International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 6, December 2024, pp. 6433~6444
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i6.pp6433-6444

Exploring optimal resource allocation methods for improved efficiency in flying ad-hoc network environments: a survey

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Article Info

Article history:

Received May 23, 2024
Revised Aug 6, 2024
Accepted Aug 14, 2024

Keywords:

Efficiency optimization
Flying ad-hoc network
Intelligent algorithms
Network performance
Resource allocation
Unmanned aerial vehicles

ABSTRACT

This survey explores optimal resource allocation methods to enhance the efficiency of flying ad-hoc networks (FANETs). Unmanned aerial vehicles (UAVs), commonly known as drones, are widely deployed in military and civilian applications, necessitating effective coordination and communication to overcome challenges. FANETs facilitate wireless communication among UAVs, improving coordination and information exchange in environments lacking traditional networks. The dynamic mobility of UAVs introduces unique considerations for network design and connectivity, distinguishing FANETs from conventional ad-hoc networks. This survey reviews various optimization techniques, including genetic algorithms, ant colony optimization, and artificial neural networks, which optimize resource allocation by considering mission requirements, network topology, and energy constraints. The paper also discusses the critical role of intelligent algorithms in enhancing network energy management, quality of service (QoS), maximizing resource allocation, and optimizing overall performance. The systematic literature review categorizes resource allocation strategies based on performance optimization criteria and summarizes their strengths, weaknesses, and applications. This survey highlights the potential of FANETs to revolutionize various industries and unlock new opportunities for UAV-based applications.

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1. INTRODUCTION

The deployment of unmanned aerial vehicles (UAVs), commonly known as drones, has experienced a significant increase in both military and civilian contexts, driven by the widespread availability of cost-effective electronic sensors and communication technologies [1]. However, effective coordination and communication among multiple UAVs present considerable challenges. To overcome these challenges, flying ad-hoc networks (FANETs) have emerged as practical solutions. Wireless communication among UAVs enables improved coordination and facilitates information exchange [2]. In various contexts, terms like UAV network, FANET, and drone ad-hoc network are often interchangeable. This paradigm proves especially useful in environments lacking traditional communication networks, such as disaster zones, remote areas, and offshore installations [3].

The dynamic mobility of UAVs introduces unique considerations for connectivity and network design within FANETs, setting them apart from conventional ad-hoc networks [4]. With the increasing demand for wireless systems, preserving quality of service (QoS) and meeting user expectations pose increasing challenges. Consequently, efficient resource allocation policies are crucial to optimize power and bandwidth utilization. Resource allocation involves assigning available resources-such as time, energy, and bandwidth-to network nodes based on their requirements and priorities, thereby ensuring effective resource utilization and QoS provisioning [5]. In the context of FANETs, optimal resource allocation plays a critical role in improving network efficiency and effectiveness. Achieving optimal resource allocation among unmanned aerial vehicles is imperative to enhance network performance and establish reliable communication channels. Intelligent algorithms are employed within FANETs to enhance network QoS, maximize resource allocation, and optimize overall performance [6]. Examples of such algorithms include genetic algorithms, ant colony optimization, and artificial neural networks, which optimize resource allocation by considering various factors such as mission requirements, network topology, and energy constraints.

Flying ad-hoc networks (FANETs) represent networks of unmanned aerial vehicles (UAVs) collaborating to form an integrated system, with each UAV operating under resource constraints that encompass processing power, storage capacity, and battery life limitations. Effective resource management is essential to ensure optimal network performance. Intelligent resource allocation within FANETs involves analyzing network traffic, predicting future demands, and allocating resources accordingly [7]. This optimization of resource utilization enhances network performance, reduces latency, and facilitates efficient data throughput. Intelligent resource allocation plays a pivotal role in extending UAV battery life, ensuring continuous network connectivity, and meeting mission objectives. Optimal and intelligent resource allocation is vital for the smooth operation of FANETs, allowing them to fulfill various application needs like surveillance, search and rescue, and environmental monitoring [8]. FANETs offer distinct advantages, functioning effectively in areas with limited communication networks and finding applications across diverse domains, including surveillance, search and rescue missions, and environmental monitoring. Continuous advancements in resource allocation and control algorithms hold promise for further enhancing FANET capabilities. In summary, FANETs have the potential to revolutionize numerous industries and unlock novel opportunities for UAV-based applications [9].

