Challenges and Innovations in Routing for Flying Ad Hoc Networks: A Survey of Current Protocols

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ABSTRACT
The proposed study provides a comprehensive overview of the unique challenges faced by Flying Ad Hoc Networks (FANETs), which utilize Unmanned Aerial Vehicles (UAVs) as dynamic nodes in three-dimensional space. The inherent high mobility of UAVs leads to rapidly changing network topologies, frequent link failures, and difficulties in maintaining reliable communication. Traditional routing protocols often struggle to adapt to these conditions, necessitating the exploration of advanced solutions. This survey emphasizes the potential of machine learning, particularly reinforcement learning, to optimize routing paths in such dynamic environments. By categorizing recent developments in reinforcement learning-based routing protocols for FANETs, the paper identifies areas for improvement and ongoing challenges, aiming to guide future research and innovation in enhancing aerial communication systems. Ultimately, the findings contribute to the advancement of intelligent routing solutions tailored to the complexities of FANETs, with implications for applications in disaster response, military operations, and environmental monitoring.

Keywords: FANETs, operations, monitoring, UAVs.

1. INTRODUCTION
In today's technologically advanced society, wireless ad hoc networks (WANETs) have become indispensable components of communication systems. Among these, Flying Ad Hoc Networks (FANETs) have emerged as a critical technology, particularly in applications requiring rapid deployment and high mobility, such as disaster response, military operations, and environmental monitoring.FANETs, characterized by the use of unmanned aerial vehicles (UAVs) as dynamic nodes, face significant challenges in maintaining reliable and efficient communication. These challenges include frequent link failures, high node mobility, and rapidly changing network topologies, which can severely impact the Quality of Service (QoS). Traditional routing algorithms often struggle to adapt to these conditions, necessitating the exploration of more advanced solutions.Machine learning (ML), and particularly reinforcement learning (RL), offers a promising approach to addressing the complexities of routing in FANETs. RL's ability to continuously learn and adapt to the network environment makes it well-suited for optimizing routing paths in such dynamic and unpredictable settings.While there has been significant progress in applying RL to routing in various types of ad hoc networks, the specific challenges of FANETs require tailored approaches that go beyond existing methodologies. Moreover, the integration of RL with emerging technologies such as software- defined networking (SDN) and blockchain has the potential to further enhance routing performance in FANETs.This paper provides a comprehensive survey of reinforcement learning-based routing protocols designed for FANETs. By categorizing recent developments, identifying potential areas for improvement, and highlighting ongoing challenges, this survey aims to guide future research and innovation in optimizing routing algorithms for FANETs, ultimately contributing to the advancement of intelligent aerial communication systems.

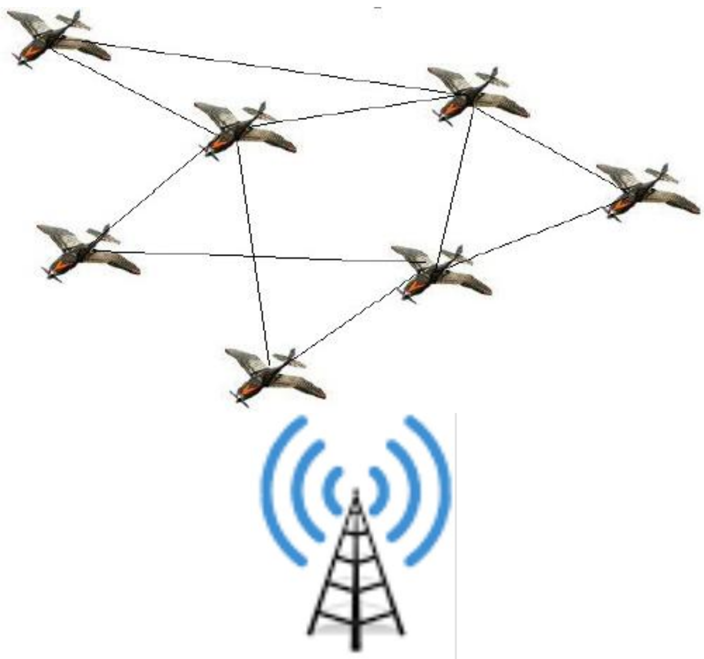

Figure 1. Flying Adhoc Network

2. Routing Challenges in FANET

2.1 High Mobility of UAVs and Dynamic Network Topology

The integration of Unmanned Aerial Vehicles (UAVs) into Flying Ad Hoc Networks (FANETs) brings forth unique challenges due to their inherent high mobility. Unlike traditional ground- based networks, where node positions tend to remain relatively stable, UAVs operate in a three- dimensional space and can exhibit a wide range of speeds and altitudes. This results in a constantly shifting network topology, characterized by varying degrees of separation between nodes and the potential for rapid movement into and out of communication range. Consequently, the dynamic nature of UAV movement complicates the establishment and maintenance of stable communication links, which are crucial for effective data transmission and overall network reliability [1] .

