

A Mobility- and Information-Freshness-Aware Adaptive Federated Learning Framework for Collaborative Routing in Dense Flying Ad Hoc Networks (MAFA-FANET)

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Abstract:

Dense Flying Ad Hoc Networks (FANETs) experience rapid topology changes, unstable wireless links, and highly dynamic communication conditions due to the mobility of unmanned aerial vehicles (UAVs). These characteristics create significant challenges for collaborative routing, particularly when federated learning updates become outdated before model aggregation. This study proposes a Mobility- and Information-Freshness-Aware Adaptive Federated Learning framework for FANETs (MAFA-FANET) to improve collaborative routing in dense and highly dynamic networks. The framework integrates mobility-aware information freshness, adaptive participant selection, event-driven aggregation, temporary aggregator selection, stale-update management, and freshness-aware model aggregation. These mechanisms enable the framework to evaluate the relevance of local routing knowledge according to changing network conditions before incorporating updates into collaborative learning. Simulation results demonstrate that MAFA-FANET outperforms FL-CARE, RL-MPEAOLSR, and MP-QGRD, achieving 4.6% to 23.0% improvement in packet delivery ratio, 24.3% to 55.7% reduction in p99 end-to-end delay, and 11.1% to 38.5% reduction in energy consumption per delivered bit. The results indicate that incorporating mobility and information freshness into federated coordination improves the relevance of routing knowledge and provides an effective reliability, latency, energy trade-off under the evaluated dense FANET scenarios. These findings support MAFA-FANET as an adaptive framework for collaborative routing in rapidly changing UAV network environments.

Keywords: FANETs, federated learning, UAV networks, information freshness, mobility-aware routing

1. INTRODUCTION

Flying ad hoc networks (FANETs) form wireless networks among unmanned aerial vehicles (UAVs) without requiring a fixed communication infrastructure (Akmuratovich et al., 2021). Their mobility supports rapid deployment and flexible coverage, but it also produces link interruptions and topology changes that are more pronounced than in conventional mobile ad hoc networks. Routing therefore has to react to network conditions that may change during the lifetime of a route (Al-Bataineh et al., 2026). Federated learning provides a way for distributed nodes to train a common model while keeping local observations at participating devices (Zhang et al., 2025). The conventional federated averaging procedure aggregates locally trained model parameters, making communication efficiency and client participation important design considerations (Chen et al., 2026).

In wireless environments, however, a locally generated update is not characterized only by its training quality; the network state that produced the update also determines how relevant that update remains after transmission and waiting time. This issue is particularly important for dense FANET routing (Das et al., 2024). A UAV can train a routing

policy while a neighboring link is stable, channel contention is moderate, and queue occupancy is low (Baktayan et al., 2024). Before that update reaches the temporary aggregator, the UAV may have moved, the neighbor may have left the communication range, or contention may have increased (Chu et al., 2025).

The update can therefore be mathematically valid while being operationally stale. Recent federated-learning research has explicitly connected information freshness and federated learning, while the Khujamatov et al (2026) study combines federated learning with contention-aware and energy-balanced routing in dense FANETs.

The gap addressed by MAFA-FANET is narrower than general federated-learning optimization: the framework focuses on the temporal and network-state relevance of routing updates in a dynamic FANET. It does not claim to solve privacy leakage, Byzantine behavior, differential privacy, or model poisoning. Its scope is the joint management of mobility, network dynamics, information freshness, participation, aggregation timing, temporary aggregation responsibility, and stale routing knowledge.

A. Contributions

The main contributions of this study are summarized as follows:

1. A unified network-state representation is developed to jointly describe routing conditions, UAV mobility, network dynamics, and the freshness of local learning updates.
2. A mobility- and information-freshness-aware participant-selection mechanism is proposed using information freshness, link stability, residual energy, UAV mobility, and channel contention to identify suitable UAVs for federated-learning participation.
3. An event-driven aggregation mechanism is developed to initiate aggregation according to relevant changes in network conditions rather than depending entirely on a fixed aggregation interval.
4. A temporary aggregator-selection mechanism and three-level stale-update policy are introduced to reduce the effect of outdated routing information on the global model.
5. A normalized freshness-aware aggregation formulation is provided with consistent weighting and notation to support clear implementation and reproducibility.

2. RELATED WORK

Recent studies have addressed routing, clustering, energy efficiency, and federated learning in UAV networks. However, the freshness of learned routing information under continuous UAV mobility remains insufficiently addressed. Khujamatov et al. (2026) proposed FL-CARE, a federated-learning-based routing protocol for dense FANETs that considers link stability, channel contention, queue occupancy, and residual energy. However, it does not explicitly model how the relevance of routing updates changes with network mobility and topology variations.

Zhang et al. (2025) developed a hierarchical clustering and UAV scheduling method using K-means++ and a modified genetic algorithm. Although it improves energy balance and data-collection performance, it focuses on clustering and scheduling rather than collaborative FANET routing or routing-update freshness. Almasoud (2023) proposed JA-RC, a jamming-aware UAV routing and IoT clustering approach. While it adapts routing to interference conditions, it does not consider routing-update freshness. Husnain et al. (2026) proposed COANET, an energy-aware routing and clustering approach for IoV. The method improves several routing metrics but does not address federated learning, UAV mobility, or routing-information freshness.

Sun et al. (2025) introduced an AoI-aware cooperative federated learning framework for UAV-enabled edge computing. The study demonstrates the importance of freshness in UAV federated learning, but its focus is on data freshness and computing rather than the freshness of learned routing information in FANETs. Chen et al. (2026) developed ATM-Net, a lightweight UAV object-detection model. Although relevant to resource-constrained UAV learning, it does not address FANET routing, topology dynamics.