The paper's structure is outlined below. In section 2, we introduce the systematic literature review framework. In section 3, we offer background information on key concepts pertinent to this paper, including FANET, resource allocation, and intelligent algorithms. Section 4 explores related research on optimization techniques to elevate the energy efficiency, quality of service, routing protocols and flight trajectories in FANET. Section 5 presents an analysis and discussion. Finally, the paper concludes in section 6.

2. SYSTEMATIC LITERATURE REVIEW SCHEME

In this section, we will review survey papers on FANET found in the literature. These articles introduce FANET thorough review of resource allocation, including answers to energy efficiency, quality of service, and routing protocol challenges. Resource allocation strategies are classified based on performance optimization criteria, and we will summarize these categories and optimization strategies, highlighting their strengths, weaknesses, and area of applications. Several articles related to resource allocation in FANET, including specific solutions to address issues such as energy consumption, quality of service, routing protocols, and flight trajectory, were reviewed, and cite 50 articles selected for the review study in this paper. The percentage distribution of the total articles for related work (50 papers) published in IEEE, MDPI, Springer, Hindawi, and others, as shown in Figure 1. Scholars have explored utilizing optimization techniques to upgrade various aspects of FANET networks, including energy consumption, quality of service, routing protocols, and flight trajectory.

In summary, the optimization of resource allocation in FANETs through the integration of optimization methods has served as a foundational approach for enhancing various facets of FANET networks. Figure 2 illustrates the percentage distribution of optimization techniques employed to enhance diverse aspects of FANET networks. These techniques have been applied to enhance quality of service within FANET networks [10], and address energy consumption reduction as discussed in study [11]. Furthermore, optimization techniques have found utility in improving routing protocols and flight trajectories within the FANET context [12]. Figure 3 illustrates the number of papers published related to resource allocation in FANET over the past years in IEEE, MDPI, Springer, Elsevier, and other journals.

