JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 12 Issue 01
2026

Research Article
https://doi.org/10.56979/1201/2026/1644

FANET Based Health Assistance Mechanism During Flood Situation

Huma Iqbal[1], Muhammad Azhar Mushtaq[1*], Muhammad Kaleem[1], Hamza Zaheer[1], and Sayyid Kamran Hussain[2]

[1]Department of Information Technology, Faculty of Computing & IT, University of Sargodha, Sargodha, 40100, Pakistan.
[2]Department of Computer Science, TIMES University, Multan, 60000, Pakistan.
[*]Corresponding Author: Muhammad Azhar Mushtaq. Email Address: azhar.mushtaq@uos.edu.pk

Received: June 03, 2026 **Accepted:** September 15, 2026

Abstract: Due to their ease of access and maneuverability within disaster-affected areas, Unmanned Aerial Vehicles have become vital in disaster management. To facilitate the coordination of flood-response and emergency medical missions, this paper focuses on data communication within Flying Adhoc Networks, a crucial component of UAV deployment. A comparison of three FANET routing protocols, AODV, DSDV and OLSR, is presented using the NS-3 simulator with a three-dimensional Gauss-Markov mobility model. The protocols are evaluated through controlled experiments on node density (5-25 UAVs), UAV speed (5-40 m/s), relay-UAV failures and transmission-range degradation, and under two composite flood scenarios, using packet delivery ratio, packet loss ratio, throughput, end-to-end delay and routing overhead. Every configuration was run ten times with independent seeds and reported as mean with 95% confidence intervals, and differences were tested with ANOVA and Tukey HSD. AODV achieved the highest packet delivery ratio and throughput in most conditions (significantly higher than at least one competitor in 16 of 18 conditions), for example 68.2% against 41.5% (DSDV) and 38.9% (OLSR) in the baseline scenario, but with the highest end-to-end delay. OLSR gave the lowest delay (about 1-7 ms) with a lower delivery ratio, and DSDV was competitive only at low mobility and in sparse networks, where differences were not statistically significant. The results indicate that no single protocol is best for all health-assistance traffic: reliability-oriented traffic favours AODV, whereas latency-critical alerts favour OLSR. The findings are simulation-based and the limitations for real flood deployments are discussed.

Keywords: FANET; UAV; Disaster Management

1. Introduction

Flying Adhoc Network is the evolution of Unmanned Aerial Vehicles (UAVs). Mobile Ad-hoc Networks (MANETs) also have a subclass called FANET which is used for UAV communication. The technology enables the UAVs to fly in formation, making their application more versatile in many aspects such as surveillance, search and rescue operations, and monitoring of the environment. The terrestrial networks deal with issues of low mobility, fixed geometry, and 2D communication while FANET addresses issues of high mobility, dynamic geometry, and 3D communication, thereby coming up with smart solutions in aerial networking [1]. The FANETs enable UAVs to form a mobile and autonomous network in the air that provides viable communications in disaster situations, where the ground infrastructure may be lacking or destroyed. Various protocols are hereby tested in a controlled manner using NS-3 simulation technique to compare their performance and suitability [2] [3] [4].

This paper fills this gap by providing a comparative study of routing protocols that underlie FANET's performance and dependability. The present study presents a systematic review of the research that has been carried out concerning the potential of various contemporaneous technologies including but not limited to FANET for improving the disaster management systems. The findings on AODV, DSDV, and OLSR protocols of this study seek to establish which among the three is capable of providing the most

optimal performance under the typical usage of FANET. It has been concluded that given the features of FANETs, such as high node mobility, variations in node density, and frequent changes in the network topology, routing protocols must be effective and dynamic. The results of this study will be useful in developing future UAV networking strategies [5] [6] [7].

The contribution of this paper is threefold. First, it relates the choice of FANET routing protocol to the communication needs of flood-time health assistance, namely emergency alerts, patient information and situational imagery, rather than treating routing performance in isolation (Section 3.11). Second, it compares AODV, DSDV and OLSR under a three-dimensional Gauss-Markov mobility model through controlled experiments in which node density, UAV speed, relay failures and transmission range are varied one at a time (Section 4). Third, every result is based on ten independent runs with 95% confidence intervals and statistical tests, and the full NS-3 configuration is reported so that the experiments can be reproduced (Table 1).

The paper unfolds across five sections. Section one, Introduction, opens with the backdrop of worsening flood disasters under climate change and builds the case for why FANETs deserve serious attention in rescue operations. Section two, Literature Review, moves through the existing body of work, pulling together what researchers have established about UAV networks and disaster response while pinpointing where the literature falls short. Section three, Research Methodology, lays out how the study was conducted, covering the research design, data collection process, and the analytical approach used to examine FANET deployment. Section four, Results and Discussion, presents what the study found and works through what those findings mean when held against prior research. Section five, Conclusion, draws the threads together, reflecting on whether the original objectives were met and what the research ultimately contributes.

2. Literature Review

There are various existing approaches to the topic like, the deep learning techniques, UAVs, Firefly, Swarm strategies, and etc. All these strategies have their benefits and the best strategy is often dependent on the need of the application most of the time [8] [9]. Flood disasters invariably represent the utmost challenge for the conventional humanitarian interventions since they are non-linear and are on the high alert as they occur very fast [10]. The existing Literature on the research topic including all these strategies have their benefits and the best strategy is often dependent on the need of the application most of the time.

2.1. Drone Surveillance Paths

A paper on drone path planning for search and rescue in flood-affected areas is presented in paper [11]. Stranded survivors tend to seek refuge on dry land, and the authors implemented and improved a weight-based path planning algorithm on an off-the-shelf UAV, in which waypoints near the reported survivor location receive higher exploration priority. The implementation was reported to outperform conventional search patterns. Nature-inspired meta-heuristics such as the Firefly Algorithm, introduced by Xin-She Yang in the year 2008 and based on the flashing behavior of fireflies, are further candidates for this kind of path planning problem. This work can be extended to the monitoring of floods using drones, to other forms of disaster and to the integration of data feeds. The addition of AI or machine learning could improve the decisions of drones.

2.2. Disaster Management and Prehospital Care

A study on Drone Applications for Streamlining the Disaster Management & Pre-hospital Care in Saudi Arabia in the year 2023. It has created regulations and guidelines as to the use of robots in health care facilities in Saudi to safe guard against misuse. The methodology examines the applicability, fosters implementation of the technology in the context of the Health Sector Transformation Program, formulates the regulatory relations, and secures the finance and partnership for the responsible drones' use. The paper provides an account of the broad impact of drones in the context of healthcare, and lays the approaches to research, control, and collaboration among all interested parties so that it may increase patients' well-being and reduce costs [12].

2.3. Drone-Based Medical Supply Delivery

Paper [13] explained their hurdles and experiences of the medical supply using drones based system and they made their strategies. The study faced numerous permissions and coordination issues with aviation authorities, district administration, and health officials while presenting a good evidence of multifaceted challenges involved in this novel approach. An ice-breaking program launched in South Asia and aimed at delivering twenty thousand medical aids to North-East India, ran into operational obstacles as regards technical clearance, ethical clearance, and flying permit. New drone rules in India permits some freedom in the operating of BVLOS but the implementation is not without issues. Possible effectiveness of the use of drones for the improvement of the healthcare system is being investigated.

2.4. Emergency Medicine with Drone

A study concerning with the research question: Impact of Using Drones in Emergency Medicine was carried out by authors in paper [14]. The issues that still exist in the use of emergency medical drones include; regulation, safety, flying conditions, and maintenance. Advancements in innovation are necessary for development of capability and for including the application of drones in health care systems. Other concerns that are risks to be solved are the establishments of the medical drone network, management and sustainability. The particular enabling technical bases for which there is currently little representation are: First, databases, second, regulatory organizations, third, pilot development. Other opportunities that should be further explored technical, safety, security and administrative sides.

2.5. UAVs Roles in Flood Prevention

UAVs are aircraft systems that don't need an operator to be present inside the car or aircraft. These systems may be controlled remotely, or they may include dynamic automation systems, an integrated flight plan, or both. The primary advantages of unmanned aerial vehicles (UAVs) are their ability to maneuver into areas that are challenging for humans to access, their precision in performing repetitive tasks, and their ability to carry out missions without posing a threat to human life [15].

2.5.1. Types of UAVs

- Fixed wing UAVs for surveying applications.
- Rotary wing UAVs for surveillance of area.
- Combined UAVs a mix of both.

2.5.2. UAV Applications

- In agriculture; crop inspection, chemical application, precision farming.
- In disaster management; search and rescue, assessment of the affected area, and delivery of medical aid.
- In military; for surveillance, reconnaissance, and attacks. UAVs are used in such areas as environment surveillance, engineering structure inspection, and sometimes in entertainment to capture aerial shots.

