounded control strategy that jointly optimizes PDR, worst-case delay (p95/p99), and network lifetime under high node density and fast mobility

Literature Review

FANETs routing has unique difficulties following the high mobility, which is three-dimensional velocity, high frequency of the topology and strict energy limit of UAVs (Almasoud, 2023; Gharib et al., 2022). Early research mostly borrowed protocols of Mobile Ad Hoc Networks (MANETs) and Vehicular, reactive, proactive and hybrid Ad Hoc Networks (VANETs) (Almasoud, 2023). Their methods do not work well in FANETs since they rely on only relatively stable network topologies and produce too much control overhead due to the continual route discovery or periodic updates, not sustainable in the fast case of mobility (Gharib et al., 2022). Das et al., 2024 proposes a mobility-aware geographic routing algorithm of FANETs that has the crucial goal of MP-QGRD of enhancing reliability in routing and energy efficiency in extremely dynamic tests in UAVs.

The authors integrate calculated mobility prediction based on extended Kalman filter with adaptive Hello controlling programs to reorganize packet schedules in order to keep the neighbourhood information up to date and with minimum control overhead, and use Q-learning-based routing decisions, which collaboratively makes use of link stability, residual. distance to destination, energy, and distance to destination. Since simulation models show an increase in PDR, a reduction in delay, and minimized energy usage in comparison with GPSR, QGeo, and QMR. However, the in large-scale networks, approach is more computationally complex, which is an indication that it requires more optimization towards scalability.

Primarily, (El-Basioni, 2025) focuses on enhancing the reliability of the routing and efficiency of the energy of highly dynamic routing FANETs by suggesting a Multidimensional Perception based RL and Link State Routing Energy-Aware Optimized (RL-MPEAOLSR). The methodology combines RL and a more powerful framework of OLSR, in which routing decisions are made. They have multidimensional perception parameters like node mobility, link stability, residual energy, congestion and link expiration time and multipoint relays which are adaptively chosen so as to minimize control overhead. There are improvements in experimental simulations which is Delay, bandwidth consumption and density of network used versus traditional OLSR based protocols. Better disaster and large-scale adaptability are shown in the result scenarios, but there is a constraint in terms of scalability, computation, and performance in case of extreme mobility and security threats.

Gharib et al. (2022) addresses the faults of traditional geographic routing in FANETs, especially temporary communication blindness and untrustworthy connection due to high mobility of nodes. The key objective is aimed at improving routing reliability and real-time performance in aerial networks with high dynamic. In order to do so, the authors come up with an Airborne Greedy Geographic Routing (AGGR) protocol which integrates an adaptive Hello mechanism, which varies control message intervals according to relative node motion, having a relative motion greedy forwarding algorithm that is motivated by relative motion range of communication range, time-to-enter. Results of simulation indicate better PDR, throughput, and lower delay than GPSR and AeroRP. Nonetheless, the strategy includes a higher degree, computational complexity and makes an assumption about positioning that may act as a barrier to scalability in credulously thick or confined environments.

Li et al. (2024) suggested a prediction-based reactive-greedy routing protocol (LPAR) FANETs, whose primary goal is to enhance. It stabilises along routes and delivery of packet over highly dynamic UAV environments. The methodology presents a Time-Interval based Link Stability (TILS) measure that is a mutual model of node location, velocity, future motion prediction, and adaptive HELLO packet control and an active-to-unscrupulous forwarding switch to cope with link disruptions effectively. Simulation NS-3 results have much higher PDR, lower high-mobility end-to-end delay scenarios and reduced routing overhead in comparison to AODV, RGR, LAOD and LB-OPAR. The protocol however has a delay marginally higher in low mobility or dense network which is characterized by higher computer complexity through prediction schemes.

To improve scalability, positional data made use of geographic routing protocols decisions in local forwarding (Das et al., 2024; Gharib et al., 2022). Although this minimizes the global routing state requirement maintenance and behavioural dependency on periodical beaconing (e.g., Hellos messages) and instantaneous location information can frequently lead to old fashioned neighbour table, short term links and routing fails in conditions of high mobility (Das et al., 2024). To deal with this, in order to predict mobility, methods of mobility prediction have been combined to approximate future node locations, which increases the stability of links and minimizes packet loss (Das et al., 2024; Li et al., 2023). However, prediction-based schemes do not work in dense situations FANETs in which wireless channel contention is one of the main performance bottlenecks (Zhang et al., 2025).

As a result, routing mechanisms, in which Reinforcement Learning (RL) is applied, have become popular because of their capability to operate under the changing FANET conditions (Mohammad et al., 2025; Steinhoff, 2021). These approaches allow UAVs to achieve the best routing policies by making contacts with the environment and maximizing reward. Calculations such as link stability, hop count, energy and delay are used to compute functions (El-Basioni, 2025). Some studies apply RL to augment geographic routing to improvement next-hop choice, and others incorporate it link-state protocols in order to minimize the flooding overhead in dense networks (Tarif et al., 2025). Although promising, the majority of the RL-based FANET protocols use single-agent learning, in which each UAV understands itself without being instilled out of local observations (Zhang et al., 2025). This laboratory learning does not explain the swarm-level interactions, which can tend to result in suboptimal global performance especially in dense deployments, where the individual routing policy contributes to a network contention, energy balance, and latency.

One of the weaknesses in a lot of FANET routing research is the absence of a critical overview of plain awareness of contention (Zhang et al., 2025). Quite a number of protocols have the implicit assumption that stability in links or reduction in the hop count will reduce congestion, an invalid assumption in dense scenarios where there is a constant channel contention resulting in packet collisions, reroutes and delays in queue, waste of power per bit conveyed (Wang et al., 2025; Zhang et al., 2025; Zheng et al., 2024). In addition, where average end-to-end delay is usually optimized, tail latency measures are also used (e.g. 95th/99th percentile delay)-necessary in time and sensitive UAV deployments- are still, not yet, zero and largely unexplored (Zheng et al., 2024). The energy efficiency is often also considered only on total basis and consumption, in which we pay enough attention to energy fairness or energy per delivered bit, which has the potential to cause routing hot points and early network shelling (Hao et al., 2024; Maakar et al., 2025; Wang et al., 2008). Although some protocols attempt to minimize overhead through adaptive Hello interval or selective flooding, they are seldom. Restricted by the control traffic strictly, to be increased in high density beyond control and mobility (Li and Sun, 2025).

More so, the possibilities of shared learning paradigms such as: FANET routing has little research on Federated Learning (FL) (Baktayan et al., 2024; Zhou and Liu, 2025). FL enables distributed intelligence provision with the support of the cooperative model training and reducing communication overhead and preserving scalability (Maakar et al., 2025; Maleki et al., 2025; Zhou and Liu, 2025). It is not so integrated with contention-aware, energy balanced, though. Dense FANETs routing has not been sufficiently researched (Zhou and Liu, 2025). These identified the gaps, when combined, support the necessity of a new routing framework, which is synergistic uses a concerted multi-agent learning, overt contention awareness, power matching and limited bandwidth to control overhead to achieve good, reliable, and scalable communication in dense FANET environments (Zhou and Liu, 2025).