The unpredictable mobility patterns of UAVs exacerbate the inherent instability of FANETs, leading to frequent link breakages and disruptions in connectivity4. As UAVs navigate their operational environments, their rapid acceleration, deceleration, and change in flight trajectories can result in sudden disconnects or the formation of new links with neighboring nodes. Such fluctuations make it increasingly difficult to maintain reliable, long-term routes essential for data transmission between users. Existing routing protocols that depend on static node positioning are often ill-equipped to handle this level of dynamism, necessitating the development of adaptive routing mechanisms that can quickly respond to changing topologies [2].

The need for more sophisticated routing protocols becomes evident, as they must not only cope with the frequent re-establishment of links but also optimize data pathways based on real-time mobility patterns. Addressing these challenges requires innovative strategies that leverage machine learning, rapid topology discovery techniques, and real-time data dissemination methods. By allowing FANET to intelligently adapt to changing network conditions, such protocols can enhance the reliability and efficiency of communications in environments characterized by the inherent uncertainties of UAV operations. [3] Introducing a mobility model,such as the Random Waypoint Model, to simulate UAV movement can help predict topology changes. The model typically involves UAVs moving toward random destinations, pausing for a period, and then moving again, representing a typical UAV movement pattern in FANETs.

2.2 Communication Limitations Due to Rapid Movement

The rapid movement of UAVs in FANETs poses significant challenges for communication, primarily due to Doppler shifts, signal fading, and interference. The Doppler effect, caused by the relative velocity between the UAVs and the ground stations, can result in frequency shifts that degrade signal quality. Additionally, as UAVs move rapidly, they encounter varying environmental conditions, leading to signal fading and increased interference.

These communication limitations can cause packet loss, delays, and reduced throughput, impacting the overall performance of the network. As a result, routing protocols in FANETs must account for these factors, ensuring that routes are selected not only based on the shortest path but also on the quality of communication links. This requires incorporating real-time link quality assessment and prediction into routing decisions.

2.3 Energy Constraints of UAVs

Energy constraints are a critical concern in FANETs, as UAVs are typically powered by batteries with limited capacity. The energy consumed by a UAV includes not only the power required for flight but also the energy needed for communication, data processing, and other onboard activities. Efficient energy management is crucial for prolonging the operational time of UAVs, particularly in missions where long-duration flight or extended network coverage is required. Routing protocols in FANETs must be designed with energy efficiency in mind. This can be achieved by minimizing the energy consumption associated with communication, such as by reducing the transmission power, optimizing the routing path to avoid unnecessary retransmissions, and selecting routes that balance energy usage among UAVs. Energy-aware routing metrics can be incorporated into routing decisions to ensure that the network remains operational for as long as possible. [4].

2.4 Need for Adaptive Protocols

Given the dynamic and challenging environment of FANETs, there is a pressing need for adaptive routing protocols that can respond gracefully to changes in network topology, communication quality, and energy availability. Adaptive protocols are designed to be flexible, allowing them to adjust their behavior based on real-time network conditions.These protocols can leverage various techniques, such as machine learning and reinforcement learning, to predict changes in the network and proactively adjust routes. For example, a reinforcement learning-based protocol might learn the optimal routing strategies over time by interacting with the network environment, selecting routes that maximize network performance while minimizing energy consumption.Despite advances in adaptive routing, there are still gaps in developing fully autonomous protocols that can handle the extreme variability in FANETs.

3. Reinforcement Learning and Applications of Reinforcement Learning in Routing

Reinforcement Learning (RL) is an advanced area of machine learning that focuses on how agents interact with their environment to achieve specific goals through trial and error. Agents are designed to take actions in specific states within an environment with the objective of maximizing cumulative rewards over time. This process involves key components: the agent, the environment, states, actions, rewards, policies, and value functions. The agent learns a policy, which is a mapping from states to actions that guides its decision-making process. [5]A fundamental principle underlying RL is the exploration-exploitation trade-off. This balance requires the agent to explore new actions that might lead to better rewards while exploiting known actions that yield high rewards1. Its adaptability and iterative learning capabilities make RL particularly useful in complex and dynamic environments, including those characterized by unpredictable changes, such as wireless communication networks.