Shou et al. (2026) proposed a DRL-based adaptive routing strategy for ultra-high-speed FANETs, improving routing performance under high mobility. However, it does not explicitly consider federated routing-update freshness or adaptive participant selection. Overall, existing studies address individual aspects of UAV networking, including routing, clustering, energy efficiency, interference, and federated learning. However, there is limited integration of mobility, topology dynamics, routing-update freshness, adaptive federated participation, and aggregation control for collaborative FANET routing. This gap motivates the proposed Mobility- and Information-Freshness-Aware Adaptive

Federated Learning for FANETs (MAFA-FANET) framework, which jointly considers network dynamics and information freshness when selecting participants, weighting updates, and determining aggregation decisions.

3. SYSTEM MODEL

A. Network Model

Consider a dense FANET consisting of N UAVs deployed in a three-dimensional operational environment. The network is modeled as a time-varying directed graph $G(t)=(V,E(t))$, where $V=\{v_1,v_2,\dots,v_N\}$ is the set of UAVs and $E(t)$ is the set of available wireless communication links at time t . Continuous UAV movement causes the link set and network topology to vary over time (Khujamatov et al., 2026).

$$G(t) = (V, E(t)) \quad (1)$$

Each UAV operates as an autonomous communication node and a local learning agent. Federated coordination is performed by exchanging model updates rather than raw network observations. The model assumes that each UAV can measure or estimate the local quantities required by the routing and coordination rules.

B. Normalized Network-State Representation

To avoid mixing quantities with different physical units in a single suitability score, all state variables used in the proposed scoring functions are normalized to $[0, 1]$. Let $\hat{L}_i(t)$ denote normalized predicted link stability, $C_i(t)$ normalized channel contention, $Q_i(t)$ normalized queue occupancy, $E_i(t)$ normalized residual energy, $M_i(t)$ normalized mobility, $T_i(t)$ normalized topology-change rate, and $F_i(t)$ the current update-freshness measure (Khujamatov et al., 2026).

$$S_i(t) = [L_{ij}(t), C_i(t), Q_i(t), E_i(t), M_i(t), T_i(t), F_i(t)] \quad (2)$$

The vector is defined at the UAV level. If neighbor-specific link values are available, $\hat{L}_i(t)$ may be computed using a clearly specified statistic over the candidate neighbors; the same definition must then be used throughout training and evaluation.

C. Energy and Propulsion Model

In dynamic dense FANETs, energy consumption is governed by mechanical flight dynamics, transceiver electronics, and computational execution. The total energy expended by UAV v_i over a operational time interval Δt is modeled as (Backofen et al., 2002).

$$E_{total,i}(\Delta t) = E_{prop,i}(\Delta t) + E_{comm,i}(\Delta t) + E_{comp,i}(\Delta t) \quad (3)$$

1. Propulsion Power Model: Flight power dominates total onboard consumption. For a rotary-wing UAV flying at velocity V_i , the propulsion power $P_{prop}(V_i)$ is formulated using aerodynamic momentum theory (Backofen et al., 2002).

$$P_{prop}(V_i) = P_0 \left(1 + \frac{3V_i^2}{U_{tip}^2} \right) + P_i \sqrt{1 + \frac{V_i^4}{4v_0^2} - \frac{V_i^2}{2U_0^2}} + \frac{1}{2} d_0 \rho s A V_i \quad (4)$$

where P_0 is the blade profile power, P_i is the induced hovering power, U_{tip} is the tip speed of the rotor blade, v_0 is the mean rotor induced velocity in hover, d_0 is the fuselage drag ratio, ρ is air density, s is rotor solidity, and A is rotor disc area. The propulsion energy over interval Δt is (Backofen et al., 2002).

$$E_{comm,i}(\Delta t) = E_{prop,i}(\Delta t) \cdot \Delta t \quad (5)$$

2. Communication Power Model: Transceiver consumption accounts for frame transmission, reception, and channel sensing (Xie & Kumar 2004).

$$E_{comm,i}(\Delta t) = b_{tex,i} \cdot (E_{elec} + \epsilon_{amp} d^\alpha) + b_{rx,i} \cdot E_{elec} + t_{idle} \cdot P_{idle} \quad (6)$$

where $b_{tex,i}$ and $b_{rx,i}$ denote the number of bits transmitted and received, $E_{elec} = 50nJ/bit$ is hardware circuit dissipation, ϵ_{amp} is the path-loss amplifier coefficient, d is transmission distance, α is path loss exponent, and P_{idle} is the idle-listening power over period t_{idle} .

3. Computational Power Model: Executing local learning iterations incurs processor energy expenditure (Xie & Kumar 2004).

$$E_{comm,i} = K_i \cdot N_{FL-ops} \cdot C_{cap} \cdot f_i^2 \quad (7)$$

where K_i is the number of local gradient step iterations, N_{FL-ops} is floating-point operations per local epoch, C_{cap} is effective switched capacitance, and f_i is operating clock frequency.

D. Local Routing Decision

At a routing decision epoch, UAV v_i evaluates the candidate next-hop set $N_i(t)$. The learned routing model maps the local state and candidate action to a utility or action value. The selected next hop is the candidate with the highest learned value (Lisangan et al., 2026).

$$v_j^* = \arg \max(v_j \in N_i(t)) U_{ij}(t) \quad (8)$$

Equation (3) is a decision rule rather than a complete reward definition. The supplied model states that the utility should favor stable and less congested paths while avoiding excessive energy depletion and highly dynamic forwarding conditions. The exact learning algorithm and reward function must therefore be specified before numerical evaluation.

