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RESEARCH ARTICLE

An Energy-Efficient Bio-Inspired Mobility-Aware Cluster p-WOA Algorithm for Intelligent Whale Optimization and Fuzzy-Logic-Based Zonal Clustering Algorithm in FANET

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Abstract

The newest research topic is flight ad hoc network (FANET). The primary obstacles faced by unmanned aerial vehicles (UAVs) are their limited flight duration and inefficient routes resulting from their great mobility and low battery power. Compared to MANETs or VANETs, FANETS routing is thought to be more difficult because of these topological restrictions. Artificial intelligence (AI)-based clustering techniques can be applied to resolve intricate routing issues in situations when both static and dynamic routing are ineffective. To overcome these path difficulties, clustering techniques based on evolutionary algorithms, including intelligent, probabilistic, bio-inspired whale optimization algorithms (*p*-WOAs), we suggest fuzzy-logic-based zonal clustering-based routing algorithms in this study to be used in FANET to build clusters. In addition to requiring fewer cluster heads (CHs) for routing, *p*-WOA offers good coverage and low energy consumption. The stochastic whale optimization technique, which draws inspiration from nature, is utilized in this paper to build networks and deploy nodes. The next step is to choose cluster heads using a region clustering technique based on fuzzy logic. By selecting the right cluster head, you can decrease routing traffic and increase cluster longevity. Routing overhead is also decreased. The data are then sent to the best path using a reference point group mobility model. The proposed *p*-WOA was used to test fuzzy integral and fuzzy logic ant optimization, fuzzy integral and neural network interference system, fuzzy integral and whale optimization algorithm (ANFIS-WOA), and fuzzy integral and FL-ALO. An array of indicators, such as cluster count, longevity, cluster configuration time, cluster head consistency, and energy usage, are employed to assess the effectiveness of the suggested methodology. The suggested algorithm works better than the most advanced techniques available today, as demonstrated by the experimental findings presented in this paper.

Keywords FANET · Bio-inspired · Clustering · Routing · Fuzzy logic

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1 Introduction

The communication between multiple unmanned aircraft systems facing many design challenges is also important to provide support and association between nodes [1]. However, because of nodes client mobility, and quick structural changeover, infrastructural-based communication structures are not suitable for many unmanned aircraft systems. Therefore, FANET is the most effective solution to the problems associated with the entire node network infrastructure [2]. The FANET node client independently sends information to the base station surrounded by range and infrastructure, which is shown in Fig. 1. Unlike MANET (Ad Hoc Mobile Network) or VANET (Ad Hoc Vehicle Network, FANET nodes can have fast topology changes and limited communications. However, the computing power of FANET is high than that of MANET and VANET [3]. Since FANET's communication mode is wireless, nodes are exposed to malicious attacks from public intruders [4].

Manufacturing small nodes paved the way for the concept of a temporary low-altitude flight network. Because of their adaptability, elasticity, easy way of installation, and comparatively low operating costs, nodes include border control, transfer control, tragedy and combustion management, universal security, isolated sensing evaluation for agriculture, wind assessment, etc. [5, 6]. Various applications are as follows: retransmission network, damage operations, investigation, disaster management, armed and national sectors, and further significant purpose area. Recently, FANET has developed one large nodes that can perform a given task and a cluster of small nodes to facilitate the specific tasks [7, 8]. Compared with a single node, the use of multiple nodes makes it simple to perform specific tasks, and has the following advantages: Compared to deploying a single nodes, multiple nodes connect independently and wirelessly, working together to improve network connectivity and reduce mission completion time [9]. Large nodes have a limited range. However, many unmanned aircraft systems are more adaptable because they can easily expand operational scalability [10]. If the drones fail in a single drone system, they will not complete the mission. However, if a drone fails in multiple drone systems, the system can still use a completely original path without conflict, while the other drone can perform its tasks [11]. The radar cross-section produced by many unmanned aircraft systems is tiny, rather than the larger radar cross-section, which is more accurate and important for military applications. Routing protocols have long been the basic technology of various wired and wireless networks [12]. For high dynamic FANET networks, dominant movement of nodes can easily lead to path interference. The packet loss rate is increasing, and the routing protocol is invalid [13].

Geospatially dispersed linked devices that exchange wireless media with one another make up ad hoc networks. Short-term uses including military, video conferencing, infotainment, disaster relief, and rescue missions are usually supported by their deployment. While cellular networks run on batteries, ad hoc networks are different in that they do not have a fixed infrastructure and require distributed computing. So, a key area of emphasis is energy efficiency. The three primary ad hoc network types—MANETs, VANETs, and FANETs—are compared and matched in Fig. 1. It is necessary to develop new routing techniques that accommodate the primary features of FANETs because ad hoc networks differ from one another.

Ad hoc networks have four primary link types (FANET BS, cellular BS, satellite, and other) between UAVs and various radio access equipment. Figure 2 illustrates these sorts of links.

- Ad hoc communications between drones can be supported by UAV–UAV connectivity. The link is a portion

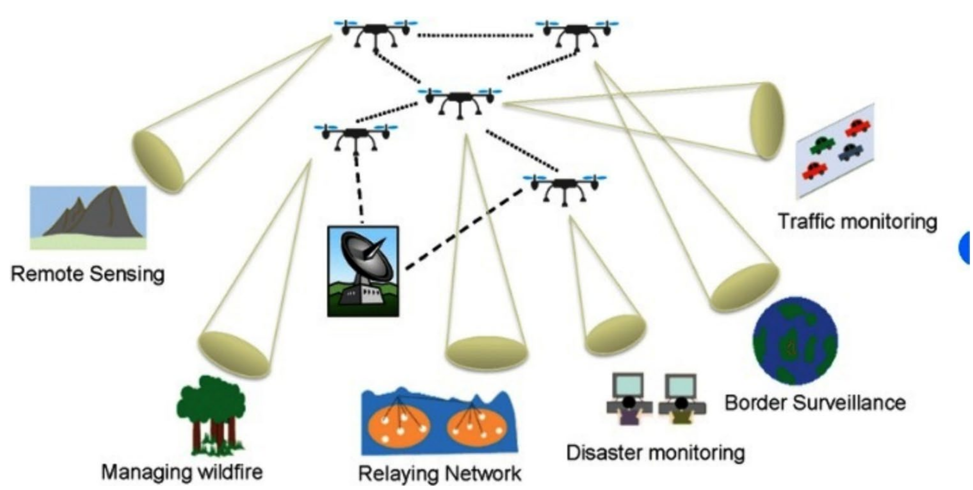

Fig. 1 Flying Ad hoc Networks (FANETs)

