Cluster Head Selection using Spotted Hyena Optimizer for Energy-Efficient Routing in MANET

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***Abstract*—Mobile ad-hoc network with the Internet of Things (MANET-IoT) environment is the focus of many researchers on developing a next-generation mobility network. Many real-time problems, such as military, smart cities, precision agriculture, intelligent traffic, smart healthcare, etc., are resolved by MANET-IoT due to its simplicity and effectiveness. However, the main problems with MANET devices are portability and limited battery life. Advanced technologies are important to improve MANET power performance and extend network life. Clustering is one of the tried and tested ways to increase network life by reducing and balancing energy use. Choosing the right Cluster Head (CH) from the group of clusters increases the energy efficiency of the network. Because of the extra workload, CHs use more power than normal nodes. Therefore, in this research work, a new algorithm for CH selection using the Spotted Hyena Optimizer (SHO) is developed to improve the energy efficiency and longevity of the MANET network. The proposed SHO technique has been developed for effective CH selection according to the gravitation law and mimics the social behavior of spotted hyenas. The technique is a mathematical model discussed using three steps: searching, encircling, and attacking the prey. The NS-2 platform is used in this research to implement the proposed network. The existing techniques, such as PSO-GA, GBTC, FCO, and CMBCA, are used to compare with the proposed SHO in terms of network parameters such as energy consumption, throughput, etc. The experimental results proved that the projected SHO achieved more efficient results than the existing techniques.**

***Index Terms*—Clustering, Energy Consumption, Mobile Adhoc Network, Cluster Head, Spotted Hyena Optimizer, Network Lifetime**

I. INTRODUCTION

In the IoT era network, a breakthrough development in the Information Technology department has been shown by the 5G network advancement. A large number of devices can be able to attach to the Internet by using tremendously low latency and high bandwidth, which is allowed by these 5G models [1]. In addition, Cisco predicts that by 2023, more than 15 billion mobile devices will be associated with the Internet. These sensor devices have IoT modules to establish direct interconnections without relying on base stations (MANET-IoT Networking Policy) [2]. MANETs are a family of portable radios that can manually set parameters for data communication and transmission over the network. Despite its limited capabilities, the MANET environment can significantly contribute to designing the future of the Internet.[4].

Nowadays, MANET-IoT received good attention from the research community for helping humanity by proposing various solutions in different fields such as retail utilities, smart cities, precision agriculture, and intelligent transportation system [5-8]. These devices use a large amount of electricity. Hence, researchers focused on saving the power consumption for MANET-IoT networks with great interest [9] by modifying the developed existing systems [10]. In the MANET-IoT network, the mobile network terminals use low-power batteries. Clustering is the most important method in the MANET environment to improve network life with a balanced force. Cluster-based methods balance network strength, increase lifespan, and reduce communication overhead. There are several ways to create groups and CH [11]. Therefore, researchers found that clustering-based routing is the most important technique for creating effective energy-efficient routing on MANETs.

CH selection is the process of selecting the leader node of a node within the cluster. The cluster head (CH) stores information about its group. This information includes a list of nodes in the cluster and the path to each node [12]. CH is responsible for communicating with all nodes in its group. However, the CH must communicate directly with the nodes of the other groups, either through the respective CHs or gates. When deciding which node will serve as the best CH, several criteria can be taken into account [13]. Some of these elements include the node's position, movement, energy, self-assurance, and performance in relation to other nodes. The resources and battery life of WSN and MANET nodes are depleting.The selection procedure raises the network's general processing effectiveness. The selection method must therefore take into account processing and power limitations. The CH for each cluster must be specified during the selection process since multiple cluster heads within the cluster can create cluster upgrades, the

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quality of service (QoS), and routing management issues [14].

Five types of CH selection and classification algorithms are presented. It depends on traffic, identifier, connectivity, power, and cost [15]. CH is selected in the energy-saving assembly approach due to its high energy and low mobility. After CH selection, an energy-saving path was also chosen for data transmission [16]. Mobility awareness and energy efficiency are the two major issues faced by MANET. The nodes tend to move in the wrong direction due to mobility awareness, which causes less capacity for node battery and minimizes the overall topology network's performance. CH node loses most of the energy because of topological changes and node mobility. Hence, it is essential to design an energy-efficient protocol for CH selection to solve the problems faced by the network. The main contribution of the research work is categorized as follows:

- ❖ This research work designs a performance-enhancing energy-efficient CH selection algorithm and longevity of MANET
- ❖ The main aim of creating an efficient mass/cluster with a weight function is to improve the effectiveness of CH selection methods for energy conservation.
- ❖ The SHO approach is used to determine the optimal CH node for MANET.