4. PROPOSED MAFA-FANET FRAMEWORK

A. Framework Architecture

MAFA-FANET contains the following operating stages: network-state monitoring, local routing learning, mobility- and freshness-aware evaluation, participant selection, aggregation triggering, temporary aggregator selection, stale-update management, freshness-aware aggregation, and global-model dissemination. The stages are executed repeatedly as the FANET evolves.

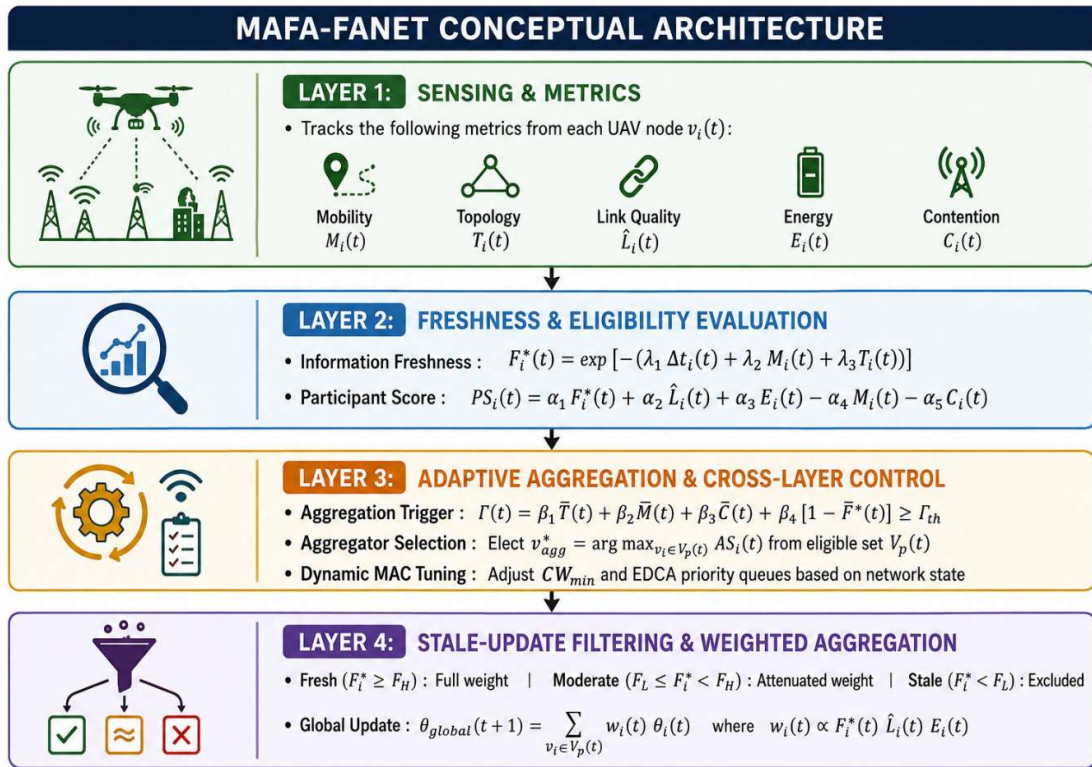


Figure 1. Conceptual Framework of MAFA-FANET

B. Mobility-Aware Information Freshness

The age of a local routing-model update generated by UAV v_i at time $t_{u,i}$ and evaluated at time t is (Khujamatov et al., 2026).

$$\Delta t_i(t) = t - t_{u,i} \quad (9)$$

A conventional exponential freshness function is:

$$F_i(t) = e^{(-\lambda \Delta t_i(t))} \quad (10)$$

For FANETs, elapsed time alone does not describe how rapidly the underlying network state may have changed. MAFA-FANET therefore incorporates normalized mobility and topology-change rate:

$$F_i^*(t) = \exp[-(\lambda_1 \Delta t_i(t) + \lambda_2 M_i(t) + \lambda_3 T_i(t))] \quad (11)$$

For dimensional consistency, λ_t has units of inverse time, whereas λ_m and λ_T are dimensionless when $M_i(t)$ and $T_i(t)$ are normalized. The parameters are nonnegative. Hence $0 < F_i^*(t) \leq 1$.

C. Federated Participant Selection

Participant selection uses a weighted suitability score. The variables entering the score are normalized, and the coefficients are nonnegative:

$$PS_i(t) = \alpha_1 F_i^*(t) + \alpha_2 L_i(t) + \alpha_3 E_i(t) - \alpha_4 M_i(t) - \alpha_5 C_i(t) \quad (12)$$

For interpretability, the recommended implementation imposes $\alpha_k \geq 0$ and $\sum_k \alpha_k = 1$. Because the negative terms can make PS_i range below zero, η should be selected according to the resulting score range rather than assumed automatically to lie in $[0, 1]$.

$$V_i \text{ Participates if } PS_i(t) \geq \eta \quad (13)$$

$$V_p(t) = \{v_i \in V \mid PS_i(t) \geq \eta\} \quad (14)$$

A practical implementation should additionally impose a minimum residual-energy or communication-quality condition if those conditions are not already guaranteed by the score (Das et al., 2024).

D. Event-Driven Aggregation Trigger

Fixed aggregation intervals can cause unnecessary exchanges during stable periods and can delay synchronization after abrupt network changes. MAFA-FANET defines a network-dynamics indicator using normalized network-wide averages:

$$\Gamma(t) = \beta_1 T(t) + \beta_2 M(t) + \beta_3 C(t) + \beta_4 [1 - F^*(t)] \quad (15)$$

The coefficients satisfy $\beta_k \geq 0$ and $\sum_k \beta_k = 1$. Aggregation is triggered when:

$$\Gamma(t) \geq \Gamma_{th} \quad (16)$$

When the network remains stable and current updates remain fresh, $\Gamma(t)$ remains low. When mobility, topology variation, contention, or information aging increases, $\Gamma(t)$ rises and can initiate an earlier aggregation cycle.