Shou et al. (2026) is concerned with the enhancement of routing in FANETs, especially at those scenarios in which ultra-high-speed UAVs generate large interactions and unstable communication connections. The paramount goal of the work is to create an adaptive routing scheme with the prospect to preserve quality communication within the extremely dynamic UAV swarm networks. To realize this, the authors present a deep reinforcement learning routing strategy dubbed the RDQN-HERP routing strategy, which combines an experience replay mechanism hierarchy based on priorities and an instability factor to control the learning process. The approach will train the DRA model in a virtual environment of high-speed UAV network and test the model with the traditional routing protocol compared to AODV, DSR, GPSR, Hybrid, and QGEO. The experimental results have shown that the proposed strategy will greatly enhance the rate of packet delivery, minimize end to end delay, minimize per hop delay, and better control queue length. Nevertheless, even with these increases in routing performance and routing flexibility, the method exhibits increased energy consumption with the need to further optimize energy use in high-speed FANET-based communication systems.

Xu et al. (2026) takes into consideration the currently rising role of FANETs in emerging low-altitude economy, in which UAVs are becoming a part of IoT and next-generation wireless infrastructure to serve in smart cities, disaster response, and environmental sensors. The most important goal of the work is to come up with a smart networking system that would be able to sustain multifunctional swarms of UAVs within the most dynamic and resource-saturated backgrounds. To achieve this, the authors present a foundation model-based architecture that involves sensing, communication, control, and security via a cloud-edge-air cooperative structure. The process utilizes large-scale foundation models to optimize cross-layers and make decisions in real-time at the network edge, which effectively helps coordinate UAV nodes. The results suggest that such smart models can enhance adaptability, scalability, and operational efficiencies and can be nearly close to theoretical performance limits in complicated aerial networks. Nonetheless, the framework also points to the real-world implementation issues, such as computational cost, model complexity, and light-weight training and reliable inference functions that are necessary to implement AI in the real world. The paper by

Husnain et al. (2026) discusses the problem of routing optimization in Internet of Vehicles (IoV) networks when the high mobility, dynamics of topology, and intermittency of connectivity make established routing protocols like AODV, DSR and GPSR less effective. The key idea of the work should be to create an adaptive routing architecture enhancing reliability, energy efficiency, and scalability in IoV settings. To this end, the authors introduce COANET, a bio-inspired routing protocol modeled after Crayfish Optimization Algorithm (COA) to replicate crayfish behaviors in the foraging, competition and summer resort so as to balance exploration and exploitation during route determination. The methodology is comprised of energy conscious clustering, multi-metric analysis and hybrid exploration-exploitation approaches to optimize the latency, the energy consumption and the packet delivery performance. The simulation data prove that COANET results in the improvement of the packet delivery ratio, the decrease of end-to-end delay and management overheads much in comparison to the use of the current routing protocols. Nevertheless, the method might have to be reconsidered in the conditions of adversarial scenarios and real-world IoV applications to thoroughly test its resilience and power consumption in the scales of the implementing large systems.

The study conducted by Chen et al. (2026) is dedicated to the enhancement of object identification in the UAV aerial imagery, where factors like extreme changes in the scale and the bird-eye angles combined with the different environment-related factors degrade the efficiency of traditional detection approaches. The main idea behind the work is the creation of a light and efficient multimodal detection network that can work on resource-limited UAV platforms. In their quest to do so, the authors introduce ATM-Net, a multimodal RGBinfrared fusion framework incorporating three major elements: The Asymmetric Recurrent Fusion Module (ARFM) to maintain the balance between the interactive features of cross-modal and the Tri-Dimensional Attention (TDA) Network to sustain the enhancement of feature representation among multiple dimensions and the Multi-scale Adaptive feature Pyramid Network to enhance the detection of objects at multiple scales. The setup of the methodology is a combination of the multimodal feature fusion and lightweight architecture design to achieve high detection rates and less computational complexity. The experimental findings, on the VEDAI and DroneVehicle datasets, show that ATM-Net is able to perform high detection accuracy with far fewer parameters than other approaches, thereby being applicable in real-time use with UAV edge deployment. Nevertheless, the method can still be improved by adding more sensing modalities, time modeling and rotated object detection to enhance robustness in real-world complex aerial environments.

Problem Formulation

Dense FANETs operate under highly dynamic topology, shared wireless channels, and stringent energy constraints, making reliable and scalable routing a challenging task. Let $G(t) = V, E(t)$ denote the time-varying network graph, where Vrepresents the set of UAVs and $E(t)$ denotes the set of active communication links at time t. For a UAV v_i, routing decisions depend on the predicted link stability $L_i(t)$, channel contention $C_i(t)$, queue occupancy $Q_i(t)$, and residual energy $E_i(t)$. The objective is to determine a routing policy $R(t)$that maximizes communication reliability while minimizing latency, energy consumption, and routing overhead. Accordingly, the routing optimization problem is formulated as follows:

$$\max_{R(t)} J\big(R(t)\big) = \omega_1 PDR(t) + \omega_2 Rel(t) - \omega_3 D_{tail(t)} - \omega_4 E_{bit(t)} - \omega_5 O_{ctrl(t)} - \omega_6 C_{avg(t)} \quad (1)$$

Subject to:

$$C_{i(t)} \leq C_{max}, \forall\, v_i \in V \quad (2)$$

$$Q_{i(t)} \leq Q_{max}, \forall\, v_i \in V \quad (3)$$

$$E_{i(t)} \geq E_{min}, \forall\, v_i \in V \quad (4)$$

$$\sum_{t=1}^{T_w} C_{ctrl(t)} \leq B_{max} \quad (5)$$

Where $J\big(R(t)\big)$ denotes the overall routing objective value for the selected routing policy $R(t)$. In Eq. (1) $PDR(t)$ represents the packet delivery ratio, while $Rel(t)$ denotes route reliability based on predicted link stability. $D_{tail(t)}$ represents tail end-to-end latency, such as p95 or p99 delay. $E_{bit(t)}$ denotes the energy consumed per successfully delivered bit, $O_{ctrl(t)}$ represents routing control overhead, and $C_{avg(t)}$ denotes the average channel contention level in the network. The coefficients ω_1, ω_2, …, ω_6 are non-negative weighting factors used to balance the importance of reliability, latency, energy efficiency, overhead, and contention.

The constraints in Eqs. (2)-(5) ensure that the selected routing policy operates within practical FANET limitations. Eq. (2) limits the channel contention level experienced by UAV. Eq. (3) prevents excessive queue occupancy and packet buffering delay. Eq. (4) avoids selecting UAVs with critically low residual energy as forwarding nodes. Finally, Eq. (5) restricts the total number of routing and learning-related control messages within the observation window T_w. To solve this optimization problem, the proposed FL-CARE framework integrates contention-aware routing, energy-balanced forwarding, bounded control-overhead management, and federated collaborative learning to achieve reliable, scalable, and energy-efficient communication in dense FANET environments.

Materials and Methods

To systematically address the challenges identified in dense and highly dynamic FANET environments, it is essential to first establish a clear system-level understanding of the network characteristics and operational assumptions. Accordingly, this section introduces the underlying system model and network assumptions that form the foundation for the proposed routing framework. These assumptions capture the dynamic topology, shared wireless medium, and energy constraints of multi-UAV networks and provide the basis for the design of the proposed FL-CARE routing mechanism.

