Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Improved Jellyfish Search Algorithm based Multipath Routing with Atom Search Algorithm for Best CH Selection

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Article Info
Page Number: 7389 - 7411
Publication Issue:
Vol 71 No. 4 (2022)

Abstract

Several regions that are inaccessible to people have benefited from the deployment of Mobile Ad hoc NETwork (MANET) apps. There is a new topic of study related to low-power usage in MANET. To maximize energy efficiency and extend the MANET's lifespan, it is necessary to use clustering and routing strategies. Despite this, one of the primary obstacles in sensor networks is routing, which is crucial for the timely transmission of sensed data to the base station. Clustering, which increases scalability, and Multipath Routing, which uses many paths to transmit data, has been employed recently to make MANETs more dependable and scalable. Clustering and routing are examples of problems that are classified as NP-Hard. Meta-heuristic optimization is well suited to this particular kind of challenge. When it comes to clustering, this research makes use of atom search optimization (ASO), and when it comes to achieving effective shortest route communication, the researchers turn to ad hoc on-demand multipath distance vector routing with enhanced jellyfish search optimization (AOMDV IJSO). IJSO method development anticipates the best course of action. Therefore, the ad hoc on-demand multipath distance vector (AOMDV) generates a set of potential pathways, and IJSO selects one that is close to ideal. Using the NS-2 simulator, the proposed protocol's effectiveness is measured across various use cases. Simulated findings show that the proposed protocol excels over the state-of-the-art in terms of Quality-of-Service network longevity.

Article History
Article Received*: 25 March 2022*
Revised*: 30 April 2022*
Accepted*: 15 June 2022*
Publication*: 19 August 2022*

Keywords: - Mobile Ad hoc network; Jelly Search Optimization; Enhanced Atom Search Optimization; Clustering; Multipath Routing).

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1. Introduction

To transmit data from one location to another, a network may be quickly assembled. It is a decentralized, distributed, and self-repairing network. The open wireless medium and the dynamic topology of MANETs make them vulnerable to security threats. Cost-effective methods of providing reliable, secure communication in dangerous environments like conflict zones are elusive [1]. Finding the best stable multicast route while accounting for host mobility is the primary focus of multicast routing approaches [2]. Security issues in MANET data transport include unreliability, accidents, and energy consumption in mobile nodes. Trust-based protocol [3] ensures that information travels from sender to receiver without a hitch. By encrypting and decrypting it with a key, the routing secures data throughout both forward and reverse transmission. The trust method improves latency, throughput, and efficiency while using less power [4]. When using Multicast, data packets are sent to a group of zero or more nodes with a single destination address. Multi-path Quality-of-Service Multicast Routing (MQMR) lowers the cost of transmitting the same message to numerous receivers simultaneously. It is particularly useful for situations when WiFi is available, but mobile device storage space is restricted [5]. Therefore, reliable connections between neighboring nodes are required for group communication to be possible.

Among them are arenas of military conflict, sites of urgent search and rescue, campaigns of liberation, and virtual classrooms. It is also used in times of crisis when individuals can send vital information to one another through their mobile phones [6]. In the literature, many QoS multicast routing algorithms have been explored for WMA networks. Networks may prioritize certain data over others [7] because of the quality of service mechanisms like QoS. It is desirable for a channel from a source to a set of destinations to have lower values for end-to-end latency and energy spent and greater values for throughput [8-10]. Battery life and energy consumption rate are only two of the variables considered in the design of such networks [11]. Recent years have seen the development of several methods for cutting down on the energy consumption of wireless ad hoc networks. QoS is significantly impacted by the most common MANET parameters, including packet delay, channel bandwidth, loss, battery lifetime, jitter, and energy usage [12].

More effective and efficient routing in MANETs may be achieved via the use of the tried-and-true method of clustering-based routing. Cluster-based methods are used to maintain a consistent energy level across the network and increase its lifespan while also minimizing the amount of overhead involved in communications. Several methods for creating clusters and cluster leaders are available. CHs are chosen for each cluster while clustering. In order to determine the CH (Cluster Head), several elements are considered. CH's purpose is to facilitate information sharing and coordination across different clusters and different nodes. Additionally, CH will be responsible for the upkeep of cluster members, the gathering and aggregation of data from mobile nodes, the upkeep of topology information, resource, routing, and packet transport [14]. The Cluster leader also acts as a local coordinator and is in charge of the IDS, which keeps tabs on all kinds of activities and potential intrusions [15]. CH is used in the energy-efficient clustering strategy because it has lower mobility and produces more energy per unit of mass. Once a candidate channel has been chosen (CH), an energy-efficient data transmission method is then chosen.

Energy conservation and awareness of the need to move about are the primary challenges of MANETs. The nodes in a (MANET) may travel in the incorrect direction if they are uninformed of their own mobility. A node's battery life will be shortened and the network's structure will be altered as a result of this procedure. Due to the mobility and topological change difficulties of nodes in a MANET, the CH node loses most of its energy. Therefore, a CH selection that minimizes energy consumption is essential for fixing the network issue. In this research, we combine an ASO strategy for choosing the optimal node as CH with a clustering technique that minimizes energy consumption in a MANET. Multiple nomadic nodes are in charge of routing in this suggested system. IJSO determines the best path to take, with the associated research provided in Section 2. Section 3 explains the suggested technique, while Section 4 provides a validation analysis. Section 5 then presents the last contribution.