2.5.3. Challenges of UAVs

- Policies and safety issues.
- Privacy concerns due to lack of adequate rules.
- Battery power to enable longer durations in space,
- Upgrading the command and control system.
- Bad weather in operational environment.

2.5.4. UAV Technology in Public Health

The authirs in paper [16] discussed how UAV technology can help improve the field of public health. Their research identifies four main opportunities for UAVs to support public health: morgue access, biomedical sample transportation, community health interventions, and surveillance.

2.5.5. Emergency Medical Response

Elsewhere in paper [17] UAVs in medical services in their work titled “A Safe Road to Health.” The study gives great importance to this problem of Indian society, which is that ambulances take a long time to reach their destination, which results in increased traffic accident mortality due to the lack of immediate medical intervention. In response to this issue, the authors propose hexacopter UAVs as fast responders in accidents. These UAVs are fitted with cameras attached to their body to offer a live video feed to emergency response teams. As a form of UAV, hexacopters can well transport required basic medical provisions to

the scene of the incident, increasing the probability of the rescue. The research includes assessing the different forms of drones and their capacity to do something [17].

2.6. Swarm-based Algorithms

Swarm-based UAV technology refers to countless subgroups of unmanned aircraft, with each subgroup having many small UAVs working cohesively; the aspect is similar to movements exhibited by any insect, bird, or fish. This is particularly based on the swarming strategy whereby a cluster of drones cooperate to culminate activities that are difficult for a single UAV to perform. The use of these mathematical models and tools allows for a system of UAVs to share information and coordinate their responses to changes in local environments and to other UAVs within their swarms, thus maximizing the efficiency and effectiveness of said UAVs [18].

2.6.1. Video Delivery of Mobile Objects

The authors in [19] aims to explore and propose ways of tracking different mobile entities including humans and animals, vehicles, and floods through UAVs with efficiency. The decision-making process of the SUAV algorithm involves UAV repositioning depending on the position of target objects and the position of the rescue teams. The algorithm calculates the probabilities of movement of the tracked objects further helping UAVs position themselves and outlining the required paths for tracking. The authors also simulated the SUAV strategy to compare it with the previous methods to show that it can better offer video streams with the QoE and QoS. The proposed SUAV system decreases energy usage during transmission while guaranteeing real-time video transport. The researcher have plan to further apply the SUAV system to other disaster situations.

2.7. Routing Protocols

2.7.1. AODV Routing

Paper [20] focuses on the problem encountered during disasters with an emphasis on the problem of searching for and rescuing trapped populace due to the destruction of their infrastructure. The authors develop an extensive protocol architecture for FANETs comprising physical, data link, network, transport, application, clustering, time synchronization, and localization layers. One new approach proposed is a time-slotted version of the AODV protocol. This adaptation designates particular periods for message assertions meaning that more time is available for channel use and the chances of collisions are decreased.

2.7.2. Mobility Models

Since FANETs involve the movement of nodes, mobility models are important tools in assessing the performance of algorithms and protocols in FANETs. One such model is the M-AODV, multicast AODV, which connects a group of nodes employing a multipath distance vector that supports multicast communication in ad-hoc networks. The study emphasizes energy-efficient routing protocols and networks adequately supporting connection variety. It also highlights the importance of concerns on simulators and emulators of UAV networks, as well as clustering protocols that improve cost and performance. In another paper, "A survey on position-based routing protocols for Flying Ad hoc Networks (FANETs)" by Oubbati et al., the authors propose a classification and taxonomy of position-based routing protocols for FANETs, describe the routing scheme used in each category, and compare the protocols on several criteria, discussing the advantages and weaknesses of each [21].

2.7.3. Position-based Routing Protocols

The approach entails analyzing conventional positional parameter-based routing protocols in FANETs which is significant in determining their practicality as well as exploring areas for future studies. The paper should also consider the fluctuations in UAV network capability and the kind of changes in the network topology that it brings to the table; these factors include flexibility in the qualities that define what makes for the best alternative routing methods. Furthermore, although existing routing approaches can also cope with fast motion and changes in topology, there is still room for extending the flexibility and creativity of these solutions. Hence, it is recommended that future work should consider refining the position-based routing protocols for FANETs. Inevitably, developments will need experimental evaluations and simulations to give necessary knowledge of their performance in practice [21].

2.8. Deep Learning Techniques

2.8.1. Aerial Imagery Features and Flight Parameters

Yang et al. [22] reported a study, released in May 2022, entitled "Flood Detection Based on Unmanned Aerial Vehicle Systems and Deep Learning." It reveals that the integration of UAV aerial imagery with deep learning models can greatly improve the framework of flood assessment as shown in figure 1. In future studies, the authors laid out plans for enhancing the performance of the deep learning outcomes and research into better methods such as radar methods. By incorporating real-time data and other systems, there are ways that real-time data can be used to create automated methods to avoid a lot of manual analysis of data. [22]

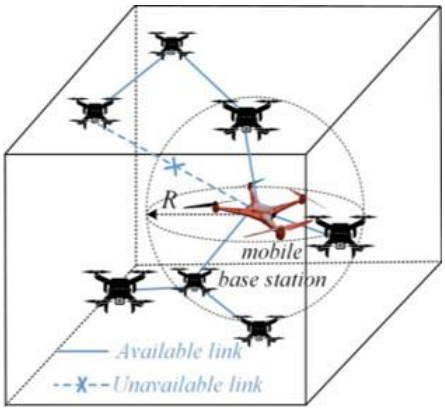


Figure 1. Deep Learning based UAV's working scheme

2.8.2. Reinforcement Learning-Based Methods

The paper titled "Reinforcement Learning-Based Routing Protocols in Flying Ad Hoc Networks (FANET)" was written by Lansky et al. in 2022. The purpose of this work is to design efficient solution to routing problem in FANETs due to number of constraints typically attributed to FANETs such as availability of mobile nodes, dynamic nature of topology, low density of nodes, high overhead cost, and low scalability and high energy consumption [23].

The paper present a review on the use of RL in FANET's routing protocols, which we classify according to learning algorithms, routing paradigms and data dissemination methods. Here, the authors discuss the difficulty for algorithms for training where exploration relates to exploitation intensively, particularly due to the interference management issues as the bandwidth will always be limited. Due to their mobility, the management of interference in FANETs is harder than in more fixed networks. This paper presents the background of the research and points out the fact that while FANETs are developing rapidly routing has to be efficient in the long run.

2.9. Remote Sensing and 5G Networks

A related study by Michail Giannitsopoulos et al. also focuses on using and adapting Unmanned Aerial Systems (UAS) for flood risk management in England. Yang et al. [22] developed a deep learning algorithm for the detection of flooded buildings in constructing a model from UAV aerial images and demonstrated their analysis on the Kangshan levee at Poyang Lake. It was highlighted that clustering algorithms would help pinpoint more strategic areas to place specific UAVs, and how this would minimize the drones required and optimize the network's performance. The improvement in information transfer between UAVs and the rescue coordination center concerns the application of a new 5G network, and underpins the constant exchange of data between aerial assets and the base, enhancing situational awareness during emergency events. Six out of ten deep learning models used in the study proved capable of accurately identifying flooded buildings using UAV photographs [22], [24].

2.10. Unmanned Aircraft Systems (UAS)

2.10.1. Gaussian Markov 3D Mobility Model

The GMMM in 3D is the expansion of the one-dimensional Gaussian Markov model that will capture the altitude and the distance between the points. In this model complex three-dimensional dynamics of UAV trajectories are mimicked, which is more realistic to their mission behaviors during real-life disaster relief operations. In the GMMM, a UAV's future position is computed based on the current position and velocity, with a small off-displacement added in the form of the unpredictable nature of its flying motion.

The randomness is therefore governed by a Gaussian distribution to guarantee that the changes brought on by the fluctuation of velocity and direction are smooth as opposed to the abrupt changes that would be deviation from the actual patrol behavior of a UAV [25].

There is a large gap in the literature when it comes to evaluating AODV, OLSR, and DSDV routing protocols under the Gaussian Markov 3D mobility model, despite plenty of research comparing them using different mobility models. The majority of research has been on 2D mobility models, such as Gauss-Markov or Random Waypoint, which fall short of capturing the intricacies of 3D settings, especially in applications like FANETs and UAV networks. Research comparing AODV, OLSR, and DSDV in the context of the Gaussian Markov 3D model is lacking, which offers a chance for new studies to examine how these protocols function in more dynamic, real-world 3D network conditions [26].

2.11. Positioning and Novelty

Existing FANET studies in disaster response are mostly surveys of architectures and routing protocols [3], [8], [20], [33] or single-purpose applications such as flood imaging and path planning [10], [11], [22]. Studies of medical drones for health care concentrate on logistics, regulation and operational feasibility [12]-[14], [16], [17] and say little about the communication network that must carry the health data. The present work is positioned between these two bodies of literature. It does not propose a new routing protocol; its novelty lies in (i) relating routing-protocol selection to the delay and reliability needs of flood-time health-assistance traffic, (ii) evaluating AODV, DSDV and OLSR under a three-dimensional Gauss-Markov mobility model, which the literature on these protocols has rarely used [26], through controlled experiments that isolate node density, UAV speed and topology change, (iii) adding flood-specific stress conditions (relay-UAV loss and range degradation) and (iv) supporting every claim with repeated runs, confidence intervals and statistical tests.