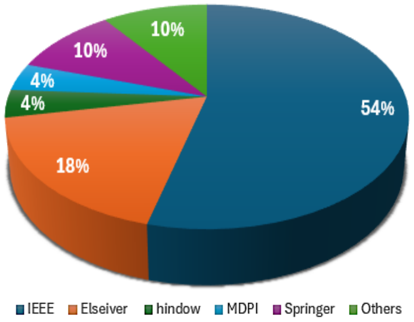

Figure 1. Percentage distribution of total articles for related work

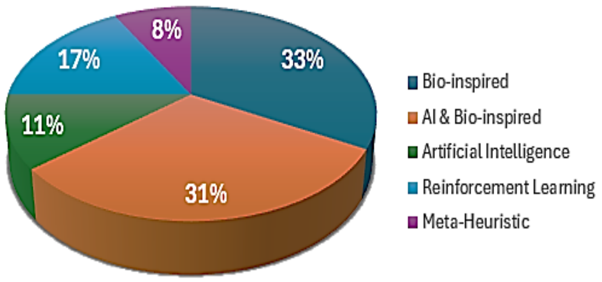

Figure 2. Percentage distribution of optimization techniques of FANET

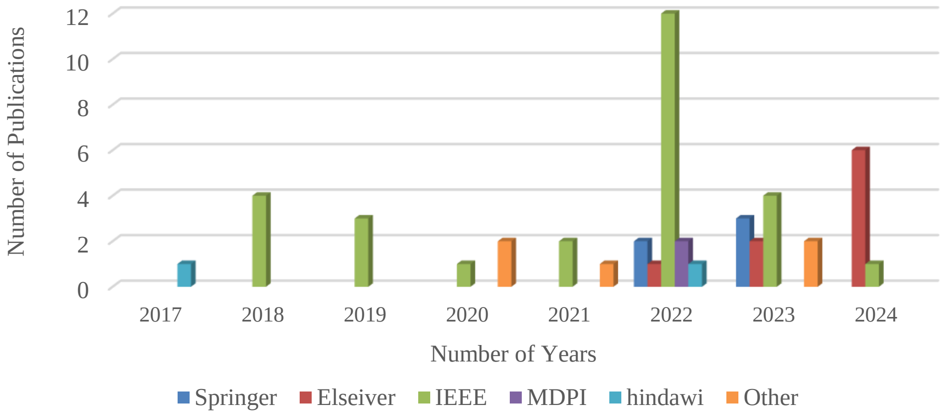

Figure 3. Number of publications for years

3. FANET RESOURCES ALLOCATION

This section summarizes the key concepts discussed in this paper, including FANET, resource allocation, and intelligent algorithms. UAVs have diverse applications, such as surveillance, logistics, rescue operations, and communication support [13]. There are two primary types of UAVs: fixed-wing and rotary-wing, each with distinct characteristics and capabilities [14]. Fixed-wing UAVs offer high speed and payload capacity but require continuous movement, limiting their suitability for stationary tasks. Rotary-wing UAVs, such as quadcopters, provide excellent maneuverability but have a lower capacity. The selection of the appropriate UAV depends on the specific requirements of the applications. A group of UAVs that enable high-speed wireless communication over extensive areas, connecting with ground nodes, forms FANETs. Different communication architectures, such as direct communication, satellite networks, cellular networks, and ad-hoc networks, can be employed within UAV networks, as depicted in Figure 4. UAVs function as standalone aircraft, while FANETs refer to networks of UAVs communicating to establish a wireless network [15]. Here are many key differences between UAVs and FANETs:

- Function: UAVs function as autonomous aircraft capable of executing specific tasks, whereas FANETs consist of networks of UAVs collaborating to accomplish a shared objective.
- Communication: UAVs typically operate in isolation and do not engage in communication with other UAVs. In contrast, FANETs necessitate UAV-to-UAV communication to establish a network.
- Network topology: UAVs can be employed in diverse network topologies, including point-to-point or point-to-multipoint configurations. In contrast, FANETs typically adopt a mesh topology, wherein each UAV communicates with multiple neighboring UAVs to establish the network [16].
- Complexity: FANETs generally exhibit greater complexity compared to standalone UAVs due to the additional infrastructure and communication protocols required to form and maintain a network.

FANETs are specialized networks for UAVs, distinct from mobile ad hoc networks (MANETs) and vehicular ad hoc networks (VANETs), with unique connectivity, sensor types, and service discovery mechanisms [17]. They face challenges like high UAV mobility and dynamic network topographic [18]. Unlike MANETs, FANETs rely online-of-sight communication with ground control stations, making efficient routing critical despite limited route durations. Various routing protocols are used, including static, proactive, on-demand, hybrid, and geographic approaches. Effective resource allocation is crucial to optimize bandwidth and power for quality of service [19]. Resource allocation in FANETs is structured with inputs, constraints, objectives, and outputs, aiming to maximize network performance metrics [20]. In Figure 5, the taxonomy of enhanced resource allocation methods is presented, divided into static and dynamic categories. Static methods are ideal for stable networks with predictable traffic patterns, while dynamic methods adapt in real-time to fluctuating conditions, optimizing resource utilization and ensuring reliable communication [21].

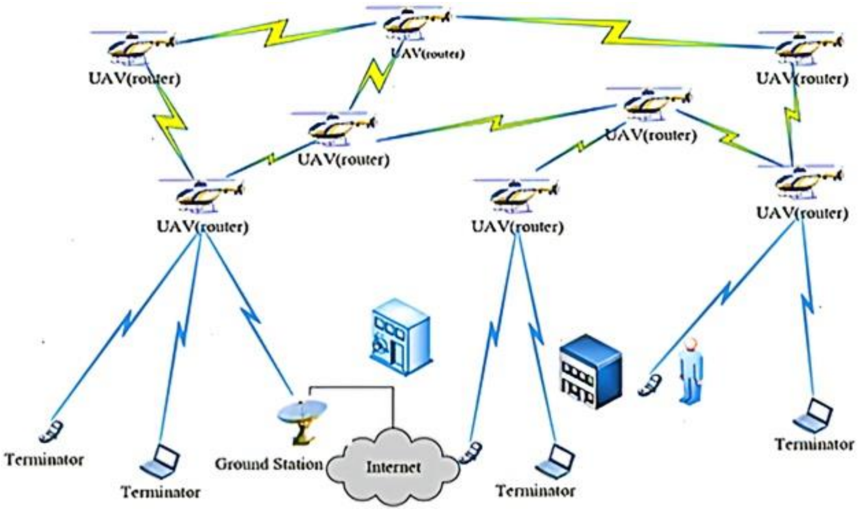

Figure 4. Flying ad-hoc networks (FANETs)