2. Related Works

Using the MANET optimization technique, Neenavath and Krishna [16] offer a multipath routing protocol that minimizes energy consumption. Using fuzzy clustering for head collection and fuzzy NB for intrusion detection presents a formidable challenge to MANET's energy efficiency. The bird Swarm-Whale Optimization Algorithm combines BSA (bird swarm optimization) and WOA (whale optimization) to accomplish multipath routing (BSWOA). Fitness characteristics, including connectedness between nodes, energy consumption, maximum trust value of the route, and throughput, are taken into account while choosing the best routes. In comparison to Naive Bayes Trust, the proposed BSWOA achieved minimum energy consumption or maximum energy efficiency.

Stable node prediction, stability willpower, route research, and packet are some of the four stages outlined by Hemalatha et al. [17]. In the first step, a recurrent neural network and a tweaked version of the seagull optimization method are used to determine which nodes are stable (RMSG). Garson's pruning-based to choose stable neighbours, and it is supplemented with a modified version of the seagull optimization technique. Stable nodes are connected along the path from origin to destination to establish the network's routing. Whenever a link in the routing process fails, the route recovery procedure will begin. Data packets are, therefore automatically spread over many pathways. The effectiveness of the suggested method is measured in terms of many key characteristics and usage.

Cluster head selection and alternate cluster head selection to prevent cluster head failure are proposed in a paper by Sivapriya and Mohandas [18]. The research also suggests establishing the route based on maximum energy and amount of hops.

The MR-AOMDV protocol, developed by Sarkar [19], is a reliable multipath routing scheme that takes into account mobile nodes. For dependable and mobile-aware data transfers, the proposed MR-AOMDV creates numerous pathways from source to destination based on the mobility and dependability of nodes as a whole. During the route discovery phase, a trust management module compares the mobility and dependability values to predetermined levels in order to design routing pathways. To make the created pathways more mobility-aware and trustworthy, they undergo an adaptive modification in the path maintenance phase, whereby a node may be added, removed, or replaced. Results from simulations show that the created pathways are stable and trustworthy. By transferring data over the malicious-node-free pathways, MR-AOMDV boosts speed and guarantees security.

Attempting to create a load-balancing, Alghamdi [20] proposes a meta-heuristic in the style of a cuckoo search. To distribute routing overhead fairly across all participating nodes, the proposed protocol uses the cuckoo search method to choose a route that maximizes the remaining power of each node. Energy-aware modifications of on-demand Multipath Distance vector, packet-count-based routing mechanisms, an ad hoc on-demand multipath distance vector protocol with load balancing, vector protocol with enhanced metrics, and the Ant HocNet routing protocol have all been used as benchmarks against which the new protocol has been measured. Simulation findings indicated that the suggested routing architecture significantly improved packet delivery ratios, battery life, and delay time.

For optimal route selection (ORS), Suresh Kumar, R. et al. (2022) [21] suggest selecting a cluster head and an alternate cluster head in case of failure of the cluster head, generating hops between the nodes (minimum number of hops). When compared to more traditional methods, ORS's ability to provide a channel between the base station and the cluster head, and the member node while simultaneously minimizing energy consumption is clear. Compared to prior art methods, the proposed ORSMAN shows considerable improvements in throughput, latency, jitter, and packet delivery ratio. The Greedy Weight Matrix Topological Adaptive Ad hoc On-demand multipath distance vector protocol was developed by Praveenkumar and Anbukaruppusamy [22] to improve the Quality of Service (QoS) during high-velocity node movement (GWMTA-AOMDV). A constant connection between node and node resources (such as power, maximum data transmission, and queue length) is possible via the use of a consistent path-selection mechanism during trajectory selection. Using an improved routing approach concept that contains a link interference forecasting feature, the proposed protocol would keep tabs on and respond to sudden changes in the topology. After applying the provided suggestions, the suggested channel's quality of service measurements significantly improved. From the user's point of view, our protocol for reactive multipath networks shows why high-speed MANETs are necessary.

3. Proposed Methodology

The MANET is made up of roving nodes. The nodes can exchange information and carry out conversations with one another. Clustering is an important method for increasing the scalability and lifespan of MANETs while also improving their energy efficiency. As a means of facilitating data transfer from the origin to the destination of the network, the nodes will be partitioned into distinct clusters, each of which will have a CH that will act as the cluster's local coordinator. A novel fitness for selecting CH and an inspired swarm optimization method are both important parts of improving the network model's flexibility and vitality. The two biggest obstacles of a MANET are choosing a CH and its energy so that it is both mobile and efficient. The goal of the CH selection method is to find the finest candidates from the set of nodes that have maintained their network with various additional nodes for the longest amount of time and assign them the role of CH. To cope with the issue of increasing the MANET's network lifespan, it is reasonable to outline an effective clustering technique with little cost.