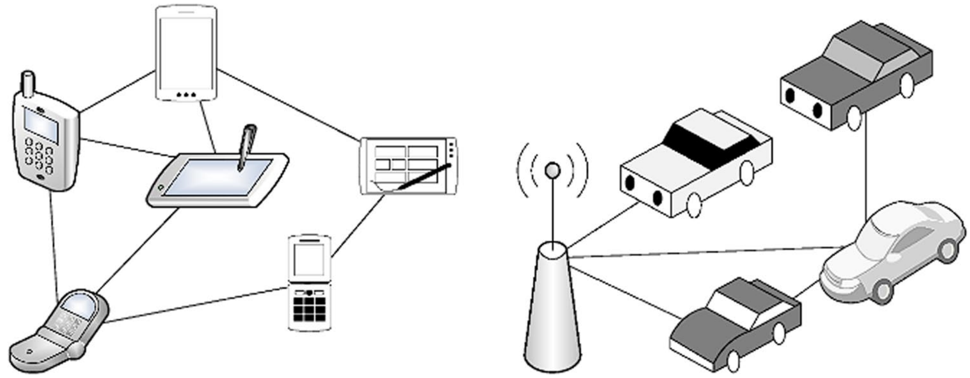

Fig. 2 Ad hoc networks fall into two categories: vehicular ad hoc networks (VANETs) and mobile ad hoc networks (MANETs): The connectedness between two nodes is shown by the solid line

of a path that enables packets to be forwarded to the wireless access infrastructure by straggling drones.
- A direct link, or UAV–BS link, connecting a UAV to a FANET BS.
- A UAV-to-cellular base station connectivity via cellular technology.
- A long-distance ground link connecting a UAV to a satellite is called a UAV satellite link. Drones and satellites can build a star topology. When there is no other wireless access infrastructure available, this link is necessary (i.e., FANET BS and cellular BS).

Infrastructure for wireless access is vulnerable to failure in times of crisis. Hence, even though routes are necessary to create routes, ad hoc networks created with drone-to-drone links are more effective and simpler to set up.

This paper's primary contributions are outlined below:

1. Suggest a novel cluster strategy with dynamic transmission power from CH to FANET to increase the stability and longevity of FANET. By reducing the energy consumption of the CHs, choosing the CHs, and maintaining the cluster, the suggested DTPCH-C strategy is implemented.
2. We suggest a CH variable power transmission device. Using movement prediction and grid mode-based transmit power adjustment, CH may adapt transmit power in response to distance from other CMs, conserving energy and extending the life of FANET.
3. In contrast, we suggest a CH selection algorithm based on weighted addition, where the selection criteria also take into account adaptive node degrees, residual energy ratios, and inter-node distances. The UAV node with the most weight should be chosen as CH.
4. For cluster optimization, a mathematical model of the intelligent whale optimization algorithm (p-WOA) has been created. To eliminate randomness, a predictive vehicle initializer was built. For optimum performance, we developed each bike's weight to automatically adapt based on fitness level. The created method and other well-known methods were put through statistical analyses to see how they compared.
5. The packet delivery rate (PDR) increases as a result, increasing the likelihood that the CH node is the best option. It raises the network's dependability. The suggested DTPCH-C scheme provides more advantages over conventional clustering methods in terms of reliability, longevity, and energy consumption, according to simulation results.

The rest of the paper is organized as follows: Sect. 2 provides a detailed discussion of the related work; Sect. 3 elaborates on the implementation of the proposed method; Sect. 4 presents simulation results; and Sect. 5 concludes the paper and proposes future research directions.

1.1 Literature Survey

Reference. [14] discussed the most important design issues of multiple UAV (unmanned aerial vehicle) systems as the important statement for collaboration and collaboration with nodes. Ad hoc networks with nodes can solve problems that arise in nodes networks based on the entire infrastructure. This paper introduces the FANET network, which is a self-organizing network that connects nodes. Differences between FANET, MANET, and VANET are first clarified, followed by the introduction of the major FANET design issues and explanation of the available FANET protocol.

Reference [15] proposed that FANETs are the promising solution for UAVs-related application situations. In ad hoc networks, there are many mobility models that can replicate the behavior of mobile nodes, but some of them cannot simulate the actual motion of UAVs. This article presents a list of mobility models, in which existing models with other FANET applications, and explains their advantages and disadvantages.

Reference [16] discussed the unmanned teams with temporary links of FANET and integrated with advanced network types with the target level. In the lethal situation where the shared communications infrastructure cannot be used, FANET can be used for providing a flexible and uniquely configurable network that can be deployed quickly with low operational costs. Connecting many drones toward a self-organizing network is a major challenge.

Reference [17] proposed that FANET routing is a very complex issue. This article introduces the API algorithm, and describes routing method in the peer network. The bee colony-based heuristic biological detection algorithm showed excellent results and reviewed the various routing troubleshooting methods based on bee algorithm. The facts prove that the routing protocols based on the swarm method are more effective than other algorithms. Here, the shortcomings of individual algorithm can be compensated by the advantages of another algorithm to provide better convergence speeds, thus reducing hardware requirements for the node.

Reference [18] discussed that location sharing (LIS) is the most important challenge facing FANET. The token distribution method is one of the LIS solutions. In this method, FANET loop tokens are used to exchange location information between nodes, and to increase the quantity of nodes and token circulation on the network, concurrently to achieve LIS with minimal delay. This research provides LIS circulation of multiple tokens on the FANET.

2 Problem Formulation

In emergency scenarios where real-time data transmission is essential, FANETs' major problem is to guarantee ubiquitous connectivity. Because of its complexity, FANET routing is substantially more challenging than it is in MANET or VANET. Strong or broken routing links on the network may result from high mobility and quickly changing topologies. Protocol was followed. Selecting the most precise path among the UAV nodes is a major problem that comes up in FANET [19]. Through an examination of the literature, it was discovered that a prevalent issue with standard ad hoc routing protocols is that they fail to take into account the crucial elements of bandwidth, mobility, and link quality when deciding on the best routing path to take for routing that is more effective and efficient. This is a powerful route that requires good technique to solve the problem. Given that FASNET demands a clustered network G (VU, E), we can infer that modeling the clustering problem is a dynamic optimization problem [20]. The number of UAVs in the domain is denoted by VU, and the number of communication links between them is denoted by E. It turns out that CH set identification is the formulation of the multi-graph clustering problem. I want to make each CH set as small as feasible by maintaining a constant number of drones in each CH set. FANET UAV swarm structure (e). The fitness function is based on weights that are taken into account when choosing UAV CHs from FANET for other networks like MANET and WSN.

3 Motivation

Several approaches have been proposed for FANET communication, which usually consist of proactive or reactive routing mechanisms. Reactive routing works better than proactive routing in a typical network scenario where nodes are looking for new paths to convey data as proactive routing necessitates routine maintenance of routing tables. A dynamic environment with regular topology changes necessitates the maintenance of a topology table and the constant discovery of new pathways, which leads to significant communication overhead and delay. The end result is a decrease in network speed and a waste of the drone's meager battery power. Clustering is the answer to this issue with limited resources. Swarming is a technique for efficient data transfer and routing between drones on a network that increases scalability, lowers communication overhead, increases throughput, and enhances overall network performance. The network is split up into clusters, which are smaller subsets of the network. There is a cluster head (CH) and cluster members (CM) in a cluster. For efficient and effective cluster management and performance control, CHs are chosen from among all cluster members. Since each CM has the potential to be a candidate for CH selection, CH selection is one of the key responsibilities of clustering. Topology design is the central issue for academics studying clustering algorithms. The best CH should be chosen, the network topology should be managed, each CM should have an energy conservation strategy, and there should be a plan to optimize network performance while moving around, among other things, while designing clustering algorithms.