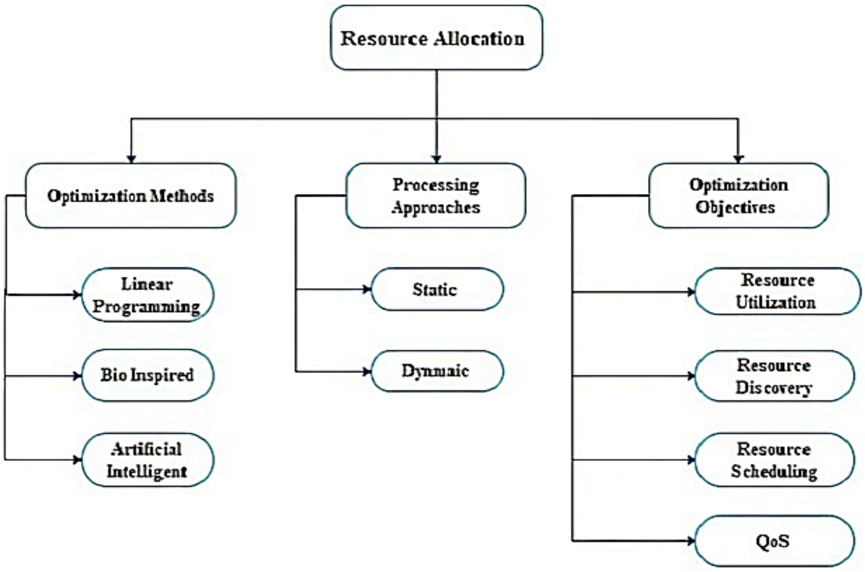

Figure 5. Taxonomy of enhanced methods for resource allocation schemes

Various artificial intelligent (AI) techniques have been applied across numerous domains, including FANETs, to enhance system performance. In FANETs, AI plays a pivotal role in routing tasks by employing a decision-making paradigm. The decision-maker assesses the environment, selects optimal actions, receives feedback as rewards, and refines its decision-making capabilities through learning processes [22]. Energy management is another critical aspect of FANETs, primarily due to the limited battery life of UAVs. AI techniques, such as machine learning, facilitate energy optimization by anticipating future energy requirements, adapting network operations to conserve energy, and improving energy storage and distribution efficiency [23]. For instance, AI-based algorithms can dynamically adjust UAV power levels based on many factors, such as location, network traffic, and battery status, minimizing energy consumption while ensuring reliable communication [24].

4. RELATED WORKS

This section examines various approaches proposed in recent research to enhance the performance and efficiency of FANETs and related technologies. FANETs, comprising networks of UAVs communicating wirelessly, have garnered significant attention due to their diverse applications in fields such as surveillance, disaster response, and communication support. These studies delve into innovative methodologies, algorithms, and protocols aimed at optimizing resource utilization, improving energy efficiency, and enhancing overall network performance in FANETs and related systems. Zhao *et al.* [25] proposed a new method to enhance FANET performance using the improved artificial bee colony optimization (IABC) algorithm for better cluster head selection demonstrated in Figure 6 and the AI-proof of witness consensus algorithm (AI-PoWCA) for mining.