The rest of this paper is arranged as follows. Section 2 describes a survey of existing works on MANET-IoT. Section 3 describes the planned CH selection mechanism.Following its validation in NS-2, Section 4 presents the findings and conversation of the proposed work.Section 5 concludes with a scientific contribution from studies on future development.

II. Related Works

An energy-efficient routing algorithm using learning automata is developed by the author S.Hao et al. [17]. According to learning automata theory, the rate function of effective energy is defined and developed as a model for node stability measurement. When compared with traditional routing protocols, this model is validated using latency, consumption of energy, and the packet delivery ratio in the simulation process.

In the urban IoT network, a framework of an energy-aware data delivery model is designed for multimedia application by F. Al-Turjman et al. in [18]. According to the QoS, guarantee routes only; the packets are transferred from nodes to the base station. Three parameters such as energy consumption, throughput, and latency, are used for validating the performance of the model in mobility scenarios.

In the tactical MANET environment, a routing algorithm based on TDMA scheduling is proposed by J. S. Lee et al. [19]. According to the schedule, the energy efficiency is improved by processing the TDMA slot at the commander node. However, the consumption of energy is high in this approach, but it enhances the overall network performance.

The author proposes a routing protocol based on the MAC layer for improving energy efficiency [20]. To achieve a multi-objective optimizer, routing metrics such as residual energy and transmit power from the MAC layer are considered in this model. In the MANET-IoT environment, the network performance is enhanced by this model when compared with the traditional routing protocols.

A meta-heuristic-based routing algorithm is developed for flying ad-hoc networks (FANET) by the author U. Khan et al. [21]. According to the selected energy parameters, the route is optimized by using the ant colony algorithm in FANET. There is less energy consumption by the developed ACO algorithm, and network presentation is also improved, which is proven by the simulation process when compared with traditional techniques in FANET scenarios. AOMDV-FFN protocol is developed by the author A. Bhardwaj[22]. An integration is developed with a genetic algorithm into fitness function for developing a new routing protocol in the mobility MANET environment. The residual energy parameter is used to compare the presentation of the developed model with existing protocols such as AODV, FF-AOMDV, and AOMDV.

Masood Ahmad et al. [23] introduced a Tabu Clustering technique based on honey Bee and Genetic procedure (GBTC). This structure reduces the overhead of topology maintenance. This combined algorithm provides dynamic solutions with improved quality.

Amutha S et al. [24] focused on CH's energy issues and workload by developing a (CMBCH) selection scheme. The CH is in charge of packet delivery between network sensor nodes.This approach offers low bandwidth, consistent energy.However, there is a key flaw in this research, which is the employment of an additional apparatus for a selection procedure that results in low bandwidth automatically.

Fuzzy constraint-based cluster optimization (FCO) is designed by Amin Saleh Muhammad and others [25]. The efficient use of energy is a problem that cannot be solved in temporary networks. To calculate the fitness value of the node, the fuzzy parameter uses hop count, energy, speed of movement, and position of devices. Then, the selection process for CH is carried out according to the exercise value. However, this method did not address uncertainties such as topographic variance, energy depletion, and failure for CH.

A. Research Gap

The severe primary problem faced by temporary networks is power consumption. Power consumption and network life are strongly correlated in temporary networks. Current research focuses on improving network durability, power consumption, general issues, etc. In addition, most low-power technologies use more CH, leading to defective data distribution. Some existing works minimize the number of CH; however, the strength of the received signal is weak. Therefore, every routing algorithm has its advantages along with a few drawbacks. The authors concentrated on optimization methods that offer the greatest solution to these issues.

II. Proposed Methodology

In order to improve the MANET-IoT environment, the weight function for cluster formation with the SHO approach is developed. The clustering approach includes formation, is carried out using the optimal weight function, and the selection of CH is processed by the SHO method.

Various parameters such as distance, a ratio of neighborhood nodes, and residual energy are considered to create clusters, and the simplification process helps in calculating the center of mass. SHO is used to determine CH depending on the formed clusters. To determine CH using SHO, factors such as energy, degree, and mobility are evaluated. According to the energy value of CH, the placement process is taken in this research work, where Fig.1 shows the block diagram of the research study with the SHO approach.

