

AN EFFICIENT ROUTING PROTOCOL TECHNIQUE IN FLYING AD HOC NETWORK USING TOPOLOGY-SWARM BASED APPROACH

Ayobami Taiwo Olusesi (1*)
Ayo Isaac Oyedeji (1)
Olusogo Julius Adetunji (1)
Etinosa Noma-Osaghae (1)

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¹ Department of Computer Engineering, Faculty of Engineering, Olabisi Onabanjo University, Ago-Iwoye, Ogun State, Nigeria.

*Corresponding Author's Email: olusesi.ayobami@oouagoiwoye.edu.ng

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Ayobami Taiwo Olusesi

Department of Computer Engineering, Faculty of Engineering,
Olabisi Onabanjo University, Ago-Iwoye, Ogun State, Nigeria
Email: olusesi.ayobami@oouagoiwoye.edu.ng

Ayo Isaac Oyedeji

Department of Computer Engineering, Faculty of
Engineering, Olabisi Onabanjo University, Ago-
Iwoye, Ogun State, Nigeria
Email: ayo.oyedeji@oouagoiwoye.edu.ng

Olusogo Julius Adetunji

Department of Computer Engineering, Faculty of
Engineering, Olabisi Onabanjo University,
Ago-Iwoye, Ogun State, Nigeria
Email: adetunji.olusogo@oouagoiwoye.edu.ng

Etinosa Noma-Osaghae

Department of Computer Engineering, Faculty of
Engineering, Olabisi Onabanjo University, Ago-
Iwoye, Ogun State, Nigeria
Email:
etinosa.noma-osaghae@oouagoiwoye.edu.ng

Abstract— Unmanned aerial vehicles (UAVs) have been made possible by developments in technology. Clusters of UAVs that communicate while in close proximity to achieve a common goal make up a Flying Ad Hoc Network (FANET). FANETs have garnered huge interest in recent times due to their potential uses across numerous fields, including agriculture, environment, rescue operations, and surveillance, among others. High-speed nodes, low density, constrained energy resources, and quick topology changes are just a few of the difficulties FANETs have encountered. Because of this, routing in these networks is a difficult problem. Therefore, this study developed an efficient routing technique for FANETs using the enhanced mayfly algorithm and optimal link state routing (EMAOLSR). The study model is based on the topology technique of OLSR, while the enhanced mayfly algorithm (EMA), which is a swarm-based approach, was utilized for optimal selection of multipoint relays (MPRs) in FANET to improve the performance of OLSR. EMAOLSR optimally selects a node as the MPR that has a high residual energy and a high-quality connection. The developed EMAOLSR was simulated using the MATLAB toolbox. EMAOLSR was compared with the existing technique of firefly algorithm optimized link state (FAOLSR) and OLSR. Results show that our routing technique (EMAOLSR) performed better than FAOLSR and OLSR in terms of energy consumption, throughput, end-to-end delay, packet delivery rate, packet loss rate, and network efficiency.

Keywords— *Unmanned Aerial Vehicles (UAVs), Flying Ad Hoc Network (FANET), Routing Protocol, Optimised Link State Routing (OLSR), Enhanced Mayfly Algorithm (EMA).*

I. Introduction

The development of unmanned aerial vehicle (UAV) technology has brought improvement into the wireless communication domain. These aerial platforms are essential for increasing network capacity and coverage because they function as high-altitude base stations. Their ability to be moved to maximize signal dispersion and guarantee better service delivery makes them especially useful for deployment

in areas without strong ground infrastructure (Union, 2020; Shahzadi et al., 2021). As a result, they have caught the interest of numerous academics and industries (Lee et al. 2021; Rahmani et al. 2022). UAVs have several benefits. First off, in comparison with traditional infrastructure, which may be costly and consumes so much time to install, UAVs offer quick and affordable deployment. Second, they are crucial for emergency response and catastrophe recovery because they can function in dangerous or difficult-to-reach locations, guaranteeing connectivity when it's most required. Because they may be moved to accommodate changing demand or coverage gaps, UAVs also provide flexibility in network administration. By offering substitute communication channels, they can also facilitate high-capacity data transfer and improve network resiliency. All things considered, UAVs greatly improve wireless networks' dependability and efficiency (Adelantado et al. 2022).

Flying ad hoc network (FANET) is a group of flexible, dynamic, distributed, WiFi-capable UAVs that create communication channels on their own (Hutchins et al. 2025). UAV nodes make up the rapidly developing FANET, which is a wireless ad hoc network created when several UAVs work together to complete a specific goal (Shokrollahi & Dehghan, 2023; Pasandideh et al., 2022). In essence, FANETs are made up of several tiny UAVs that enable flexible and portable links among devices in places that lack network infrastructure. As a result, the UAVs are outfitted with sensors, a GPS module, and an onboard monitor that can be controlled remotely or independently. FANETs are self-configured, rapidly deployable, and provide an affordable communication data network to circumvent the limits of the traditional infrastructure-based communication architecture in a catastrophic event (Khan et al. 2018). FANETs are applicable in the military, transportation systems, agriculture (such as monitoring of crops), rescue operations, and theft detection, among others (Beegum et al. 2023). Also, FANETs can provide prompt and dependable services, guaranteeing continuous communication (Shamsoshoara et al. 2021). As previously said, FANET is a collection of UAVs that are linked together without the use of infrastructure in order to

accomplish a shared goal. Figure 1 shows an overview of a FANET architecture.

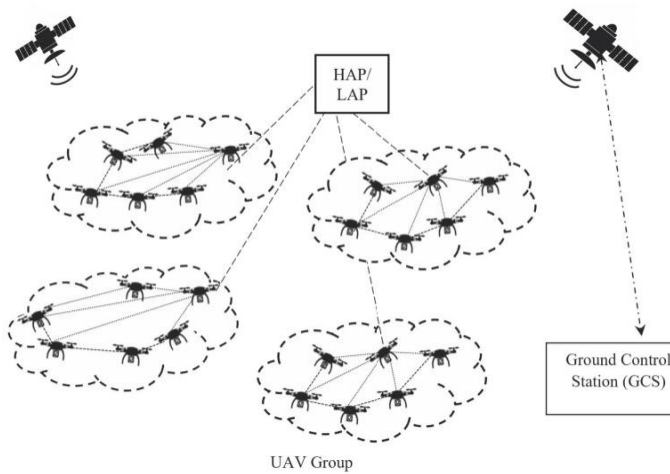


Figure 1: Flying Ad Hoc Network Architecture

In addition to collecting and exchanging the data among the UAVs, FANETs may also transmit the data to the base station. Furthermore, they can use the remaining UAVs to connect to the network in the event that bad weather causes some of them to be disconnected (Sharma & Kumar, 2015).