3.1 Mobility model

The routing algorithm's execution is affected by the nodes' mobility since the number of average related ways varies depending on the nodes' mobility. Poor cluster stability is caused by the increased frequency with which CH elections must be held and by the need to frequently update interfaces in response to mobile users' demands. In order to reduce the amount of effort required to maintain control, our method establishes a constant route between entities that move around less often by analyzing their mobility patterns.

3.2 Energy model

One of the primary goals of a routing procedure is to keep the network operational as much as possible rather than just establishing correct and efficient paths between a set of nodes. With max-min routing, the path with the highest bottleneck residual node energy is selected, whereas, with standard routing, the path with the lowest aggregate energy use for packet transmission is chosen. The value of this energy node at a particular interval of time is

$$\mathrm{E_{energy}}\ (\mathrm{t_i}, \Delta\mathrm{t}) = \mathrm{E_{residual}}\ (\mathrm{t_i}, \mathrm{k_0}) - \mathrm{E_{residual}}\ (\mathrm{t_i}, \mathrm{k_1}) \qquad (1)$$

Here, $\mathrm{E_{residual}}$ signifies the energy node at the period 0 and 1, correspondingly.

3.3 Clustering perfect for MANET

By broadcasting a packet describing their relative mass, the node was able to get information about its neighbours. The node's degree and the rate of data transmission are stored in its weight esteem. It is the system's mobility and energy that first shapes the cluster and CH determination during the increment. As a result of mobility-driven increases in CH selection and interface refreshment, cluster stability suffers.

3.3.1. Cluster Formation:

When enough sensor nodes within the radio range of the CHs are present, the CHs will send out a broadcast request for a packet to create a cluster. If just one node is present, transmission to the CH is unambiguous; otherwise, all sensor nodes will relay their information through their nearest neighbors.

3.3.2 Cluster head selection

Apart from providing its members with access to radio infrastructure, a CH has also been implemented to direct traffic between nodes belonging to different clusters.

At the beginning of each round, each node chooses itself to be a CH with the likelihood pr i(t)* chosen such that the anticipated sum of CHs is C. Because of this if a network has nodes,

$$C = \sum_{i=1}^{N} pr_i(t)^{*}1. \qquad (2)$$

Here, N → Sum of nodes in the network, and N-k is the usual nodes.

$$Pr_i(t) = \frac{Expected\ \ number\ \ of\ cluster\ \ head}{s\ Expected\ \ number\ \ of\ nodes\ are\ not\ cluster\ \ heads\ in\ most\ recent\ \ rounds} \qquad (3)$$

Once every N/k hops, every node will be a CH hop. There is an equal likelihood that each node in a cluster will be designated as CH. Following each iteration, the amount of energy at each node will be about equal. Energy-rich nodes are preferential clustering candidates over energy-poor anodes. An approximate count of cluster nodes would be

$$Energy[CH] = C \Longrightarrow (N - C^{*}\left(r\ mod\ {}^{N}\!/_{C}\right) * {}^{C}\!/_{N} - C^{*}(rmod\ {}^{N}\!/_{C})) \qquad (4)$$

If keys are generated for each node in the cluster, as is the case when a key administration mechanism is used to distribute them, then the process introduces key overhead. In this case, the nodes are represented by different colours to highlight the distinct clusters shown. The CH in each cluster is the node with the least total weight.

3.4 Optimal model for CH assortment

It is one of our suggested clustering's primary roles to maximize the efficacy of CHs. This is a crucial need for achieving cluster stability in a MANET. It's important to keep in mind that in networks where data is sent from source to goal-finished CHs, just selecting the greatest qualified nodes to operate as CHs does not ensure efficient clustering. Below we will discuss how ASO determines which CH is best.

3.4.1 Atom Search Optimization

Recently, Zhao et al. [23] created a metaheuristic technique called atom search optimization (ASO). The potential function, and force of atomic motion provide inspiration for the ASO. ASO, like other metaheuristic algorithms, begins with a population of solutions, or atoms. Each atom in ASO keeps track of its location and motion using two vectors::

$$X_i = [X_i^1, X_i^2, \ldots, X_i^D]$$

$$V_i = [V_i^1, V_i^2, \ldots, V_i^D]$$

where X i, V i, and D are atom positions and velocities, respectively, atomic motion. A mathematical expression for the atomic velocity is:

$$a_i = \frac{F_i + G_i}{m_i} \qquad (5)$$

where F and G are the contact force and constraint force, and m is the atomic mass.