E. Temporary Aggregator Selection

A temporary aggregator should be capable of receiving updates and disseminating the resulting global model without becoming a short-lived bottleneck. MAFA-FANET ranks candidate UAVs using residual energy, link stability, freshness, mobility, and contention. An Aggregator Suitability Score (ASS) is defined as:

$$AS_i(t) = \gamma_1 E_i(t) + \gamma_2 L_i(t) + \gamma_3 F_i^*(t) - \gamma_4 M_i(t) - \gamma_5 C_i(t) \quad (17)$$

With $\gamma_k \geq 0$ and $\sum_k \gamma_k = 1$, the selected aggregator is:

$$vagg^* = \arg \max(v_i \in V_j(t)) AS_i(t) \quad (18)$$

The optimization domain is corrected here to $V_p(t)$ because an aggregator should normally be selected from the eligible participating UAVs. If the intended architecture permits a nonparticipant to aggregate, that exception must be defined explicitly.

F. Stale-Update Management

Let $0 \leq F_L < F_H \leq 1$. The freshness score is used to classify local updates into three operational categories.

$$F_i^*(t) \geq FH \quad (19)$$

Updates satisfying (14) are classified as fresh and are fully eligible for aggregation.

$$FL \leq F_i^*(t) < FH \quad (20)$$

Updates satisfying (15) are moderately stale and may be retained with reduced aggregation influence.

$$F_i^*(t) < FL \quad (21)$$

Updates satisfying (16) are highly stale and are excluded from the current aggregation round. The thresholds are design parameters and should be calibrated through sensitivity analysis.

G. Freshness- and Reliability-Aware Aggregation

The aggregation equation in the supplied document contains a formatting error in its denominator. A mathematically explicit version first defines an unnormalized relevance factor:

$$q_i(t) = [F_i^*(t)L_i(t)E_i(t)] \quad (22)$$

The aggregation weight is then:

$$w_i(t) = \frac{q_i(t)}{\sum_{j \in V_p(t)} F_j^*(t)L_j(t)E_j(t)} \quad (23)$$

For a nonempty participating set with $\sum_j q_j(t) > 0$, $w_i(t) \geq 0$ and $\sum_i w_i(t) = 1$. The global model is updated by weighted parameter averaging:

$$\theta_{global}(t+1) = \sum_{i \in V_p(t)} w_i(t)\theta_i(t) \quad (24)$$

This correction preserves the intended mechanism while making the normalization explicit. If local sample size is intended to affect aggregation, $q_i(t)$ can be extended to $n_i F_i^*(t)L_i(t)E_i(t)$, where n_i is the local sample count. That extension is not included in the primary formulation because the supplied model does not specify sample-count weighting.

H. Global Model Dissemination

After aggregation, the temporary aggregator disseminates $\theta_{global}(t+1)$ to the participating UAVs. Each UAV combines the received global routing model with current local network observations, and the process repeats as the network evolves.

I. Cross-Layer MAC Optimization

To translate freshness-aware routing parameters into lower delay and reduced channel contention at the link layer, MAFA-FANET establishes a cross-layer coupling with the IEEE 802.11 MAC protocol.

Dynamic Contention Window Adaptation: Instead of relying on static binary exponential back off, each node v_i dynamically adjusts its minimum Contention Window ($CW_{min,i}$) based on real-time network states:

$$CW_{min,i} = \text{clamp}(CW_{default} \times (1 + \mu_1 C_i(t) + \mu_2 T_i(t) - \mu_3 F_i^*(t))) \quad (25)$$

where $\mu_1, \mu_2, \mu_3 \geq 0$ are weighting factors. Highly fresh updates ($F_i^* \rightarrow 1$) in low-contention zones yield smaller contention windows to accelerate channel access, whereas nodes experiencing higher contention $C_i(t)$ or topology instability $T_i(t)$ enlarge their contention windows to reduce collision probability.

Priority Queue Assignment (EDCA Mapping): Local MAC queues leverage IEEE 802.11e Enhanced Distributed Channel Access (EDCA) to prioritize federated control and high-freshness model parameter transfers:

Voice Access Category (AC_VO): Aggregation control triggers and aggregator selection updates (v_{agg}^*).

Video Access Category (AC_VI): Fresh local model weights satisfying $F_i^*(t) \geq F_H$.

Best-Effort Access Category (AC_BE): Standard data routing packets.

Background Access Category (AC_BK): Moderately stale model updates ($(F_L \leq F_i^*(t) < F_H)$).

J. Computational and Communication Overhead Analysis

Federated updates introduce overhead that must be regulated to maintain scalable operation in dense deployments. MAFA-FANET controls resource demands through bounded communication, computation, and MAC mechanisms:

Communication Overhead: The network-wide communication overhead per aggregation cycle is $O(|V_p(t)| \cdot |\theta| + |E(t)| \cdot S_{ctrl})$, Where $|\theta|$ is the model parameter size, $|V_p(t)|$ is the number of active participants, and S_{ctrl} is control packet size. Selective participant scoring ($PS_i \geq \eta$) filters out redundant nodes, drastically restricting parameter transmissions compared to legacy federated schemes.

Computational Overhead: Local computation scales as $O(|V_p(t)| \cdot K \cdot B \cdot |\theta|)$, where K is local epoch count and B is mini-batch size. The event-driven trigger ($\Gamma(t) \geq \Gamma_{th}$) eliminates unnecessary background training when topology and freshness metrics remain steady, conserving compute power.