FANET is suitable for extremely sensitive devices that require guaranteed data transmission in a real-time and dependable manner. Although FANETs' distinctive features make them a good fit for a variety of application scenarios, they also provide some difficult networking and communication challenges for the numerous UAVs (Khan et al. 2018), such as low density, high node speed, and high dynamic topology (Kuar et al. 2021; Khanmohammadi et al. 2021). The cooperative communication amongst the UAVs is the fundamental issue with FANETs, coupled with a link variation problem that normally arises from the network's architecture that changes rapidly (Khan et al. 2018), leading to an increase in latency, packet loss, and signalling overhead. The FANET nodes can travel at speeds between 30 and 460 km/h. As a result, the communication connections between UAVs are incredibly erratic and volatile. Link interruption is caused by high movement speeds, lengthy distances between nodes, environmental uncertainties, node failures, and other factors, necessitating the creation of a new routing path (Zhigao et al. 2018). Additionally, UAVs have short-lived communication links. This has made routing a difficult problem in FANET. The choice of the optimal routing path determines how well a routing protocol performs (Khan et al. 2021; Tan et al. 2020; Ibrahim & Shanmugaraja, 2021). Therefore, designing and selecting the right routing protocols is crucial in these situations to maintain the stability and activity of FANET applications and improve packet transfer between the UAVs (Khan et al. 2018). Because FANET networks are so complicated, creating an ideal routing protocol is a challenging task that is still being studied.

Several techniques have been found and recently used to solve network routing problems (Jubair et al. 2019) and to provide effective communication between the UAVs in FANET. A routing method called Cellular Automata African Buffalo Optimization (CAABO) was developed by Hassan et al. (2018). The CAABO looks for routes that improve the network's energy consumption while meeting delay criteria and constraints. Lucia et al. (2023) presented a method of data transfer for the Internet of Drones (IoD). Because energy is a significant issue that impacts UAVs' flight duration and mission capability, this solution was able to reduce the high rate of energy consumption in UAVs. Ali et al. (2021) created greedy perimeter stateless routing (GPSR) and OLSR to reduce network latency and communication overhead. It is therefore appropriate for applications that cannot tolerate delays. This approach is appropriate for FANET since it is simulated in three dimensions. Nevertheless, unstable routes could be produced in G-OLSR because G-OLSR disregards link quality and energy during the routing procedure. Ye et al. (2021) presented an improved routing method to reduce the communication noise and interference in UAVs. The work made use of a deep reinforcement learning-based approach to address the disruption challenges in UAVs, which are usually caused by high node mobility and frequent topology changes.

Due to the resource limitation of the UAVs, a probabilistic technique was developed for clustering formation purposes for assigning route duties. The Ad Hoc On Demand Vector (AODV) approach was utilized by Biomo et al. (2014), which allows UAVs to establish routes by building up a route stability factor based on the node link and mobility. The work focused on enhancing the routing performance and quality of service (QoS) in FANETs. The method was able to solve two key issues, which are the high level of network topology and the economic factor, most especially the routing overhead, which can lead to an increase in network complexity and energy consumption. Abdulhae et al. (2023) presented a centralized agent, which is located in a distant ground station, to improve the roles of cluster heads in FANETs. This technique was able to serve both the horizontal and vertical routing. This made routing over several plans easier through the creation of a clustering technique where each plan stands as a network cell with a distinct coverage radius of nodes. A rise in network partitions among FANET nodes made Omar et al. (2017) suggest a routing strategy that will enable UAVs to create a route by themselves. This is to reduce the challenges of node partitioning. When FANETs nodes connect with one another during regular operation, the existing network partitions may not allow some nodes to do so. Due to this factor, a vehicular node needs to create routes with UAVs. The route was made up of links between vehicles, between vehicles and UAVs, and between UAVs. For the purpose of improving the route lifetime in FANET, Ganbayar et al. (2017) developed a routing strategy that selects the routes based on the possibility of link disconnection between nodes. The work tackles the challenges of low residual energy and complexity in the network topology. Rosati et al. (2016) proposed a dynamic routing technique for FANET.

The study enables each node within the network to choose a next-hop node with the best connection lifetime. The high dynamic nature of FANET architecture, which always leads to frequent routing updates, was addressed by this routing method. An energy-aware cluster formation was developed by Khan et al. (2019) using the glowworm swarm optimization algorithm. This work focuses on reducing unstable routing, which is usually caused by high mobility of UAVs and limited power resources during the route discovery stage. In the scheme, each node sends a control message containing residual energy information, and from there, a neighboring set was created. The neighboring set are selected and sorted based on the fitness value and residual energy level of each node. During the route selection stage, clusters are formed based on mobility metrics, which made nodes form a cluster with a nearby cluster head in order to minimize node energy consumption. Khelifi et al. (2018) proposed a routing scheme that enables each node to pick the best next-hop node as part of a route using fuzzy logic. In a situation where the geographical location of the next node is unknown, fuzzy logic helps to predict the geographical location of nodes based on their signal strength. To reduce the issue of position failure caused by the high node dynamics during the time slot interval of position direction, Guoyong et al. (2025) presented a geographic routing decision method in FANET based on mobile prediction using an extended Kalman filter (EKF) prediction model of node positions. The Hello packet sending gap was dynamically adjusted, the neighbor discovery procedure was optimized, high-speed mobile nodes' neighbor discovery needs were decreased, and routing detection overhead was much reduced. Arafat et al. (2019) developed a UAV network using a swarm-intelligence-based localization and clustering method. Particle swarm optimization (PSO) was used as the swarm intelligence method to improve convergence time and accuracy of the network. This method was able to increase energy efficiency.