3. Methodology

This section shifts the focus to the practical aspects of this research. The methodology is framed in such a manner that it not only answers the research questions that were introduced from the literature review but also fills the gap between theory to practice within the fast-evolving realms of FANETs. A flow digarm of proposed methodology is give in figure 2.

3.1. Routing Protocols under study

Particularly for FANETs, routing protocols are key as this must cope with a highly mobile network and spontaneously changing topologies. This research delves into an in-depth exploration of three essential routing protocols: AODV, DSDV and OLSR. AODV stands out as a reactive routing protocol that sends a request to find a route to the destination only after the request has been sent. Both OLSR, which is the proactive routing protocol, and MPR, which is an optimization vector of OLSR, are used to reduce the amount of routing-related traffic. By using the dissemination of sub-net nodes to forward broadcast messages, OLSR decreases traffic control by a considerable margin, which is a good thing, especially in scenarios of FANETs where heavy loads of control traffic could very quickly absorb large amounts of limited bandwidth and energy resources. The adoption of the OLSR protocol gives this research to ability to compare the working design of two proactive routing protocols with different methods of the reduction of traffic and the optimization of the network overhead [27] [28]. The protocols follow their original specifications: AODV [36], OLSR [37] and DSDV [38].

3.2. Research Design

The objectives of the research are going to be achieved by using a quantitative approach to conducting simulations and to evaluate the efficiency of various routing protocols for FANETs. Setup is an abstract rail of a network environment that is of FANET type, where UAVs are prime factors of movement and dynamics

3.3. Experimental setup

This is done by specifying the experimental mechanisms, simulations, and performance metrics which is used in the study to ensure that all the results are reproducible and also based on sound scientific principles.

Machine: The machine used for this experiment was ASUS X415 having Intel ® Core i7 processor with 16 GB 2400 MHz RAM and NVIDIA ® MX discrete graphics and extended hard disk.

The simulation framework of the network will include nodes varying from 5 to 25 and will try to address the scenario where node scaling is conducive to better network performance. The nodes in this simulation are UAVs with dynamic networking capabilities which will integrate with other UAVs, and shape the structure of such network. Every case has its features like network density, transmission patterns, and communication load, these are to be considered before the conduct of the tests and the success of the protocols is determined.

The scenario and NS-3 configuration are summarised in Table 1. The simulated FANET consists of 5 to 25 UAVs (baseline 20) moving in a 1000 m x 1000 m area at altitudes of 50 to 150 m under a three-dimensional Gauss-Markov mobility model (memory parameter 0.85, one-second time step), which is a reasonable approximation of smooth patrol flight. Nodes communicate through IEEE 802.11b in ad hoc mode with a fixed transmission range of 300 m in the baseline case. Five constant-bit-rate UDP flows between randomly chosen source-destination pairs carry the data traffic, and the routing protocols are used with their default NS-3 parameters. Every configuration was run ten times with independent random seeds, and the same seeds were used for all three protocols so that they face identical node placements and trajectories.

Table 1. Simulation scenario and NS-3 parameters

Parameter	Value
Simulator	NS-3 version 3.44 (discrete-event)
Routing protocols	AODV, DSDV, OLSR (NS-3 default parameters)
Number of UAVs / density	5, 10, 15, 20, 25 (baseline 20), i.e. 5-25 UAVs per km²
Simulation area	1000 m x 1000 m, altitude 50-150 m
Mobility model	3-D Gauss-Markov, alpha = 0.85, time step 1 s
Mean UAV speed	5, 10, 20, 30, 40 m/s (baseline 10 m/s)
Initial positions	Uniformly random in the simulation volume
PHY/MAC	IEEE 802.11b ad hoc, DsssRate11Mbps
Propagation / range	Range-based loss model: 300 m (baseline); 250, 200, 150 m for range degradation
Traffic	5 CBR/UDP flows, 512-byte packets, 4 packets/s per flow, start 10-20 s, stop 99 s
Simulation time	100 s
Topology change	0-40% of relay (non-endpoint) UAVs switched off at t = 50 s
Independent runs	10 per configuration (seed 12345, runs 1-10; identical for all protocols)
Statistics	Mean, 95% t-confidence interval, one-way ANOVA, Tukey HSD (alpha = 0.05)

3.4. Simulation Environment

The Network Simulator 3 (NS-3) has been used as owing to its widespread acceptance, high simulation accuracy for ad-hoc networks simulation, and its ability of implementing modelling as a discrete-event mechanism. In order to provide freedom to consumers, the FANET of the NS-3 environment is built up by means of UAVs installed as mobile nodes. Each individual node includes a communication stack that reproduces the hardware characteristics of a real-world UAV such as range and bandwidth limitations. The area of simulation is selected in such a way to mirror the spatial mobility of the UAVs in the FANET, allowing the nodes free movement in any directions and thus would closely imitate the movements of the implementation case. The performance data on the preset selected metrics are also collected via NS-3' which will be tweaked for the purpose. The software has a packet flow log function, which can display the location of data on packets down to each network pyramid [29][30][31].

3.5. Experimentation Procedure

The experiment setup is rigidly designed by the objectives of the study, which is putting into a test the performances of routing protocols that have been selected and these are AODV, DSDV, and OLSR that work in a simulated FANET environment. The NS-3 network simulator is employed to create a virtual

setup that is replicable of a FANET environment in the early stages. The inter-distal simulation area is set to a specified one kilometer from the square, encompassing sufficient space for simulated UAVs to operate. The UAV nodes are tuned following the moving pattern and the mode of the real drones. The parameters include speed, acceleration, and maneuvers that have to resemble the actual drone's working platform. Artificial node units are the first requirement; by dispatching into the simulation unit, UAV nodes are installed. The roles are assigned by the situations in which arrays of FANETs can be utilized for network modeling and surveillance FANETS is one of the important parts of modeling to outline a civil emergency in which drones and electric cars are used to patrol or provide data. These nodes are next blessed with transport-layer protocols under the study. Every protocol is assessed in terms of its performance on one condition applied to the entire network, which guarantees a fair summation of the whole idea based on these operational conditions. The system is switched on then the route protocols are in operation. Performance metrics are recorded during the simulation period, which reflects the loss of packets, delivery ratios, throughput rate, and the number of packets sent and received. Each configuration is executed ten times with independent random seeds (Table 1); the node count, mobility speed, number of failed relay UAVs and transmission range are varied one at a time while all other parameters are held at their baseline values.

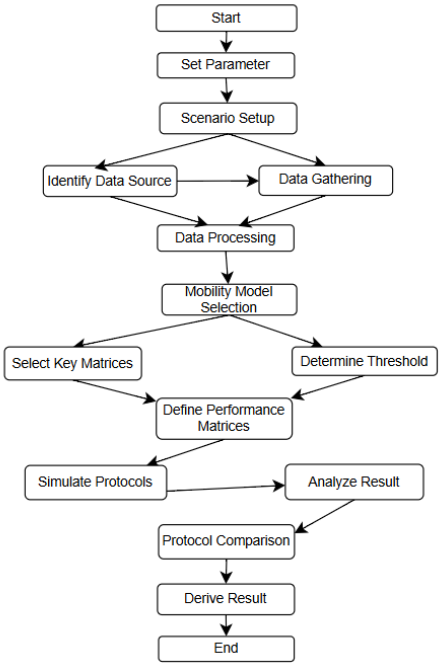


Figure 2. Proposed Methodology

3.6. Performance Metrics

- Throughput: For FANETs, high throughput has a relationship with the strength of data management, especially in surveillance operations [32].
- PLR: showing the number of lost packages within the transmission, impacts the system performance directly because of the relativity of transmission and low PLR requirement high mobility FANET.
- PDR: A high PDR is important to ensure that all the necessary data for mission success are received [33].
- Packets received, and packets transmitted: indicators of packets received and transmitted are calculationable figures of network activity and workload management.
- End-to-end delay: the mean time between packet generation and delivery, which is decisive for time-critical medical traffic.
- Routing overhead: the network-wide control traffic (kbit/s) generated by the routing protocol, counted at every transmission of AODV, DSDV and OLSR control packets.