MAC Overhead: Channel access overhead scales with collision resolution duration $O(N_{retrans} \cdot T_{backoff})$. *Dynamic* CW_{min} tuning mitigates retry penalties, keeping protocol signaling efficient even as network density increases.

5. MAFA-FANET OPERATING PROCEDURE AND ALGORITHM

MAFA-FANET operates through sequential adaptive stages executed by UAV nodes ($v_i \in V$) and the elected temporary aggregator (v_{agg}^*) at each routing decision epoch.

Algorithm 1: MAFA-FANET Distributed Operational Procedure

Input: ($G(t)=(V,E(t))$), thresholds ($\eta, \Gamma_{th}, F_L, F_H$), and weighting coefficients ($\alpha_k, \beta_k, \gamma_k, \lambda_k, \mu_k$).

Output: ($\theta_{\text{global}}(t+1)$), MAC configuration, and next-hop routing decision.

1: Initialize UAV network parameters and routing epoch (t).

2: For each UAV ($v_i \in V$) **do**

3: Sample and normalize local state ($S_i(t)$) using (2).

4: Update the local routing model and record ($t_{u,i}$).

5: Compute update age ($\Delta t_i(t)$) using (9).

6: Compute freshness ($F_i^*(t)$) using (11).

7: Compute participant score ($PS_i(t)$) using (12).

8: If ($PS_i(t) \geq \eta$) **then**

9: Add (v_i) to eligible participant set ($V_p(t)$).

10: Else

11: Exclude (v_i) from federated participation and perform local routing.

12: End If

13: End For

14: Compute network dynamics indicator ($\Gamma(t)$) using (15).

15: If ($\Gamma(t) \geq \Gamma_{\text{th}}$) **then**

16: Compute ($AS_i(t)$) for ($v_i \in V_p(t)$) using (17).

17: Select ($v_{\text{agg}}^* = \arg\max AS_i(t)$) using (18).

18: For each received update ($i \in V_p(t)$) **do**

19: If ($F_i^*(t) \geq F_H$), retain with full weight.

20: Else if ($F_L \leq F_i^*(t) < F_H$), retain with attenuated weight.

21: Else, discard the update.

22: Compute ($q_i(t)$) and ($w_i(t)$) using (22)–(23).

23: End For

24: Compute ($\theta_{\text{global}}(t+1)$) using (24).

25: Broadcast ($\theta_{\text{global}}(t+1)$) to ($V_p(t)$).

26: Else

27: Defer aggregation and continue local model updates.

28: End If

29: For each UAV ($v_i \in V$) **do**

30: Adjust ($CW_{\text{min},i}$) and EDCA priorities using (25).

31: Select next-hop (v_j^*) using the utility function in (8).

32: End For

33: Proceed to the next routing decision epoch ($t+1$).

34: Repeat Steps 2–33 until the termination condition is satisfied.

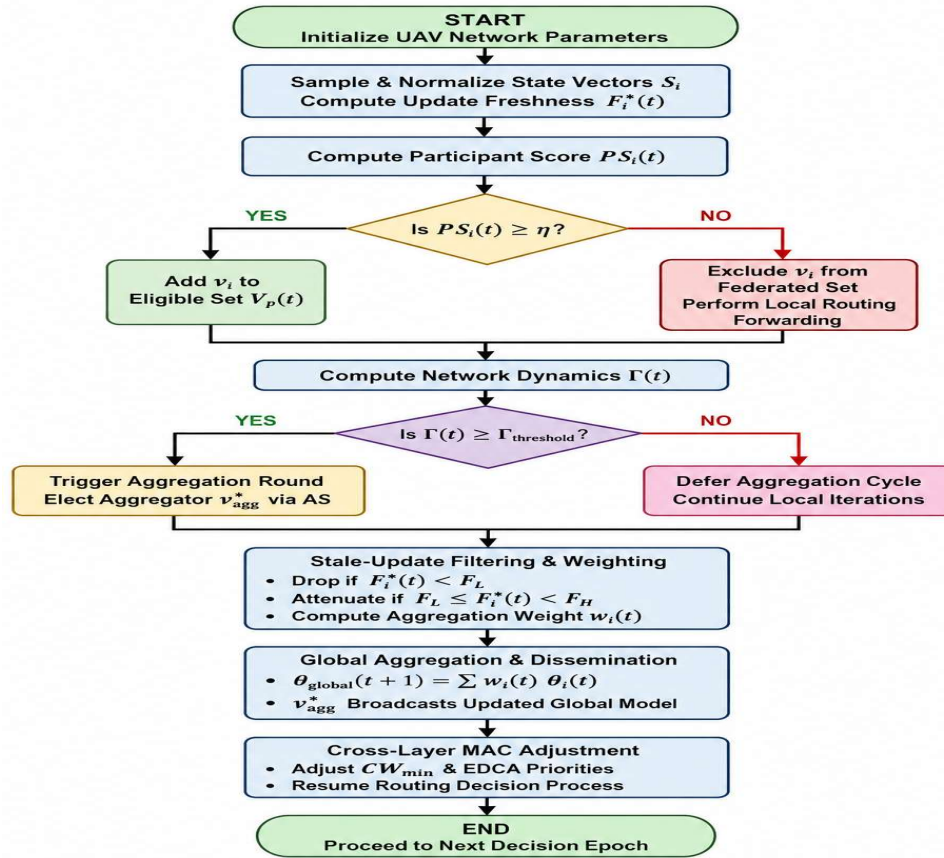


Figure 2. Execution Flowchart of MAFA-FANET

6. EXPERIMENTAL METHODOLOGY

This section describes the experimental protocol used to evaluate MAFA-FANET against the comparison methods shown in the supplied graphs. The simulations were implemented in Python. The evaluation is organized around packet delivery ratio (PDR), tail end-to-end delay (p99), and energy consumption per delivered bit because these metrics jointly reflect delivery reliability, delay robustness under congestion, and communication efficiency.