The Bee colony technique for FANET was used as a routing technique in the work of Leonov (2016). The first phase of this technique is made up of forward and backward scouts, which include source ID, the step number, and the leftover energy, which are fairly distributed among the UAV's nodes so as to create several communication paths. In the second phase, the forager drones transport informative packets from the sender to the receiver. Results show that the work was able to improve communication among UAVs. Darabkh et al. (2019) provided a location estimation technique for a congestion-aware routing technique. This is a delay-tolerant network (DTN), which is based on a routing strategy in addressing two major issues in DTN schemes. The first issue is congestion control, while the second issue is high energy usage. A path-planning mechanism and location map were used by each node for self-determination of its location as well as other neighboring nodes. During the routing stage, the closest node to the receiver has enough capacity to receive the data packet from the sending node. This scheme was able to avoid network congestion. However, this method increases the routing overhead and causes some significant delay.

Wang et al. (2023) developed a routing scheme that was based on the arithmetic optimization routing protocol. The multipath routing protocol was improved by lowering latency during data transmission. However, the approach experienced poor link stability in highly dynamic situations and also caused high latency in route identification. Sakar et al. (2021) proposed an improved ant-AODV routing protocol.

This method was based on the ant colony algorithm to determine elements such as hop count, node reliability, node congestion, and energy optimization and improve routing path selection in mobile ad hoc networks (MANET). However, the technique still has issues in adjusting quickly to the frequent topology changes in the network, especially in a high dynamic situation. Joon et al. (2022) developed a routing scheme based on energy-efficient connected-aware data transmission. The technique set priorities on high-energy nodes for route discovery so as to reduce energy consumption. The Q-learning algorithm was used to select cluster head nodes and dynamically modifies routing strategies based on environmental changes and past experience of the routing process. Proactive ant colony routing, an active ant colony update technique, was presented by Wang et al. (2025). This method can react swiftly to changes in network architecture by transmitting pheromones more frequently. Nevertheless, there is still additional computational and communication cost associated with frequent routing adjustments. Cui et al. (2022) presented a topology-aware elastic routing technique based on adaptive Q-learning. The change rate of neighboring nodes and the arrival time were determined by using queuing theory to analyze the dynamic behavior of nodes.

A geographic routing system based on Q-learning was proposed by Jung et al. (2017). This method used the Q-learning algorithm to select the routing paths and Q-values to assess the quality of various routing paths. Energy-efficient connectivity-aware data delivery for FANETs was developed by Oubabati et al. (2019). This approach rebuilds failed routes and also avoids route failure. It considered the energy parameter and link lifetime of FANET, making sure that UAVs do not partake in this process until there is sufficient energy to rebroadcast messages. The network energy consumption was also balanced by this technique. It is a good approach, but when choosing routes, the approach disregards the link quality and movement direction of nodes. Chen et al. (2020) presented an enhanced routing technique using a traffic-aware Q-network. The mechanism is based on balancing the congestion information and network traffic. It also uses the Q-network to analyze link quality using the network congestion information. It selects routes based on the Q-value, which includes low delay, rate of packet loss, and low traffic. However, the method ignores the energy parameter and link lifetime, which are crucial when designing a routing protocol. Zheng et al. (2018) presented a prediction-based directional MAC (PPMAC) strategy to manage communication and data transfer while predicting the locations of other nodes.

To find the shortest path with the least amount of delay between the source and the destination, the authors employed self-learning reinforcement learning. The suggested algorithm incorporates the partially observable Markov decision process (POMDP), where the end-to-end data transmission delay is given as a reward. Like QMR, RLSRP keeps track of network topology changes by maintaining a neighbor table. The discount factor and learning rate are examples of fixed learning parameters. Additionally, RLSRP chooses the path with the largest value function, where the end-to-end delay is the lowest, using a greedy policy. Khan et al. (2022) developed a FAnt-Hocnet routing protocol, which is based on fuzzy logic and the Ant-Hocnet bioinspired ACO algorithm. Their method seeks to enhance routing in a FANET with 100 nodes moving randomly under a Gauss-Markov mobility model. The FAnt-Hocnet protocol has demonstrated increased throughput and decreased End-to-End (E2E) latency, highlighting the role fuzzy logic plays in enhancing protocol performance and intelligence. However, the absence of a universal design standard and the complexity of the rule-based interference process in fuzzy logic may affect the robustness of FANETs' operation.

To improve node performance within the MANET, Jubair et al. (2019) combined the routing strategy of the bat algorithm with OLSR. However, this method is not appropriate for FANET because of the problem of premature convergence and getting stuck in local optima that the bat algorithm faces. Rahmani et al. (2022) combined OLSR with fuzzy-based routing technology. The developers of this method suggested a novel way to determine the link's lifetime between two UAVs. According to the simulation results, the method performed well in terms of energy usage and latency, but OLSR has a significant communication overhead. A routing technique based on OLSR and the firefly algorithm was introduced by Lansky et al. (2023). Although this approach slightly increased the routing overhead, it showed potential for improving FANET efficiency. The firefly algorithm, which was used as a technique in MPRs selection, is known for its inability to escape from local, which is one of the major challenges facing swarm-based routing techniques. To improve wildfire monitoring and detection, Ma et al. (2019) provided the routing technique for FANETs based on velocity awareness and stability estimate (VaSe). Additionally, VaSe chooses multiple routes between the transmitter and receiver and determines the link stability time. Consequently, the packet delivery rate is increased by Vase-MRP. Nevertheless, it is not appropriate for FANET because it is implemented in a 2D environment. VaSe simulates this system by taking into account a very low speed for nodes. Consequently, it needs to be assessed for high-speed nodes. Utility functions for GPSR were presented by Kumar et al. (2023) for FANETs. In order to adjust the greedy routing method, this technique takes into account the fundamental elements of UAVs, such as distance, movement angle, velocity, communication link risk, and energy level.