Lennard-Jones (L-J) potential is used to derive the interaction force among the atoms [23]:

$$F_{ij} = \frac{24\varepsilon}{\sigma}\left[2\left(\frac{\sigma}{r_{ij}}\right)^{13} - \left(\frac{\sigma}{r_{ij}}\right)^{7}\right]\frac{r_{ij}}{r_{ij}^{d}} \qquad (6)$$

And

$$F_{ij}^{'} = \frac{24\varepsilon}{\sigma}\left[2\left(\frac{\sigma}{r_{ij}}\right)^{13} - \left(\frac{\sigma}{r_{ij}}\right)^{7}\right] \qquad (7)$$

where F' is the model of the contact force, is the potential depth, is the length scale, r is the separation between atoms (I and j), and d is the search space dimension. In order to simplify the optimization procedure, we write down Eq. (7) as:

$$F_{ij}' = -\eta\left[2(h_{ij})^{13} - (h_{ij})^{7}\right] \qquad (8)$$

where is the depth function that determines the range of attractive or repulsive forces::

$$\eta = \alpha\left(1 - \frac{t-1}{T}\right)^{3} e^{-\frac{20t}{T}} \qquad (9)$$

where denotes the depth weight and T denotes the maximum number of iterations. The scaled distance between two atoms, denoted by the function h, may be written as [23]:

$$h_{ij} = \begin{cases} h_{min}, & if\ \frac{r_{ij}}{\sigma} < h_{max} \\ h_{max}, & elseif\ \frac{r_{ij}}{\sigma} > h_{min} \\ \frac{r_{ij}}{\sigma}, & otherwise \end{cases} \qquad (10)$$

where the maximum and minimum values of h are denoted by h max and h min, respectively [23]. How to Determine the Length Scale:

$$\sigma = \left\| X_{ij} \frac{\sum_{j \in K} X_{ij}}{k} \right\|_2 \qquad (11)$$

And

$$\begin{cases} h_{min} = g_0 + g \\ h_{max} = u \end{cases} \qquad (12)$$

where K is a collection of the atoms with higher fitness values and g 0 and u are equal to 1.1 and 2.4, respectively [23]. G, the drift factor that regulates the trade-off between discovery and exploitation, is defined as:

$$g = 0.1 \times sin\left(\frac{\pi}{2} \times \frac{t}{T}\right) \qquad (13)$$

The total communication force can be uttered as:

$$F_i^d = \sum_{j \in K} rand_j F_{ij}^d \qquad (14)$$

If you want a random number, just plug in rand and it will be picked at random from the range [0,1]. Newton's third law states that for each given pairwise interaction, the force on the ith atom is equal and opposite to the force on the jth atom.

$$F_{ij} = -F_{ij} \qquad (15)$$

In addition, the ith atom's geometric constraint and constraint force may be written as:

$$\theta_i = \left[|X_i - X_{best}|^2 - b_{i,best}^2 \right] \quad (16)$$

$$G_i^d = -\lambda \nabla \theta_i^d = -2\lambda (X_i^d - X_{best}^d) \quad (17)$$

where X_{best} is the position of finest atom, $b_{i,best}$ is the fixed bond distance, and λ is the Lagrangian multiplier. By making $2\lambda = \lambda$, the constraint force is signified as:

$$G_i^d = \lambda \left(X_{best}^d - X_i^d \right) \qquad (18)$$

The Lagrangian multiplier can be uttered as:

$$\lambda = \beta e^{-\frac{20t}{T}} \qquad (19)$$

where β is the weight of multiplier.

$$a_i^d = \frac{F_i^d}{m_i^d} + \frac{G_i^d}{m_i^d}$$

$$= -a \left(1 - \frac{t-1}{T}\right)^3 e^{-\frac{20t}{T}} \sum_{j \in K} \frac{rand_j \left[2(h_{ij})^{13} - (h_{ij})^7 \right] \left(X_j^d - X_i^d \right)}{m_i \|X_i, X_j\|_2} + \beta^{e^{-\frac{20t}{T}}} \frac{X_{best}^d - X_i^d}{m_i} \qquad (20)$$

where m is the atom, and it is distinct as:

$$M_i = e^{-\frac{Fit_i - Fit_{best}}{Fit_{worst} - Fit_{best}}} \qquad (21)$$

$$m_i = \frac{M_i}{\sum_{j=1}^{N} M_j} \qquad (22)$$

where Fit is the fitness value. Considering the minimization problematic, the Fit_{best} and Fit_{worst} can be signified as:

$$Fit_{best} = min_{i=1}^{N} Fit \qquad (23)$$

$$Fit_{worst} = max_{i=1}^{N} Fit \tag{24}$$

Then, the velocity and position of the atom are efficient as shadows:

$$V_i^d(t+1) = r_1 V_i^d(t) + a_i^d(t) \tag{25}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{26}$$

where X i, V i, a, d, r1, and t represent the current iteration, an is the acceleration, d is the search space dimension, r1 is a random vector in [0,1], and an is the iteration number.

The ASO algorithm uses the number of excellent atoms in subset K to strike a good balance between the exploration and exploitation phases..

$$k = N - (N-1)\sqrt{\frac{t}{T}} \tag{27}$$

where N is the total number of atoms. A larger k value allows the atoms to first probe into uncharted territory. A smaller value for k encourages exploitation near the conclusion of the iteration, which conducts the search centred on the best answers.