3.7. Data Collection Methodology

To acquire data during the simulated FANET scenario, a comprehensive dataset is required that sets base for the research authenticity and reliability. NS-3 simulator presented an excellent tool for data harvesting in real-time, where performance measures were synchronized with corresponding network events to highlight their co-occurrence. This operational data collection and analysis enables the statistics calculation of at least the average throughput, packet loss ratio, the ratio of transmittable packets, as well as the total number of packets received. To accomplish this, every point has a timestamp stamp and a unique status tag that makes the data in doubt sortable or correlated to broadcast exactly the real simulation status. This repetition is one of the crucial points that allows the excluding data inconsistencies that appear in the background of short-term numerical noises. In a concordant way, the stage of collection is algorithmised, making it impossible for human error to occur, while using the same data for the same analysis. This automation has the advantage of ensuring the objectivity of the data collection process resulting into an undyed dataset which is pure and accurate enough to represent the routing protocols behavior under intentional or unintentional circumstances [34].

3.8. Analysis Technique

The analysis of this study is structured and supported by strong statistical methods. The results from NS-3 simulations go through a descriptive data analysis process in which the mean, median, and standard deviation of the performance metrics are calculated. The ANOVA was used to determine statistically significant differences in performance among the route protocols (AODV, DSDV, and OLSR) that did not perform in the same manner under changing network conditions. Moreover, post-hoc tests were executed which helped us to select a specific pair of protocols which for example, show major differences. Hence, ANOVA's application in this research project is highly germane to the research objectives through the above-mentioned statistical methods, the analysis will accordingly indicate which routing protocols show superior performance on aspects like mobility ratios, throughput transmission counts, and deliver ratios [35].

Each metric is reported as the mean of ten independent runs with a 95% confidence interval based on the t-distribution. For every operating condition a one-way ANOVA across the three protocols was followed by Tukey HSD post-hoc comparisons at a significance level of 0.05; the packet delivery ratio is computed over the offered load of each run, so packets dropped at the source for lack of a route are counted as lost. Delay is computed over delivered packets only, and runs in which no packet was delivered (two runs of DSDV at 150 m range) are excluded from the delay statistics [34].

3.9. Challenges and Solutions

Simulating FANETs using NS-3 a serious problem is the availability of the modeling capabilities of UAV mobility and environmental factors periodicity like ever-changing weather conditions or physical features, which can disrupt the communication voiced flow. The simulation parameters are chosen with high accuracy, simultaneously, those parameters are inserted into the mobility models and environmental dynamics in the simulation. The notion of scalability of a network is also a problem. To solve this, the simulations are made to grow topologically in a hierarchical fashion where the original model is examined in the smaller domain. The corrections are applied before going to the big domain. Lastly, as the environment undergoes a process of changeover, the reproducibility of results in this dynamic atmosphere is another problem. It does thus enable identical repetitions of the experiments under identical conditions, which is indispensable for determining the finding's credibility [36].

3.10. Implementation Evidences

Figure 3 presents direct results from NS3 simulator where 20 nodes with different cordinates are formulated and figure 4 provides the nodes stats.

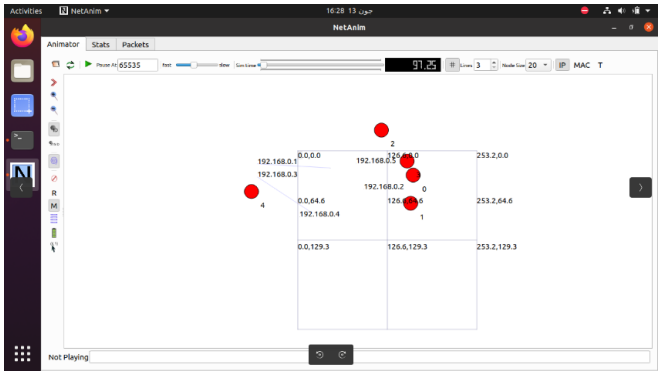


Figure 3. Network simulation at 20 nodes

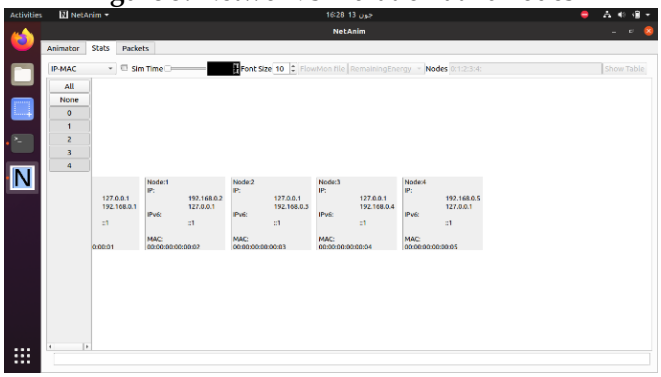


Figure 4. Nodes Stats

3.11. Health-Assistance Communication Mechanism

The proposed mechanism uses a swarm of UAVs as a self-organising aerial backbone when ground infrastructure is damaged by flooding. The backbone links three groups: community health workers and victims' devices on the ground, field medical teams, and the hospital or command centre. The UAVs relay four classes of health-related traffic, summarised in Table 2: emergency alerts and vital-sign alarms, patient and triage records, situational imagery used to direct medical response, and routine telemetry such as supply tracking. The routing profile is selected according to what each class needs, and the simulation results of Section 4 are used to guide the choice.

The distinction matters because the protocols behave differently: in the experiments AODV delivered the largest share of packets but with the highest delay, whereas OLSR delivered fewer packets with a delay of only a few milliseconds. Short alerts are therefore best sent over a proactive, low-latency route with application-level repetition, while patient records and imagery, which can tolerate delay but not loss, are best sent over a reactive route. The delay targets in Table 2 are design assumptions of the mechanism and not values taken from a standard. Only the routing layer was simulated; the traffic in the simulation is generic CBR traffic, so the mapping in Table 2 is design guidance and has not been evaluated with medical applications.

Table 2. Health-assistance traffic classes and suggested routing profile

Traffic class	Typical content	Main requirement	Suggested protocol (from results)
P1 Emergency alerts	Vital-sign alarms, distress calls	Lowest delay (design target below 100 ms)	OLSR (delay 1-7 ms in all scenarios) with repeated transmission
P2 Patient records	Triage forms, patient information	Reliable delivery, moderate delay	AODV (highest PDR in 16 of 18 conditions)
P3 Situational imagery	Aerial images, short video	High throughput	AODV (highest throughput)
P4 Routine telemetry	Supply tracking, UAV status	Low overhead, delay tolerant	DSDV or OLSR when mobility is low

4. Results and Discussion

This section focuses on the results of the simulations from the previous section, critically evaluating the outcomes collected from using AODV, DSDV, and OLSR protocols within the study wireless FANET, provides the findings in their entirety, interprets them in the content of the currently available literature, and suggests the impact of the results on the creation of efficient FANETs.

4.1. Findings

4.1.1. Throughput Analysis

Table 3 and Figure 5 give the mean network throughput with 95% confidence intervals over ten runs; the offered load is about 82 kbit/s. Throughput rises with node density for all three protocols because connectivity improves. AODV is highest at every density, from 23.9 kbit/s with 5 UAVs to 59.9 kbit/s with 25 UAVs, whereas DSDV and OLSR reach 35.0 and 40.3 kbit/s with 25 UAVs. With 5 and 10 UAVs the confidence intervals of the protocols overlap, so the ranking in sparse networks is not statistically supported (Section 4.1.8).

Table 3. Average Throughput (kbit/s), mean ± 95% CI

Number of Nodes	AODV (kbit/s)	DSDV (kbit/s)	OLSR (kbit/s)
5	23.9 ± 8.2	16.2 ± 5.1	18.5 ± 3.5
10	25.6 ± 7.1	25.0 ± 7.8	20.6 ± 6.2
15	41.8 ± 11.2	29.7 ± 7.0	23.9 ± 7.1
20	54.9 ± 6.8	33.4 ± 8.8	31.4 ± 7.0
25	59.9 ± 6.7	35.0 ± 7.4	40.3 ± 7.6

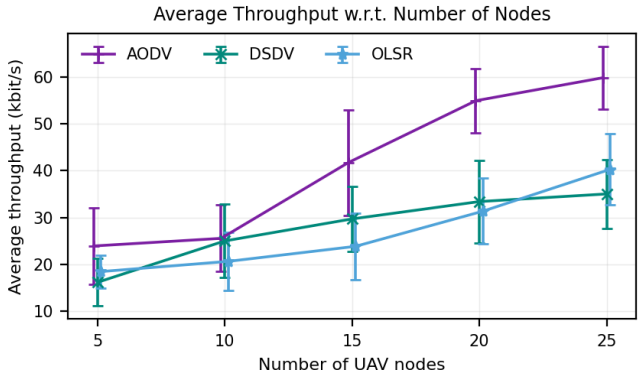


Figure 5. Average Throughput w.r.t. Number of Nodes (error bars: 95% CI)

4.1.2. Packet Loss Ratio

The packet loss ratio (Table 4, Figure 6) reflects how well each protocol copes with a network that is partly partitioned at low density. With 5 UAVs in a 1 km² area, loss is high for all protocols (70.6% for AODV, 80.1% for DSDV and 77.3% for OLSR) because many source-destination pairs have no path. With 25 UAVs the loss falls to 26.0% for AODV, 56.7% for DSDV and 50.1% for OLSR. Because loss is the complement of delivery, the ordering is the mirror image of the delivery ratio below.