System Model and Network Assumptions

This section describes the system model and network assumptions adopted in this work to design and evaluate the proposed federated learning–based contention-aware and energy-balanced routing framework for dense FANETs. We consider a dense FANET consisting of a set of N UAVs deployed within a three-dimensional operational space. The FANET is modeled as a time-varying directed graph $G(t) = (V, E(t))$, where $V = \{v_1, v_2, \dots, v_N\}$denotes the set of UAV nodes and $E(t) \subseteq V \times V$represents the set of wireless communication links at time t. A directed link $(v_i, v_j) \in E(t)$ exists if UAV $v_j$is within the communication range of UAV $v_i$and the wireless channel conditions allow successful packet transmission. Each UAV is equipped with a Global Positioning System (GPS) module that provides real-time information about its three-dimensional position and velocity. UAV mobility follows a continuous-time 3D mobility model with variable speed and direction, capturing realistic flight dynamics. Due to node mobility, the network topology changes frequently, resulting in short link lifetimes and intermittent connectivity. Communication among UAVs is multi-hop in nature, and no fixed infrastructure or centralized controller is assumed. All UAVs have a similar wireless media and access scheme based on contention. The channel contention, retransmission and collisions of packets when transmitting between many UAVs pose a problem in the system particularly in dense deployment. The metrics that are observable and used to estimate local channel contention include channel busy time, packet collision rate, and medium access delay. There is a congestion level that is evident in the existing network, it slows down the delay of packets, decreases the reliability of links, and enhances energy use. UAVs operate on small power sources that supply power to communication, computation, and flight. The routing decisions determine the amount of energy that the network consumes to transmit, receive and retransmit packets and control messages. All UAVs are initiated with the same energy. Network lifetime is reduced due to asymmetric forwarding of traffic that results in energy hotspots that run out batteries of UAVs which are transporting heavier traffic. The routing framework proactively utilizes the residual energy in the process of choosing routes that allocate energy consumption between swarm members and of minimal energy consumption on data transfer. The data traffic is performed through two ways, scheduled operations and event-based operations, which are selected depending on the application requirements. The network employs multi-hop routes to transmit the packets to the ground stations or the destination nodes. The use of a limited packet buffer is like a queue of incoming packets and outgoing packets. The queue occupancy is used to show that certain sections are very congested and are used to establish the duration vehicles should spend in the traffic lanes. The end-to-end latency and packet loss rise as queues become congested in the case of high traffic. The system is based on the self-learning objects- UAVs, which detect the network condition, predict the consistency of links, measure channel rivalry, and monitor the remaining power and queue position. The lightweight reinforcement learning adopted by UAVs adapts the routing decisions according to these observations. Federated learning allows swarm intelligence, wherein the UAVs transfer short model updates rather than complete system information. Federated aggregation is done by cluster leaders which may serve as rotating aggregators as well, and is more scalable and reliable. To avoid degradation of performance by having numerous devices interacting in a similar space, the system restricts the exchange of messages in control and learning processes.

The system model along with network assumptions show that FANETs with dense node distribution need routing protocols which can manage quick node movements, persistent wireless interference, unequal power consumption and restricted system capabilities. The defined assumptions demonstrate how multi-UAV environments function with their dynamic nature and restricted resources but a routing solution requires these findings to develop adaptable systems which maintain energy distribution equilibrium and adapt to changing conditions. The following section describes the proposed FL-CARE routing framework which implements distributed routing through federated learning to achieve contention awareness, energy balancing and tail-latency optimization.

Proposed FL-CARE Routing Framework

This with the system characteristics and assumptions given in the foregoing subsection, the system description takes the following form- It describes the suggested FL-CARE framework, which is aimed at overcoming the limitations of the operating FANET routing at dense and highly dynamic scenarios. FL-CARE simultaneously optimizes the performance of the system in terms of packet delivery reliability, tail latency, energy efficiency and scalability.

The organization should conduct its operations using a system that strictly controls all its overheads. The architecture of the framework has a fully-distributed system architecture. The routing strategy makes every UAV choose forwarding routes based on autonomous decision-making that relies on its present position. The system functions based on observations whereby it learns the swarm-level federated learning sessions which are conducted on a scheduled basis. The system is intelligent to generate a control data that is not more than what is necessary. FL-CARE framework has two algorithmic core algorithms that act as a single system. Algorithm 1 (Local Routing and Learning) which checks the decision cycle of the system works in accordance with the rules of it to find out what the UAVs should do - Every agent in the system must monitor its present environment. The system employs a multidimensional state that contains four performance indicators that are forecasted link stability and contention as well as queue occupancy and residual value energy) which calculates a contention-sensitive and energy-optimal utility to each neighbor to choose which is the best next-hop, and reimburses its local reinforcement learning policy according to a tail latency sensitive reward.

Algorithm 2 (Federated Learning Aggregation) activates swarm-level intelligence through its designated aggregator UAV which retrieves compact model updates from participating nodes while performing verification against the strict control-overhead budget and executing weighted aggregation to create an improved global routing model and broadcasts this model back to the swarm. The symbiotic process allows individual UAVs to enable nodes to make adaptive routing choices through their ability to obtain benefits from the shared knowledge base. The system maintains network performance through its experience-based operation which enables it to scale up and maintain strong operational stability. At any time, instant t, each UAV $v_i$identifies its set of candidates forwarding neighbours based on the current network connectivity. The forwarding neighbours set is defined as $\mathcal{N}_i(t)$, as given in Eq. (6):

$$N_i(t) = \{ v_j \epsilon V \mid (v_i, v_j) \in E(t) \} \tag{6}$$

At each routing decision epoch, UAV $v_i$executes Algorithm 1, which governs local routing behavior. As part of Algorithm 1, the UAV constructs a multidimensional local state vector $\mathbf{s}_i(t)$, defined in Eq. (7), incorporating predicted link stability $\hat{L}_{ij}(t)$, channel contention level $C_i(t)$, queue occupancy $Q_i(t)$, and residual energy $E_i(t)$:

$$s_i(t) = [\hat{L}_{ij}(t), C_i(t), Q_i(t), E_i(t)], \forall v_j \in \mathcal{N}_i(t) \tag{7}$$

The term $\hat{L}_{ij}(t)$denotes the predicted stability of the wireless link between UAV $v_i$and its neighbor v_j, obtained through short-term mobility prediction using position and velocity information. The $C_i(t)$ is a parameter that reflects the level of contention of the channel that UAV experiences which is congestion of medium access due to heavy deployments. The queue occupancy $Q_i(t)$ captures the local buffering and delay heading, and $E_i(t)$ denotes the residual energy of UAV v_i. A combination of these parameters represents a multidimensional representation of mobility, congestion, and energy conditions, and allowing informed and adaptive routing decisions. Link stability prediction predicts changes in the topology that occurs rapidly so that it can be anticipated and adapted to mobility-prediction-based routing, and explicit and contention and queue modelling enable the logic to react to the congestion effects which dominate dense FANET performance. Based on this is the state that is observed, Algorithm 1 assesses each candidate neighbor based on the contention-aware and energy-balanced utility defined in the Equation of (8). Selection is done based on the next-hop UAV it is this utility that maximization as in Eq. (9) strives to guarantee that routing decisions are not made to cause congested links, redistribute energy consumption equally and reduce the amount of energy spent on serving a given bit:

$$U_{ij}(t) = w_1\hat{L}_{ij}(t) - w_2C_i(t) - w_3Q_i(t) - w_4E_{bit,ij}(t) - w_5\sigma_E(t) \tag{8}$$