A. Simulation Environment and Network Configuration

The simulated FANET consists of UAVs randomly deployed in a $1000 \times 1000 \times 300$ m³ three-dimensional operational area. The number of UAVs is varied from 20 to 150 to represent sparse, moderate, and dense network conditions. UAV mobility follows a three-dimensional Random Waypoint model with speeds between 5 and 30 m/s. Each UAV communicates over a 250 m transmission range using a contention-based IEEE 802.11-type MAC model. The wireless channel is represented using free-space or two-ray-ground propagation, consistent with the configuration used to motivate the evaluation.

Traffic is generated using both constant-bit-rate (CBR) and event-driven patterns, with packet generation rates of 1–10 packets/s and a fixed packet size of 512 bytes. Each UAV begins with 100 J of energy. Communication energy is represented using a first-order radio model with 50 nJ/bit for transmission and 50 nJ/bit for reception; retransmission and control-message costs are also included. Each UAV has a finite queue of 50 packets. These settings provide a controlled environment in which the effects of density, contention, mobility, queuing, and energy balancing can be examined.

Table 1: Simulation Parameters for MAFA-FANET Evaluation

Parameter	Value
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Simulation area	1000 × 1000 × 300 m ³
Number of UAVs	20–150
Mobility model	3D Random Waypoint
UAV speed	5–30 m/s
Transmission range	250 m
MAC protocol	IEEE 802.11-based
Channel model	Free-space / Two-ray ground
Traffic type	CBR / Event-driven
Packet size	512 bytes
Packet generation rate	1–10 packets/s
Initial energy/UAV	100 J
Energy model	First-order radio model
Tx energy	50 nJ/bit
Rx energy	50 nJ/bit
Queue size	50 packets
Learning rate α	0.01–0.1
Discount factor γ	0.9
FL aggregation interval	5–20 s, adaptive
Aggregation method	Weighted averaging
Control window T_w	10 s
Control budget B_{max}	Fixed per window
Simulation time	500–1000 s
Independent runs	10–20

B. Evaluation Metrics

1. Packet Delivery Ratio (PDR) measures the fraction of generated packets successfully delivered to their destinations (Khujamatov et al., 2026):

$$PDR = \frac{N_{delivered}}{N_{generated}} \quad (20)$$

2. End-to-end delay is the elapsed time between packet generation and successful reception. Because dense FANETs can exhibit occasional severe delays, the p99 delay is also reported to capture the upper tail rather than only the average (Khujamatov et al., 2026).

$$P_{p99} = \text{percentile } 99 \{d_1, d_2, \dots, d_K\} \quad (21)$$

3. Energy consumption per delivered bit normalizes energy expenditure by useful data delivery and therefore penalizes schemes that consume more energy without improving successful throughput (Khujiyatov et al., 2026).

$$E_{\text{bit}} = \frac{E_{\text{total}}}{B_{\text{delivered}}} \quad (22)$$

7. RESULTS AND DISCUSSION

The results are interpreted in relation to the three principal objectives of MAFA-FANET: maintaining reliable packet delivery under increasing density, reducing delay especially tail delay under contention, and improving energy efficiency while avoiding uneven forwarding load. The graphs should therefore be read as evidence of how the integrated mobility-, freshness-, learning-, and energy-aware design responds to increasing network stress rather than as a collection of isolated numerical comparisons.

A. Packet Delivery Ratio Analysis

Figure 4 shows PDR as the number of UAVs increases from 30 to 120. All methods exhibit a downward trend, indicating that increasing network density creates progressively more difficult forwarding conditions. In a dense FANET, additional UAVs increase the number of potential neighbors, but they also increase contention and the frequency with which routing decisions can become inconsistent with the current topology. Thus, higher node density does not automatically translate into higher delivery reliability.

MAFA-FANET maintains the highest PDR throughout the tested range, decreasing from 0.97 at 30 UAVs to 0.91 at 120 UAVs. More importantly, its absolute degradation is 0.06, compared with 0.07 for FL-CARE, 0.10 for RL-MPEAOLSR, and 0.12 for MP-QGRD. The smaller decline indicates greater robustness as the network becomes denser. At 120 UAVs, MAFA-FANET is about 4.6% above FL-CARE, 15.2% above RL-MPEAOLSR, and 23.0% above MP-QGRD when the improvement is calculated relative to each baseline PDR.

The most plausible mechanism supported by the framework design is the joint use of mobility-aware freshness, participant selection, event-driven aggregation, stale-update filtering, and freshness-weighted aggregation. These components reduce the likelihood that routing knowledge learned under an obsolete topology will dominate the current global model. This interpretation is consistent with the framework objective, but it should be stated as a mechanism-based explanation rather than as a causal proof until component-level ablation experiments are reported.