3.5. Multipath Routing

The use of energy for communication in a MANET is significant. Consequently, it is necessary to enhance the routing protocol, which takes the best route, in order to prolong the life of the network. Our suggested method uses the AOMDV protocol to choose numerous pathways between the source and the sink, and then SI approaches are employed to determine the optimal one. Many different kinds of routing problems may be solved by using SI-based solutions. If a node accepts all of the duplicate route request packets that it gets during the route discovery phase, routing loops will be established because the packets will be sent back and forth between the nodes in the network. Therefore, AOMDV-IJSO (explained in Section 3.5.1) proposes using publicized hop count to avoid loop formation and ensure loop freedom, as shown in Figure 3.5. If several routes can reach that node, the highest hop count of those routes is broadcast. This value is dynamically updated when the sequence number increases or decreases. The suggested technique utilizes all of the IJSO characteristics to help identify the optimal route among several candidate pathways. The central concept is to execute operations on populations in order to determine the fitness of new populations repeatedly. This is done by first calculating the fitness function over an initial population. The best answer gives us the ideal values of the population, which we can then use to find the optimal routing strategy.

3.5.1. Artificial Jellyfish Search Optimizer

In order to find food in the water, the JSO [24] exhibits behaviour that includes both following the ocean current and touching around inside the swarm, with the ability to switch between the two based on a timer. The authors in [24] studied a number of chaotic maps in addition to more standard random methods for initialization in an effort to identify the optimal strategy for distributing solutions across the search space of the problem, which would speed up convergence and avoid getting stuck in local minima. The logistic map, which can be mathematically represented as follows [24], has been shown to be optimal for JS after observation.

$$\vec{X}_{i+1} = \eta \vec{X}_i (1 - X_i), 0 \leq \vec{X}_0 \leq 1 \qquad (28)$$

$\vec{X}_i$ is a vector that covers the chaotic logistic values of the ith jellyfish. $\vec{X}_0$ is an initial vector of jellyfish 0, generated arbitrarilyamong 0 and 1. This vector serves as the seed from which the chaotic logistic values for the rest of the jellyfish are generated. Using the formula in [24], we can determine that h equals 4. Afterward, the fitness of each solution is measured, and the one with the highest value is selected as the best place to find X * * food. The current position of each jellyfish is then updated according to the temporal control system that toggles between swimming with the ocean current and swimming inside the swarm. A mathematical description of the ocean circulation looks like this [24]:

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{r}.* \, (\vec{X}^* \beta * r_1 * \mu) \qquad (29)$$

If r is a random vector among 0 and 1, and the dot product is performed on each component of the vector. The mean of the population is denoted by m, and a random integer between 0 and 1 is denoted by the variable r 1. The distribution coefficient is denoted by > 0, and = 3 is the result of the sensitivity analysis in [24].

There are two kinds of movements that may be seen inside the jellyfish swarm: passive and active. Jellyfish migrate passively about their current positions, with the new position being determined by the formula [24] below.

$$\vec{X}_i(t+1) = \vec{X}_i(t) + r_3 * \gamma * (U_b - L_b) \qquad (30)$$

where r 3 is a random integer between 0 and 1 and represents the distance travelled in a circle centred on the current location if it is greater than 0. In this problem, the search space is bounded at both ends by upper and lower bounds, denoted by U b and L b. The mathematical expression of the dynamic motion [24]:

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{r} * \vec{D} \qquad (31)$$

where r is a zero-to-one random number vector. The current generation of jellyfish uses D to move in the direction toward the finest food, and this movement is always calculated using the following formula. [24]:

$$\vec{D} = \begin{cases} \vec{X}_i(t) - \vec{X}_j(t), & if\ f(\vec{X}_i) < f(\vec{X}_i) \\ \vec{X}_j(t) - \vec{X}_i(t), & otherwise \end{cases} \qquad (32)$$

where j is the index of a randomly chosen jellyfish and f represents the fitness function. The time control mechanism, which consists of a constant c0 and a time control function mathematically described as follows [24] and used to toggle between the ocean current, passive and active movements, is as follows:

$$c(t) = \left(1 - \frac{t}{t_{max}}\right) * (2 * r - 1) \qquad (33)$$

where (t, t max) is the current evaluation, (r, 0) is a random integer, and (s) is the greatest evaluation. When c(t) c 0, the jellyfish swim with the ocean current; otherwise, they swim with either passive or active motion within the swam, depending on whether the random integer r4, created between 0 and 1, is higher than (1 c(t)). This is described in detail in [24]..

3.5.2. Proposed Improved JSO (IJSO)

Here, the JSO is combined with a new approach to promoting in order to deal with the many paths taken by AOMDV. This new approach is tied to a control variable that can toggle between the method's exploitation capacity (which helps the solution converge faster) and its exploration capability (which helps the solution avoid being stuck in a local minimum). Below, we break down each component of our proposed method in further depth.

3.5.2.1. Initialization

The suggested technique begins with a population of N solutions X I (iN), where d is the number of dimensions in each solution corresponding to the number of unknown parameters being optimised.

After that, the chaotic logistic map from Section 3.5.1 is applied to each unknown parameter's search space to initialise those dimensions. Following initialization, the quality of each solution is determined by comparing it to all other solutions and to solutions acquired in subsequent generations using the objective function (OF) given below.