4 Methodology

4.1 Network Building and Nodes Positioning

A communication model for FANETs called EEBMC-*p*-WOA reduces communication costs, energy usage, and processing. Increasing the cluster life cycle and maintaining a basic cluster mechanism can both lower communication and compute costs. Network creation commences as soon as the drone takes off. Unmanned aerial vehicles (UAVs) are outfitted with altitude and GPS sensors in addition to mission-focused sensors. The drone nodes' three-dimensional position data is fed into the controller by these two devices. To further account for potential variations, let us say the drone has four different power levels and three different transmission grid levels, or a communication range of 1000–3000 m.

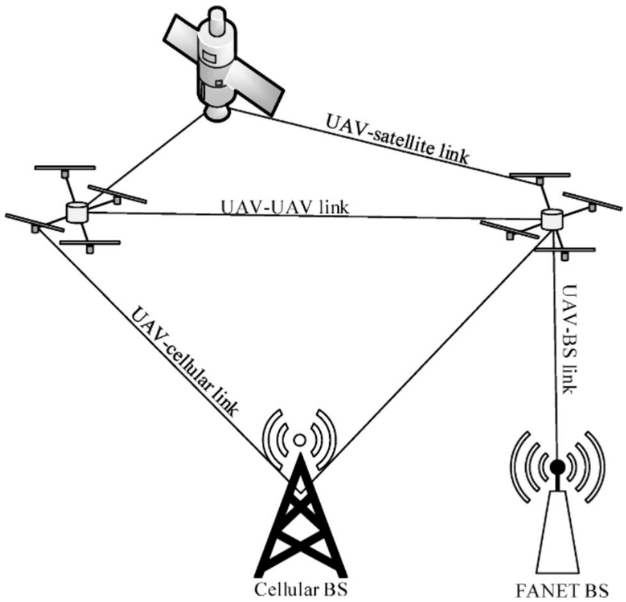

Fig. 3 Four types of links in FANETs

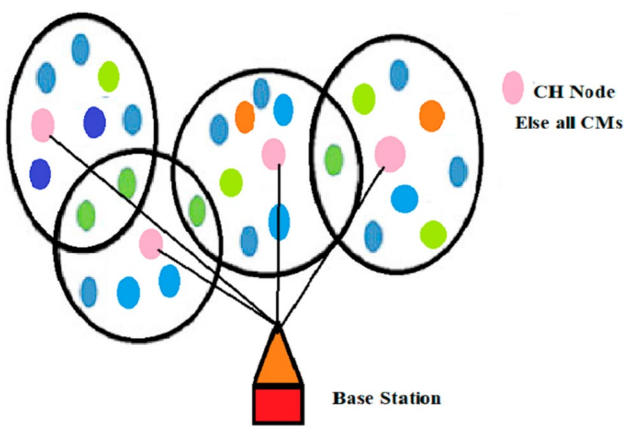

Fig. 4 Clustering structure

The highest power level that is available is first chosen by nodes. Later, nodes can select the optimal power level for them depending on neighboring nodes' positions as well as their own. Utilizing this tactic helps the node preserve its energy.

A workflow diagram for the proposed EEBMC-*p*-WOA algorithm is presented in Figs. 3 and 4. A random location in the solution space (m x n) is allocated to every whale along with its corresponding whale array based on the fitness score. Generated similarly to whales are matrices and arrays. With regard to probability, the whale matrix has the highest value. The procedure is carried out again until the optimal search space probability is obtained, each time the finest whale is discovered in relation to the likelihood. The whale's position is updated following every successful iteration. Navigating the solution space like a whale is how one finds the best solution. The array of whales is the final destination of fitness values, which are maintained successively in the $m \times n$ solution space, beginning with the random position assigned to each whale in the first phase. The generation of associative arrays and probability matrices is similar. So far, the best whale values may be found in the probability matrix. To either reach the best answer or end the search phase, the whale navigates through the solution space.

In doing so, the search space's upper and lower bound dimensions are exploited. Depending on where a whale is in the search space, it is also utilized to calculate its fitness value. An iterative technique is used to create the fitness matrix. Updating the values as it goes along puts them in ascending order in the matrix. Each whale receives a lower fitness value from the fitness matrix. The computation involves the integration of the whale's fitness rating and its position within the search space. The whale's position inside the search space is updated as a result of this mechanism. To attain convergence, the optimal solution employs a linear reduction factor "x". A cluster as depicted in figure will be formed upon selecting the cluster head. Node density, number of nodes, remaining energy, and load balancing parameters are a few examples of the elements that can influence the choice of CH. Prior to sending these parameters to the fitness function, they are given weights. Suitability functions are a key component of the EEBMC-*p*-WOA selection procedure. It eliminates superfluous broadcast overhead, minimizes network energy consumption, chooses the optimal CH, and lengthens cluster lifetime [26]. Formula (1) can be utilized to determine the goodness-of-fit value of the EEBMC-*p*-WOA method.

$$\text{Fitness Function} = \frac{W1 \times \text{Residual}_{\text{energy}}}{\left(W2 \times \text{Avg}_{\text{Distance}}\right) W3 \times \text{Delta}_{\text{Difference}}} \tag{1}$$

$\text{Avg}_{\text{Distance}}$ describes the average distance between neighboring nodes, Delta_Difference represents the load balancing factor (LBF), and $\text{residual}_{\text{energy}}$ is the residual energy of the FANETS node as determined by Eq. (2). If everything proceeds as planned, clusters with the same number of members can only form. Nevertheless, due to sensor nodes; tendency to shift and alter in characteristics, its practical application is challenging. By utilizing the delta difference, the load balancing factor is determined. W1, W2, and W3 are the variables that represent energy, average distance, and difference weight. A CH with the same amount of nodes would be great. When nodes frequently shift their locations and their adjacency, this is impractical in real-world settings. It is known as a delta car when the degree of neighboring nodes deviates from the optimal degree. Using the following formula, neighboring example SN nodes are determined.

$$\mathrm{Delta}_{\mathrm{Difference}} = \mathrm{ABS}(\text{Ideal degree} - \text{Node degree}) \quad (2)$$

We consider that one parameter could lead to a bias in the fitness function and that the CH selection criteria are static. Maybe you choose the incorrect CH in this instance. To address this distortion issue, which has a negative impact on the fitness value, EECP-MFO dynamically allocates weights to parameters based on the circumstances. All of the parameter values were first standardized to range from 0 to 10.