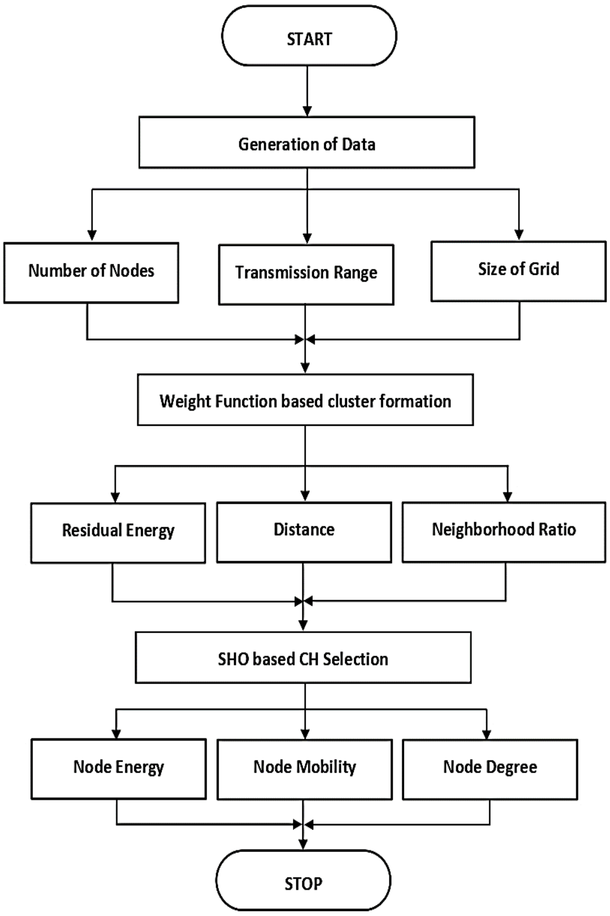

Fig.1. Selection of CH in MANET for an effective Energy Efficient Scheme

There are three stages in this architecture, where stages include the generation of data, weight function for the formation of cluster nodes, and the election of CH using the SHO technique. By identifying the size of the grid, transmission range, and the total sum of nodes, the data generation process is carried out as the first step. The second stage is cluster formation based on residual energy, distance, and the ratio of the neighborhood. Finally, the CH is selected based on energy, mobility, and the degree of nodes from the formation of clusters using the SHO methodology.

A. Clustering Model of MANET

The major issue of MANET's concept is limited battery life and mobility issues, which should be addressed by an effective energy-efficient system. The clustering model for MANET is given in Fig. 2, which contains CH, gateway, and nodes. Gateway and CH are used for the communication process by connecting with nodes. Here, each cluster head(CH) is connected with two gateways, as shown in Fig.2. The node with parameters such as energy, mobility, and degree is selected as CH. Once the selection process is done, data transmission occurs using a routing algorithm.

B. Cluster formation

In MANET-IoT, the identification of optimal CHs can lead to optimal cluster formation and network lifespan. In this process, clusters are formed using residual energy, the ratio of neighborhood nodes, and distance from the. To generate the optimal formation of clusters, the researchers create a weight function at leads locally

$$CH_w(T_i, CH_j) = K * \frac{E_R(CH_j)}{\theta(T_i, CH_j) \times \theta(CH_j, BS) \times DN(CH_j)} \quad (1)$$

Where K is the value of the constant parameter (i.e.K = 1), E_R $(CH_j)$is the residual energy of the CH. $(T_i,\ CH_j)$ is the distance between the target sensor node (i.e., the standard sensor node) and the jth node of CH. $(CH_j, BS)$is the distance between the CH and the base station. $D(CH_j)$ is expressed as the surrounding ratio of CH. The high weight value of $the\ ith$ sensor will have the capacity to join with jth CH.