Even though several studies have been done to address this routing issue, the majority of these routing protocols are

unable to effectively satisfy the needs of FANETs. This has created concern for researchers due to FANET architecture's complexity, frequent changes in communication links, and the UAVs' rapid mobility (Hosseinzadeh et al. 2024; Khan et al. 2018). Topology, position, and swarm-based techniques are the three major routing techniques in FANET, but the topology-based techniques are seen to be the most important strategy for resolving FANET routing problems (Khan et al. 2017). However, the path staying fixed onto a collection of nodes is one of the topology-based system's drawbacks, despite its benefits. This protocol does not allow for the determination of the quality or fitness of the nodes chosen for the route, especially in the OLSR approach. Also, the OLSR has difficulty in selecting optimal multipoint relay (MPR), and this can lead to excess draining of FANET resources such as energy and bandwidth (Lansky et al. 2023; Jubair et al. 2019). Several swarm-based algorithms have been used to improve the OLSR performance, especially in the optimal selection of MPR, but they face the challenges of converging prematurely, getting stuck in local optima, having difficulty in balancing the exploitation and exploration search space, and taking so much time to find ideal parameter values (Bazi et al. 2021).

Therefore, this study developed an efficient routing protocol for FANET integrating topology routing protocol with swarm-based technique. The OLSR is the topology-based model for this study. Additionally, the study used the enhanced mayfly algorithm (EMA) as the swarm-based technique in choosing multipoint relays (MPRs) so as to improve the OLSR performance for optimal selection of MPR in FANET. The simulation of this study was carried out in MATLAB. The performance of this study was compared with the existing technique of the OLSR firefly algorithm using end-to-end delay, packet delivery rate, throughput, energy consumption, packet loss rate, and network efficiency as evaluation metrics. This study's other sections are arranged as follows. In section 2, present the materials and method. Results and discussion are presented in Section 3. Finally, the conclusion and future research were discussed in section 4.

II. MATERIALS AND METHOD

An efficient and robust routing protocol for the FANET is proposed in this study. The OLSR, enhanced mayfly algorithm, MATLAB software environment, and evaluation metrics are the main components of the study.

A. Optimized Link State Routing

OLSR uses the link-state (LS) technique with fewer signaling packets and controls traffic flooding (Zhang et al. 2019). It establishes a link among the UAVs by using a unique packet. This particular protocol's capacity to exhibit periodic flooding behavior leads to a significant control overhead. To improve network latency and lower routing overheads, OLSR takes advantage of the MPR. However, choosing the MPR-UAV wisely becomes one of the most crucial and challenging aspects influencing the OLSR's performance (Muhammad et

al. 2018). Therefore, to improve the OLSR performance, this study used the enhanced mayfly algorithm, which is a swarm-based optimization approach for optimal selection of MPR nodes.

B. Mayfly Algorithm (MA)

MA is made up of the strengths of particle swarm, firefly, and genetic algorithm (Zervoudakis & Tsafarakis, 2020; Yang & Pan, 2023). It is a novel kind of intelligent optimization system with a strong optimization ability and high research value. Additionally, it draws inspiration from mayflies' social behavior, particularly their mating activities (Lei et al. 2022).

i. Male Mayfly Movements

The mayflies that are in male categories come together, and they update their positions using their own and their neighbors' experiences. Assume is the present position for the mayfly. This position is changed with the addition of velocity. This turns the current position to be updated as shown in Equation (1) (Lei et al. 2022).

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{1}$$

Male velocity is updated as shown in Equation (2)

$$V_{ij}^{t+1} = V_{ij}^t + a_1 e^{-\alpha r_p^2} (pbest_{ij} - x_{ij}^t) + a_2 e^{-\alpha r_g^2} (gbest_{ij} - x_{ij}^t) \tag{2}$$

where v_{ij}^t is the male mayfly velocity, x_{ij}^t is the male mayfly initial position, x_i^{t+1} is the male mayfly updated position, a_1 and a_2 are constant that measure the social component, $pbest_{ij}$ is the position best reached, i is number of mayfly, $j = 1, \dots, \dots, n$ which is searching space

i. Female Mayfly Movement

Female mayflies do not cluster compare to their male counterpart. But they move closer in the direction of male mayflies with change in position as shown in Equation (3) (Yang and Pan, 2023)

$$y_i^{t+1} = y_i^t + v_i^{t+1} \tag{3}$$

The velocity update formula for female mayflies is shown in Equation (4) (Lei et al. 2022)

$$V_{ij}^{t+1} = \begin{cases} v_{ij}^t + a_3 e^{-\beta r_{mf}^2} (x_{ij}^t - y_{ij}^t), & \text{if } f(y_i) > f(x_i) \\ v_{ij}^t + fl * r & \text{if } f(y_i) \leq f(x_i) \end{cases} \tag{4}$$

where v_{ij}^t is the female mayfly velocity, y_{ij}^t and x_{ij}^t is the velocity of male and female, position of male and female velocity, a_3 and β is constant and coefficient, r_{mf} is distance of Cartesian among the flies, fl is walking coefficient.

A. Enhanced Mayfly Algorithm (EMA)

MA has better accuracy and convergence speed in comparison to other swarm intelligence algorithms (Lei et al. 2022). But the velocity has been affected by fluctuation, which can cause low stability and poor output. MA also has a bad performance when dealing with multimodal functions due to its inability to exit the local optimal zone, especially in a complex nonlinear

task (Wang et al. 2022). An enhanced approach is put out in this study using the non-linear gravity coefficient and media position.

i. Non-Linear Gravity Coefficient

This study uses a non-linear gravity coefficient (NLGC) to strike a balance between the exploitation and exploitation searching space of MA thereby optimizing the search for the best solution. The formula for NLGC is shown in Equation (5) (Lei et al. 2022)

$$g(t) = 0.5 \times \sqrt{1 - (t/Xt)^2} + 0.4 \tag{5}$$

where, t and X are iteration number and maximum number of iterations respectively and $g(t)$ is the gravity coefficient. Enhancing MA with NLGC, it makes Equation 2 becomes Equation (6)

$$V_{ij}^{t+1} = g(t)V_{ij}^t + a_1 e^{-\alpha r_p^2} (pbest_{ij} - x_{ij}^t) + a_2 e^{-\alpha r_g^2} (gbest_{ij} - x_{ij}^t) \tag{6}$$