Eq. (8) defines the contention-aware and energy-balanced utility function $U_{ij}(t)$, which quantifies the suitability of selecting neighbor $v_j$as the next hop. The coefficient w_1 weights the importance of link stability prediction function $L_i(t)$, and encourages routes with an expected stability of stable. The weights expressed as w_2 and w_3 form a penalty occupancy $Q_i(t)$, respectively, to prevent congested routes. The expression $E(t)$ by w_4, symbolizes the energy used for every successfully transmitted bit through the neighbor v_j energy-efficient forwarding. Finally, $\sigma_E(t)$, scaled by w_5, represents the variance energy among neighboring UAVs, which discourages routing decisions that create energy hotspots and energy equity in the swarm. Equation (9) depends on the best next hop index UAV v_j* by choosing the neighbor with which the utility function $U_i(t)$ is maximal out candidates for $N(t)$. This greedy maximization guarantees that every forwarding decision made locally optimizes link stability, congestion avoidance, and energy balance, and is driven by learned policy updates:

$$v_j^* = arg \max_{v_j \in \mathcal{N}_i(t)} U_{ij}(t) \tag{9}$$

The expectation operator captures the stochastic network dynamics, while γ is the discount factor controlling the importance of future rewards. The notation $PDR(t)$ encourages reliable packet delivery, whereas $D_{tail}(t)$ represents tail end-to-end latency (p95/p99), directly this solution will address delay-sensitive FANET applications:

$$\max_{\pi} \ \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \left(PDR(t) - \lambda_1 D_{tail}(t) - \lambda_2 E_{bit}(t) - \lambda_3 C(t)\right)\right] \tag{10}$$

Eq. (10) defines the long-term reinforcement learning objective optimized by the local policy π_{θ_i}. The expectation operator reflects stochastic network dynamics, while $\gamma$is the discount factor controlling the importance of future rewards. The term $\mathrm{PDR}(t)$ encourages reliable packet delivery, whereas $D_{\mathrm{tail}}(t)$ represents tail end-to-end latency (p95/p99), directly addressing delay-sensitive FANET applications. The penalties $E_{bit}(t)$ and $C(t)$, weighted by $\lambda_2$and λ_3, discourage energy-inefficient and contention-heavy routing behavior. This is the objective function that aligns precisely with your goal of minimizing worst-case latency and energy per delivered bit rather than only average performance. By explicitly incorporating tail latency into the reward formulation, Algorithm 1 guarantees that routing decisions remain robust for delay sensitive FANET applications, which is an aspect that existing learning-based routing does not address schemes.

In order to avoid isolated and localized learning, FL-CARE presents collaborative intelligence for effective reasoning and decision through Algorithm 2, which describes how federated learning takes place. Algorithm 1, on one hand, mainly tackles problems related on per-node routing decisions, Algorithm 2 repeatedly gathers knowledge of the UAV swarm. At adaptive intervals based on network dynamics, the control budget will be available. The UAVs involved in executing algorithm 1 transmit compact updates $\Delta\theta_i$ to of their local models to a temporary aggregator UAV. Algorithm 2 implements the global routing model through the weighted aggregation applies the rule specified in Eq. (11) and broadcasts the updated model among the UAVs. This process allows for learning at the level of the swarm without exchanging the underlying state information, which is a reducing the communication overhead and maintaining scalability. Additionally, it has to be possible to specify routing policies. to evolve based on collective network experience:

$$\theta^{global} = \sum_{i \in V_p} \alpha_i \left(\theta_i + \Delta\theta_i\right) \tag{11}$$

Eq. (11) describes the federated aggregation rule used in Algorithm 2. Here, θ^{global} represents the aggregated global routing model, $V_p \subseteq V$ is the set of participating UAVs in the current communication span federated round. In this stage, the notation θ represents the locally maintained replica of the previous global model at UAV v_i, and $\Delta\theta_i$ denotes the update learned in this federated round. The weight α captures the contribution of UAV v_i with respect to aggregation. The proposed collaborative swarm-level learning without the need to share raw data, ensuring scalability and minimizing data communication overhead.

An essential component of FL-CARE is the enforcement of an upper bound for routing and relay functions to ensure that they remain within reasonable limits. These functions are designed to guarantee control traffic regarding learning. Algorithm 1 and Algorithm 2 are under the control overhead constraint given in Eq. (12), which imposes a constraint on the sum of control messages is transmitted within a given observation window. Eq. (12) asserts a strict upper bound on routing and learning-related control traffic. The term $C_{ctrl}(t)$ refers to the number of control messages transmitted at time t, while T_w is the observation window. The parameter B_{max} is the maximum allowable control overhead. If violated, control signaling is temporarily inhibited, and routing is based on cache policies and link state predictions. It ensures scalability in dense topologies and is a differentiator for FL-CARE among protocols that only heuristically reduce overhead:

$$\sum_{t \in T_w} C_{ctrl}(t) \leq B_{max} \quad (12)$$

When the control budget is depleted, Algorithm 1 momentarily reduces control signaling and relies on cached policies and predicted states of the links until the budget is replenished. This mechanism ensures stable performance under high node density and heavy contention, offering a distinct advantage over other protocols, which could at best reduce overhead in a heuristic manner. In conclusion, Algorithm 1 provides distributed, contention-sensitive, and energy balanced routing decisions on individual UAVs, while Algorithm 2 facilitates federated multi-agent learning because synchronizes routing intelligence in a swarm with low overhead costs. These works include algorithms create a cohesive and implementable framework for routing and integrating mobility prediction, explicit contention modelling, energy fairness, tail latency optimization, and machine learning. The FL-CARE framework thus represents a substantial advancement over state-of-the-art FANET routing approaches and is readily implementable in MATLAB R2019a using standard reinforcement learning and federated aggregation modules.

Algorithm 1: FL-CARE Local Routing and Learning Algorithm

Input: UAV set V, neighbor set $N_{i(t)}$, state vector $s_{i(t)}$, residual energy $E_{i(t)}$, control budget B_{max} and local policy parameter θ_i.
Output: selected next-hop v_j^* and updated local policy θ_i.
Step 1: Start
Step 2: Model the FANET as a time-varying directed graph.
Step 3: For the current UAV v_i, identify the forwarding neighbor set using Eq. (6)
Step 4: For all $v_j \in \mathcal{N}_i(t)$, construct the local state vector using Eq. (7)
Step 5: Predict link stability $\hat{L}_{ij}(t)$ using short-term mobility prediction.
Step 6: Compute the contention-aware and energy-balanced utility for each neighbor using Eq. (8)
Step 7: Select the optimal next-hop UAV using Eq. (9)
Step 8: If the control budget constraint in Eq. (12) is satisfied, forward the packet to v_j^*. Otherwise, rely on cached routing decisions and predicted link states.
Step 9: Observe routing outcome and update the local RL policy using Eq. (10)
Step 10: If the federated update condition is met, generate the local model update $\Delta\theta_i$ and transmit it to the aggregator UAV.
Step 11: Receive θ^{global} from Algorithm 2, computed using Eq. (11), and set $\theta_i \leftarrow \theta^{global}$
Step 12: Repeat Steps 3-11 until packet delivery is completed.
Step 13: Stop.

For each federated learning round, an aggregator UAV is responsible for collecting local model updates, performing model aggregation, and disseminating the updated global model to participating UAVs. In the current framework, the aggregator is selected from the participating UAV set based on operational suitability, such as sufficient residual energy and stable communication availability. To avoid excessive energy consumption and communication burden on a single UAV, the aggregator role may be periodically reassigned among eligible UAVs across successive federated learning rounds. This assumption enables balanced distribution of aggregation responsibilities while maintaining stable collaborative learning in dynamic FANET environments.