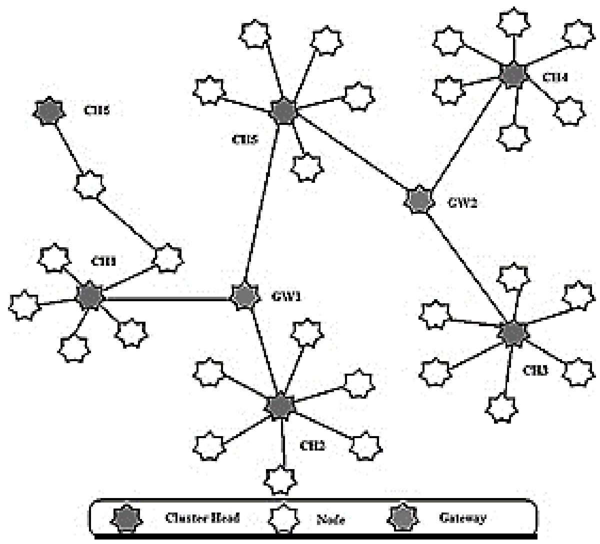

Fig. 2 Clustering Model of MANET

C. SHO approach for Electing the CH

From the formation of clusters based on distance, residual energy, and neighborhood ratio, the SHO is used to elect the CH, where this bio-inspired algorithm is introduced by the author [26]. This algorithm's core idea is to pretend the social behaviours of spotted hyenas. This algorithm, which is based on the behaviours of spotted hyenas, only has four steps: encircling, hunting for prey, attacking, and searching. Towards the best search agent for CH, a group of trusted hyenas, as shown in Fig. 3(redrawn based on [28]),

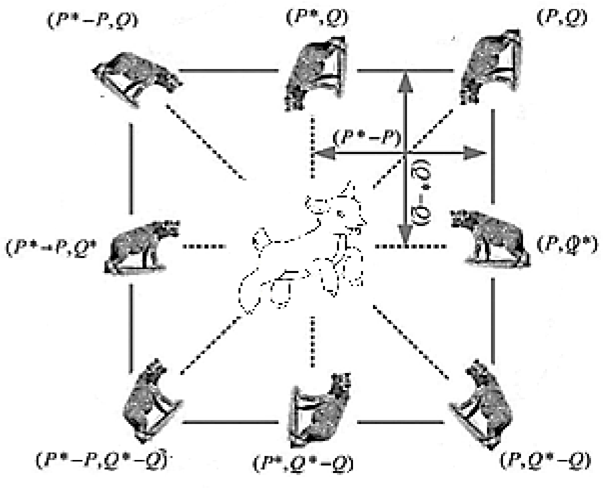

Fig 3: Spotted Hyena Optimization Algorithm (redrawn based on [28])

C.1. Embedding Prey

Here, the ideal response is viewed as either an object or a prey(i.e., CH selection based on three parameters), where the other search agents' positions and locations are updated in accordance with the best search result found. Equations (1) and (2)

$$\vec{D}_h = \left|\vec{A} \times \vec{P}_p(x) - \vec{P}(x)\right|, \quad (2)$$

$$\vec{P}(x+1) = \vec{P}_p(x) - \vec{C} \times \vec{D}_h, \quad (3)$$

At the position of the prey, the distance among the hyenas is shown as$\vec{D}_h$, the shared vectors are shown as open$\overrightarrow{A}$ and$\overrightarrow{C}$, , the current frequency is shown as$x$, the prey's location vector is shown as$\overrightarrow{P_p}$, and finally, the location vector of the hyena is utilised as $\vec{P}$.The common vectors are calculated using equations (4 and 5), and equation (6) is used to determine the number of limit iterations that should be utilised in equation (5).

$$\overrightarrow{A} = 2 \times r\vec{d}_1 \quad (4)$$

$$\vec{C} = 2\vec{s} \times r\vec{d}_2 - \vec{h} \quad (5)$$

$$\vec{s} = 5 - (Iteration \times \frac{5}{Max_{Iteration}}) \quad (6)$$

$$Iteration = 0 \; to \; Max_{Iteration}.$$

The symbols $r\vec{d}_1$ and $r\vec{d}_2$, refer to random vectors with a range of 0 and 1 where $\vec{s}$ is a parameter from 5 to 0.

C.2. Hunting

The following Equations. (7-9) is used to describe the strategy of SHO for the hunting process.

$$\vec{D}_h = |\vec{A} \times \vec{P}_h - \vec{P}_k| \quad (7)$$

$$\vec{P}_k = \vec{P}_h - \vec{C} \times \vec{D}_h \quad (8)$$

$$\vec{C}_h = \vec{P}_k + \vec{P}_{k+1} + \cdots + \vec{P}_{k+N} \quad (9)$$

Where $\vec{P}_h$,stands for the originalbest-spotted hyena location and $\vec{P}_k$ for the other spotted hyena position..

$$N = Count_{nos}(\vec{P}_h, \vec{P}_{h+1}, \vec{P}_{h+2}, \ldots, \vec{P}_h + \vec{M}) \quad (10)$$

The value of the random vector,$\vec{M}$, which is used to candidates, ranges from 0.5 to 1.The optimal set's solution is denoted by$\vec{C}_h$for the number N.