3.1. Mobile Ad Hoc Networks (MANETs)

In MANETs, nodes are characterized by their ability to move freely and change their interconnections, posing significant challenges for routing protocols. Reinforcement Learning (RL) has been integrated into routing algorithms to enhance decision-making and resource allocation in these dynamic environments. Studies have demonstrated that RL-based approaches can effectively learn and adapt to changing network topologies, resulting in improved path selection and reduced packet loss.

3.2. Vehicular Ad Hoc Networks (VANETs)

RL has been extensively applied in VANETs, where vehicles engage in dynamic communication to ensure traffic safety and efficiency. RL algorithms optimize routing decisions by predicting traffic conditions, managing congestion, and adjusting routes in real-time based on vehicle movement. Research indicates that RL enhances routing efficiency and improves traffic management, contributing to safer and more efficient transportation systems.

3.3. Flying Ad Hoc Networks (FANETs)

The integration of Unmanned Aerial Vehicles (UAVs) into FANETs introduces additional complexities, such as high mobility and constantly shifting network topologies. RL algorithms are employed to swiftly adapt to these changes, ensuring reliable and efficient data transmission. Research has shown that RL plays a critical role in overcoming routing challenges in FANETs, allowing UAVs to dynamically learn optimal routing paths while considering variables like altitude and speed fluctuations.The classification of Reinforcement Learning (RL)-based routing protocols based on thedata dissemination process reveals four primary categories: unicast, multicast, broadcast,and geocast. Each of these routing techniques has distinct characteristics, advantages, and disadvantages which influence their suitability for specific applications within FlyingAd Hoc Networks (FANETs). A comparative table is provided to summarize the main features and challenges of each method.

Table 1 . Routing Methods

Routing Method	Description	Strengths	Weaknesses
Unicast-based	Point-to-po in communication with onesource and one destination. Requires precise localization(GPS).	Direct communication and simplicity.	High communication over head, delays, and band width consumption; poor performance in dynamic topologies.
Multicas t-based	Dissemination of data packets to a defined group of UAVs. Requires membership in multicast groups.	Efficient use of bandwidth and energy for group communication.	Needs constant reconstruction of routing trees; challenges in dynamic topologies.
Broadca st-based	Flooding messages throughout The entire network.	Simple implementation And does not require spatial information.	High bandwidth use, potential for network congestion, and redundancy issues.
Geocast-based	Sending data to all UAVs within a specified geographic area. Geographic areas are part of the packets.	Focused communication to specific regions.	Relies on positioning systems; requires knowledge of geographical locations9.

Table 2. Related Works

Author(s)	**Protocol**	**Reward Influencing Factors**	**Evaluation Metrics**
Ji et al.	RHR	Control packet types	Packet Delivery Ratio (PDR), Round-Trip Time (RTT), Overhead (OH)
Li et al.	QGrid	Message delivery to the target grid	PDR, Hop Count (HC), Delay, Number of Forwarding Nodes, Threshold (TH)
Wu et al.	DTNP	Direct connection status or HC, elapsed time since last connection	Delay, PDR
Zhang et al.	RSAR	HC, Link Reliability (LR), Bandwidth (BW)	PDR, End-to-End Delay (E2ED), Average Route Length, OH
Roh et al.	Q-LBR	Load of UAV relay node, Ground network congestion	PDR, Network Utilization, Delay
Wu et al.	ARPRL	Arrival of control packet from sender	PDR, E2ED, HC, OH
Wu et al.	QTAR	Link Quality (LQ), Link Expiration Time, Delay	PDR, E2ED
Li et al.	ECTS	Arrival of charging data at destination	Communication Cost, Connection Probability, PDR, OH
Luo et al.	IV2XQ	Packet forwarding to the destination	PDR, E2ED, HC, OH
Yang et al.	HAEQR	Current node’s membership in the one-hop neighbor set of the destination	PDR, E2ED, HC
BouzidSmida et	LEQRV	Link Lifetime (LQ), Distance to	MOS, Peak Signal-to-Noise