For the female mayfly, the velocity in Equation 4 becomes is updated to Equation (7)

$$V_{ij}^{t+1} = \begin{cases} g(t)v_{ij}^t + a_3 e^{-\beta r_{mf}^2} (x_{ij}^t - y_{ij}^t), & \text{if } f(y_i) > f(x_i) \\ g(t)v_{ij}^t + fl * r, & \text{if } f(y_i) \leq f(x_i) \end{cases} \tag{7}$$

ii. Median Position of MA group

The updated velocity as shown in Equation 2 is calculated by three parts. The first component pertains to the mayfly i at velocity v_{ij}^t . The distance between optimal position ($pbest_{ij} - x_{ij}^t$) and mayfly present position, which indicates individual ability is the second component. The third component is the social component that symbolizes knowledge sharing within the group ($gbest_{ij} - x_{ij}^t$). Thus, it is evident that the mayfly's flight process is impacted by both other members of the group and the finest position it has ever encountered. But the only way for the populations to share and transmit information is through p_{best} and g_{best} . The mayflies have no other means of doing these things. As a result, there is only one information source and minimal information sharing between the mayflies (Lei et al. 2022). Therefore, this study improves MA performance by making use of group's median position concept. The expression is shown in Equation (8).

$$m_p = \begin{cases} x(g + 1)/2, & \text{if } g \text{ is odd} \\ (x_{g/2} + x_{g/2+1})/2, & \text{if } g \text{ is even} \end{cases} \tag{8}$$

where g is the group numbers. The m_p is used into the male mayfly velocity and the expression is shown in Equation (9)

$$V_{ij}^{t+1} = g(t)V_{ij}^t + a_1 e^{-\alpha r_p^2} (pbest_{ij} - x_{ij}^t) + a_2 e^{-\alpha r_g^2} (gbest_{ij} - x_{ij}^t) + a_3 e^{-\alpha r_m^2} (m_p - x_{ij}^t) \tag{9}$$

where a_3 forms the social effects attraction coefficient, r_m is the distance between media and current position, $gbest_{ij}$ is the global best position of the node among other nodes in the network and $pbest_{ij}$ is the personal best position of the node.

Selection of MPR nodes using EMA

EMA was utilized in this study for optimal selection UAV_{MPR} because of its accuracy and high rate of convergence. UAV_{MPR} are in charge of establishing the path from a source node to any network destination when calculating different routes. Algorithm 1 shows the steps for choosing UAV_{MPR} , which is based on the enhanced mayfly algorithm (EMA).

Algorithm 1: Enhanced Mayfly Algorithm for MPR selection

Input: UAV_{MPR} sizes N ; $iter_{max}$; β ; a_1 and a_2 ; d ; fl ; $f(x)$

Output: Optimal solution g_{best}

Initialize the UAV_{MPR} velocities V_m and V_f
 Evaluate all solutions according to the objective function $f(x)$
 Find the best value from all solutions (g_{best})

for $iter = 1$ to $iter_{max}$ **do**

Update UAV_{MPR} speed using equation 7;

$$V_{ij}^{t+1} = \begin{cases} g(t)v_{ij}^t + a_3 e^{-\beta r_m^2} (x_{ij}^t - y_{ij}^t), & \text{if } f(y_i) > f(x_i) \\ g(t)v_{ij}^t + fl * r, & \text{if } f(y_i) \leq f(x_i) \end{cases}$$

Adjust the position of UAV_{MPR} using Equation 3;

$$y_i^{t+1} = y_i^t + v_i^{t+1}$$

Update UAV_{MPR} using Equation 9;

$$V_{ij}^{t+1} = g(t)V_{ij}^t + a_1 e^{-\alpha r_p^2} (pbest_{ij} - x_{ij}^t) +$$

$$a_2 e^{-\alpha r_g^2} (gbest_{ij} - x_{ij}^t) + a_3 e^{-\alpha r_m^2} (m_{p_{ij}} - x_{ij}^t)$$

Adjust the position of UAV_{MPR} using Equation 1

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Sort the UAV_{MPR} rank them based on $f(x)$

Update the worst individuals with finest new ones

Update p_{best} and g_{best}

End for

End

III. RESULTS AND DISCUSSION

The results of this enhanced mayfly algorithm optimized linked state routing (EMAOLSR), which is the novel approach used for this study, are discussed in this section. MATLAB software was used to carry out the simulation. MATLAB was chosen as the simulation tool because it provides the user with an appropriate environment for carrying out a variety of calculations in quick, easy, and effective methods. MATLAB makes it easier to construct algorithms that need to be iterated and use particular functions in order to get the best results. Additionally, it contains libraries that offer data analysis, a symbolic solution, and visual graphs of the outcomes. The EMAOLSR-obtained result was compared with the existing techniques of OLSR and firefly algorithm OLSR (FAOLSR) using end-to-end delay (ED), packet delivery rate (PDR), throughput (TP), and energy consumption (EC).

A. Simulation Model and Parameters

The simulation's aim is to increase FANET's lifespan and performance. Finding the best routing protocol with the most energy and the least amount of latency is the goal of EMAOLSR. As seen in Figure 2, the simulation model consists of five parts. Module A formed the FANET environment, the routing protocol was implemented in Module B, and the quality of the OLSR, FAOLSR, and EMAOLSR protocols was assessed in Module C. The performance metrics using end-to-end delay (ED), packet delivery rate (PDR), throughput (TP), and energy consumption (EC) were implemented to evaluate the developed and existing protocols. The result was obtained in Module E. The simulation parameters used are in Table 1.