C.3. Attacking the Target

The spotted hyena attacks its target or prey using the following equation (11).

$$\vec{P}(x+1) = \frac{\vec{C}_h}{N} \quad (11)$$

The best answer is safeguarded using $\vec{P}(x+1)$,which updates the status of additional spotted hyena search agents, in accordance with the state of the best search agents.CH can be determined for parameter values from $\vec{P}(x+1)$ based on node energy, motion, and degree.

C.4. Search for Prey

When using equation (5) to determine an appropriate answer, $\vec{C}$ is in charge if it is greater than or equal to 1..In addition, the SHO algorithm uses the other important component, i.e. the $\overrightarrow{A}$, for in equation (4), The random value offered in this other component determines the prey's random weight.The vector $\vec{A}$>1is chosen over $\vec{A}$<1 in order to prove the inconsistent behaviour of the SHO algorithm and the impact of divergence.

By resolving the high-dimensional problems with minimal processing cost, the SHO algorithm gets rid of the optimal local problem. The following algorithm shows the simple step of the SHO algorithm.

Input: Spotted hyenas population/number of clusters formed in the group, $P_i \; where \; i = 1, 2, \ldots, n$
Output: Selection of CH based on best search agent.

SHO process
1: start with parameters h, A, C, N
2: Estimate the suitability of each search agent
3: P_h= best search agent for CH
4: C_h = set or set of optimal solutions
5: while $(x < MaxIteration)$ do
6: for each spotted hyena's search agent, do
7: By using Eq. (10), update the current agent's status
8: end for
9: update the parameters
10: Find whether the specified location of the search agent is exceeding. If so, fix it
11: Estimate the suitability of each search agent
12: If a healthier solution is achieved than the previous optimal solution, then update P_h
13: Inform the $C_h$group according to P_h
14: x = x + 1
14: end while
15: Return the output of SHO
16: End the decision-making process

VI. Results and Discussion

The whole research work is implemented using the NS-2 simulator, where Table 1 shows the parameter specification of the network. Here, the random-way point is considered as a movement model, set the maximum speed limit as 20m per second, and considered the constant bit rate is traffic type.

TABLE I
SIMULATION PARAMETERS.

Parameters	Value
Area	1000*m* x 1000*m*
Antenna direction	Omni-directional
Number of Network nodes	500
Transmission range	30*m*
Packets Size	512 bytes
Cluster heads	17
Bandwidth	11 *Mbps*
Initial energy	0.65mJ
Time of Simulation	500 sec
Number of iteration	100
Packet Range	35 *packets / s*
Area	1000*m* x 1000*m*
Antenna direction	Omni-directional
Number of Network nodes	500
Transmission range	30*m*

A. Performance Metrics

Six different types of parameters, such as the lifetime of the network, consumption, the ratio as PDR, are considered in this research work for the validation process.

A.1. Delay time/End-to-end delay

Over the whole network, the total time taken for transmitting the packets is defined as delay time.

$$\text{End} - \text{ to } - \text{End Delay} = \sum_{e_g=1}^{e_g max} \frac{E(W_{u,}W_v)}{A} \quad (12)$$

Where e_g, denotes the hop count between nodes, A indicates the signal speed. The $E(W_{u,}W_v)$ provides the distance between nodes such as $u\ and\ v$.

A.2. PDR

The ratio among arrived packets at the final destination to the packets developed by the nodes in the network defines the PDR.

$$PDR = \frac{overall\ packets\ reached\ at\ destination}{total\ packets\ created\ at\ the\ sensor\ node} \times 100 \quad (13)$$

A.3. PLR

This PLR defines the overall lost packets with the entiresum of packets that are transferred from starting point to the final destination.

$$Packet\ Loss\ Ratio = \frac{total\ number\ of\ losing\ packets}{the\ total\ number\ of\ packetstransmitted} \times 100 \quad (14)$$

A.4. Throughput

Within a given particular period, throughput is used to calculate the transmitted cumulative information from source to destination.

$$Throughput = \frac{total\ number\ of\ delivered\ packets}{value\ of\ time\ taken} \quad (15)$$

A.5. Consumption of Energy

During the overall successful communication, the quantity of energy taken by the CH and nodes is calculated as energy consumption.

$$E_C = \sum_{c=1}^{1}[CH_E(C) + \sum_{r=1}^{cc} H_E(Zc)] \quad (16)$$

Where E_C is used to denote the overall consumption of energy, and $CH_E(C)$ is used to represent the CH's energy consumption. Finally, H_E is used to characterize the energy ingesting of nodes.