Table 4. Packet Loss Ratio (%), mean ± 95% CI

Number of Nodes	AODV (%)	DSDV (%)	OLSR (%)
5	70.6 ± 10.0	80.1 ± 6.2	77.3 ± 4.3
10	68.7 ± 8.7	69.3 ± 9.7	74.7 ± 7.6
15	48.3 ± 14.0	63.2 ± 8.7	70.4 ± 8.9
20	31.8 ± 8.5	58.5 ± 10.8	61.1 ± 8.6
25	26.0 ± 7.9	56.7 ± 9.0	50.1 ± 9.4

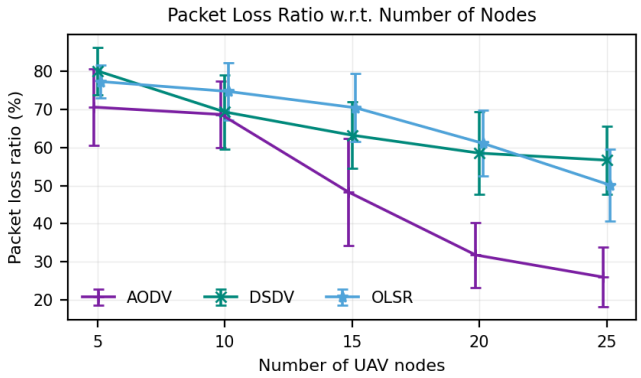


Figure 6. Packet Loss Ratio w.r.t. Number of Nodes (error bars: 95% CI)

4.1.3. PDR

The packet delivery ratio (PDR) of AODV rises from 29.4% with 5 UAVs to 74.0% with 25 UAVs, against 19.9% to 43.3% for DSDV and 22.7% to 49.9% for OLSR (Table 5, Figure 7). The advantage of AODV over at least one other protocol is statistically significant from 15 UAVs upward. OLSR is slightly above DSDV with 25 UAVs, but their intervals overlap. The reactive discovery of AODV lets it find paths that exist only for a short time, which the periodic updates of DSDV and OLSR do not capture as quickly in a sparse and moving network.

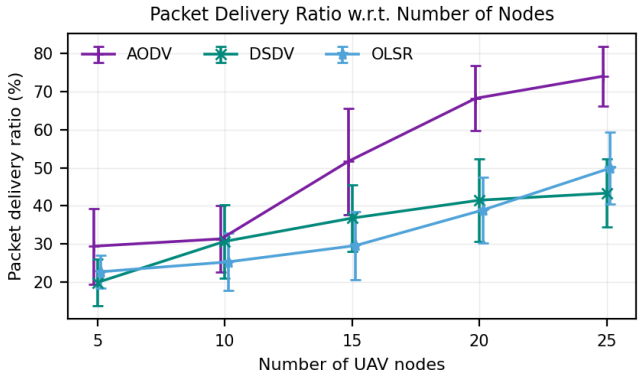


Figure 7. PDR Graph (error bars: 95% CI)

Table 5. PDR (%) for Different Protocols, mean ± 95% CI

Number of Nodes	AODV (%)	DSDV (%)	OLSR (%)
5	29.4 ± 10.0	19.9 ± 6.2	22.7 ± 4.3
10	31.3 ± 8.7	30.7 ± 9.7	25.3 ± 7.6
15	51.7 ± 14.0	36.8 ± 8.7	29.6 ± 8.9
20	68.2 ± 8.5	41.5 ± 10.8	38.9 ± 8.6
25	74.0 ± 7.9	43.3 ± 9.0	49.9 ± 9.4

4.1.4. Performance under Varying Network Conditions

To isolate the effect of each factor, one parameter was varied at a time while all others were kept at the baseline values of Table 1 (20 UAVs, 10 m/s, 300 m range, no failures): node density (Section 4.1.5), UAV speed (4.1.6), topology change caused by relay-UAV failures, and range degradation caused by heavy rain or interference (4.1.7). Two combined flood scenarios are reported in Section 4.1.9.

4.1.5. Impact of Increased Node Density

Table 6 and Figure 8 show the number of packets received per run; AODV delivers the most packets with 20 and 25 UAVs. End-to-end delay (Table 7, Figure 9) differs by orders of magnitude between the protocols. AODV has the highest delay, 691 ms with 5 UAVs, because a route must be discovered across sparse partitions before data can flow, falling to 48-58 ms with 20-25 UAVs. DSDV lies between 19 and 51 ms with very wide confidence intervals, and OLSR is lowest at 1.1-3.4 ms because routes are already available when a packet is generated.

Table 6. Packets Received per Run (#), mean ± 95% CI

Number of Nodes	AODV (#)	DSDV (#)	OLSR (#)
5	499 ± 170	337 ± 106	385 ± 73
10	532 ± 148	521 ± 163	430 ± 129
15	870 ± 234	619 ± 145	497 ± 149
20	1145 ± 142	696 ± 184	653 ± 146
25	1247 ± 140	730 ± 154	840 ± 158

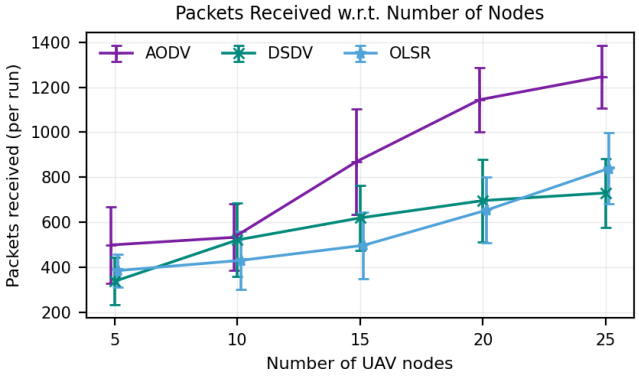


Figure 8. Packets Received vs Number of Nodes (error bars: 95% CI)

Table 7. Average End-to-End Delay (ms), mean ± 95% CI

Number of Nodes	AODV (ms)	DSDV (ms)	OLSR (ms)
5	691.2 ± 335.7	48.7 ± 44.6	1.1 ± 0.6
10	172.5 ± 120.6	44.0 ± 29.4	1.2 ± 0.2
15	147.0 ± 75.0	50.8 ± 39.3	3.4 ± 1.9
20	48.1 ± 23.2	42.7 ± 74.3	3.4 ± 1.8
25	57.8 ± 33.9	19.3 ± 12.7	3.3 ± 1.4

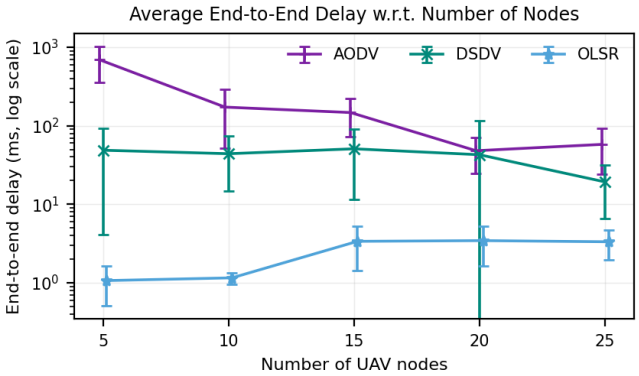


Figure 9. Average End-to-End Delay vs Number of Nodes (log scale, error bars: 95% CI)

Routing overhead (Table 8) grows with density for all protocols, from 2.6, 0.3 and 1.2 kbit/s (AODV, DSDV, OLSR) with 5 UAVs to 16.7, 18.8 and 15.6 kbit/s with 25 UAVs. DSDV, which floods periodic table updates, becomes the most expensive protocol at 25 UAVs, while the overhead of all three remains small compared with the offered data load of about 82 kbit/s.

Table 8. Routing Overhead (kbit/s), mean ± 95% CI

Number of Nodes	AODV (kbit/s)	DSDV (kbit/s)	OLSR (kbit/s)
5	2.6 ± 0.1	0.3 ± 0.1	1.2 ± 0.0
10	5.5 ± 0.4	2.1 ± 0.3	2.9 ± 0.1
15	8.5 ± 0.5	5.5 ± 0.5	6.0 ± 0.4
20	12.2 ± 0.9	11.1 ± 0.4	10.5 ± 0.6
25	16.7 ± 1.4	18.8 ± 0.5	15.6 ± 1.0

4.1.6. Effects of Varying Speeds and Mobility Patterns

Speed was varied from 5 to 40 m/s with 20 UAVs under the Gauss-Markov model (Table 9, Figures 10 and 11). The PDR of AODV declines gently, from 69.9% to 53.0%, whereas DSDV falls from 62.1% to 18.8% and OLSR from 51.3% to 17.6%, because their periodic updates are overtaken by link changes. At 5 m/s the difference between AODV and DSDV is not significant, so DSDV is competitive when mobility is low. The price of AODV is delay, which grows from 49 ms to 236 ms as route repairs become more frequent, while the delay of OLSR stays at 3-7 ms. AODV control traffic also rises with speed (10.9 to 17.4 kbit/s), whereas the overhead of DSDV and OLSR stays almost constant at about 10-12 kbit/s.