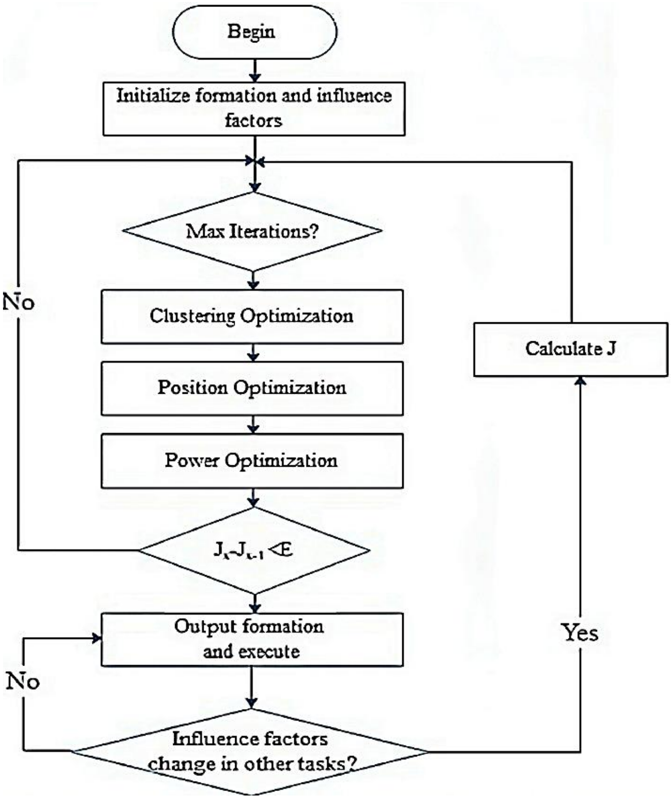

Figure 6. Efficient clustering protocol for FANETs

This approach improved efficiency and resilience against attacks by up to 51%, achieving high packet delivery ratios and minimal end-to-end delays. Escobar *et al.* [26] explored network resource management in advanced internet of things (IoT) applications, introducing a virtual network embedding (VNE) framework for optimizing dataflow applications in FANETs and airborne networks. UAVs in a FANET provided edge computing for rescue operations, using model-based reinforcement learning for dynamic deployment decisions [27]. Chen *et al.* [28] applied deep reinforcement learning (DRL) to enhance multi-UAV-assisted uplink communication, achieving significant improvements in coverage rate, latency, and energy usage. In study [29], a DRL-based system managed UAV fleets as mobile base stations, optimizing coverage, fairness, and energy utilization. Qian *et al.* [30] minimized energy consumption in maritime-IoT (M-IoT) networks with UAVs using a dual-layered DRL and Lagrangian minimization approach. You *et al.* [31] reduced energy consumption in a layered FANET for mobile edge computing (MEC) with an iterative algorithm (AFU) algorithm, optimizing task scheduling and UAV trajectories. Namdev *et al.* [32] introduced AI-based clustering algorithms for FANETs, improving cluster lifespan, energy consumption, and construction time. Mansour *et al.* [33] presented cross-layer and energy-aware AODV (CLEA-AODV), an energy-aware routing protocol for FANETs, outperforming traditional methods in delay and packet delivery ratio. In study [34], a method optimized energy efficiency and QoS in multi-UAV systems using Lyapunov optimization for gateway selection and task scheduling improvements, as displayed in Figure 7.

Liu *et al.* [35] introduced a collaborative optimization method for reducing power consumption in MEC networks with multiple UAVs. They integrated compressive sensing-based user association and fuzzy c-means clustering for user association, power control, computation capacity allocation, and location planning. In study [36], a joint optimization model coordinated charging operations across multiple UAVs acting as aerial base stations, achieving a 9.1% reduction in energy usage. Priya and Mohanraj [37] explored UAV utilization in VANETs, introducing the resource and energy balancing (RAEB) method to enhance efficiency through load balancing, energy optimization, and improved packet delivery ratio. He *et al.* [38] proposed an approach for enhancing FANET efficiency through energy-efficient clustering and fuzzy-based path selection, aiming to reduce energy usage, extend cluster lifespan, and improve packet transmission. Grasso *et al.* [39] introduced multi-agent intra-FANET (MANIA-F), a multi-agent deep reinforcement learning framework for horizontal offloading among FANET UAVs as shown in Figure 8, demonstrating superior performance in simulation experiments compared to other mobile edge computing frameworks. Yang *et al.* [40] proposed a meta-heuristic optimization model for flight path planning in FANETs, enhancing device-to-device throughput and contributing to more efficient communication systems.