al.		Destination, Mean Opinion Score (MOS), Neighbor Count, Buffer Level	Ratio, Structural Similarity, E2ED, Frame Loss
Lolai et al.	RRIN	Vehicle speed difference, direction, queue data packets, signal fading, LR	PDR, Packet Loss Ratio (PLR), Delay, TH
Nahar et al.	RL-SDVN	Distance from destination vehicle	Delay, TH
Dai et al.	QLASS	Reputation gain, Node action payoff	PDR, Reputation, Utility
Jiang et al.	QAGR	Received Signal Strength (RSS), Transmission Distance, Collision Events	PDR, E2ED, HC
Wu et al.	V2R-CBR	Observed node's one-hop neighbor status, HC, Payoff, LQ	PDR, Number of Collided MAC Frames, E2ED, TH
Zhang et al.	FLHQRP	Cluster's adjacency to destination cluster, Traffic Density	PDR, E2ED, HC, OH
Chang et al.	CEVCS	Observed node's one-hop neighbor status, HC, LQ	PDR, TH
Saravanan et al.	DRLV	Maximum link utilization under future strategy, Optimal link utilization	PDR, E2ED, OH
Ye et al.	VMDRL	Energy loss, Transmission Range (TR)	Energy Cost (EC), Packet Loss Ratio (PLR), Transmission Time, Communication Interruption Probability
Zhang et al.	TDRL-RP	Trust-related information	PDR, TH
Yang et al.	VDDS	HC, LQ	TH, Number of Gateway Cluster Heads
Nahar et al.	SeScR	Quality of available routes, Vehicle Speed, Location	Cluster Stability, Lifetime, Alienation Time, Delay, TH, Computation Delay
Zhang et al.	SD-TDQL	Trust value per vehicle, Reverse Delivery Ratio	Packet Loss Ratio (PLR), Delay
Zhang et al.	T-DDRL	Trust-related information	TH, E2ED
Zhang et al.	blockSDV	Threshold (TH)	TH
Bi et al.	RLRC	Current node's neighbor status, HC, Link Utility, BW	PDR, HC
Jafarzadeh et al.	RRPV	Link Quality (LQ), Distance from Neighbor to Destination	PDR, Delay, OH
Li et al.	QMPS	Proportion of delay-sensitive messages, Probability of successful message reception	E2ED, TH, PLR
Arafat et al.	QTAR	Next-hop node type, E2ED, Node Velocity, EC	PDR, E2ED, EC, Network Lifetime, OH
Zheng et al.	RLSRP	Conditional success/failure probability of packet transmission to next-hop	Success Rate, Average Route Lifetime, HC, PDR, TH, No Retransmissions, Delay
Mowla et al.	AFRL	Detection of jamming	Accuracy, Success Rate, HC, Iterations to Convergence, Cumulative Reward
Sliwa et al.	PARRoT	Link Expiry Time, Changes in Neighbor Set of Forwarding Node	PDR, E2ED
Da Costa et al.	Q-FANET	Link to destination, Local Minimum	E2ED, Jitter, PDR
Liu et al.	QMR	Link to destination, Local Minimum, E2ED, EC	E2ED, Packet Arrival Ratio, EC
Khan et al.	RL-	Successful Packet Transmission	EC, Number of Links
Yang et al.	QL-FLRP	HC, Shortest Path Distance (SPDT)	HC, Remaining Node Energy,

			TR
Liu et al.	ARdeep	Link to destination, Local Minimum, Distance, Energy of Neighbor	PDR, E2ED
Ayub et al.	AI-Hello	Transmission Range, Allowed Airspace, Number of UAVs, Speed Ranges	EC, OH, PDR, TH, E2ED
He et al.	FLRL	Optimality of Neighbor Node, Link Cost (LC)	HC, LC