Table 9. Effect of UAV Speed (20 UAVs), mean ± 95% CI

Level	PDR AODV (%)	PDR DSDV (%)	PDR OLSR (%)	Delay AODV (ms)	Delay DSDV (ms)	Delay OLSR (ms)
5 m/s	69.9 ± 8.6	62.1 ± 10.5	51.3 ± 15.1	48.9 ± 35.6	20.1 ± 22.8	3.0 ± 1.9
10 m/s	68.2 ± 8.5	41.5 ± 10.8	38.9 ± 8.6	48.1 ± 23.2	42.7 ± 74.3	3.4 ± 1.8
20 m/s	60.6 ± 8.9	28.1 ± 8.2	32.1 ± 8.0	141 ± 104	12.5 ± 8.0	7.3 ± 7.4
30 m/s	54.3 ± 8.2	24.0 ± 3.4	27.7 ± 7.1	220 ± 87	23.6 ± 33.7	5.2 ± 3.3
40 m/s	53.0 ± 7.0	18.8 ± 3.0	17.6 ± 3.9	236 ± 46	25.2 ± 30.4	6.3 ± 5.5

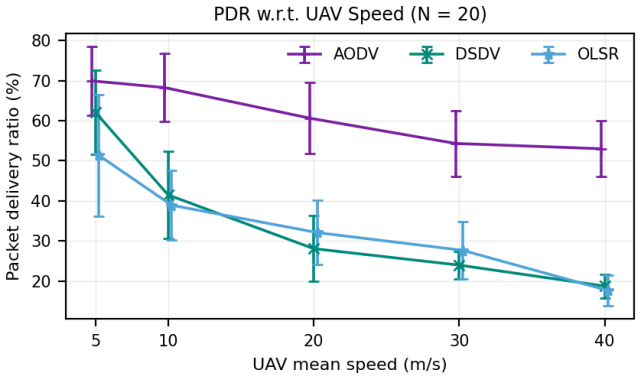


Figure 10. PDR vs UAV Speed (error bars: 95% CI)

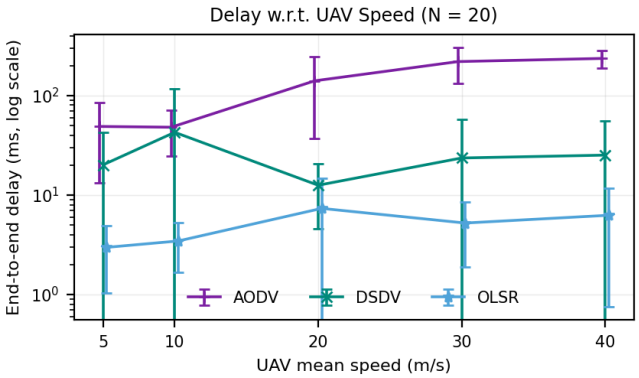


Figure 11. End-to-End Delay vs UAV Speed (log scale, error bars: 95% CI)

4.1.7. Adaptation to Topology Change and Environmental Degradation

Topology change was introduced by switching off 10-40% of the relay UAVs (those that are neither source nor destination) at t = 50 s, which represents UAV loss due to battery depletion, wind or water damage. As Table 10 and Figure 12 show, the PDR of AODV falls from 68.2% to 54.4% with 40% relay loss and that of DSDV from 41.5% to 35.0%. The OLSR values are not monotonic (38.9%, 48.2%, 54.4%, 33.6%, 29.2%) and their confidence intervals overlap, so the apparent improvement at 10-20% loss is within simulation noise and is not interpreted as a benefit of failures. Overall, AODV remains significantly better than DSDV at every failure level.

Table 10. Effect of Relay-UAV Failures at t = 50 s (20 UAVs), mean ± 95% CI

Level	PDR AODV (%)	PDR DSDV (%)	PDR OLSR (%)	Delay AODV (ms)	Delay DSDV (ms)	Delay OLSR (ms)
0 %	68.2 ± 8.5	41.5 ± 10.8	38.9 ± 8.6	48.1 ± 23.2	42.7 ± 74.3	3.4 ± 1.8
10 %	62.1 ± 10.2	38.8 ± 5.5	48.2 ± 6.2	130 ± 72	27.8 ± 24.1	3.3 ± 1.9
20 %	68.0 ± 10.8	30.1 ± 10.0	54.4 ± 12.4	69.9 ± 56.4	51.9 ± 67.2	2.6 ± 1.4
30 %	53.9 ± 8.7	33.9 ± 8.1	33.6 ± 8.4	90.9 ± 45.2	22.2 ± 21.6	3.7 ± 3.1
40 %	54.4 ± 11.6	35.0 ± 7.7	29.2 ± 6.7	133 ± 67	58.7 ± 83.4	3.3 ± 2.0

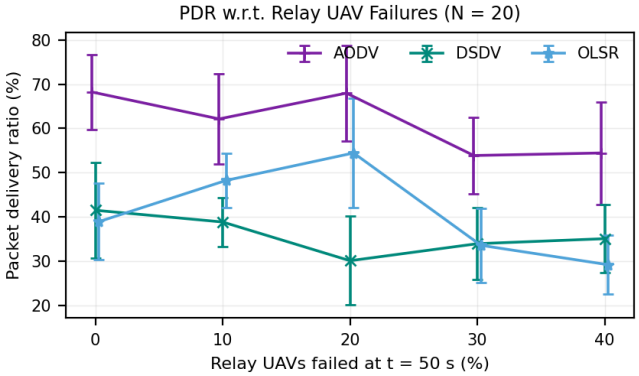


Figure 12. PDR vs Relay-UAV Failures (error bars: 95% CI)

Environmental degradation such as heavy rain or interference was represented by a reduced effective transmission range (Table 11, Figure 13). Reducing the range from 300 m to 150 m cuts the PDR of AODV from 68.2% to 9.2%, of DSDV to 3.5% and of OLSR to 6.3%, because the network fragments, and the delay of AODV rises to 750 ms. Range is the most damaging of the factors studied; AODV remains ahead, but at 150-200 m the absolute delivery of all protocols is too low for reliable medical traffic without additional UAVs or relays.

Table 11. Effect of Transmission-Range Degradation (20 UAVs), mean ± 95% CI

Level	PDR AODV (%)	PDR DSDV (%)	PDR OLSR (%)	Delay AODV (ms)	Delay DSDV (ms)	Delay OLSR (ms)
300 m	68.2 ± 8.5	41.5 ± 10.8	38.9 ± 8.6	48.1 ± 23.2	42.7 ± 74.3	3.4 ± 1.8
250 m	41.7 ± 9.4	22.4 ± 6.4	24.6 ± 6.4	111 ± 72	30.6 ± 27.1	3.3 ± 2.1
200 m	27.6 ± 11.8	10.0 ± 3.8	15.9 ± 8.2	405 ± 227	35.7 ± 52.1	1.4 ± 0.4
150 m	9.2 ± 3.5	3.5 ± 2.1	6.3 ± 2.2	749 ± 426	160 ± 156	1.1 ± 0.2

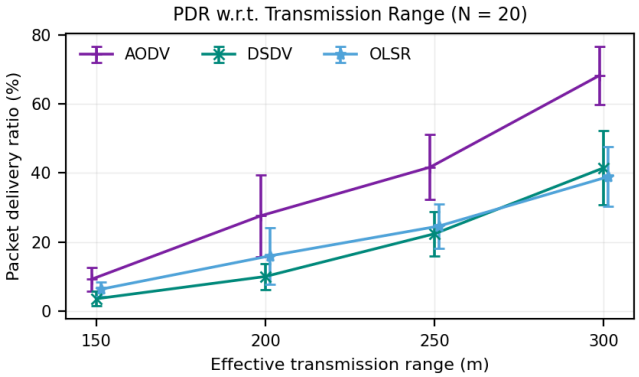


Figure 13. PDR vs Transmission Range (error bars: 95% CI)

4.1.8. Data Analysis

For each of the 18 distinct operating conditions a one-way ANOVA with Tukey HSD post-hoc tests was applied to PDR and delay (Table 12; A = AODV, D = DSDV, O = OLSR, and X>Y means that X is significantly higher than Y at the 0.05 level). AODV had a significantly higher PDR than at least one other protocol in 16 of the 18 conditions. The exceptions are the sparse networks with 5 and 10 UAVs, where the

confidence intervals overlap; at 5 m/s only the difference between AODV and OLSR is significant, not that between AODV and DSDV. The claim that AODV performs better is therefore supported for dense, fast-moving and degraded networks, but not for sparse ones and only partly for slow ones. For delay, AODV was significantly higher than DSDV and/or OLSR in 16 of the 18 conditions. Because many tests were performed, individual p-values close to 0.05 should be read with caution.