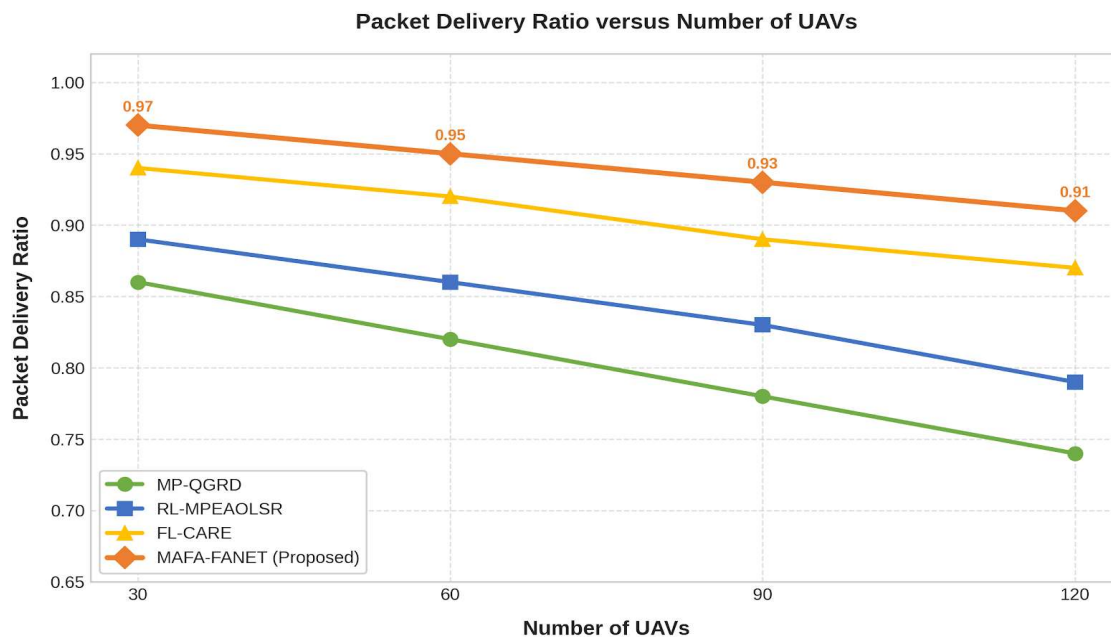


Figure 3. Packet Delivery Ratio versus Number of UAVs

B. Tail End-to-End Delay Analysis.

Figure 5 reports the p99 end-to-end delay, which is particularly informative for FANET routing because a small number of severely delayed packets can be operationally important even when the average delay appears acceptable. The p99 delay increases for every method as the UAV population grows from 60 to 150, showing that denser operation increasingly stresses forwarding and channel access.

MAFA-FANET has the lowest p99 delay at every tested density: 140, 175, 220, and 265 ms for 60, 90, 120, and 150 UAVs, respectively. Relative to FL-CARE, this corresponds to reductions of about 26.3%, 25.5%, 25.4%, and 24.3%. The advantage over RL-MPEAOLSR is approximately 48.1%–47.0%, while the reduction relative to MP-QGRD is approximately 52.7%–55.7% across the four densities.

The near-parallel growth of the MAFA-FANET curve suggests that its principal benefit is not the complete removal of density-related delay, which would be unrealistic, but a reduction in the severity of delay growth. The event-driven aggregation mechanism can update collaborative routing knowledge when network conditions change rather than waiting solely for a fixed period, while stale updates are prevented from receiving full influence. Together with participant and aggregator selection, these mechanisms are intended to reduce decisions based on obsolete or poorly positioned network information. However, the current experiment cannot isolate which component produces the largest delay reduction.

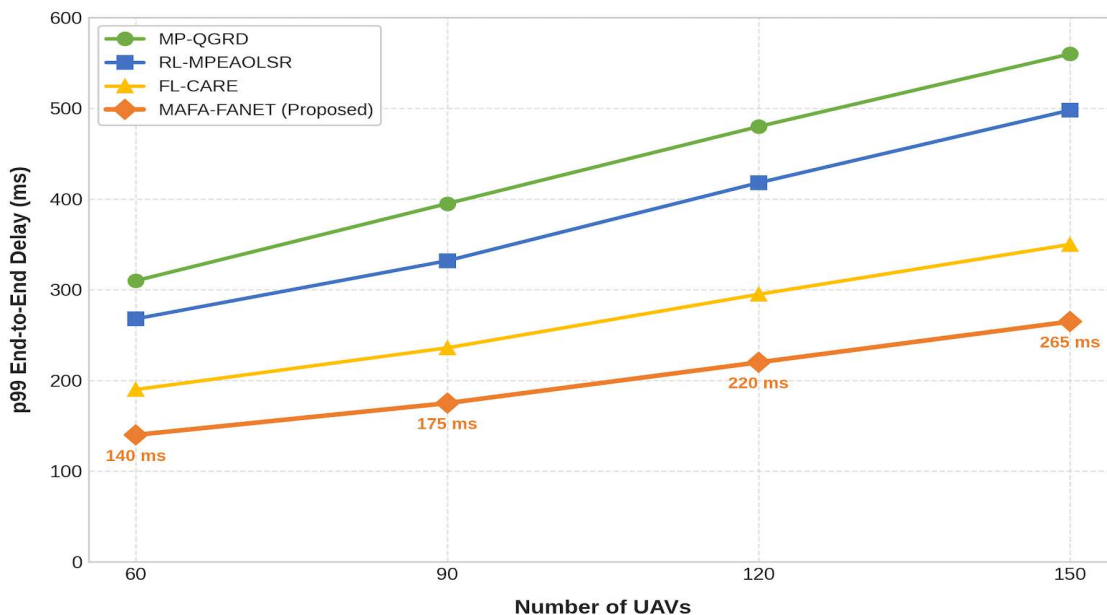


Figure 4. Tail End-to-End Delay (p99) versus Number of UAVs

C. Energy Consumption per Delivered Bit Analysis

Figure 6 shows energy consumption per delivered bit for 60–150 UAVs. The metric increases with network density for all methods, indicating that the additional communication and forwarding activity required in denser networks is not free in energy terms. MAFA-FANET remains the most energy-efficient method across the full range, with values increasing from 0.018 to 0.032 J/bit.