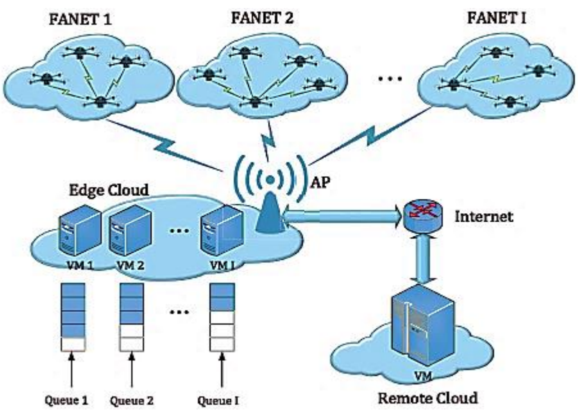

Figure 7. The structure of the heterogeneous cloud-multi-UAV

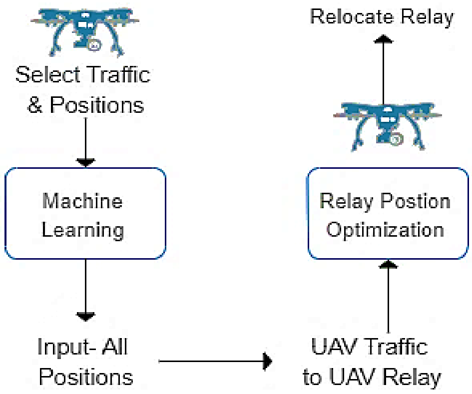

Figure 8. Traffic problem optimization

In study [41], Attuned slicing-dependent concurrent resource allocation (AS-CRA) enhances UAV service reliability in 6G-NIB architecture through learning-based slicing and resource allocation, improving capacity, latency, resource utilization, response ratio, and blocking rate. Jailton *et al.* [42] utilizes multi-agent reinforcement learning (MARL) for coordinating heterogeneous resources, reducing task time. Tong *et al.* [43] applies reinforcement learning (RL) with double deep Q-learning (DDQN) for central processing unit (CPU) allocation in virtual function virtualization, optimizing UAV deployment via integer linear programming (ILP). Pasandideh *et al.* [44] introduces MPRdeep for dynamic resource allocation in FANETs, reducing energy consumption. Manogaran *et al.* [45] explores dual-based iterative search algorithm (DISA) and sequential exhausted allocation algorithm (SEAA) algorithms for slot and power allocation, enhancing network capacity and fairness. Rovira-Sugranes *et al.* [46] proposes long short term memory (LSTM) for bandwidth efficiency in C-V2X with UAVs, promising improved air slicing for vehicular communication. In study [47], a mathematical framework optimizes virtual functions (VF) allocation for edge service chaining, considering UAV capabilities, battery constraints, and latency requirements, integrating with network function virtualization orchestrators (NFVO) standards. Liu *et al.* [48] optimizes UAV positioning via genetic algorithms to maximize FANET throughput in disaster scenarios. Saeed *et al.* [49] introduces reinforcement learning Handoff (RLH) to minimize handoffs in UAV networks, achieving a 75% reduction. Galluccio *et al.* [50] utilize flying caches on UAVs for LTE-U systems, outperforming Q-learning in convergence and performance.

Li *et al.* [51] introduces Q-learning-based smart clustering routing method (QSCR), a Q-learning-based clustering routing algorithm for FANETs. It enhances energy efficiency and network longevity while increasing end-to-end delay and communication overhead slightly compared to an intelligent clustering routing approach (ICRA). Authors also explored UAV swarm flight paths for reconnaissance missions, addressing power constraints and propagation models with a heuristic algorithm based on modified rapidly-exploring random tree (RRT). Bayerlein *et al.* [52] presented a reinforcement learning approach optimizing UAV trajectory for multiple users, focusing on maximizing transmission rates using Q-learning. Ren *et al.* [53] introduced K-means online learning routing protocol (KMORP), a K-means online learning routing protocol for UAV ad hoc networks, improving load balancing and packet delivery ratio with dynamic clustering. Additionally, Xu *et al.* [54] enhanced the optimized link state routing (OLSR) protocol into S-OLSR with fuzzy logic for node trust assessment and improved multipoint relays (MPR) node selection. Hosseinzadeh *et al.* [55] proposed a Q-learning-based routing scheme using an intelligent filtering algorithm (QRF), a Q-learning-based routing scheme optimizing network performance, energy distribution, and routing delay. Wang *et al.* [56] explored UAV integration with mobile edge computing (MEC) servers using deep deterministic policy gradient (DDPG) for optimal offloading and resource allocation. Zhang *et al.* [57] presented the joint prediction and entropy (JPE) protocol for FANETs, using LSTM to predict UAV mobility and enhancing packet delivery ratio. Lastly, Nahi *et al.* [58] introduced RL-multidimensional perception and energy awareness optimized link state routing (RL-MPEAOLSR), which minimizes message overhead and control flooding in FANETs, outperforming existing protocols in various metrics, as shown in Figure 9.

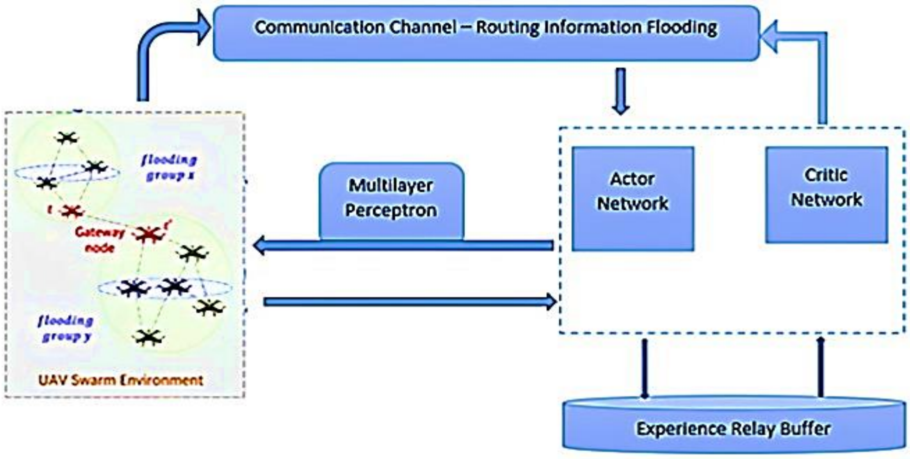

Figure 9. Adaptive communication-based UAV swarm routing algorithm

5. RESULTS AND DISCUSSION

In this section, we explore various optimization strategies aimed at enhancing FANETs by focusing on energy consumption, QoS, and routing protocols. We examine energy-efficient techniques such as adaptive routing and energy harvesting, QoS improvements through optimized data transmission and bandwidth allocation, and advanced routing protocols for reliable and efficient data delivery. These strategies collectively highlight their potential to significantly boost the performance and efficiency of FANETs across diverse operational scenarios. The analysis underscores the critical impact of these optimizations on achieving more sustainable and effective FANET operations.