A.6. Lifetime of Network

In the network, the time taken for the initial node to run out of energy is used to calculate this parameter.

$$N_t = \min(N_{ts}) \quad (17)$$

Where N_t represents the overall network lifespan, and N_{ts} is denoted as the sensor's lifespan.

The validation of SHO is measured by using all the six explained parameters, and its effectiveness is compared with existing techniques such as GBTC from [23], CM-BCA from [24], FCO from [25], and hybrid PSO-GA from [27]. In this hybrid work, cluster formation is carried out by a soft k-means clustering algorithm, and PSO-GA is used for electing the CH from those formed cluster groups for data transmission. Different parameters are used for cluster formation, such as speed, where the whole process is implemented in the NS-2 simulator. But, in our research work, three different parameters are chosen for generating the clusters and use a single meta-heuristic algorithm for electing the CH.

B. Proposed System Evaluation

The node density for each technique, including the proposed SHO, lies in the value of 100 to 500. The experiments are carried out to test the energy consumption of every technique, and Fig. 4 shows its graphical representation.

The existing methods have high energy consumption, where the proposed SHO has low consumption of energy, i.e., 0.61mJ for the node density 100, where the FCO has 1.11mJ, GBTC has 1.32mJ, PSO-GA has 0.78mJ, and CMBCA has 1.26mJ for the same node density. When the number of node densities is high, the consumption of energy, even for the proposed method, is also high. For instance, the proposed SHO consumes 0.93mJ, whereas the other techniques, such as GBTC, CMBCA, FCO, and