Every parameter deviation has a negative influence that can be calculated using Eq. (3).

$$\mathrm{dev}(i) = \mathrm{ABS}(\mathrm{mean} - \mathrm{parameters}(i)) \quad (3)$$

Updated parameter values are obtained using Eq. (3), which uses penalized outlier parameters to adjust for divergence from the mean. The following formula is included in another Eq. (4), which is used to penalize the outlier penalty:

$$w(i) = \frac{1}{\mathrm{dev}(i)} \quad (4)$$

Equation (1) may be utilized to calculate the fitness of every node for every sensor node, as the total of all weights equals "1."

4.2 The Bio-Inspired Mobility-Aware Cluster p-WOA Algorithm for Intelligent Whale Optimization

The FANET clustering scheme, which is based on bee intelligence, describes how to create and maintain mobile-aware balanced clusters as well as how to choose the best CH in each cluster. The sub block of of UAVs converted into distinct discontinuous clusters poses as a challenge of optimization due to the enormous number of UAVs in flight.

This section focuses on cluster-based routing, an optimization technique that makes use of bee intelligence to show how to give an ideal cluster design. High mobility and flexibility for UAVs are provided by a balanced cluster with dynamic node order, which also regulates the communication load. Mobility problems are exacerbated by frequent changes in FANET topology. Typically, route selection is dependent on previous speed and direction thanks to autonomous systems. Flying Ad Hoc Networks employ a stochastic waypoint movement model where flexibility in path selection is given priority over flying UAVs. The low-resolution biomimetic mobile recognition clustering method is thought to be superior. Think on CH mobility and selection during cluster formation.

The best CH is chosen if the rate of readmission is low. The drone's motion is primarily to blame for the topological deformation. Given the relative mobility in the CH selection process, the clustering is stable and the need for re-clustering is less frequent. The development of a probabilistic whale optimizer reduces FANET unpredictability, which in turn cuts down on processing time, computational expense, network overhead, packet delay, and end-to-end latency between vehicles.

4.3 Mathematical Modeling

In this study, we show to search for UAV, to build clusters, and to pick a cluster leader for clustering best performance using numerical examples—the mathematical analysis of encircling a target, planning an attack using a bubble circle, and utilizing an unmanned aerial vehicle to hunt.

4.4 Exploration Phase

Combining Eqs. (5) and (6) enables cars to locate cluster heads and establish communication after allocating cluster heads, where D is the separation between the vehicle (X (t)) and the cluster head (X × (t)), and X (t + 1) denotes the number of iterations needed to reach the cluster head. The ideal cluster head array will be the focus of *p*-WOA because it is unsure of the precise region it is exploring.

$$\vec{D} = |\vec{C}.\vec{X}^{*} \times \vec{X}(t)| \quad (5)$$

$$\vec{X}(t+1) = \vec{X}^{*}(t) - \vec{A}.\vec{D} \quad (6)$$

where t is the current iteration, A and C denote coefficient vectors, X* denotes the best placement so far, X denotes the position direction, and || is the current iteration number.

4.5 Exploitation Phase

It is possible to consider any element of (a) to be included in the interval [-a, a] for a given focus set where an is minimized from 2 to 0. The unused search agent position can be adjusted anywhere between the operator's current position and the current best operator position by varying the value of A between − 1 and 1.

In the presence of convergent vehicles (cluster heads), movement of the vehicles takes the form of a spherical or helical pattern. As seen, since both actions hardly ever happen simultaneously before the cluster is optimized, we assume that they have a 50% chance of happening. The car also performs arbitrary searches in addition to searching specifically for your location. A is used for the word "vehicle," and its arbitrary range is − 1–1. Unlike the operational phase, the search vehicle operator is given a better rating in this situation than the randomly chosen specialist. The vector A converted can be used for the hunt (survey)'s comparison section.

$$D = |\vec{C}.\overrightarrow{X_{\text{rand}}} - \vec{X}| \tag{7}$$

To improve the effectiveness and population coverage of the suggested technique, a probabilistic model was included to retrieve the vehicle's most recent location. Equation provides more details on the crossover process.

$$P_n^m(t+1) = \begin{cases} P_n^m(t), \text{if } b < cp \\ P_n^m(t+1), \text{if } b \geq cp \end{cases} \tag{8}$$

In this equation, P_n^m stands for the mth reading obtained from the current nth agent, b for any node or search vehicle in the swarm, and cp for the time required for the algorithm to run and the convergence rate.

Although it converges more quickly and has a lower cp, this technique requires more time to operate and provides less population coverage. The following equation is used to calculate the cp value:

$$\text{cp} = c + (0.5 - c) - \sin\left(t \times \frac{\pi}{2} \times \text{tmax}\right) \tag{9}$$

The constant c is utilized in this formula to control the fluctuation of the parameter cp. Its range of values is [0, 0.5], and tmax is the maximum number of iterations that can be performed. The generality and precision of vehicle location estimate can be increased by changing the value of cp in Eq. (9).

To prevent the loss of any vehicle, adaptive weights are applied to the projected *p*-WOA. The adaptive probability "ap" that we select ensures that all cars are linked to the best one thus far, as shown in Eq. (10), where tmax is the maximum number of cycles permitted.

$$\text{ap} = 1.2 - 0.9\cos\left(t \times \frac{\pi}{\text{tmax}}\right) \tag{10}$$

The pseudocode generated by the algorithm is shown in Algorithm 1.

Algorithm 1:

Initialization of UAV positions and velocity randomly on a freeway by creating a mesh between UAV. All vehicles in the above mesh should have the same values for their search agents.

while (Iteration = = Iterations = 350) or Convergence Factor = 0.001 do.

for Node I = 1–100 do.

Nodes for Clustering = {All Nodes}.

while (Nodes for clustering! = empty) do.

Compute the likelihood of each node's selection.

CH = Roulette Wheel selection [All nodes for clustering are possible].

Node. tour. append (CH).

Neighbors of CH = find Neighbors (CH).

(Nodes for clustering) = (Nodes for clustering)–CH.

(Nodes for clustering) = (Nodes for clustering)–Neighbors of CH.

end while.

Nodesi. cost = evaluation (Nodei. tour).

If (Nodesi. cost < Best Node. cost).

Best Node = Nodei.

Node i++

end for.

for Node I = 1 to population size do.

Update Search (Nodei. tour, Nodei. cost).

If (Best Node. cost = = Last iterations Best. Node. cost) do.

Compute PDR for each node;

Compute Latency between nodes;

Compute the Average Throughput of the medium;

Stall Iteration++;

Else.

Stall Iteration = 0;

end if.

Iteration++;

end for.

end while.

Output: CHs = Best Node. tour;

4.6 Fuzzy Model

In this section, we present the proposed fuzzy model used for CH election and a clustering technique based on the proposed fuzzy model to accomplish optimal clustering in WSN. Different factors influence CH election in WSN. Therefore, they must be combined appropriately for the best decisions. FIS is an efficient mechanism for such a purpose. It allows combining all input parameters in such a way that reflects their effectiveness in CH election. To achieve maximum benefits from fuzzy logic for CH election, it is necessary to explore the factors that have an impact on CH election, use effective means to measure each of these factors, and build an efficient fuzzy model characterized by the effective combination of fuzzy rules and the appropriate design for the fuzzy sets. Accordingly, the proposed FIS model scheme in Fig. 5 is built to meet the above-mentioned requirements to achieve an efficient CH election in WSN.