5.1. Energy consumption

Researchers have explored various optimization strategies to reduce energy consumption within FANETs, as summarized in Table 1. One approach involved using DRL to optimize UAV movement and mobile unit (MU) association, resulting in a closed-form solution for MU transmit power [59]. Another study introduced a decentralized DRL-based system to control multiple UAVs acting as mobile base stations (BSs), ensuring continuous communication coverage for ground mobile users. Optimization aimed to reduce energy consumption in a UAV-assisted M-IoT network using non-orthogonal multiple access (NOMA) by jointly power control, offloading ratio, resource allocation, and UAV trajectory [60]. Moth flame optimization-based clustering algorithms were proposed as an energy-efficient strategy for network construction and node deployment in scenarios where static and dynamic routing approaches were ineffective. The CLEA-AODV routing protocol was suggested to improve FANET performance [44]. Lyapunov optimization developed an optimal solution for network association in multi-UAV systems supported by heterogeneous clouds. Finally, Yang *et al*. [61] introduced a fuzzy c-means clustering-based algorithm to minimize total power consumption in a MEC network with multiple UAVs.

Table 1. Optimization techniques for energy consumption improvement in FANET

Ref	Optimization methods	Result
[24]	Deep reinforcement learning	In terms of MU coverage rate, system latency, and system energy consumption, the algorithm exceeds earlier benchmark algorithms in simulations.
[30]	Deep reinforcement learning	The results proved our model's superiority in terms of energy efficiency when compared to the cutting-edge DRL-EC3 approach based on DDPG and three additional baselines.
[31]	NOMA-based MEC model for the UAV-assisted maritime IoT system	On average, NOMA reduces its total energy use by 17.6%. These findings demonstrate that the NOMA is an efficient multiple access strategy that can be applied to the M-IoT MEC system using UAVs.
[32]	An iterative algorithm (AFU)	When compared to Local, FixU, and Guangxi University (GGU), AFU reduces overall energy usage by 60.52% and 41.56%, respectively.
	Moth flame optimization	Zone routing technique, according to simulation results, has kept communication routes secure and promises increased security without incurring computational expenses.
[60]	Glow swarm optimization (GSO)	When various types of information transmission are carried out over FANETs, we provide an optimized CH selection model that greatly enhances cluster lifetime and minimizes energy usage.
[44]	Lyapunov optimization	The proposed gateway selection technique used less energy than existing systems, however the proposed job scheduling and resource allocation strategy increased QoS performance and obtained the best solution after only a few iterative rounds.
[61]	Fuzzy c-means clustering-based algorithm	The proposed algorithm outperforms conventional approaches, according to numerical results.

5.2. Quality of service

Numerous research endeavors have focused on optimizing techniques to enhance the quality of service in FANETs, as outlined in Table 2. Grasso *et al.* [62] introduced MANIA-F, a multi-agent deep reinforcement learning framework for managing horizontal offloading among FANET UAVs. Li *et al.* [63] proposed a flight path planning model based on meta-heuristic optimization techniques to improve communication efficiency in FANET scenarios [64]. AS-CRA is presented to enhance service reliability in UAVs within the 6G-NIB architecture [65]. In study [66], MPRdeep was introduced as a DRL approach for UAV positioning and resource allocation in FANETs dealing with dynamic network conditions and immediate communication demands. Integrate double deep Q-learning (DDQN), reinforcement learning (RL), and integer linear programming (ILP) techniques to deploy virtual functions within active UAVs in FANETs [67]. A genetic algorithm was utilized in [68] to optimize UAV positions to maximize FANET throughput. Finally, Saeed *et al.* [69] introduced RLH, an innovative user association algorithm designed to minimize redundant handoffs within UAV networks [70]–[72].