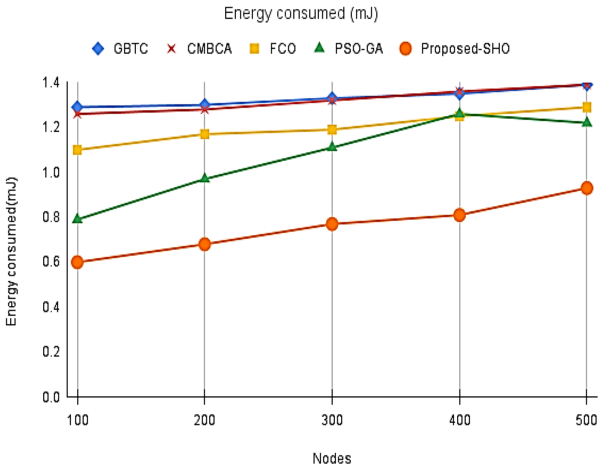

Fig 4: Performance Analysis of Energy Consumption

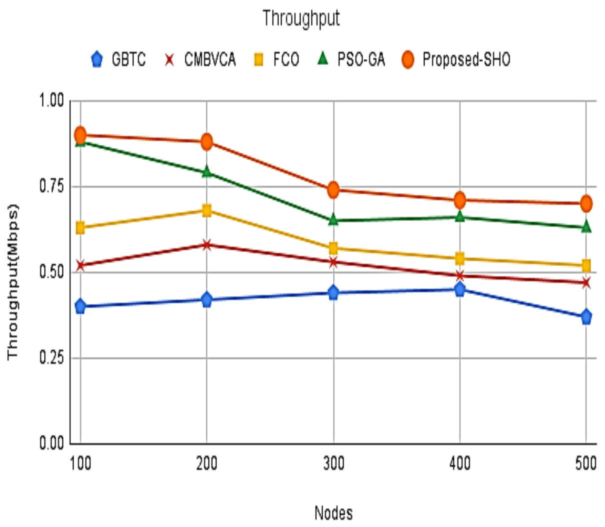

Fig. 5: Performance Analysis of Throughput

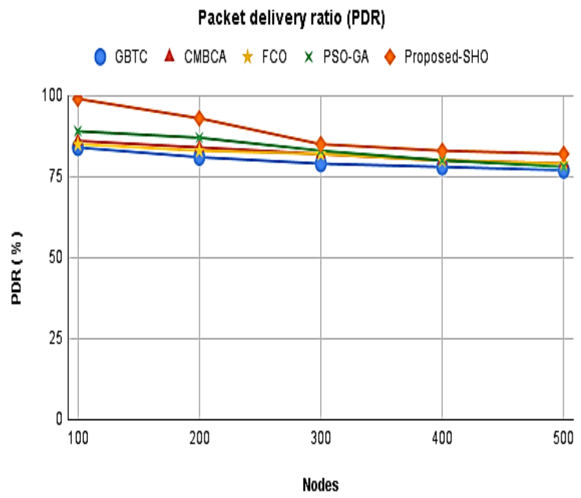

Fig 6: Performance Analysis of Packet Delivery Ratio

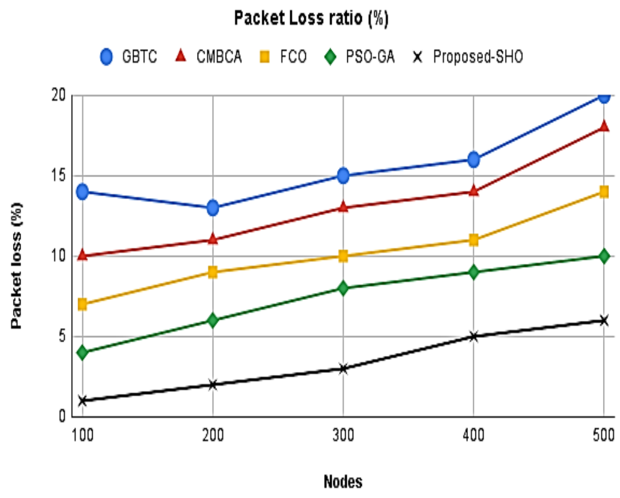

Fig 7. Performance Investigation of Packet Loss Ratio

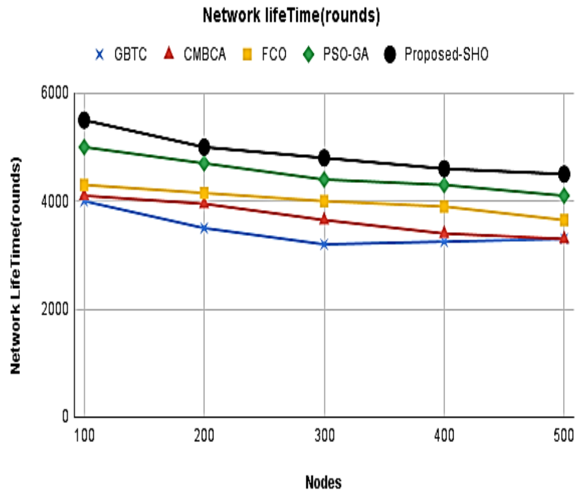

Fig. 8: Graphical Representation of Proposed SHO in Terms of Network Lifetime

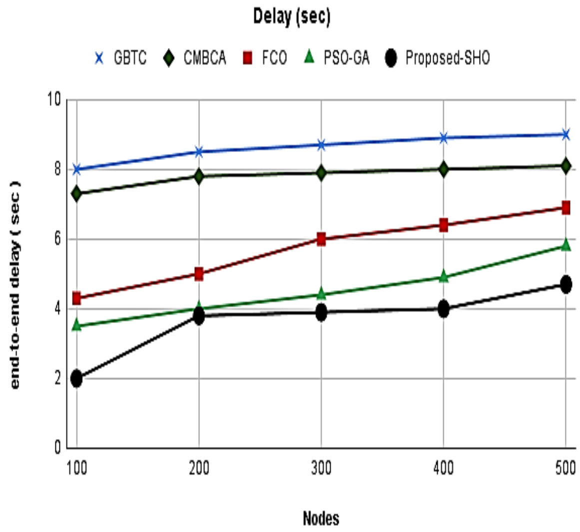

Fig 9: Presentation Analysis of End-to-End Delay

PSO-GA consumed 1.4mJ, 1.38mJ, 1.16mJ, and 1.15mJ. The reason for the better performance of the projected method is that the convergence investigation of the SHO algorithm is based on only three parameters such as search history, trajectory, and average fitness. The throughput performance of the proposed SHO with other procedures is shown in Fig.5.

The proposed SHO method offers higher performance than other technologies. Initially, when the node is 100, the SHO method reaches a performance value of 0.91 Mbps. Other methods offer 0.63 Mbps (FCO), 0.52 Mbps (CM-BCA), 0.41 Mbps (GBTC), and 0.89 Mbps (PSO-GA). However, the same techniques, such as GBTC, CM-BCA, FCO, and PSO-GA, achieved 0.36Mbps, 0.48Mbps, 0.53Mbps, and 0.63Mbps, but the proposed SHO achieved 0.71Mbps of throughput for node 500. It can be seen from the results that the proposed SHO takes less time to transmit data. The GBTC gives lower throughput performance due to more number of iterations and a lot of tunable parameters in Tabu clustering. The assessment of other techniques with the proposed SHO in terms of PDR analysis is given in the Fig.6.