4.7 Fuzzy-Logic-Inspired Zone-Based Clustering Algorithm

The following presumptions are taken into consideration by the algorithm.

1. The sensor nodes that have been deployed do not know where they are.
2. All nodes have the same functions for communication and adjusting the transmission range.
3. Nodes might start out with varying energy levels, but they might also have varying computing capacities.
4. Each round, nodes communicate a sufficient amount of data.
5. The data are combined at the node to create a single data packet to save energy.
6. One CH is all that is present in a cluster.
7. Energy does not set BS's boundaries. Compared to SN, they possess higher vigor and communication abilities.
8. Radio communication between the sensor nodes is symmetrical. To put it another way, two locations that communicate in both directions experience the same energy loss.
9. Following the total discharge of the battery, the node ID is not taken into account.

Clustering, as was already noted, boosts WSN performance by lengthening network lifetime and enhancing system scalability. The positioning of sensor nodes and the consideration of inter-node distances, which can significantly increase the energy efficiency of WSNs, are not the main concerns of most cluster-based algorithms. The NN is located in region 0, and regions 1 and 2 are home to the AN, which manages data flow to the BS. This is how Z-SEP

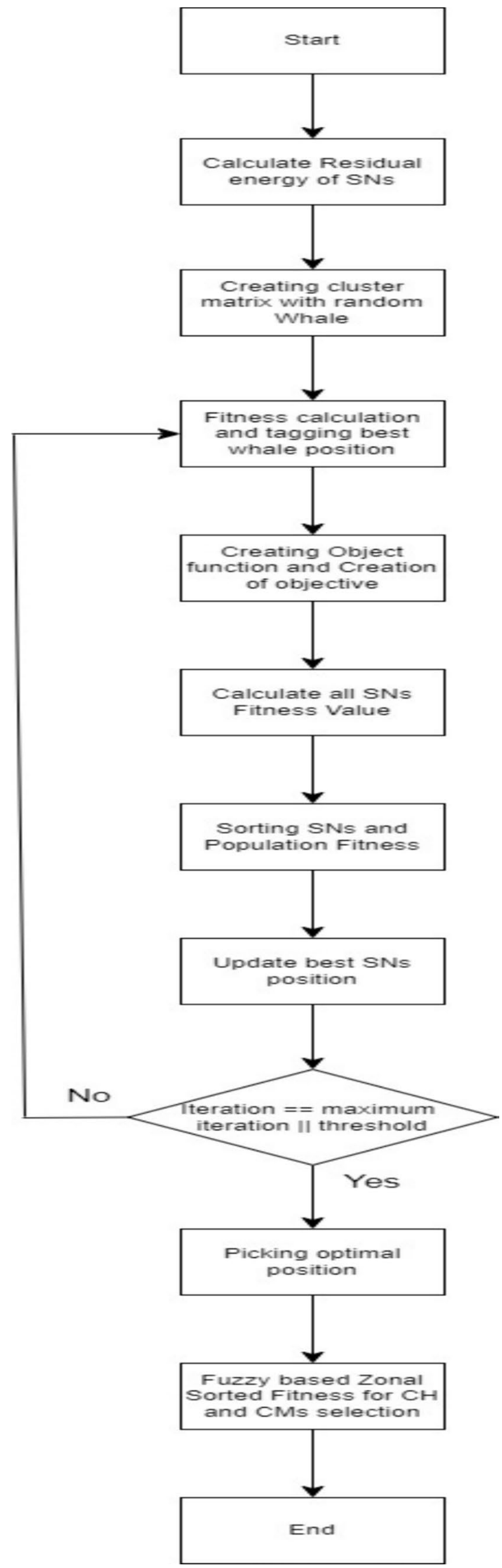

Fig. 5 Proposed flowchart

divides the domain into three regions. To gather data from the whole network, the BS is positioned in the center of the target region. Only the head regions 1 and 2 experience clustering, whereas region 0's NNs transfer directly with BS. This strategy is obviously invalid given that regions 1 and 2 are significantly smaller than region 0. To increase energy efficiency, FZC suggests in this study that nodes be distributed semi-randomly throughout the regions. Depending on how far away the base station is from the target WSN, the area is separated into five zones. The next section's description provides various criteria for the final area, taking into account a 100×100 m site.

Zone 1: NNs are only consistently distributed in Area 1 in the intervals $0 \leq X \leq 100$ and $40 \leq Y \leq 60$.

Zone 2: Both NN and AN extend to values of $0 \leq X \leq 100$ and $20 \leq Y \leq 40$ and $60 \leq Y \leq 80$, respectively.

Zone 3: Only AN is distributed in region 3 in the interval between $0 \leq 100 \leq X$ and between $0 \leq 20 \leq Y$.

To serve as sinks for the network's overall information flow, two BSs with the coordinates (50, 175) and (50, -75) are positioned in that order. FZC suggests positioning the NN and AN near the field's edge and the area's center, respectively, beneath the target WSN. The greatest option for CH_Sel is AN because it is near to BS. Since it requires a lot of resources, the NN transmits the information it has collected to the BS only through the CH in the proposed system, not directly. Two basic steps comprise the FZC protocol: a transfer step and a fuzzy-based clustering step.

4.8 Fuzzy-Logic-Based Zonal Clustering

The stages of cluster development are proposed in this work using an inequality method. Instead of employing a predetermined threshold, FZC cleverly calculates a threshold using probabilistic analysis, which is then applied to the selection of an acceptable CH. The fuzzy model employed in CH_Sel was then run using the three input variables. The third step involves choosing a provisional CH (Provisional_CH) for non-provisioned nodes using a fuzzy model with two input parameters.

Algorithm 2:

Input Set of CM s: J = {j1, j2, j3,…, jn}, Number of dimension.

Predefined Swarm size:Np.

Output: Optimal positions of CMs, CM = {CM1, CM2, CH3}.

Steps:

At each round, determine T (probabilistic value for selecting).

Provisional_CH = false.

for.

temp = random (0,1).

state_of_node = CM.

if temp < T then.

Provisional_CH = true.

// Making use of rules iterated in Table 1 for.

calculating comp_rad.

Comp_Radius = Fuzzy_Model 1 (Dist_to_BS Remanant_energy, node_deg).

end if.

end for.

BroadcastMsg (id, Comp_Rad, Res_Ener) to all neighbors of the Provisional_CH.

Every node P on receiving BroadcastMsg form Provisional_CH decides:

while (!(Stopping criterion)).

if Provisional_CH (Res_Ener) < P (Res_Ener) then.

Provisional_CH = false.