Table 2. Summary of articles that enhance the quality of service in FANET

Ref	Optimization methods	Result
[62]	A multi-agent deep reinforcement learning framework (MANIA-F)	The results show that the proposed framework outperforms other state-of-the-art mobile edge computing frameworks.
[63]	Bat algorithm and generalized regression neural network (GRNN)	The simulation findings suggest that the approach improves network performance.
[64]	AS-CRA	The proposed solution outperforms the competition in terms of capacity, latency, resource utilization rate, response ratio, and blocking rate, with metrics of 89.726%, 81.32%, 0.963%, 92.309%, and 0.047%, respectively.
[65]	MARL	The results show that the proposed technique increases computing resource utilization and reduces task execution time significantly.
[66]	DISA and SEAA	According to numerical calculations, both DISA and SEAA can efficiently allocate resources for UAVs while maintaining link fairness and priority.
[67]	LSTM	When compared against two benchmark schemes, the simulation results show that the proposed scheme is valid: deep Q-network and deep policy gradient.
[68]	MPRdeep	MPR deep converges rapidly and has strong generalization ability under dynamic network conditions and user locations, according to the results.
[69]	RLH	According to simulation results, the RLH algorithm can reduce the number of handoffs by 75%.

5.3. Routing protocols and flight trajectory

Several optimization techniques have been applied to improve routing protocols and flight trajectories in FANETs, as outlined in Table 3. In study [73], the performance of three nature-inspired algorithms (NIA) for FANET routing specifically ant colony optimization (ACO), modified Firefly algorithm (MFA), and modified genetic algorithm (MGA) was assessed using metrics such as packet delivery, delay, overhead, and throughput [74]. To address FANET challenges, Hosseinzadeh *et al.* [75] introduced ASR-FANET, an adaptive software-defined networking (SDN)-based routing framework for FANET. Another approach, presented by Zheng *et al.* [76], utilized RL to predict node positions, control communication, and manage data transmission within the network. FANET routing algorithm based on fuzzy logic and RL was introduced in a separate paper [77], aiming to mitigate limitations of traditional ACO methods, such as high average hops and low link connectivity. Lastly, Huang *et al.* [78] proposed an adaptive communication-based routing algorithm explicitly designed for UAV swarms.

Table 3. Summary of articles that enhance the routing protocols and flight trajectory in FANET

Ref	Optimization methods	Result
[12]	ACO, MFA, and MGA	MFA surpasses the other two methods, making it the most efficient routing algorithm in FANET, according to the report.
[19]	An adaptive SDN-based routing framework for FANET (ASR-FANET)	The study uses comprehensive simulations to evaluate the performance of the ASR-FANET framework and discovers that it outperforms other standard protocols.
[20]	Reinforcement learning	According to the simulation results, the proposed algorithm outperforms policy in terms of choosing the route with the highest value function and the shortest end-to-end delay.
[64]	Fuzzy logic and reinforcement learning	In terms of performance, simulation findings indicate that the proposed algorithm outperforms traditional routing algorithms.
[65]	Multilayer perceptron algorithm	The results show that our algorithms can achieve efficient and effective routing for large-scale UAV swarm collaboration in a partly observable distributed environment.
[66]	K-means algorithm and genetic algorithm	The simulation findings demonstrate that the proposed scheme is successful and outperforms the benchmarks.
[67]	Deep reinforcement learning	The suggested algorithm is shown to be efficient in simulations.
[68]	Reinforcement learning	The results demonstrate that the proposal works to improve network performance.

6. CONCLUSION

This paper explored optimal and intelligent resource allocation in FANETs. UAVs, commonly known as drones, are widely deployed in military and civilian applications, requiring effective coordination and communication to address challenges. FANETs enable wireless communication among UAVs, improving coordination and information exchange in environments without traditional networks. The dynamic mobility of UAVs introduces unique considerations for network design and connectivity, distinguishing FANETs from conventional ad-hoc networks. This survey reviews various optimization techniques, including genetic algorithms, ant colony optimization, and artificial neural networks, which optimize resource allocation by considering mission requirements, network topology, and energy constraints. It also discusses the critical role of intelligent algorithms in enhancing network energy management, QoS, resource allocation, and overall performance. The systematic literature review categorizes resource allocation strategies based on performance optimization criteria and summarizes their strengths, weaknesses, and applications. This survey highlights the potential of FANETs to revolutionize various industries and unlock new opportunities for UAV-based applications.

ACKNOWLEDGEMENT

This work is supported by the Ministry of Higher Education (MOHE) Fundamental Research Grant Scheme (FRGS22-264-0873) (Grant No: FRGS/1/2022/ICT11/UIAM/01/1).

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