SHO method provides high efficiency of PDR (98%) during the initial phase, i.e., 100 nodes. The initial PDR value for the other techniques was 94% (FCO), 92% (CMBCA), 87% (GBTC), and 96% (PSO-GA). Even the proposed SHO method provides a low PDR value, i.e., 87%, when the node density reaches 500. GBTC and CMBCA give the lowest PDR performance than FCO and PSO-GA techniques. The existing FCO is not widely used for CH selection because they provide inaccurate results, and no single systematic approach is used for fuzzy constraints. But, the proposed SHO uses the three parameters for electing the CH. The simulation results of SHO with other existing techniques in terms of PLR validation are graphically described in the Fig.7.

When compared with PSO-GA, FCO, and others, SHO offers a lower PLR value (1%) at the initial node of 100. For the same node, FCO has a 7% PLR value, 10% (CM-BCA), 14% (GBTC), and 4% (PSO-GA). When the number of nodes reaches 300, the PLR for every technique provides improvement. GBTC and CMBCA offer higher PLR performance than other technologies. Finally, SHO provides 6% of the PLR, while other technologies, including PSO-GA, provide approximately 11% to 19% of the PLR when it reaches 500 nodes. Due to the high time consumption of GA for formulating the fitness function and selection of population size, the hybrid approach PSO-GA has a high PLR value. The validation of network lifetime for the SHO method is graphically represented in Fig.8.

The projected method attained a higher network lifetime value (i.e., 5500) for 100 nodes, whereas the other techniques perform a network lifetime of 4,400 (FCO), 4,100 (CM-BCA), 4,000 (GBTC), and 5,000 (PSO-GA) for the same nodes respectively. Here, network lifetime is calculated by rounds. As the sum of nodes upsurges, the lifetime of the network decreases. For instance, the SHO achieved 5100 rounds on 200 nodes, 5000 rounds on 300 nodes, and 4800 rounds on 400 and 500 nodes, whereas PSO-GA has nearly 4800 to 4600 rounds on 200, 300, 400, and 500 nodes. Among other techniques, GBTC shows poor performance for a lifetime, which is proven by experiments. Figure 9 shows the delay time investigation of the proposed SHO along with another method.

While comparing with other existing techniques, the above figure states that the proposed SHO achieved less delay time. Initially, the SHO method has 2.1sof end-to-end delay for 100 nodes. For the same initial nodes, the other meta-heuristic techniques have a delay time of 4.5s (FCO), 7.4s (CM-BCA), 8.1s (GBTC), and 3.5s (PSO-GA). The delay upsurges only when the sum of nodes upsurges; for instance, GBTC and CM-BCA achieved nearly 8.4s to 8.8s, FCO and PSO-GA achieved 6.1s to 6.8s on 500 nodes, whereas the proposed SHO achieved only 5.1s for the same number of nodes. Through these empirical analyses, SHO performed better than current techniques based on different network performance parameters and effectively selected the CH using node energy, node density, and node traffic.

V. CONCLUSION

In this work, SHO is used to first-rate the CH for the effective efficient scheme in the MANET-IoT environment. The weight function is used for generating clusters that use different parameters such as distance, neighborhood ratio, and residual energy. Then, the election of CH is carried out by the proposed SHO technique. Here, to select the CH from cluster formation, energy, degree, and mobility of nodes are considered. Six parameters, consumption, delay time, PLR, PDR, and network lifetime, are used for validating the performance analysis of SHO with existing techniques, namely GBTC, FCO, PSO-GA, and CMBCA. The contribution of SHO is implemented on the NS-2 simulator tool, where the experiments show the scientific contribution of SHO for the initial node, i.e.100 is that, 98% PDR, 2.1sec of delay time, 0.61mJ energy consumption, 5500 rounds of a lifetime for the network, 1% of PLR and 0.91Mbps of throughput. But, the data transmission using routing needs to be focused on in this research work, which will be addressed in future work. Therefore, secure shortest-path routing will be developed along with optimal CH selection may be carried out for effective data transmission and improved network performance.

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