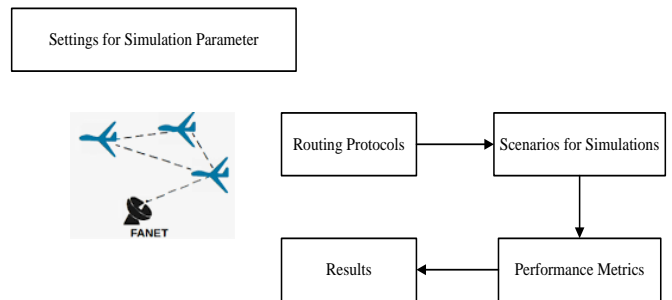


Figure 2: FANET Simulation Model

Table 1. Simulation Parameters

Parameter	Value	Unit
Simulator	MATLAB	-
MAC Protocol	IEEE.802.1a	-
Network Size	500 × 1500 × 1500	m ³
Mobility Model	Random Way Point (RWP)	-
Number of Nodes	50	-
Node speed	25	m/s
Transmission Range	250	m
Protocol	OLSR,FAOLSR, EMAOLSR	-
Initial Energy of UAVs	2000	J
Data Rate	3	Mbps
Packet Interval	0.2	s
Simulation Time	200	s

B. Performance Metrics

Network performance is done by using various measures to access its operation, EMAOLSR performance was evaluated using the measures discussed below.

i. End-to-End Delay

Overall nodes in a path are divided by the amount of time needed to transport data packets from sending to the receiving node. Figure 3 illustrate the performance of the FAOLSR in terms of the network end to end delay. This measures the accumulative delay time from the sending node to the receiver node in the network. This metric is calculated using Equations (10) and Equation (11)

$$\text{End-to-end delay} = \frac{\sum_{i=1}^n (R_i - S_i)}{n} \quad (10)$$

where n is the entire packets successfully received by the receiver node, i is the packet identifier, R_i and S_i is both the receiving and sending time of the packet.

$$D_{total} = D_1 + D_2 + D_3 + D_4 + \dots + D_n \quad (11)$$

D_{total} denote the total delay in the network, D_1, D_2 to D_n is the delay experienced by each node in the network. Where n is the total number of network component been traversed by the data packet. This end-to-end metrics evaluate and determine the network performance, identify network congestion and asses the outing protocol efficiency. A lower delay indicates a faster and more efficient routing which is very important in a scenario where immediate data delivery is needed.

As shown in Figure 3, the end-to-end of the three techniques was observed using different numbers of nodes. With the increase in node density, it was noticed that the three protocols (OLSR, FAOLSR, and EMOLSR) show an increase in end-to-end delay. This is because where there is an increase in the node density, this will lead to an increase in channel contention and further lead to an increase in the delay of data packet delivery. OLSR shows higher delay when compared with FAOLSR. However, EMAOLSR shows the least delay compared to OLSR and FAOLSR. The developed EMAOLSR considered the quality of the route and route energy in making a more stable path, thereby improving the network robustness.

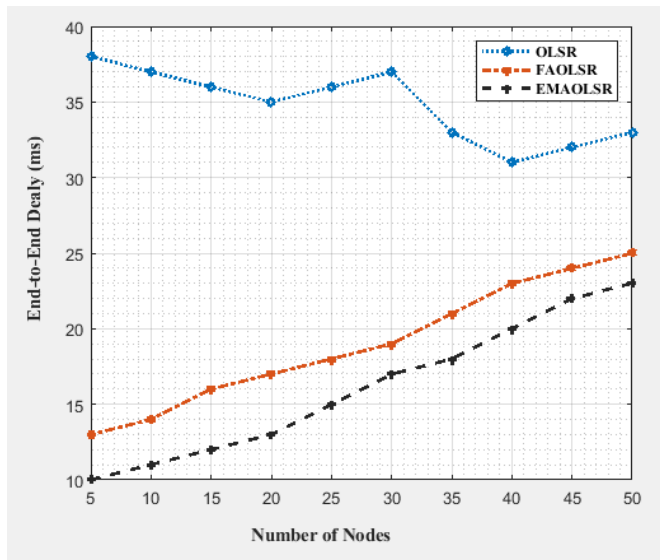


Figure 3: End-to-End delay comparison of routing techniques.

As a result, paths established between sending, intermediate, and receiving nodes are more stable and improve the network stability. This reduces delay in packet delivery compared to OLSR and FAOLSR. As shown in Figure 3, the developed EMAOLSR and FAOLSR show a decrease in delay with an increase in nodes. This is because EMAOLSR and FAOLSR can select the optimal MPRs, thereby providing an efficient routing route from source to destination. Though FAOLSR

shows more delay compared to EMAOLSR. But in OLSR, an increase in nodes even increases the delay because OLSR does not have the ability to select MPR optimally, which makes it not suitable for FANET.

ii. Packet Delivery Rate (PDR)

This metric shows the proportion of messages sent throughout the network to those received at the destination. It is computed using Equation (12).

$$\text{PDR} = \frac{\sum_{i=1}^n P_r}{\sum_{i=1}^n P_s} \times 100 \quad (12)$$

where, P_r is the received packets and P_s is the sent packets. As shown in Figure 4, EMAOLSR performs better in terms of its PDR when compared with FAOLSR and OLSR.

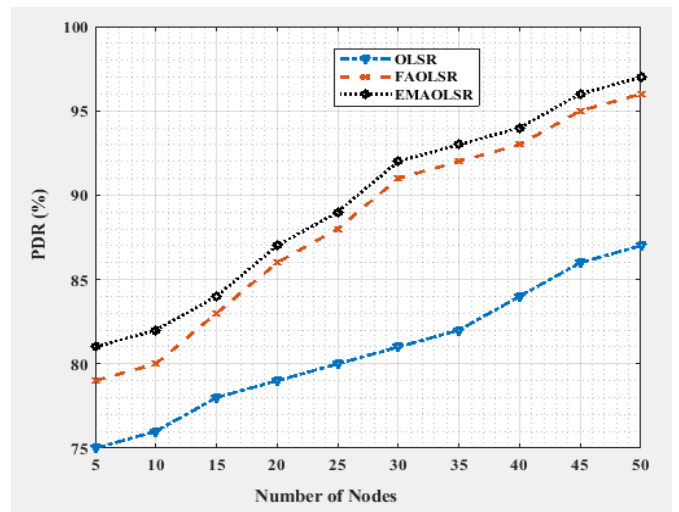


Figure 4: PDR comparison of routing techniques.