3.5.2.2. Premature Convergence Strategy (PCS)

According to Section 3.5.1 of the JSO publication, the method may take a long time to achieve a better solution since moving the current jellyfish throughout the population may not boost the convergence toward the best so far solution. The regions where the swarms are found also have little local exploration capability.which might take many rounds to search. Therefore, looking in parts of the swarm that may not be investigated by any of the other jellyfish will assist to get better results. This inspires the suggested approach, which improves the algorithm's capacity to utilise the area around the best-so-far solution when r is low and explore the area surrounding the swarm to reach new areas when r is high. The premature technique is a mathematical procedure that:

$$\vec{X}_i(t+1) = \vec{X}_i(t) + r * \left(\vec{X}_{r1}(t) - \vec{X}_{r2}(t)\right) + (1-r) * (X^* - \vec{X}_{r3}(t)) \quad (34)$$

where r is the controlling parameter and 1, 2, and 3 are indices of three randomly chosen solutions from the population. The location of the current solution is adjusted based on a parameter that ranges from 0 to 1.If the control parameter is low, the current solution is moved closer to the best-so-far solution, X _r3 (t), to speed up convergence, while if it is high, the current solution is updated. By incorporating this strategy into the JS, we may improve its efficiency and find optimal answers with less work.

4. Results and Discussion

To simulate the phenomena of interest, NS-2 is used. The art shown here makes use of a 1000m by 1000m space. Omni directional antennas may send and receive data in whatever direction they face. A total of 500 nodes will be used, with a transmission distance of 30 metres. The packet has a size of 512 bytes and a total of 17 CH. Bandwidth (BW) is measured in megabits per second. The initial state of the node's energy is 0.65mJ. The packet rate is 35 packets per second, and the iteration value is 100. Maximum speed is 20 metres per second, and the chosen traffic type is constant bit rate. Information on these factors is summarised in Table 1..

Table 1 Simulation Strictures.

Parameters	**Value**
Size of packets	512 bytes
Number of CH	17
Number of nodes	500
Range of broadcast	30m
Area	1000m x 1000m
The direction of the antenna	Omni-directional
BW	11 Mbps
The preliminary energy of nodes	0.65mJ
Simulation Time	500 sec
Value of iteration	100
Rate of packet	35 packets / s
Typical of movement	random-way point
Typical of radio propagation	two-ray ground
Type of traffic	constant bit rate
Maximum Speed	20 m / s

4.1. Performance Metrics and Measures

The End-to-End Delay, Bit Error Rate, Packet Drop Ratio, Network Lifespan, Packet Loss Rate, Data Rate, and Power Used are used to measure how well the suggested approach works.

4.1.1. End- to -End Delay

How long it takes for data to travel over a network.

$$End - to - End\ Delay = \sum_{e_g=1}^{e_g\ max} \frac{E(W_u, W_v)}{A} \qquad (35)$$

With e g standing in for the total number of hops between the uth and wth nodes. A represents the rate at which the signal travels. Uth-to-vth-node distances are denoted by$E(W_u, W_v)$.

4.1.2. Packet Delivery Ratio

It is the number of packets received divided by the number of packets sent by the sensor node..

$$PDR = \frac{overall\ \ packets\ \ reac\,hed\ at\ destination}{total\ \ packets\ \ created\ \ at\ the\ sensor\ \ node} \times 100 \quad (36)$$

4.1.3. Packet Loss Ratio (PLR)

Percentage of all packets sent between a source and a destination that never made it there.

$$Packet\ Loss\ Ratio = \frac{total\ \ number\ \ of\ lose\ packets}{total\ \ number\ \ of\ packetstransmitted} \times 100 \qquad (37)$$

4.1.4. Throughput

Data transfer rate is the total quantity of data sent from a source to a receiver in a certain time frame..

$$Throughput = \frac{total\ \ number\ \ of\ delivered\ \ packets}{value\ \ of\ timetaken} \qquad (38)$$

4.1.5. Energy Consumption

It is a measure of how much power was used for transmission between the nodes and the CH..

$$\mathrm{E_C} = \sum_{\mathrm{c=1}}^{\mathrm{l}} [\mathrm{CH_E(C)} + \sum_{\mathrm{r=1}}^{\mathrm{zc}} \mathrm{H_E(zc)}] \qquad (39)$$

Where total energy consumption is represented by E C and CH's energy consumption is shown bybyCH$_{\mathrm{E}}$(C). The node energy consumption is indicated by $\mathrm{S_E}$.

4.1.6. Network Lifetime

The time it takes for the first sensor in a network to run out of juice.

$$\mathrm{N_t} = \min(\mathrm{N_{ts}}) \qquad (40)$$

Where the lifespan of the network is signified by $\mathrm{N_t}$, and lifespan of sensor is signified by $\mathrm{N_{ts}}$.