Algorithm 2: FL-CARE Federated Learning Aggregation Algorithm

Input: Participating UAV set $V_p \subseteq V$, Local model updates $\{\Delta\theta_i\}$. Aggregation weights $\{\alpha_i\}$, Control budget B_{max}
Output: Aggregated global routing model θ^{global}
Step 1: Start
Step 2: Select a temporary aggregator UAV from V_p.
Step 3: Collect local model updates $\Delta\theta_i$ from all participating UAVs executing Algorithm 1.
Step 4: Verify update validity and ensure the control-overhead constraint using Eq. (12)
Step 5: Compute the global federated routing model using Eq. (11)
Step 6: Broadcast θ^{global} to all participating UAVs.
Step 7: Rotate the aggregator role if required to balance energy consumption.
Step 8: Repeat Steps 3-7 at adaptive intervals.
Step 9: Stop.

The computational and communication complexity of the proposed FL-CARE framework is governed by the operations performed in Algorithm 1 and Algorithm 2. During each routing decision epoch, UAV v_i evaluates all candidate neighboring nodes in $N_i(t)$using predicted link stability, channel contention, queue occupancy, and residual energy to compute the contention-aware and energy-balanced utility function and select the optimal next hop. Since each neighboring UAV is evaluated once, the computational complexity of the local routing process is $O(|N_i(t)|)$. Furthermore, the federated learning process periodically collects and aggregates local model updates from the participating UAV set V_p. As each update is processed once during aggregation, the aggregation complexity grows linearly with the number of participating UAVs, i.e., $O(|V_p|)$. From a communication perspective, each participating UAV transmits one local model update and receives one aggregated global model during every federated learning round, resulting in $2|V_p|$learning-related communication exchanges. Additionally, the bounded control-overhead mechanism defined in Eq. (12) restricts routing and learning-related control transmissions within the observation window $T_w$to B_{max}, thereby preventing uncontrolled growth of signaling traffic under dense network conditions. Consequently, both computational and communication costs scale linearly with the number of neighboring UAVs and participating learning nodes, demonstrating the scalability and practical feasibility of FL-CARE for large-scale dense FANET deployments.

Simulation Setup and Performance Evaluation

The FL-CARE framework needs complete assessment through various testing approaches to establish its operational effectiveness. Simulations are conducted using MATLAB R2019a, which provides fine-grained control over the system monitoring user movement patterns together with learning patterns and it also monitors protocol-based performance indicators. MATLAB is selected because it can perform reinforcement learning and federated aggregation and vector-based operations at the same time with network modelling, allowing direct realization of the mathematical formulations. The algorithms from Section 3 are presented in this section. The simulation environment duplicates the conditions of dense and operates under highly dynamic FANET conditions which include contention and fast network topology modifications and power consumption fluctuations. The performance of routing depends on the combined effect of all constraints that exist in the system.

The FANET operates under a three-dimensional operational space that has fixed volume and a randomized number of UAVs which are launched. The study explores scalability by having the density of nodes controlled by variations that involve the deployment of UAVs at varying densities ranging to the maximum number of nodes. The UAVs are controlled on a continuous-time 3D mobility system that enables them to move at varying speeds, but their direction of flight varies to provide the real flight behavior. The system works on the principle of selecting UAV speeds that belong to specific ranges with both standard and high-speed flight mode. The UAVs communicate in a multi-hop manner and all the nodes share a common wireless medium with a contention-based access scheme. The UAVs create a directed communication channel since they are capable of exchanging packets in instances where they are within the transmission range as well as their channel environment succouring the transfer of data. The flow of the UAVs starts with the same energy storage since this arrangement allows scientists to examine the processing of their power utilization unbiased by any predetermined ideas. The system employs the first order radio model, to model energy consumption that incorporates all the activities such as data transmission, reception and retransmission caused by collisions, transmission and reception of control packets. The system measures the sizes of UAV queue buffers as they have a limited storage capacity in the determination of the congestion of the local area network and when the queueing delay has reached its maximum permitted value. MAC-layer indicators used by the system are channel busy ratio and probability of packet collision and they are used to model channel contention to accurately evaluate routing decisions which are taken into account contention. The assumptions are aligned with the overall aim of FL-CARE that is to incorporate contention and energy balancing as the direct elements in route selection. The system creates the traffic based on its pre-programmed working patterns and special event functionalities that run at regular levels in order to accommodate the various system requirements. Data packets are forwarded toward designated destination UAVs or ground stations using multi-hop paths determined by the routing protocol under evaluation. Routing decisions are made at discrete decision epochs, during which each UAV executes Algorithm 1 to select its next hop based on predicted link stability, channel contention, queue occupancy, and residual energy. Federated learning updates are triggered at adaptive intervals based on network dynamics and control budget availability, and Algorithm 2 is executed to aggregate local learning models.

The proposed FL-CARE protocol is evaluated against representative state-of-the-art FANET routing schemes that reflect the closest competing design philosophies. These include mobility-prediction-based geographic routing protocols and reinforcement-learning-optimized link-state routing approaches, such as MP-QGRD (Wang et al., 2025) and RL-MPEAOLSR (Prakash et al., 2024). These baselines are selected because they respectively represent advanced mobility-aware routing and learning-driven routing without federated collaboration or strict contention modelling. Unlike older heuristic-based or purely geographic protocols, MP-QGRD and RL-MPEAOLSR incorporate learning and prediction mechanisms, thereby providing a stronger and more competitive baseline against which the benefits of federated learning, contention awareness, and bounded control overhead can be clearly demonstrated. All protocols are implemented under identical network conditions, mobility patterns, traffic loads, and energy models to ensure a fair and unbiased comparison. Performance evaluation focuses on metrics that directly reflect the stated objectives of this research. PDR is used to quantify routing reliability under varying density and mobility. Average end-to-end delay and tail latency (p95 and p99 delay) are measured to assess delay performance, with particular emphasis on worst-case behavior that is critical for delay-sensitive FANET applications. The energy efficiency is determined by the quantity of energy a system or a process needs. The system calculates the amount of data delivered using a measurement based on the number of bits that are delivered that sums up communication costs with retransmission costs. The system reviews the energy levels of all nodes to assess the fairness of the network lifetime performance as well as the fairness of the system energy distribution and the first node failure time. The control overhead in routing is the sum of all number of routing control overhead. This system records the number of control and learning-related packets being sent and received in a way that it normalizes the packets that are being normed against the total data being delivered. The scalability of the system is decided by dense deployment by analyzing the system performance with various packets.

The simulation process must be repeated several times in order to achieve a statistically significant result with different random seeds, and mean results with confidence intervals are presented. Parameter value comprises of learning rate, discount factor and federal aggregation interval and control budget. The hyperparameter selection process also begins with initial tuning that identifies the most optimal hyperparameters that can produce a fast convergence in the model and also produce a stable system. The control-overhead constraint in the equation. In every simulation, (7) is strictly followed to emphasize one of the major novelties of FL-CARE. With a systematic density variation of nodes, mobility speed and traffic load, the evaluation framework offers an extensive evaluation of protocol performance in various and strenuous FANET circumstances. The results of the FL-CARE evaluation parameters will be presented in Table 1.