The better value and increase in PDR show a more stable route. In this study, focus was on the stability of the route by considering node energy and optimal selection of the MPR. This approach gave preference to nodes with a high level of energy for route establishment. OLSR does not focus on these conditions. Also, FAOLSR, which uses the firefly algorithm, is known to be time-consuming in finding ideal parameter values during operation. For these reasons, EMAOLSR outperformed FAOLSR and OLSR. Both EMAOLSR and FAOLSR have a close PDR performance. This is because both of them use the swarm-based technique of mayflies and fireflies, respectively, in the optimal selection of MPR for a better and stable routing path. But EMAOLSR shows it performed better, as seen in Figure 4. In reducing the probability of route failures, it was observed in Figure 4 that the PDR of different routing schemes increases with an increase in the number of nodes within the network.

iii. Throughput

This is the maximum size of data packets that can be properly transmitted in a specific amount of time. Equation (12) shows how throughput is measured.

$$T = \frac{SPT \times P_s}{\text{time (sec)}} \quad (12)$$

T is the throughput, SPT is the data packet delivered, P_s packet size. EMAOLSR outperformed OLSR and FAOLSR OLSR, as seen in Figure 5.

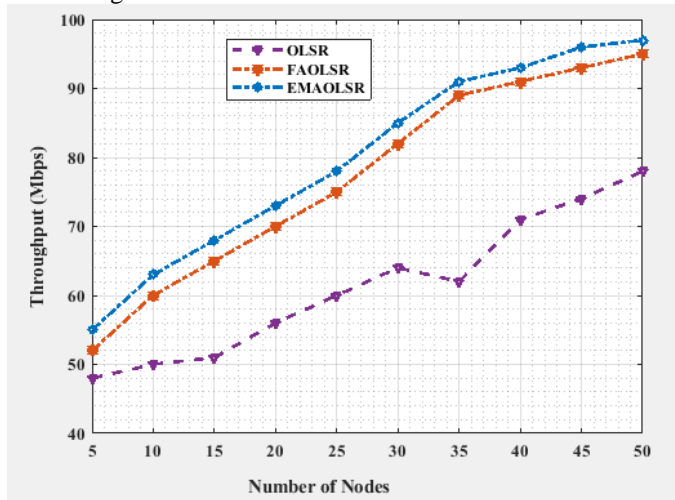


Figure 5: Throughput Comparison of Different Techniques

This demonstrates that our approach creates appropriate routes in the network. Nodes with low energy levels have a very low likelihood of being chosen as MPR nodes and do not take part in the route-building process. Routes have a longer lifespan and more energy as a result. Consequently, EAOLSR avoids unstable routes. For these reasons, our technique outperforms others in terms of throughput. As Figure 5 illustrates, throughput increases in all techniques as the number of nodes in the network increases because this enhances connections between nodes in the network and increases the likelihood of finding the best paths between nodes.

iv. Energy Consumption

This measures the total energy used by the network components over a given period of time. This includes the transmission, processing, and reception energy. The unit of measurement for this is joules as shown in Equation (13).

$$EC = \sum_{j=1}^n Sn_j \times EC(SSn) \tag{13}$$

Sn_j is the individual node j , n is the MPRs total, $EC(SSn)$ is the energy consumption for single node Sn_i . Compared to other methods, EMAOLSR uses the least amount of energy, as shown in Figure 6.

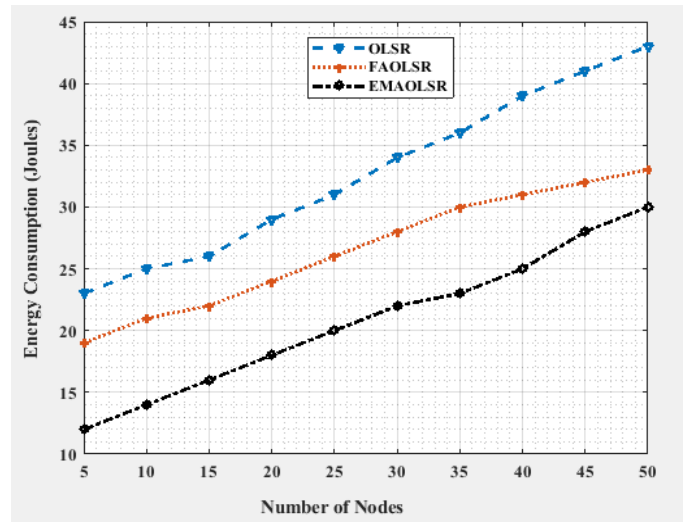


Figure 6: Energy Consumption Comparison of Different Techniques

Additionally, because this EMAOLSR takes connection quality and energy consumption into account, it was able to create more stable pathways. Paths are therefore valid for a longer period of time. Consequently, EMAOLSR requires less update of routing tables which has enable the decrease in energy consumption of nodes within the network.

v. Packet Loss Rate

This is the percentage of transmitted packets that do not successfully get to their assigned destination nodes within a given period of time. This metric was chosen to assess the EMAOLSR robustness and its behaviour in a dynamic, and inetrefrence prone FANET environment. The packet loss rate is determined using Equation (14)

$$PLR = \frac{P_{lost}}{P_{sent}} \tag{14}$$

Where PLR is the packet loss rate

P_{lost} is the number of lost packets and P_{sent} is the number of successfully sent data. Figure 7 shows the packet loss rate in respect to different node speeds. The causes of packet loss include, the non availability of robust routing path that can be able to handle the frequent topology changes of nodes, packet getting expired in the routing queue which is caused by excessive waiting time and packet dicarded when there routing disruptions. EMAOLSR, FAOLSR and OLSR show an increased in packet loss rate as the node speed increases. This is caused by decrease in the connection lifetime at high node speed which increases frequent re-routing by the protocols. The FAOLSR shows a lower packet loss when compared with the OLSR. However, when compared with both OLSR and FAOLSR, the EMAOLSR showed a better performance by delivering the lowest packet loss rate even when the node speed increases.