At 150 UAVs, MAFA-FANET consumes approximately 11.1% less energy per delivered bit than FL-CARE, 30.4% less than RL-MPEAOLSR, and 38.5% less than MP-QGRD. The relative advantage is also present at lower densities. This is important because the proposed method does not trade its higher PDR and lower tail delay for excessive energy use; the three reported metrics move together in a favorable direction.

The energy result can be interpreted as evidence that the framework's selective participation and aggregator choice may reduce unnecessary coordination and forwarding overhead while retaining routing information that is sufficiently fresh to be useful. Nevertheless, the plotted metric is energy per delivered bit, not total network lifetime or residual-energy fairness. The manuscript should therefore avoid claiming that MAFA-FANET maximizes lifetime unless lifetime, node-level energy distribution, or time-to-first-depletion results are additionally reported.

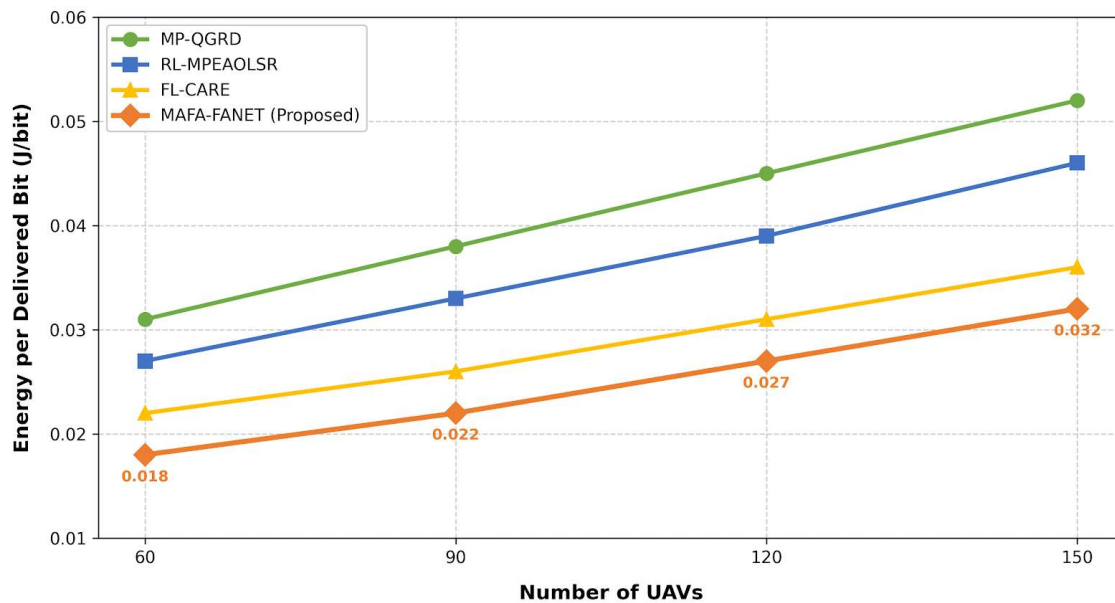


Figure 5. Energy Consumption per Delivered Bit versus Number of UAVs

D. Cross-Metric Interpretation

Taken together, Figures 2–4 provide a coherent performance pattern. MAFA-FANET has the highest PDR, the lowest p99 delay, and the lowest energy consumed per delivered bit over the displayed density ranges. The results therefore support the narrower claim that the proposed design offers a favorable reliability–latency–energy trade-off under the tested simulation conditions.

The trend is also more informative than any single endpoint. As density increases, MAFA-FANET's PDR falls by only 0.06 across the PDR experiment, while its p99 delay rises from 140 to 265 ms and its energy per delivered bit rises from 0.018 to 0.032 J/bit. The baselines experience larger degradation in the corresponding measures. This relative stability is consistent with the intended role of freshness-aware coordination: the framework attempts to keep collaborative routing knowledge aligned with the current network state rather than treating all received model updates as equally relevant.

The density ranges are not identical across all figures: PDR is plotted for 30–120 UAVs, whereas p99 delay and energy are plotted for 60–150 UAVs. Consequently, the figures should not be used to infer a single continuous performance curve from 30 to 150 UAVs. The comparison is valid within each experiment's reported range.

8. Conclusion and Future Work

This study proposed the Mobility- and Information-Freshness-Aware Adaptive Federated Learning framework (MAFA-FANET) for routing in dense and dynamic Flying Ad Hoc Networks. The framework integrates mobility- and freshness-aware participant selection, event-driven aggregation, temporary aggregator selection, stale-update management, and freshness-aware model aggregation to improve the relevance of federated routing information. Simulation results show that MAFA-FANET achieved higher packet delivery ratio (PDR), lower p99 end-to-end delay, and lower energy consumption per delivered bit than the evaluated comparison methods. At high network density, it achieved approximately 4.6%, 15.2%, and 23.0% higher PDR than FL-CARE (Khujamatov et al., 2026), RL-MPEAOLSR (Prakash et al., 2024), and MP-QGRD (Wang et al., 2025), respectively. It also reduced p99 end-to-end delay by approximately 24.3–26.3%, 47.0–48.1%, and 52.7–55.7%, respectively. At 150 UAVs, the energy consumption per delivered bit was approximately 11.1%, 30.4%, and 38.5% lower than the three comparison methods, respectively. The results indicate that incorporating mobility and information freshness into federated coordination can improve routing performance under the evaluated FANET conditions. However, the current study evaluates the integrated framework; therefore, the individual contribution of each component has not been quantified. Future work

will focus on component-level ablation studies, evaluation under larger and more heterogeneous UAV networks, and testing under higher mobility and rapid topology changes and UAV testbed or hardware-in-the-loop experiments will be considered to validate the simulation results in practical environments.

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