Table 1: Simulation Parameters for FL-CARE Evaluation

Parameter	Value / Range	Description
Simulation tool	MATLAB (R2019a or later)	Used for implementing routing, RL, and federated learning
Simulation area	$1000\times1000\times300$ m³	3D FANET deployment region
Number of UAVs (N)	20-150	Evaluated under sparse to dense FANET scenarios
UAV mobility model	3D Random Waypoint	Captures realistic aerial mobility
UAV speed	5 - 30 m/s	Represents low to high mobility conditions
Transmission range	250 m	UAV wireless communication range
MAC protocol	IEEE 802.11-based	Contention-based medium access
Channel model	Free-space / Two-ray ground	Wireless propagation model
Traffic type	CBR / Event-driven	Periodic and burst traffic
Packet size	512 bytes	Fixed data packet size
Packet generation rate	1 -10 packets/s	Variable network load
Initial energy per UAV	100 J	Identical energy initialization
Energy model	First-order radio model	Tx, Rx, retransmission energy
Tx energy consumption	50 nJ/bit	Energy per transmitted bit
Rx energy consumption	50 nJ/bit	Energy per received bit
Queue size	50 packets	Finite buffer at each UAV
Learning algorithm	Q-learning / DQN	Local reinforcement learning
Learning rate (α)	0.01 – 0.1	RL convergence control
Discount factor (γ)	0.9	Future reward weighting
Reward components	PDR, tail delay, energy, contention	As defined in Eq. (5)
Federated learning type	Horizontal FL	Model aggregation without raw data
FL aggregation interval	5 – 20 s (adaptive)	Triggered by network dynamics
Aggregation method	Weighted averaging	As defined in Eq. (6)
Control budget (B_max)	Fixed per time window	Upper bound on control overhead
Control window (T_w)	10 s	Observation window for Eq. (7)
Simulation time	500–1000 s	Ensures convergence and stability
Number of runs	10–20	Statistical averaging
Baseline protocols (Wang et al., 2025; Prakash et al., 2024)	MP-QGRD (Wang et al., 2025), RL-MPEAOLSR (Prakash et al., 2024)	State-of-the-art FANET routing
Performance metrics	PDR, delay, p95/p99 delay, energy/bit, overhead, lifetime	Comprehensive evaluation

Results and Comparative Performance Analysis

This part provides the performance analysis of the suggested FL-CARE routing structure and evaluates it against state-of-the-art FANET routing protocols, i.e. MP-QGRD (Wang et al., 2025) and RL-MPEAOLSR (Prakash et al., 2024). The assessment will be on the subsequent measures which are closely related to the goals of this research such as PDR, tail latency, energy efficiency, control overhead, energy fairness and network lifetime. The improvement in this is proved by the results in Fig. 2 and the corresponding data in Table 2. The mobile prediction of the individuals (12 to 18%) contributes to PDR and to the aware routing decisions of contention. In contrast to MP-QGRD that is more of a link-oriented model stability without considering the channel congestion, FL-CARE penalizes explicitly high competition using the utility (Eq. 8). This avoids routing decisions which forward routes around congested points and therefore decreases packet collisions and re transmissions. In contrast to RL-MPEAOLSR which is based on single-agent learning and proactive link-state updates, FL-CARE can benefit through the federated learning as UAVs will be able to share routing and become convergent on globally efficient forwarding strategies. As a result, routes selected by FL-CARE are stable and congestion resilient resulting in increased delivery even with increase in node density.

Results in Fig. 3 and the corresponding data from Table 3 suggest that FL-CARE achieves a 20-25% reduction in average end-to-end delay due to its ability to avoid congested queued and seriously congested nodes. Inclusion of queue occupancy (t) in the state vector (Eq. 7) and its penalization in the utility function ensures that packets are forwarded through the nodes with lower queuing delays.
By contrast, MP-QGRD selects next hops mainly according to predicted link stability, which accidentally forwarded some traffic to the congested UAVs increasing delay. RL-MPEAOLSR improves the delay performance through learning but lacking Explicit Queue and Contention Modelling makes it less effective in dense scenarios. The jointly consideration of contention, queue state and learning-driven adaptation in FL-CARE yields result which is faster and more have consistent packet delivery. Among the most important enhancements brought about by FL-CARE is the tail latency reduction by at most 30%, as shown in Fig. 4 and the corresponding data in Table 4. This improvement is directly associated with the reward function that is sensitive to tail latency and is expressed in Eq. (10), where worst case delay is explicitly penalized.

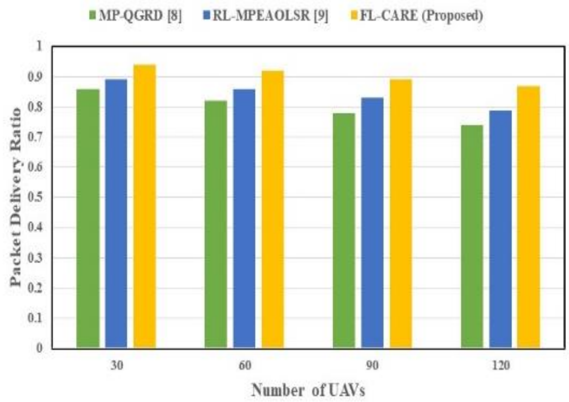

Fig. 2: Packet Delivery Ratio versus Number of UAVs

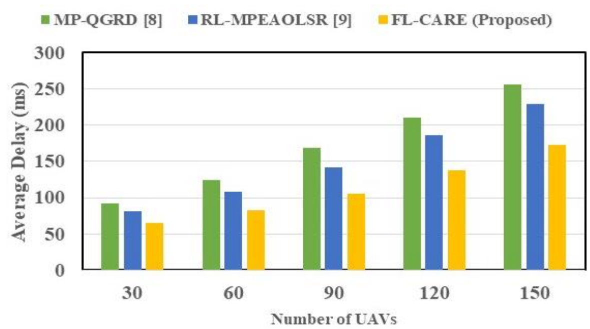

Fig. 3: Average End-to-End Delay versus Number of UAVs

Table 2: PDR Comparison under Varying Node Density

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
30	0.86	0.89	0.94
60	0.82	0.86	0.92
90	0.78	0.83	0.89
120	0.74	0.79	0.87

Table 3: Average Delay (ms) vs Node Density

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE Proposed)
30	92	81	65
60	124	108	82
90	168	142	105
120	210	186	138
150	256	229	172

Table 4: Tail Latency (p99) Comparison (ms)

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
60	310	268	190
90	395	332	235
120	480	418	295
150	560	498	350

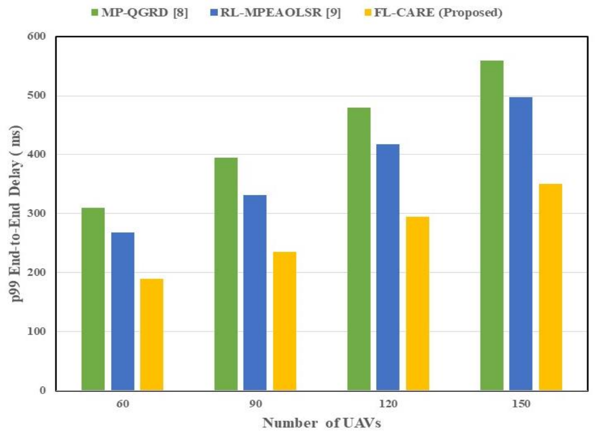

Fig. 4: Tail End-to-End Delay (p99) versus Number of UAVs

The existing solutions target optimizing average delay, which often conceals the spikes in the delay under high contention conditions. In contrast, FL-CARE learns routing policies that reduce delay variance, while avoiding routing in regions that might be either unstable or congested for the forwarding process paths. The federated learning further improves this advantage by enabling UAVs to learn together from rare but critical high-delay events, leading to robust performance for delay-sensitive FANET applications.