Table 12. ANOVA p-values and Tukey HSD results for PDR and end-to-end delay

Condition	PDR p	PDR significant pairs	Delay p	Delay significant pairs
Baseline (N = 20, 10 m/s, 300 m)	<0.001	A>D, A>O	0.241	none
N = 5 (density)	0.115	none	<0.001	A>D, A>O
N = 10 (density)	0.486	none	0.002	A>D, A>O
N = 15 (density)	0.009	A>O	<0.001	A>D, A>O
N = 25 (density)	<0.001	A>D, A>O	<0.001	A>D, A>O
5 m/s (speed)	0.055	A>O	0.019	A>O
20 m/s (speed)	<0.001	A>D, A>O	0.002	A>D, A>O
30 m/s (speed)	<0.001	A>D, A>O	<0.001	A>D, A>O
40 m/s (speed)	<0.001	A>D, A>O	<0.001	A>D, A>O
10 % relay failure	<0.001	A>D, A>O	<0.001	A>D, A>O
20 % relay failure	<0.001	A>D, O>D	0.108	none
30 % relay failure	<0.001	A>D, A>O	<0.001	A>D, A>O
40 % relay failure	<0.001	A>D, A>O	0.009	A>O
250 m range	<0.001	A>D, A>O	0.002	A>D, A>O
200 m range	0.009	A>D	<0.001	A>D, A>O
150 m range	0.008	A>D	<0.001	A>D, A>O
Moderate flood	<0.001	A>D, A>O	<0.001	A>D, A>O
Severe flood	<0.001	A>D, A>O	<0.001	A>D, A>O

4.1.9. Flood-Specific Scenarios

Two composite scenarios combine the stress factors that are characteristic of a flood: a moderate flood (250 m range, 10% relay loss, 15 m/s) and a severe flood (200 m range, 20% relay loss, 25 m/s, representing gusty wind), compared with the normal baseline (Table 13, Figure 14). The PDR of AODV is 68.2%, 33.2% and 24.3% in the three scenarios, which is roughly twice that of DSDV (41.5%, 16.6%, 8.7%) and OLSR (38.9%, 18.7%, 8.4%); the differences are significant in both flood scenarios (Table 12). The delay of AODV, however, rises from 48 ms to 321 ms and 896 ms, while that of OLSR remains between 1.6 and 3.4 ms. In a flood, AODV therefore delivers the most data but not quickly, and OLSR delivers the fastest but loses most packets.

Table 13. Flood-**specific** scenarios, mean ± 95% CI

Scenario	PDR AODV (%)	PDR DSDV (%)	PDR OLSR (%)	Delay AODV (ms)	Delay DSDV (ms)	Delay OLSR (ms)
Normal	68.2 ± 8.5	41.5 ± 10.8	38.9 ± 8.6	48.1 ± 23.2	42.7 ± 74.3	3.4 ± 1.8
Moderate flood	33.2 ± 4.7	16.6 ± 6.8	18.7 ± 7.1	321 ± 125	47.1 ± 56.8	2.2 ± 1.2
Severe flood	24.3 ± 6.8	8.7 ± 4.2	8.4 ± 4.1	896 ± 406	40.0 ± 53.5	1.6 ± 0.6

4.2. Discussion of Results

These findings which are retrieved from simulations of AODV, DSDV and OLSR among unmanned aerial systems provide principle basis for both theoretical distribution as well as a practical use of routing processes in this type of networks. Through Metric Performance—such as throughput, packet loss ratio and PDR—the competency of each protocol may be evaluated under the different net stresses that are often associated with FANET operations. This quantitative criterion is employed for evaluating the protocol competency.

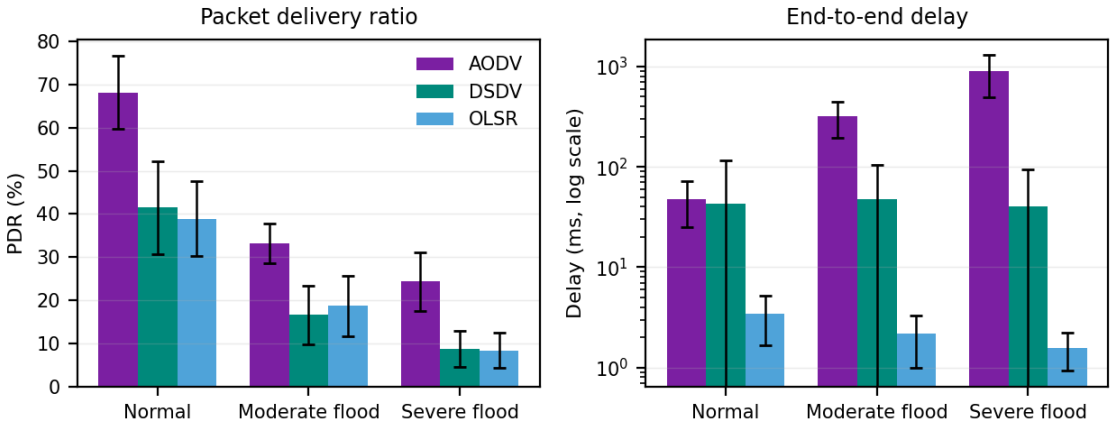


Figure 14. PDR and delay under flood-specific scenarios (error bars: 95% CI)

Taken together, the experiments show a consistent trade-off. AODV delivers the most data in dense, fast-moving and degraded networks, which supports its use in rapidly changing flood environments, but its on-demand route discovery produces the highest delay. OLSR has the lowest delay in every scenario but a lower delivery ratio, and DSDV is competitive only when mobility is low or the network is sparse, where the differences between protocols are not statistically significant. For health assistance, this means that delay-critical alerts and loss-sensitive records should not share one routing profile (Table 2): a 900 ms mean delay under severe flood conditions may be acceptable for imagery and patient records but not for an emergency alarm, while a delivery ratio below 25% is too low for records unless redundancy is added.

4.2.1. Challenges Encountered and Limitations of Study

Several limitations affect these results. The findings come from simulation with a simplified channel (a fixed transmission range without fading, shadowing or obstacles), a generic CBR traffic model instead of real medical applications, and only 5-25 UAVs in a 1 km² area. Flood-specific effects such as heavy rain, wind, debris, water reflections and battery depletion were represented only by range reduction, higher speed and relay switch-off. The default NS-3 protocol parameters were used and not tuned, and the absolute PDR values are low in sparse networks because of network partitioning, so they should not be read as expected field performance. As is common in MANET simulation studies, results depend strongly on such modelling assumptions [39]. Deploying FANET communication in a real flood also involves challenges that simulation cannot capture: unreliable power and weather, flight permissions and regulation [13], [14], limited battery endurance, privacy and security of patient data, and coordination with health authorities. Field trials and testbed measurements with real UAVs are therefore needed to validate the protocol ranking, and the mapping of Table 2 should be evaluated with real medical traffic.

5. Conclusion

The simulation results, based on ten independent runs per configuration with confidence intervals and ANOVA with Tukey HSD tests, show that AODV has the highest packet delivery ratio and throughput in dense, fast-moving and degraded FANETs, such as those formed in the aftermath of floods; its PDR was significantly higher than that of at least one other protocol in 16 of 18 conditions and, for example, 68.2% against 41.5% for DSDV and 38.9% for OLSR in the baseline scenario. This advantage comes with the highest end-to-end delay (up to about 0.9 s under severe flood conditions). OLSR, which keeps routes proactively through multipoint relays, has the lowest delay (about 1-7 ms) but a lower delivery ratio, and DSDV is competitive only in sparse or low-mobility networks, where the differences are not statistically significant. Range degradation was the most damaging factor, whereas the effect of relay-UAV failures was moderate and noisy. Consequently, no single protocol is best for all health-assistance traffic. Reliability-oriented traffic such as patient records and imagery is better served by AODV, and latency-critical alerts by OLSR with repetition. These conclusions are limited to the simulated conditions and need confirmation in field experiments.

5.1. Future Directions

The tight integration of AI and ML with FANET routing protocols, meant to provide effective solutions needs to be implemented. More research is required to look into how the protocol deals with the drones that have significantly increased in number for scalability. There is also need to investigate programs that soften energy use but not network services to be effective for power battery UAVs. There is a scope in research on automating switching between different types of networks based on their availability and reliability. In future running tests and field demonstrations to compare the interaction of protocols in real life emergency situations can be considered. Future research needs to become developed, designing a technique of prevent unauthorized access as well as maintain security of critical information. Through the application of FANET the establishment of a regulative mechanism is to be formulated. There is a need to make efforts towards unification and global friendly cooperation of the technologies in disaster tackling.