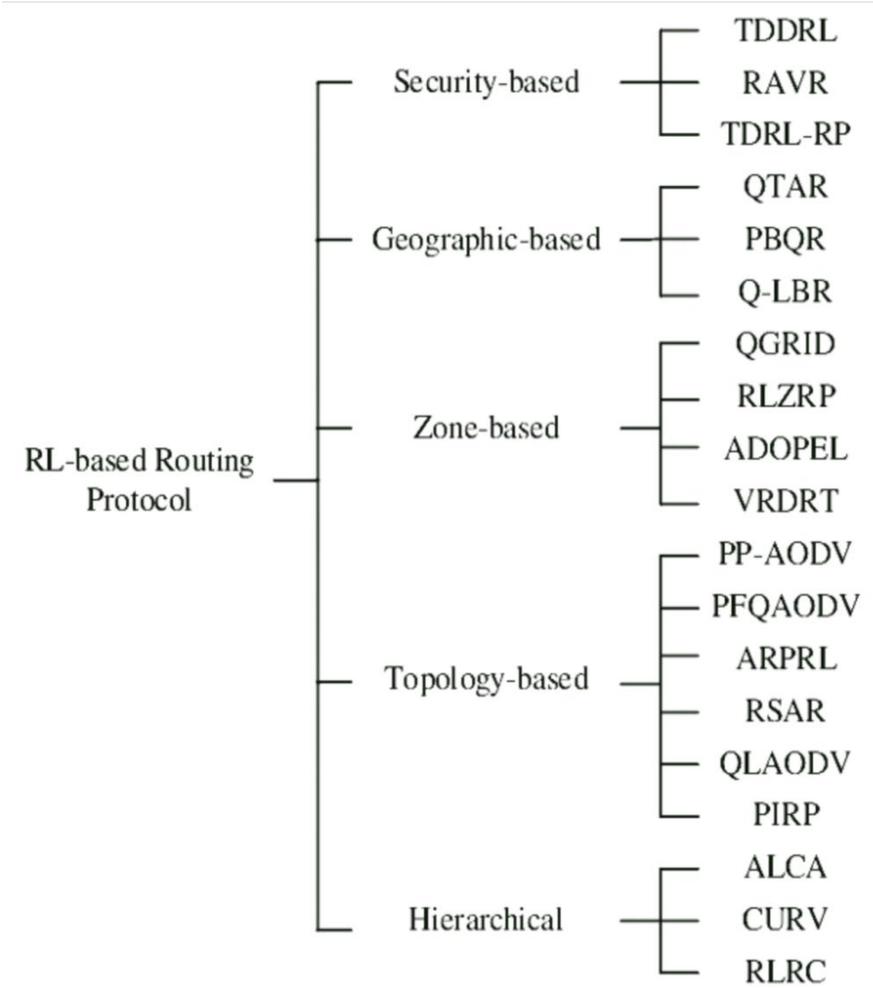

Figure 2. RL based Routing Protocols

4. Differentiation of FANET Routing Protocols: Influencing Factors, Metrics, and Evaluation

4.1 Influencing Factors and Protocol Objectives

The various routing protocols in FANETs are designed with specific influencing factors that address different aspects of network performance and routing efficiency. For instance, Ji et al. [9] proposed the RHR protocol, which focuses on the type of control packets transmitted through the network. This protocol evaluates performance using Packet Delivery Ratio (PDR), Round-Trip Time (RTT), and Overhead (OH), aiming to optimize the efficiency of control packet management. In contrast, Li et al. [10] introduced the QGrid protocol, which considers whether messages are successfully delivered to the destination grid. Key performance metrics for QGrid include PDR, Hop Count (HC), delay, and Throughput (TH). This approach highlights the protocol's emphasis on ensuring effective message delivery and minimizing routing delays. Wu et al. [11] developed the DTNP protocol, which evaluates routing effectiveness based on the direct connection status and the elapsed time since the last connection. Metrics such as Delay and PDR are used to assess performance, reflecting the protocol's focus on maintaining stable and timely connections. Zhang et al. [12]'s RSAR protocol considers Link

Reliability (LR), Bandwidth (BW), and Hop Count (HC) to enhance routing stability. It measures performance using PDR and End-to-End Delay (E2ED), showcasing an approach geared towards ensuring reliable and efficient data transmission.

4.2 Network Load Management and Resource Optimization

Several protocols address network load and resource constraints to optimize data transmission and minimize network congestion. Roh et al. [13] proposed the Q-LBR protocol, which considers UAV relay node load and ground network congestion. It evaluates PDR, network utilization, and delay, focusing on balancing network load and enhancing resource management.
Wu et al. [14]'s ARPRL protocol assesses whether control packets arrive from the sender, using metrics such as PDR, E2ED, Hop Count (HC), and Overhead (OH). This protocol emphasizes managing network load by monitoring packet arrival and ensuring efficient routing. Li et al. [16] developed the ECTS protocol, which evaluates factors like communication cost and connectionprobability. Performance metrics include PDR, communication cost, and OH, reflecting a focus on optimizing resource usage and reducing communication expenses.