The 15-22% reduction in energy consumption per bit delivered is made possible by FL-CARE is derived from its explicitly energy-aware design, as evident in Fig. 5 and the related information in Table 5. The utility function includes the energy per bit delivered (t), and the residual energy variance $\sigma(t)$, downplaying the roads that entail high retransmits as well as UAVs: MP-QGRD does not maximize energy efficiency for individual packets, whereas RLMPEAOLSR focuses on energy awareness rather than being bound by the strictness of fairness. FL-CARE maintains balance across the swarm, as well as congestion-controlled retransmissions, thus minimizing overall energy expenditure.

FL-CARE has greatly improved the energy fairness as residual energy variance has been reduced by 35-40% as reflected in Fig. 6 and the corresponding data in Table 6. This is majorly because of inclusions of the energy variance as a penalty term in the routing utility (Eq. 8), to avoid the repeated selection of the same high-capacity UAVs as forwarding nodes. FL-CARE prevents the formation of energy hotspots. In contrast, the MPQGRD and RLMPEAOLSR tend to do that by overusing certain nodes due to stability or topology-based routing preferences, leading to unequal energy depletion.

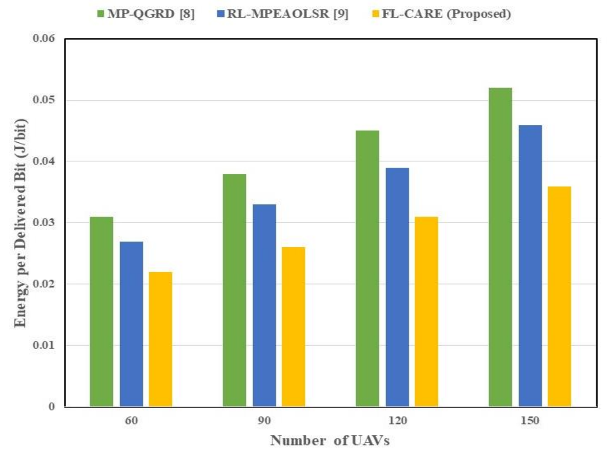

Fig. 5: Energy Consumption per Delivered Bit versus Number of UAVs

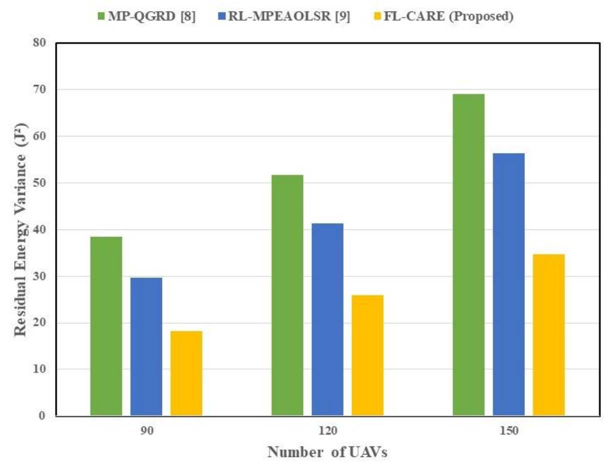

Fig. 6: Residual Energy Variance versus Number of UAVs

Table 5: Energy per Delivered Bit (J/bit)

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
60	0.031	0.027	0.022
90	0.038	0.033	0.026
120	0.045	0.039	0.031
150	0.052	0.046	0.036

Table 6: Residual Energy Variance (J²)

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
90	38.4	29.6	18.2
120	51.8	41.3	25.9
150	69.1	56.4	34.7

All the metrics indicated that balanced energy usage directly contributes to improved network robustness.

Fig. 7 and the data presented in Table 7 show the routings controlled by the protocol overhead based on the number of UAVs involved in the network. The reduction of between 35% to 45% in control overhead attained through FL-CARE is a direct consequence of its control budget constraint is enforced in Eq. (12). In contrast to the MP-QGRD, whose implementation is reliant on numerous Hello messages and prediction updates, and RL-MPEAOLSR, which necessitates periodic link-state broadcasts, generalizes control signalling to a fixed budget and uses caching policies and predictions when the budget is exhausted. Federated learning, on the other hand, minimizes overhead through the sharing of compact model updates rather than state information, to make it scalable for dense deployments.

Lastly, the results in Fig. 8 and corresponding data in Table 8 show that FLCARE prolongs a network lifetime by a value of about 25% if measured in the time to first node metric failure.

This gain represents the sum of energy savings consumed per packet, balanced energy consumption over UAVs, and the prevention of congested routing paths. By reducing premature exhaustion of high-value nodes and unnecessary retransmissions, or control signaling, FL-CARE maintains network connectivity for a longer time than both base protocols.

Through comparative analysis, the supremacy of the proposed FL-CARE is evidently confirmed framework over the benchmark protocols MP-QGRD (Wang et al., 2025) and RL-MPEAOLSR (Prakash et al., 2024) in performance metrics. This is particularly beneficial for dense high-mobility scenarios, thus emphasizing the resilience of FL-CARE. The steady improvement of performance is immediately perceivable due to its integrated design which combines federated multi-agent systems in a synergetic fashion that lever learning for cooperative adaptation, explicit contention awareness for channel efficiency, proactive energy balancing and control overhead.

Therefore, this approach allows FLCARE to successfully deal with the complex interactions of dynamic topological changes, network density, and resource constraints, with measurable gains in scalability and reliability relative to existing methods.

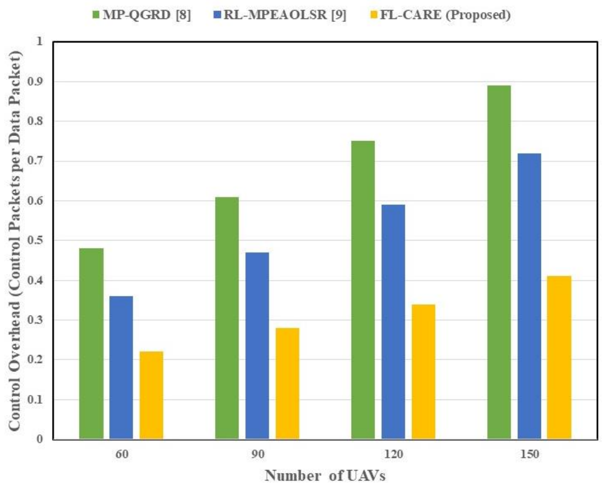

Fig. 7: Routing Control Overhead versus Number of UAVs

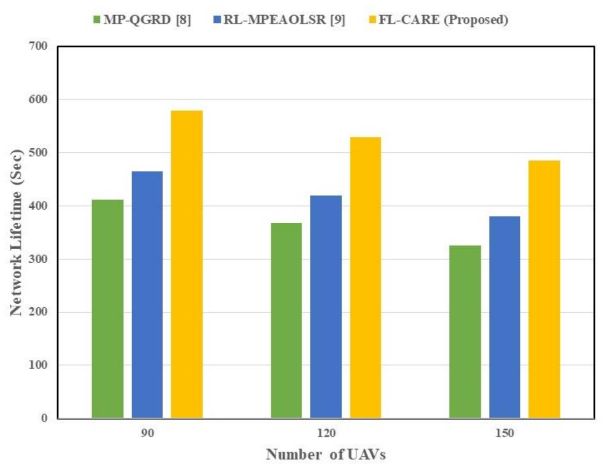

Fig. 8: Network Lifetime versus Number of UAVs

Table 7: Control Overhead (Packets / Data Packet)