Table 1 Simulation parameters

Parameters	Values
No. of nodes	15, 20, 25, 30 and 35 nodes
Distance among node (minimum)	5 m
Model of mobility	Reference point mobility model
Simulation rate	120 s
Broadcast rate	Dynamic
Transmission frequency	2.45Ghz
Constant bit range	100Kbps
Simulation range	1500 m × 1500 m
MAC layer	802.11DCF
Wireless channel bandwidth	11Mbps
Node pause time	Random

end if.

if Provisional_CH = True then.

Node_state = CH.

Add P to the list of members in each cluster.

end if.

if Node_state = CM then.

//determine ideal CH using fuzzy- model.

CH = Fuzzy_Model2 (Dist_CH, Comp_Rad).

join the appropriate cluster as CM.

end if.

The processing flow is summarized by the algorithm in Algorithm 2. Each iteration starts with random nonce generation to select a temporary_CH. If the produced value falls below the computed threshold (T), FANET designates the node as a CH for additional processing.

The threshold T(s) is, therefore, defined by the following mathematical formula:

$$T(s) = \begin{cases} \frac{X}{1-X\times\left[\mathrm{ymod}\left(\frac{1}{x}\right)\right]}, 1 \in G \\ 0, else \end{cases} \tag{11}$$

where X denotes the ideal CH selection probability, y denotes the network of the current round, and G denotes the collection of sensor nodes that were not chosen as CHs in the previous (1/X) round.

Comp_Rad is determined for each temporary CH node by FZC using a fuzzy algorithm. The three member functions Res_Ener for Node, Node_Deg for the number of nodes within the communication range, and Dist_BS and Node are those that FZC advises employing in this situation. Because of this, FZC suggests using the third member variable Node_Deg for the most accurate computation of Comp_Rad. Because Comp_Rad, which determines the coverage area under CH, falls when Comp_Rad is low and Res_Ener is high during the cluster formation phase, the third variable offers an unfair advantage.

For usage in Comp_Rad computations, the fuzzy input member functions and associated language values are:

Dist_BS: {Near, Reachable, Far}.

Res_Ener: {Poor, Average, Good}.

Node_Deg: {Few, Average, Many}.

When computing the boundary variables and the intermediate variables, which are shown as presented in Figs. 6, 7 and 8, respectively, the trapezoidal membership function and triangular membership function are both applied.

The membership functions that are used in the proposed fuzzy inference system are triangular and trapezoidal, and they are listed in Eqs. (12) and (13).

$$\sigma_1(z) = \begin{cases} 0, z \le e_1 \\ \frac{z-e_1}{t_1-e_1}, e_1 \le z \le t_1 \\ \frac{u_1-z}{u_1-t_1}, t_1 \le z \le u_1 \\ 0, u_1 \le z \end{cases} \tag{12}$$

$$\sigma_1(z) = \begin{cases} 0, z \le e_2 \\ \frac{z-e_1}{t_2-e_2}, e_2 \le z \le t_2 \\ \frac{o_2-z}{o_2-u_2}, u_2 \le z \le o_2 \\ 0, u_1 \le z \end{cases} \tag{13}$$

In special instances, the next two rules are applied.

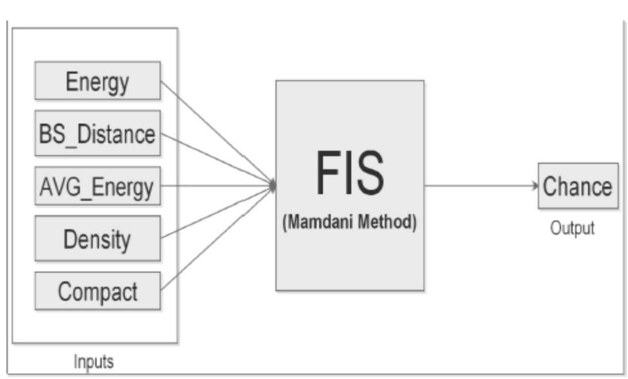

Fig. 6 Fuzzy system control model

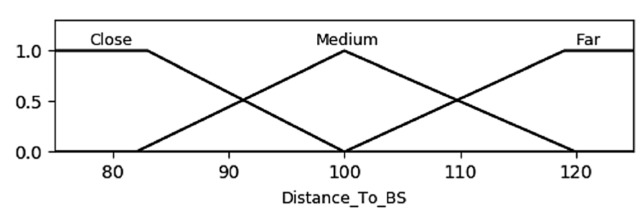

Fig. 7 Fuzzy set for the variable Dist_BS

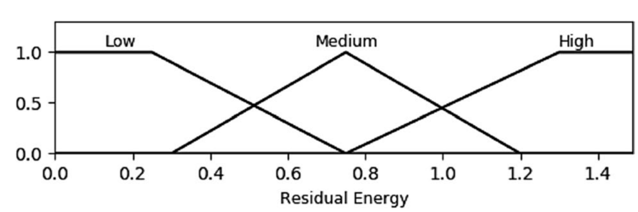

Fig. 8 Fuzzy set for the variable Res_Ener

- When Node_Deg is low, Res_Ener is high, and Provisional_CH is far from BS, Comp_Rad is very huge.
- When Provisional_CH is positioned near BS, Res_Ener is low, and Node_Deg is large, Comp_Rad is very little.

Consider the CH with the biggest Res_Ener and Comp_Rad after computing the Comp_Rad of each Provisional_CH. The non-CH node then chooses the right CH based on the second fuzzy model. To BS, send the data that were detected. Consequently, the final CH is chosen.

The following guidelines can help you choose a decent CH:

- VH is the selection criterion if Dist_CH is Near and Comp_Rad is 3XL.
- If Comp_Rad is 3XS and Dist_CH is Far, VL is the selection criterion.

This research employs the most popular model, the Mamdani inference system, to create the fuzzy model that is being presented. The center of areas (COA) approach, as shown in Eq. 14, is used for the decontamination procedure.

$$\text{Center for area} = \frac{\int \sigma_1(z)zdz}{\int \sigma_2(z)zdz} \tag{14}$$

4.8.1 Cluster Formulation and CH Selection with Fuzzy-Based Zonal Clustering

The actual clustering and CH selection are carried out using fuzzy-based region alignment fitness, a kind of cleared region density-based. For the first CH/center selection, blur-based area and clearance-based area density are combined. Figure 9 illustrates how the fuzzy region-based input parameters determine the “k” ideal center locations based on the data points’ surrounding areas. The fuzzy-based region algorithm finds the optimal solution fast because of the precomputed centers.