4.3 Metrics for Evaluating Routing Performance

The choice of performance metrics reveals the primary objectives and evaluation criteria for each protocol. Luo et al. [17]'s IV2XQ protocol focuses on packet forwarding success and node neighbor status, measuring PDR, E2ED, and HC. Yang et al. [18]'s HAEQR protocol considers whether the current node belongs to a set of one-hop neighbors of the destination, using metrics like PDR, E2ED, and HC to evaluate routing performance. BouzidSmida et al. [19]'s LEQRV protocol assesses factors such as link lifetime, link quality, and distance to the destination. It measures metrics like Mean Opinion Score (MOS), Peak Signal-to-Noise Ratio (PSNR), and Packet Loss Ratio (PLR), providing a comprehensive evaluation of link reliability and data transmission quality. Lolai et al. [20]'s RRIN protocol takes into account vehicle speed differences, vehicle direction, and the number of data packets in the queue. Performance is evaluated using PDR, PLR, delay, and TH, highlighting a focus on dynamic vehicle interactions and queue management.

4.4 Simulation Environments and Evaluation Tools

The choice of simulation environments and tools is crucial for accurately assessing the performance of routing protocols. Protocols such as RHR [9] and QGrid [10] are evaluated using ns3 and custom-made simulators, respectively. ns3 is known for its detailed network modeling capabilities, while custom simulators offer targeted evaluations based on specific protocol requirements. Protocols like Zhang et al. [25]'s FLHQRP and Chang et al. [26]'s CEVCS use ns2, which provides insights into cluster stability and node communication efficiency. Advanced simulators such as sumo and omnet++ are employed by protocols like IV2XQ [17] and SeScR [31], offering detailed evaluations in complex network scenarios. Other protocols, such as those developed by Liu et al. [42] and Khan et al. [43], use wsnet and matlab to assess performance based on factors like link quality and network lifetime. The diverse simulation tools used across these protocols reflect the need for adaptable evaluation environments to validate effectiveness under varying FANET conditions.

4.5 Comparative Analysis and Impact on Routing Efficiency

A comparative analysis of these protocols reveals their contributions to advancing routing efficiency in FANETs. The RHR protocol by Ji et al. [9] and QGrid by Li et al. [10] focus on optimizing control packet management and message delivery. Protocols like Q-LBR [13] and ARPRL [14] address network load and congestion management, demonstrating approaches to balancing resource utilization and enhancing data transmission efficiency. Protocols such as LEQRV [19] and RRIN [20] emphasize link quality and vehicle dynamics, contributing to a more nuanced understanding of routing performance in dynamic environments. The diverse set of metrics and simulation environments employed by these protocols illustrates the multifaceted nature of routing optimization in FANETs, highlighting ongoing efforts to address various network challenges and improve overall performance.

CONCLUSION

In this paper, we explored the intricate landscape of routing challenges in Flying Ad Hoc Networks (FANETs) and evaluated the role of Reinforcement Learning (RL) in addressing these issues. FANETs, characterized by their dynamic topologies and high mobility, pose significant challenges to traditional routing approaches, including issues related to network stability, communication quality, and energy efficiency. Reinforcement Learning offers a promising solution to these challenges by enabling protocols to adaptively learn and optimize routing strategies based on real-time network conditions. Our survey categorized and examined various RL-based routing methods, highlighting their applications in Mobile Ad Hoc Networks (MANETs), Vehicular Ad Hoc Networks (VANETs), and FANETs. Each method presents unique strengths and limitations, reflecting the complexity of designing adaptive and efficient routing protocols in highly dynamic environments. The comparative analysis of different RL- based routing protocols revealed their diverse approaches to managing network load, optimizing resource usage, and improving overall routing performance. While protocols such as RHR, QGrid, LEQRV, and RRIN demonstrate significant advancements in addressing specific routing challenges, ongoing research is essential to refine these methods further. Future work in this field should focus on enhancing RL-based routing protocols to better handle extreme network dynamics and energy constraints inherent to FANETs. Integrating RL with other emergingtechnologies, such as edge computing and advanced sensors, may also provide new avenues for improving routing efficiency and network reliability. In conclusion, the integration of Reinforcement Learning into FANET routing strategies represents a substantial advancement towards more resilient and adaptive communication systems. By continuously evolving and addressing the identified challenges, future research has the potential to significantly enhance the performance and applicability of FANETs in various real-world scenarios.

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