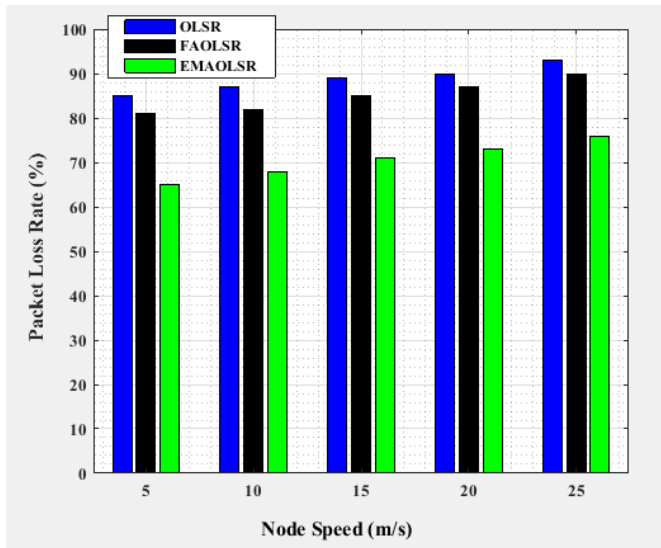


Figure 7: Packet Loss Rate Under Different Node Speeds

v. Network Efficiency

Network efficiency is a measure of routing protocol transmission effectiveness that is calculated as the ratio of data delivery success rate to overhead incurred in maintaining the network. Network efficiency is calculated as shown in Equation (15)

$$N_E = \frac{\text{packet delivery rate}}{\text{Message} + I_{avg}} \quad (15)$$

Where N_E is the network efficiency, I_{avg} is the average level of interference which was observed by the communicating nodes. Figure 8 compares the network efficiency of EMAOLSR, FAOLSR and OLSR using different node speeds. It is clearly seen that, as the node speed increases the network efficiency of each protocol was decreasing. FAOLSR has higher network efficiency compared to OLSR. However, EMAOLSR achieved the highest network efficiency compared to FAOLSR and OLSR.

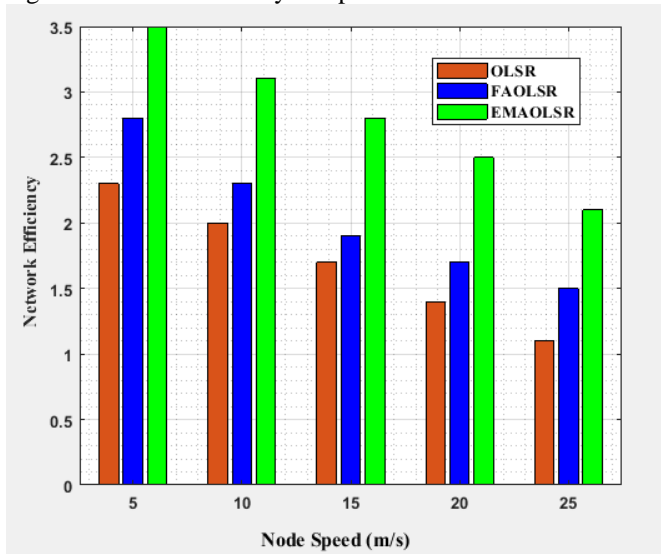


Figure 8: Network Efficiency Using Different Node Speeds

IV. DISCUSSION

This study developed an improved OLSR routing protocol based on the EMAOLSR technique. It was compared with the performance of FAOLSR and OLSR based on the number of nodes, the node speed, and the simulation scenario in terms of end-to-end delay, PDR, throughput, energy consumption, packet loss rate, and network efficiency. The purpose of these comparisons is to check and evaluate the performance of EMAOLSR in FANET. Figure 3 to Figure 8 illustrate that the developed EMAOLSR routing technique outperforms the OLSR and FAOLSR protocols. EMAOLSR shows the least end-to-end delay, as depicted in Figure 3. In contrast, OLSR and FAOLSR show higher delay. In the PDR metric, EMAOLSR shows an improved PDR when compared to both the OLSR and FAOLSR protocols, as shown in Figure 4, even as the number of nodes within the network increases. This edge over other protocols is largely attributed to EMAOLSR's ability to adapt efficiently to changes in link quality, especially in the FANET domain, where frequent link and topology changes are bound to occur. In complex and multiple node density, EMAOLSR shows a better and superior network throughput, as shown in Figure 5. In managing the limited energy resources of nodes, the EMAOLSR approach was able to prevent excessive overhead in the network, which made it possible to have the least energy consumption compared to OLSR and FAOLSR, as shown in Figure 6. In terms of packet loss rate, EMAOLSR shows the least packet loss even when the speed of the nodes within the network keeps increasing, as shown in Figure 7. Also in Figure 8, the three protocols showed a decline in network efficiency as the node speed keeps increasing. However, EMAOLSR displayed a better network efficiency when compared to the FAOLSR and OLSR techniques.

V. CONCLUSION

FANET technology has become an exciting area of study with numerous promising features. It is widely used wireless networking technology because of its affordability, use, and simplicity. Many researchers have employed FANET technology to increase bandwidth and energy consumption. In applications where standard networks are less effective, the development of the FANET can be beneficial. However, with all the promising features of FANET, routing protocol is still an issue of attention. Studies have shown that recent routing protocols largely concentrate on using stochastic node movement, which has not been able to effectively handle optimal selection of MPRs and has led to difficulty in creating an appropriate routing technique. This understanding provides the need for a robust routing protocol that will be able to handle the effective operation of FANET, especially in the optimal selection of MPRs. Hence, this study presented the EMAOLSR protocol, which was able to provide an efficient routing technique because of its ability to select the network's optimal collection of MPRs. The EMAOLSR

performance was assessed using six distinct performance metrics: end-to-end delay, throughput, packet delivery rate, energy consumption, packet loss rate, and network efficiency. According to the simulation results, for every parameter under study, the EMAOLSR protocol performs better than the FAOLSR and OLSR protocols. Future studies can focus on incorporating adaptive spectrum sensing mechanisms into the operation of FANET nodes in order to increase tolerance to different levels of interference patterns. Furthermore, real-time decision-making and the scalability issue in FANET can be examined because of the need for rapid data processing.

Conflict of interest

Regarding this study, the authors declare that there are no conflicts of interest.

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Author Contribution

A.T. Olusesi: Conceptualization, Methodology, Writing Original Draft Preparation, Editing and Design.

A.I. Oyedeji and O.J. Adetunji: Review of the manuscript for essential information.

E. Noma-Osaghae: Software and Experimentation

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