A constant value of “k” is assigned to the blur-based area density. On the other hand, the topology of the network fluctuates and nodes migrate often in FANETs. A given network configuration’s needed number of clusters is determined by the location of the nodes and the forwarding range. The number and size of clusters in fuzzy-based region alignment appropriateness should be chosen with the transmission range of the CH in mind. An output that includes the CH and its related members is produced by feeding the node’s fitness value into a fuzzy-based region alignment fitness. Figure 8 illustrates the procedure’s flow. EEBMC-p-WOA seeks to decrease the computing effort needed by simplifying the cluster functionality as much as feasible. The remaining energy of every node is determined before to CH selection in an effort to increase efficiency, as demonstrated above. We so attempt to determine the average amount of energy that remains first. Candidates for CH nodes are thought to have fewer leftover energy on average than the average. For this round of CH selection, it will be skipped. For decision-making, this function looks at fitness values. Obtaining a more precise fitness value in this case is necessary before choosing the optimal CH. The fitness values are first arranged in decreasing order for convenience of usage. All nodes with fitness values occupy CH locations. Group members (CMs) are all other nodes that fall into the chosen CH's transmission range. Remaining nodes are not those that have been chosen for CH. Once all selected nodes have been eliminated, the CH selection procedure is then carried out once more. Whether they are cluster leaders or cluster members, each node fulfills a certain purpose.

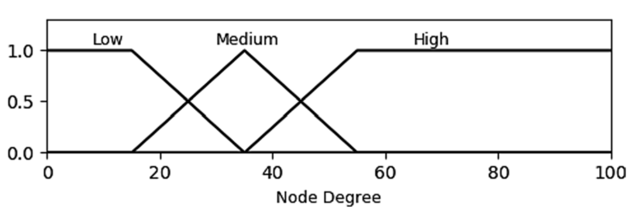

Fig. 9 Fuzzy set for the variable Node_Deg

5 Result and Discussion

This section examines the proposed performance for clustering algorithms based on FL-ACO, ANFIS-WOA, and FIGWO. The factors such as the energy consumption, PDR, packet drop analysis, and network lifetime are considered in the analysis. Using MATLAB 2018a, the performance metrics are obtained and initial simulation settings are tabulated in Table 1. Experimental results demonstrate that proposed performs better than other existing algorithms which are used for comparison purposes. The proposed algorithm is comparatively evaluated under different network densities to illustrate and validate its behavior.

5.1 Energy Consumption

Energy is an essential source for nodes. Insufficient energy source has imposed many restrictions on the widespread use of nodes. Energy-emitting nodes have three fundamental mechanisms: The energy required by nodes to fly, consumption of energy by different sensors in nodes, and energy consumed while communication with other node which is the primary sources of energy consumption. The proposed method consumes less amount of energy level because of the energy-aware CH election and cluster management.

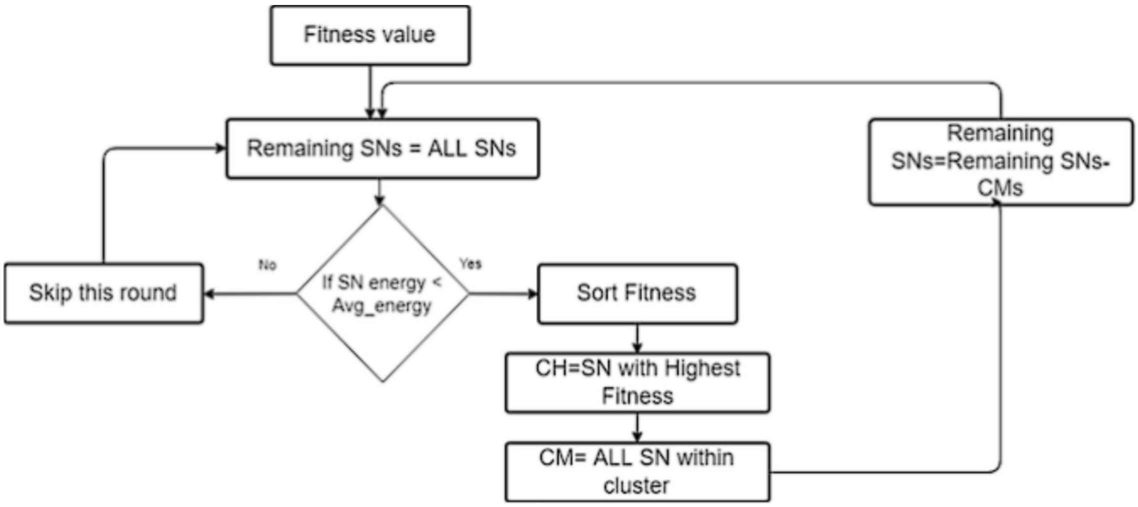

Fig. 10 Flowchart of fuzzy-based zonal sorted fitness

Figure. 8 shows the comparison of number of nodes with energy consumption at the grid size of 1500 m × 1500 m. It is observed from the figure when there is increase in the consumption of energy which will also increase the number of node in a FANET. The various clustering approaches are compared to consider the better energy consumption. For instance, when the number of nodes are 15, 20, 25, 30, and 35, Fig. 10, displaying the energy consumption of FL-ACO, ANFIS-WOA, and FIGWO algorithm which is compared with proposed algorithm, shows that energy consumption of proposed method is 2.3 J, 3.5 J, 4.7 J, 5.8 J, and 6.9 J, respectively, which indicates that less amount of energy is consumed by a cluster in the network when compared to FL-ACO, ANFIS-WOA, and FIGWO algorithm.

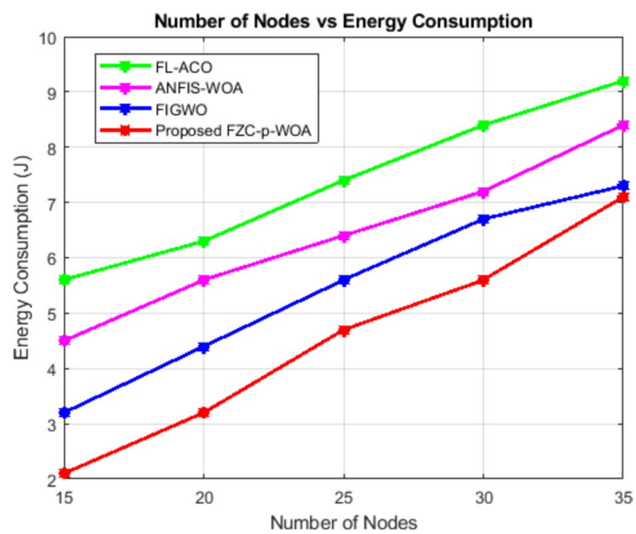

Fig. 11 Comparison of no. of nodes versus energy consumption

5.2 Packet Delivery Ratio

The probability of transmission success is a method of successfully transmitting data packets to every intermediate node by considering the average number of hops. It can be observed from the figure that when the number of node increases, network density increases. Therefore, increase in the probability of transmission results in the packet's decrease loss rate. Figure. 9 shows the comparison of number of nodes with PDR at the grid size of 1500 m × 1500 m. It is observed from the figure that when there is increase in number of node, it will also increase PDR in a FANET. The various clustering approaches are compared to consider the better PDR. For instance, when the number of nodes are 15, 20, 25, 30 and 35, in Fig. 11, which shows the PDR of FL-ACO, ANFIS-WOA and FIGWO algorithm which are compared with proposed algorithm, it has been observed that the PDR of proposed method is 0.65, 0.72, 0.77, 0.84, 0.93, respectively, which indicates better PDR when compared to FL-ACO, ANFIS-WOA, and FIGWO algorithm.