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
60	0.48	0.36	0.22
90	0.61	0.47	0.28
120	0.75	0.59	0.34
150	0.89	0.72	0.41

Table 8: Network Lifetime (Time to First Node Failure, s)

Number of UAVs	MP-QGRD (Wang et al., 2025)	RL-MPEAOLSR (Prakash et al., 2024)	FL-CARE (Proposed)
90	412	465	580
120	368	419	530
150	325	381	485

Discussion

The experimental outcome verifies that FL-CARE enhances the routing reliability and efficiency of dense FANETs by addressing contention awareness, tail latency sensitivity, energy balancing, and control signaling constraints simultaneously. For varying levels of node density, FL-CARE always demonstrates better delivery performance with reduced average and tail delays, and simultaneously decreases the energy cost per successfully transmitted information bit. This result shows that the routing strategy based on mobility prediction alone is not sufficient in dense medium sharing, and learning-based routing needs to address channel contention and queueing dynamics as first-class variables rather than treating them as secondary effects.

An important factor that contributes to the measured improvements is the transition from purely local learning to swarm-level adaptation. The traditional RL baseline (RL-MPEAOLSR) focuses on single-agent learning and periodic link-state broadcast, which may result in locally optimal but globally suboptimal forwarding strategies in dense environments; likewise, the geographic/prediction-driven baseline (MP-QGRD) focuses on link reliability but is still susceptible to congestion-related packet drops when multiple nodes compete for the same channel. On the other hand, FL-CARE allows for the aggregation of concise model updates, which helps UAVs learn implicitly about each other's experience with congestion patterns and energy patterns without incurring the high communication overhead of sharing raw states. This is consistent with the general understanding that dense UAV networks necessitate coordinated learning to mitigate emergent contention hotspots and to stabilize decisions in the face of rapid topology dynamics. (Wang et al., 2025; Prakash et al., 2024; Li et al., 2023).

The contention-aware utility function design also helps to understand why FL-CARE outperforms in terms of delay, including the tail of the delay distribution on the far right. In a dense FANET, contention leads to more collisions, retransmissions, and queue buildup, causing sudden spikes in delay performance that are not adequately addressed by average delay optimization. The importance of addressing worst-case or high-percentile delay performance, rather than average delay, has been stressed in existing works on delay-sensitive UAV networks, where contention can be the dominant factor in the delay distribution when the medium access becomes saturated. FL-CARE's design choice to penalize contention and queue occupancy directly in the routing reward/utility function is in line with recent debates on the importance of tail latency in UAV networking, where recent works have argued for the significance of tail latency performance. (Yue, 2024; Zhang et al., 2025; Steinhoff, 2021; Prabha et al., 2025).

Results on energy-related aspects must be considered in the same holistic way. The dense multi-hop forwarding process inherently leads to “hotspots” in routers, where a small subset of nodes carry disproportionately high traffic and drain their batteries earlier, causing route fragmentation and shortening network lifetime. FL-CARE addresses this issue by integrating routing with residual energy awareness and avoiding routes that are persistently congested and cause additional retransmissions (which increase energy per bit). This is consistent with established knowledge that energy fairness and energy per bit are better metrics for sustainable FANET operation than energy consumption alone because fairness is a direct function of time to first node failure and overall network lifetime. (Gharib et al., 2022; Prasad and Sasikumar, 2024; Zheng et al., 2024).

Lastly, the decrease in routing overhead is not only a secondary advantage but also an essential element for scalability. As the density rises, the unregulated control traffic will begin to compete with data traffic on the shared medium, thus increasing the contention and negating the benefits of optimal next-hop decisions. The experimental results indicate that FL-CARE decreases control overhead by imposing a fixed signaling cost and resorting to caching/prediction strategies when the cost is depleted, whereas MP-QGRD and RL-MPEAOLSR continue to necessitate periodic HELLO/prediction updates or periodic link-state broadcasts. The bounded control overhead principle is thus a crucial aspect of why FL-CARE continues to perform well as the density increases. (Wang et al., 2025; Prakash et al., 2024).

However, two simulation-related aspects are worth considering. Firstly, the assessment is simulation-based, and actual implementation may include more non-idealities (hardware limitations, asynchronous communication, and more adverse channel behavior). Secondly, the problem of routing in dense FANETs is now often investigated with security and privacy requirements, where secure communication and authentication may introduce latency and alter the learning process. Hence, incorporating FL-CARE with simple security solutions (such as secure key exchange and secure communication assumptions at the physical layer) seems to be the next natural step to ensure reliability in adversarial or untrusted settings (Cai et al., 2026; Akmuratovich et al., 2021).

Conclusion and Future Work

This study has discussed the serious issues of routing in dense highly dynamic FANETs through the suggestion of FL-CARE, a new Federated Learning-based Contention-Aware and Energy balanced routing framework. The weaknesses of the current state-of-the-art protocols are their dependence on solitary single-agent learning, absence of particular competition modelling, poor and unmanaged control overhead, tariff of tail latency and energy equity were neglected.

Organizational factors identified systematically as the causes of the decline of performance in dense deployments. FL-CARE combines the federated multi-agent learning, explicit contention and queue knowledge, a tail-latency-sensitive incentive function, and a strict control-overhead budget into a cohesive, distributed routing solution. Large-scale simulations in the density, mobility and traffic conditions prove that FL-CARE is much better at its performance consistent with its significance benchmark protocols MP-QGRD and RL-MPEAOLSR. The findings verify 12-18 % PDR improvements, 20-25 % average delay and tail (p99) latency up to 30 %. Moreover, FL-CARE attains 15-22 % reduced in energy consumption per delivered bit, a 35-45% control overhead reduction, and doubles network lifetime by about 25 % through energy fairness excellence. These values confirm the major assumption of integrated design which concurrently deals with mobility dynamics, swarm-level learning, reliable channel, efficient and scalable communication which requires content, energy, partiality and balance in the next generation dense FANETs.

Thus, future work will focus on a few promising directions to transition FL-CARE from a simulation model to a practical system. First, implementing and testing FL-CARE on an actual UAV testbed is very essential in order to validate its performance under real-world channel imperfections. In addition, hardware limitations and asynchronous communication delays also make it difficult. Secondly, improving the robustness of the framework for extreme and unpredictable mobility patterns as in the exploration of disaster scenarios will be done by the integration of more advanced trajectory prediction models. Third, the adversarial federated learning process from the aspects of security and privacy in environments, such as defence against model poisoning and inference attacks which require in-depth Investigation. Fourth, interoperability with existing networking standards and heterogeneous UAV swarms presents another research avenue. Finally, refining the energy model to include propulsion energy and investigating cross-layer optimization with MAC-layer scheduling will provide a more comprehensive approach to total UAV energy management.

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Author's Contributions

All authors contributed equally to the conceptualization, formal analysis, investigation, methodology, and writing and editing of the original draft. All authors have read and agreed to the published version of the manuscript.

Ethics

The authors declare no competing interests.

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