4.1.7. Energy Efficiency

The efficiency of the proposed model is determined by comparing the amount of energy remaining in a node after a given transmission to the amount of energy that was present in the node before the transmission..

$$\text{Energy Efficiency} = \frac{\text{energy after certain transmission}}{\text{total available energy at initial stage}} \qquad (41)$$

The suggested model is used to measure and validate the aforementioned parameters using BSWOA [16], RMSG [17], and GWMTA [22]. Energy use breakdown by model is shown in Table 2.

Table 2: Energy Consumption of proposed model

nodes **methods**	**100**	**200**	**300**	**400**	**500**
BSWOA	1.10	1.28	1.40	1.55	1.75
RMSG	0.81	1.20	1.35	1.42	1.55
GWMTA	0.71	0.79	1.05	1.15	1.30
Proposed	0.61	0.70	0.90	0.92	0.98

Table 2 shows the results of an examination of the suggested method's energy consumption using several methods. There are between 100 and 500 nodes. The suggested solution outperforms previously used routing techniques in terms of energy efficiency. With 100 nodes, the suggested ASO-IJSO uses less energy (0.61mJ). Energy consumption values of 0.71mJ (GWMTA), 0.81mJ (RMSG), and 1.10mJ were found using several methods for a network with 100 nodes (BSWOA). As more and more nodes are added, the value of Energy Consumption rises. For 500 nodes, for example, the suggested model uses 0.98mJ of energy, whereas GWMTA uses 1.30mJ, RMSG uses 1.55mJ, and BSWOA uses 1.75mJ..

Table 3: Analysis of Throughput

nodes **methods**	100	200	300	400	500
BSWOA	0.70	0.63	0.60	0.57	0.54

RMSG	0.89	0.81	0.77	0.70	0.62
GWMTA	0.90	0.86	0.80	0.75	0.68
Proposed	0.94	0.93	0.88	0.81	0.78

The comparison of the suggested method's throughput to that of certain alternative methods is shown in Table 3. In terms of throughput, the suggested ASO-IJSO technique excels above competing approaches. As the sum of nodes in use rises, the throughput value drops for all approaches. At first, 100 nodes achieve a throughput of 0.94Mbps using the suggested technique. Throughput values obtained using the other techniques are 0.90 Mbps (GWMTA), 0.89 Mbps (RMSG), and 0.70 Mbps (BSWOA). From the results, we can conclude that the suggested model is more efficient in terms of data transmission time. The BSWOA has inferior throughput performance across the board when compared to other methods. For 200–500 nodes, the respective BSWOA bandwidth requirements are 0.63 Mbps, 0.60 Mbps, 0.57 Mbps, and 0.54 Mbps..

Table 4: Comparative Analysis of PDR

nodes **methods**	100	200	300	400	500
BSWOA	0.85	0.79	0.75	0.70	0.65
RMSG	0.89	0.86	0.83	0.81	0.79
GWMTA	0.94	0.92	0.89	0.86	0.83
Proposed	0.98	0.97	0.96	0.95	0.94

The suggested model's PDR analysis using other methods is shown in Table 4. Early on, our suggested technique yields greater PDR performance (98%). Other methods have an initial PDR value of 86% (RMSG), 89% (BSWOA), and 94% (GWMTA). As the number of nodes increases, so does the value of PDR. Even if there are 500 nodes in the network, the PDR is reduced using every technique. The PDR performance of BSWOA is the worst of all the methods tested. At a node value of 400, the BSWOA was able to achieve 70% PDR, the RMSG 81%, the GWMTA 86%, and the suggested model 95%.

Table 5: PLR Analysis

nodes / **methods**	100	200	300	400	500
BSWOA	10	15	20	25	30
RMSG	7	13	18	23	27
GWMTA	5	10	15	20	25
Proposed	1	3	7	9	11