5.3 Packet Drop Analysis

Figure 12 shows how the number of nodes affects the PDR with a change in speed of the investigated routing protocols. It is represented in millisecond. Figure 12 shows the node loss analysis. It can be seen from the figure that as the number of nodes increases, the packet loss rate of FANET also increases. We compare different node methods to account for better packet loss ratios. For instance, when the number of nodes are 15, 20, 25, 30, and 35, in Fig. 12, which shows the packet drop analysis of FL-ACO, ANFIS-WOA, and FIGWO

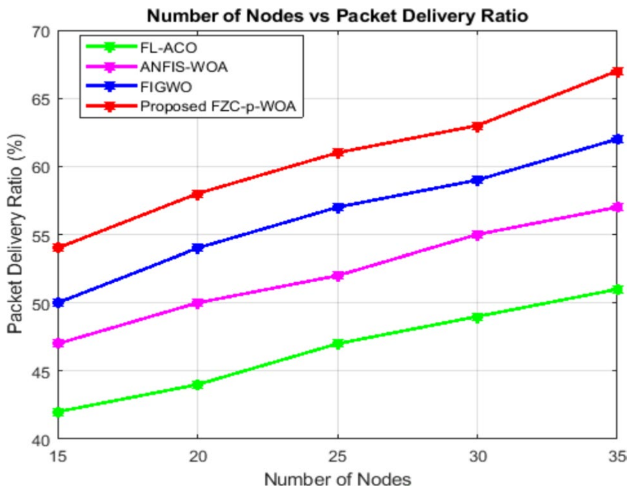

Fig. 12 Comparison of no. of nodes versus packet delivery ratio

algorithm which is compared with proposed algorithm, it has been observed that the packet drop analysis of proposed method is 0.65, 0.72, 0.77, 0.84, and 0.93, respectively, which indicates better packet drop analysis when compared to FL-ACO, ANFIS-WOA, and FIGWO algorithm.

5.4 Network Lifetime

The life of a cluster is the time required to form a cluster because of the range of clusters. When performing a clustering algorithm, the CH role selects the best node for cluster management. A brief life of the cluster means that the cluster algorithm needs to be run more frequently, which increases communication and computational overhead to the network. Figure. 10 shows the comparison of number of nodes with network lifetime at the grid size of 1500 m × 1500 m. It is observed from the figure that when the number of

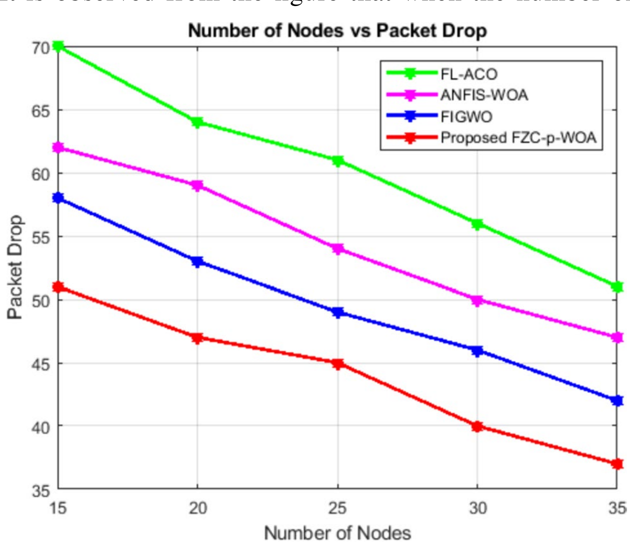

Fig. 13 Comparison of no. of nodes versus packet dropout

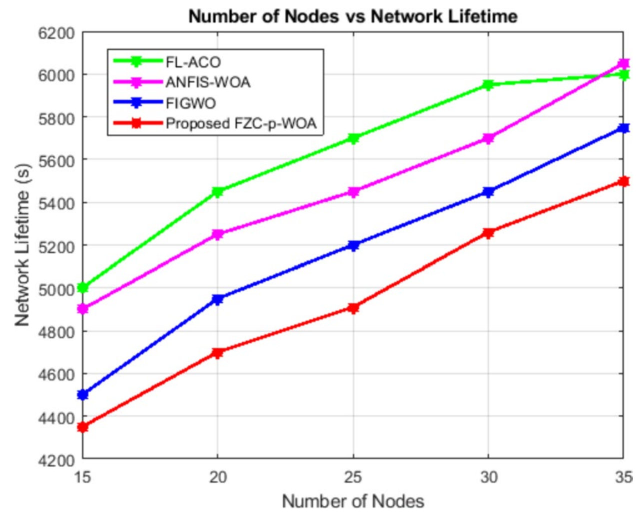

Fig. 14 Comparison of no. of nodes versus network lifetime

node increases, the network lifetime decreases due to frequent topology change in FANET. The various clustering approaches are compared to consider the better network lifetime. From Figure 14, for instance, when the number of nodes are 15, 20, 25, 30, and 35, in Fig. 13, which shows the network lifetime of FL-ACO, ANFIS-WOA, and FIGWO algorithm which is compared with proposed algorithm, it has been observed that the network lifetime of proposed method is 47 s, 41 s, 35 s, 28 s, and 22 s, respectively, which indicates better network lifetime when compared to FL-ACO, ANFIS-WOA, and FIGWO algorithm.

6 Conclusion

An effective and optimal clustering approach for FANETS is presented in this paper: the EEBMC-*p*-WOA model. Both low energy consumption and ineffective routing are significant disadvantages of fast-moving nodes. Optimizing drone routing and reducing energy consumption can be achieved by adjusting the transmission range and organizing the network appropriately. To address the FANET routing challenge, the EEBMC-*p*-WOA method suggests a novel strategy for cluster optimization. It is more affordable to decrease the number of clusters in FANET using the EEBMC-*p*-WOA technique, which lowers routing costs and speeds, while also reducing the quantity of pointless broadcasts. Simulation tests are carried out and monitored with a changing transmission range of SN to assess and validate the effectiveness of the proposed EEBMC-*p*-WOA algorithm. Making the smallest clusters in the search space, EEBMC-*p*-WOA offers a nearly optimum solution with FANETS topology limitations. Well-known evolutionary algorithms include FIGWO, ANFIS-WOA, and FL-ACO. But the optimal answer to the examined issue is EEBMC-*p*-WOA. This comes out on top in terms of both cluster lifetime and cluster count. But in terms of the energy and time needed for cluster development, EEBMC-*p*-WOA also works well. The same packets can be processed by the UAV using the suggested technique, which reduces network performance and uses up the UAV's small resources. We require a packet scheduling solution to solve these problems and enhance packet management in FANETs. The issue of congestion control in UAV networks with constrained resources will be our main focus in the future.

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Author Contributions R. C. K and D. L wrote the original draft and worked on the simulation. A. O. S. worked on the software. A. M. and M. N defined the methodology, reviewed, and edited the manuscript. D. P supervised the work. All authors read and approved the final manuscript.

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Availability of Data and Materials Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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