References

1. Maakar, Sunil Kr, Deepak Sinwar, and Kuldeep Singh Kaswan. "Performance Analysis of Proactive Routing Protocols for Flying Ad-Hoc Networks Using Group Mobility Model." International Journal of Networked and Distributed Computing 13.2 (2025): 31.
2. Ali, Syed Haider, et al. "Reliable data exchange in UAV swarm networks using advanced networking techniques." ICCK Transactions on Advanced Computing and Systems 2.3 (2026): 212-224.
3. Abbas, S.; Abu Talib, M.; Ahmed, I.; Belal, O. Integration of UAVs and FANETs in disaster management: A review on applications, challenges and future directions. Transactions on Emerging Telecommunications Technologies 2024, 35(12), e70023.
4. Riley, G.F.; Henderson, T.R. The ns-3 network simulator. In Modeling and Tools for Network Simulation; Springer: Berlin, Heidelberg, 2010; pp. 15-34.
5. Bekmezci, I.; Sahingoz, O.K.; Temel, S. Flying ad-hoc networks (FANETs): A survey. Ad Hoc Networks 2013, 11(3), 1254-1270.
6. Mozaffari, M.; Saad, W.; Bennis, M.; Nam, Y.-H.; Debbah, M. A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. IEEE Communications Surveys & Tutorials 2019, 21(3), 2334-2360.
7. Erdelj, M.; Natalizio, E.; Chowdhury, K.R.; Akyildiz, I.F. Help from the sky: Leveraging UAVs for disaster management. IEEE Pervasive Computing 2017, 16(1), 24-32.
8. Alsayyed, M.M.; Manickam, S.; Wulandari, E.R.N.; Widia, I.D.M.; Karuppayah, S. 2025. A Review of Applicable Technologies, Routing Protocols, Requirements, and Architecture for Disaster Area Networks. IEEE Access.
9. Kumar, P.A.; Manoj, N.; Sudheer, N.; Bhat, P.P.; Arya, A.; Sharma, R. UAV swarm objectives: a critical analysis and comprehensive review. SN Computer Science 2024, 5(6), 764.
10. Munawar, H.S.; Ullah, F.; Qayyum, S.; Khan, S.I.; Mojtahedi, M. UAVs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection. Sustainability 2021, 13(14), 7547.
11. Shetty, S.J.; Ravichandran, R.; Tony, L.A.; Abhinay, N.S.; Das, K.; Ghose, D. Implementation of survivor detection strategies using drones. arXiv 2020, arXiv:2003.12559.
12. Elevating healthcare: Rapid literature review on drone applications for streamlining disaster management and prehospital care in Saudi Arabia. Healthcare 2023, 11(11), 1575. doi:10.3390/healthcare11111575.
13. Aggarwal, S.; Nigam, K.; Singh, V.; Mishra, T.; Pandey, A.K.; Kant, R.; Murhekar, M. 2024. Drone-based medical delivery in the extreme conditions of Himalayan region: a feasibility study. BMJ Public Health, 2(2).
14. Rahim, Fakher, and Nameer Hashim Qasim. "A systematic literature review of drones in emergency medicine: practical applications, legal challenges, and future directions." Drone Systems and Applications 13 (2025): 1-13.
15. Hamissi, A.; Dhraief, A. A survey on the unmanned aircraft system traffic management. ACM Computing Surveys 2023, 56(3), 1-37.
16. Bryant, Nelson McNova, and Gift Mwonzora. "Operational outcomes and feasibility of medical drones for healthcare delivery and vector control in emerging economies: a systematic review." Global Health Journal (2026).
17. Monica Dev, M.; Hema, R. 2020. A safe road to health: Medical services using unmanned aerial vehicle. In International Conference on Innovative Computing and Communications: Proceedings of ICICC 2020, Volume 1 (pp. 367-375). Singapore: Springer Singapore.
18. Javed, S.; Hassan, A.; Ahmad, R.; Ahmed, W.; Ahmed, R.; Saadat, A.; Guizani, M. State-of-the-art and future research challenges in uav swarms. IEEE Internet of Things Journal 2024, 11(11), 19023-19045.
19. Medeiros, et al. Swarm-based and energy-aware unmanned aerial vehicle system for video delivery of mobile objects. IEEE Transactions on Vehicular Technology 2022 (volume and pages to be confirmed).
20. Dhall, R.; Dhongdi, S. Review of protocol stack development of flying ad-hoc networks for disaster monitoring applications. Archives of Computational Methods in Engineering 2023, 30(1), 37-68.
21. Oubbati, O.S.; Lakas, A.; Zhou, F.; Güneş, M.; Yagoubi, M.B. A survey on position-based routing protocols for Flying Ad hoc Networks (FANETs). Vehicular Communications 2017, 10, 29-56.
22. Yang, K.; Zhang, S.; Yang, X.; Wu, N.; Liu, C. Flood detection based on unmanned aerial vehicle system and deep learning. Complexity 2022, 2022, 6155300.
23. Lansky, J.; Ali, S.; Rahmani, A.M.; Yousefpoor, M.S.; Yousefpoor, E.; Khan, F.; Hosseinzadeh, M. Reinforcement learning-based routing protocols in flying ad hoc networks (FANET): A review. Mathematics 2022, 10(16), 3017.
24. Giannitsopoulos, M.L.; Leinster, P.; Butler, D.; Smith, M.; Rivas Casado, M. 2022. Towards the coordinated and fit-for-purpose deployment of Unmanned Aerial Systems (UASs) for flood risk management in England. AQUA—Water Infrastructure, Ecosystems and Society, 71(8), pp.879-895.

25. Camp, T.; Boleng, J.; Davies, V. A survey of mobility models for ad hoc network research. Wireless Communications and Mobile Computing 2002, 2(5), 483-502.
26. Amponis, G.; Lagkas, T.; Argyriou, V.; Moscholios, I.; Zevgara, M.; Ouzounidis, S.; Sarigiannidis, P. Anchored self-similar 3D Gauss-Markov mobility model for ad hoc routing scenarios. IET Networks 2023, 12(5), 250-259.
27. Kaur, Upinder, et al. "Next-Generation FANET Routing: A Systematic Review of Mobility Models, Routing Protocol Families, and Future Research Roadmap." International Journal of Networked and Distributed Computing (2026).
28. Romero, C.A.T.; Ortiz, J.H.; Rodríguez Timaná, L.C.; Varela, F.V.; Aristizábal Montufar, A.H.; Gamboa-Cruzado, J. 2025. FANET and MANET, a Support and Composition Relationship. Computers, Materials & Continua, 82(2).
29. ns-3 Consortium. ns-3 Network Simulator, version 3.44. Available online: https://www.nsnam.org
30. Carneiro, G.; Fortuna, P.; Ricardo, M. FlowMonitor: A network monitoring framework for the Network Simulator 3 (NS-3). In Proceedings of VALUETOOLS 2009.
31. Kezai, M.; Dembri, R.; Boukhari, D.E. Balancing Act: A Comparative Study of Routing Protocol Trade-Offs in MANETs. Journal of Advanced Computational Intelligence and Intelligent Informatics 2025, 29(1), 64-78.
32. Wu, Q.; Zhang, M.; Dong, C.; Feng, Y.; Yuan, Y.; Feng, S.; Quek, T.Q. Routing protocol for heterogeneous FANETs with mobility prediction. China Communications 2022, 19(1), 186-201.
33. Badawi, S.; Ahmad, N.; Akmam, R.; Mohamed, N.; Mohd, S. Routing Protocols in Fanet for Disaster Area Networks: A Review. ASEAN Engineering Journal 2025, 15(3), 81-100.
34. Jain, R. The Art of Computer Systems Performance Analysis; Wiley: New York, NY, USA, 1991.
35. Ajjaj, S.; El Houssaini, S.; Hain, M.; El Houssaini, M.A. Performance assessment and modeling of routing protocol in vehicular ad hoc networks using statistical design of experiments methodology: a comprehensive study. Applied System Innovation 2022, 5(1), 19.
36. Perkins, C.; Belding-Royer, E.; Das, S. Ad hoc On-Demand Distance Vector (AODV) Routing. RFC 3561, IETF, 2003.
37. Clausen, T.; Jacquet, P. Optimized Link State Routing Protocol (OLSR). RFC 3626, IETF, 2003.
38. Perkins, C.E.; Bhagwat, P. Highly dynamic destination-sequenced distance-vector routing (DSDV) for mobile computers. ACM SIGCOMM Computer Communication Review 1994, 24(4), 234-244.
39. Kurkowski, S.; Camp, T.; Colagrosso, M. MANET simulation studies: The incredibles. ACM SIGMOBILE Mobile Computing and Communications Review 2005, 9(4), 50-61.