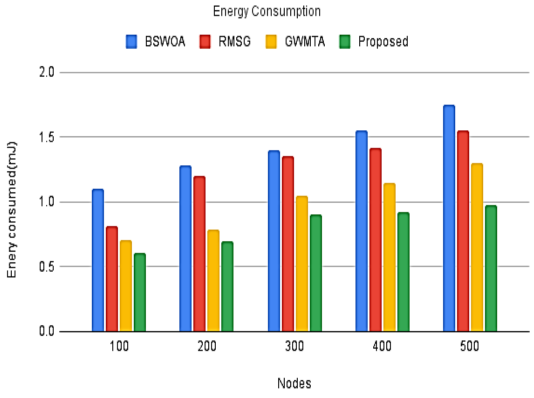

Fig. 1. Energy Consumption

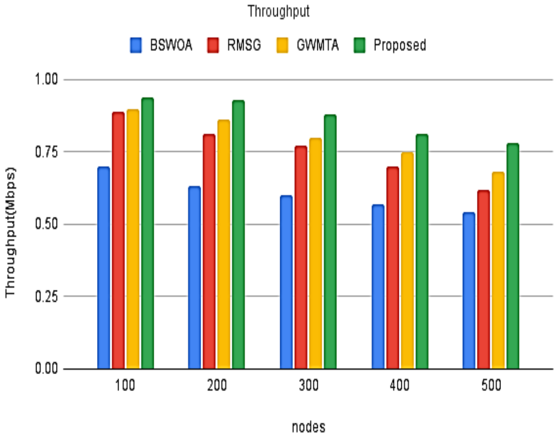

Fig. 2. Throughput

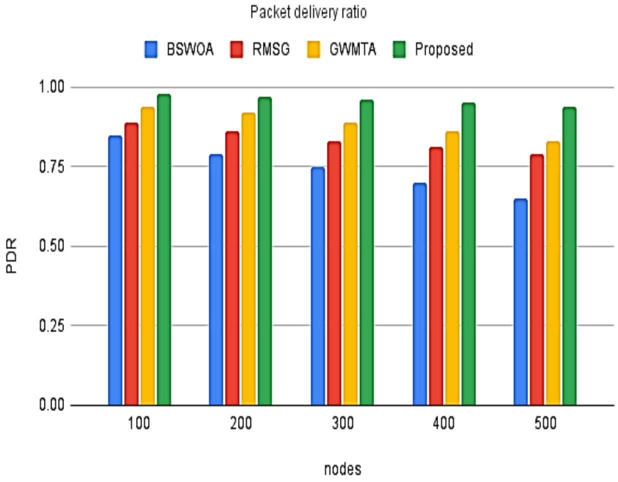

Fig. 3 packet delivery ratio

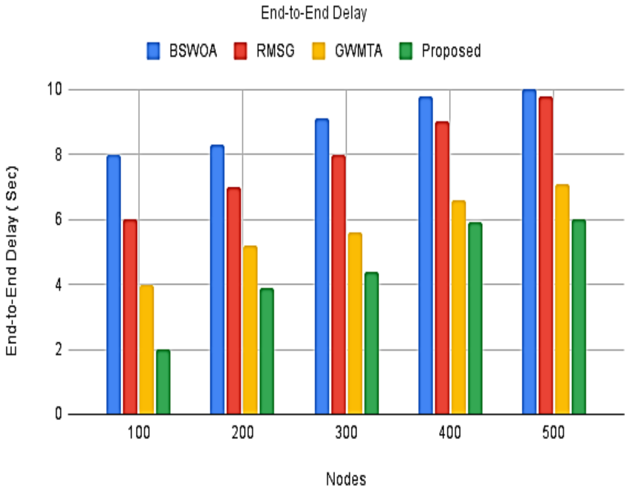

Fig.4. End-to-End delay

The PLR comparison of the projected technique to existing approaches is shown in Table 5. In the instance of 100 nodes, our suggested technique yields a PLR value that is 1 percentage point lower than the alternatives. In the instance of 100 nodes, the PLR values of GWMTA (5%), RMSG (7%), and a random forest (10%) all compare well to a random forest (5%). (BSWOA). At 300 nodes, PLR rises steadily across all approaches. In general, as the number of nodes grows, so does the value of PLR. The PLR performance of the suggested model is the worst..

Table 6: Node Density Analysis

nodes **methods**	100	200	300	400	500
BSWOA	3000	2750	2500	2250	2100
RMSG	4500	4250	4000	3750	3500
GWMTA	5000	4750	4500	4250	4000
Proposed	5500	5250	5000	4775	4500

To compare the proposed model's network's performance to that of other approaches, see Table 6. In a study with 100 nodes, the suggested technique had the longest Network Lifetime (5500 rounds). The alternative technique uses 100 nodes to demonstrate Network Performance after 5000 rounds of GWMTA, 4500 rounds of RMSG, and 3000 rounds of BSWOA. Growing the network to more nodes shortens its lifetime. Poor long-term performance is shown by the BSWOA study..

Table 7: End-to-End Delay Analysis

nodes **methods**	100	200	300	400	500
BSWOA	8	8.3	9.1	9.8	10
RMSG	6	7	8	9	9.8
GWMTA	4	5.2	5.6	6.6	7.1
Proposed	2	3.9	4.4	5.9	6

A comparison of the suggested model's End-to-End Delay to that of other approaches is shown in Table 7. Upon further inspection, it becomes clear that the suggested effort results in a shorter End-to-End Delay than competing approaches. The proposed technique has an initial End-to-End Delay of 2s for 100 nodes. Starting End-to-End Delay values for a network with 100 nodes may be found in the range of 4s (GWMTA), 6s (RMSG), and 8s (BSWOA) using the many different approaches..

5. Conclusion

When it comes to MANETs), one of the most pressing concerns is how to route data while minimising energy consumption. The appropriate clustering approach is urgently required for efficient communication in MANET. It picks a node that is less deviated from stability and depletes its less energy to function as CH, improving its life time, in order to select ideal nodes to operate as CHs that coordinate their cluster members for longer durations of time. The best CH employed ASO to generate more favourable energy and NLT for the selection process. The optimal distance between cluster nodes and CHs is determined by averaging the distances between all of the nodes in the cluster and each of the CHs. AODMV is used for multipath routing, and the IJSO algorithm determines the best path to take. In doing so, it enhances the network's performance by decreasing the amount of lost packets. As with other energy-aware routing methods, the proposed routing protocol has a minimal impact on network resources. The suggested model will be refined in further research to boost the portability and safety of MANETs.

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