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DEEP HYPERBOLIC GRAPH ATTENTION NETWORK-CLOUDED LEOPARD ROUTING ALGORITHM FOR CLUSTERED ROUTING IN IOT-MANETS

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In the context of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs), efficient routing and energy conservation are critical due to the dynamic nature of the network and the limited energy resources of the devices. The paper presented an Improved Snow Geese Deep Hyperbolic graph Attention Network based Clouded Leopard Routing Algorithm (SGA-DHGAN-CLRA) for clustering, with the goal of optimising the energy-saving performance of the MANET network. In order to select nodes that can operate at a time with the least amount of energy consumption, Snow Geese optimisation (SGO) has made CH selection more important. In addition, enhanced Deep Hyperbolic graph Attention Network-based Clouded Leopard Routing Algorithm (DHGAN-CLRA) for enhanced routing that aims to choose the best path for data transmission throughout the network. Finally, performance indicators including throughput, energy consumption, delay, packet drop rate, and network were used to evaluate the performance and compared with the existing methods. The network has 955 kbps throughput and 0.12J energy consumption and the network life time is 200 seconds lower than other methods for 1000 rounds for the proposed SGA-DHGAN-CLRA method.

Keywords: Internet of Things, Routing algorithm, Clustering, Energy consumption, Graph attention network

1. Introduction

The Internet of Things (IoT) is transforming wireless telecoms applications, benefiting industries like energy management, senior care, mobile health, and smart education. Routing is crucial in WSN applications, but challenges arise due to scattered, haphazard, and thick sensors [1-2]. Low battery life is a major issue for sensor network designers. To reduce energy usage, an AI-backed routing protocol is essential. This protocol should work in both small and large-scale environments, evenly distribute load among devices, and increase the lifespan of the IoT network [3-4]. MANETs are being used in IoT applications due to their scalability and agility. Despite their limited capabilities, MANETs have demonstrated exceptional competence and hold great promise for the future of the Internet. Low-power routing techniques have been developed because connectivity in multi-hop wireless networks depends on sensor battery power being used efficiently [5-6].

Clustering and routing are two IoT techniques for cutting down on power usage in wireless sensor networks (WSNs). Reducing the number of direct messages transmitted from the sender to the recipient, clustering divides networks into manageable sub-systems [7-8]. Without depending on centralized network architecture, information is linked and shared using portable radios. Because of their usefulness in the dynamic environment of MANETs, cluster-based routing techniques enhance service quality. Cluster heads (CHs) are chosen based on critical factors, while member nodes are the components of hierarchical or cluster-based routing systems [9-11].

From sophisticated, state-of-the-art automation to environmental monitoring, the usage of mobile sensor networks is growing quickly. (MANET) refers to a network that consists of mobile devices that are sent for certain tasks [12-14]. Because there is no government monitoring and the network is autonomous, managing a MANET is more challenging. Among the many other problems facing MANET, the need for adaptability is one of the most important. Many nodes in the far-off network are searching for limitations on data broadcasts [15-17]. The key contributions of this work are given below,

- The paper provides a unique clouded leopard routing algorithm (SGA-DHGAN-CLRA) based on the Improved Snow Geese Deep Hyperbolic graph Attention Network for clustering, with the goal of optimising the energy-saving performance of the MANET network.
- In order to select nodes that can operate at a time with the least amount of energy consumption, Snow Geese Algorithm (SGA) [22] has made CH selection more important.

- In addition, enhanced Deep Hyperbolic graph Attention Network [23]-based Clouded Leopard Routing Algorithm [24] (DHGAN-CLRA) for enhanced routing that aims to choose the best path for data transmission throughout the network.
- Finally, performance indicators including throughput, energy consumption, delay, packet drop rate, and network were used to evaluate the performance and compared with the existing methods.

2. LITERATURE SURVEY

Some of the recent papers related to the work are described below,

In 2023, Nirmaladevi, K. [18] have presented an SN-TOCRP method to pick the cluster heads after hierarchical clustering has formed node clusters. Authentication techniques are used to identify selfish nodes. Trust-based Routing Protocol (BTRP), which is bandwidth-aware, is used to locate and isolate faulty or misbehaving nodes. This helps identify common misbehaviour attacks such as Sybil and wormholes. Modified Glow swarm optimization serves as the foundation for both trust estimates and routing. The experimental analysis carried out on the NS2 simulator shows improved results with an increased packet delivery ratio of 96%, loss ratio of 0.045%, average latency of 0.325 ms, throughput of 76 Kbps, end-to-end delay of 0.425 ms, and energy usage of 88 mJ.

In 2024, Gopalan, S.H, et al, [19] have presented fuzzified PSOR framework, for selecting optimal routes to strengthen network life. By lowering redundant RREQ packets, FPSOR tests transmission metrics such as connection, coverage, neighbor covered, and coverage integrity time ratios. Simulations using NS2.34 simulators improve flooding issues in route discovery and maintenance. Non-production nodes must be removed from route selection using the FPSOR output. As a result, the MANET platform is more efficient since fewer packets are delivered and current variables are replaced, which improves system performance in route discovery and prevents needless information transfer.

In 2024, Ilakkiya, N and Rajaram, A. [20] have introduced Bi-Directional GRU and Trust-based Dijikstra's Method for secure data transport is the. In order to detect intrusions and apply a blocking mechanism to stop them, this approach employs deep packet inspection. Efficiency in terms of productivity, security, detection accuracy, time analysis, and packet delivery ratio has been increased using this technology. Improved network lifetime, higher packet delivery ratios (PDR), lower latency, and effective throughput are all demonstrated by the presented DAG-IDS in the WSN-IoT network. Network security, energy efficiency, and quality are all optimised by this method.

In 2024, Saravanan, S. et al, [21] ADR-MTS, for protecting the organisation from blackhole attack nodes by differentiating between them. The routing mechanism's job of identifying the source, that is, and the total number of nodes is what the ADR-MTS computation does. Upgrades to the route between the source node and the target node are made possible by this routing technique. Packet Delivery Ratio (PDR) improves, as demonstrated by the MATLAB simulation investigation. ADR-MTS computation yields valuable results regarding the location of black holes in MANET-based IoT organisations. A comparable assessment is conducted against the current models in order to increase the efficiency of the system. Outcomes show that the ADR-MTS approach is more efficient than other methods; it gained a PDR of 98.7% and scalability of 98.5%.

2.1 Problem statement

Clustered IoT-MANETs present a number of design issues for routing algorithms: dynamic topology, energy limits, scalability needs, bandwidth limitations, and security risks. In order to guarantee low latency and high throughput, the algorithm must balance energy usage, manage network changes, and include data aggregation and compression strategies to lower transmission overhead. In order to defend against threats, it also requires strong security measures. The objective is to provide a routing solution that is safe, scalable, and energy-efficient.

3. PROPOSED METHODOLOGY

The work presents a novel Improved Snow Geese Deep Hyperbolic graph Attention Network based Clouded Leopard Routing Algorithm (SGA-DHGAN-CLRA) for clustering in order to optimise the MANET network's energy-saving performance. With the usage of Snow Geese optimisation (SGO), CH selection has become more crucial in order to choose nodes that can function at a time with the least amount of energy consumption. In addition propose Improved Deep Hyperbolic graph Attention Network based Clouded Leopard Routing Algorithm (DHGAN-CLRA) optimized routing with the goal of selecting the optimal way to carry data throughout the network. The reduced testing set's quality was evaluated using a range of performance metrics like throughput, energy consumption, delay, network lifetime, PDR, and Packet drop. Figure 1 shows the workflow of the proposed system.

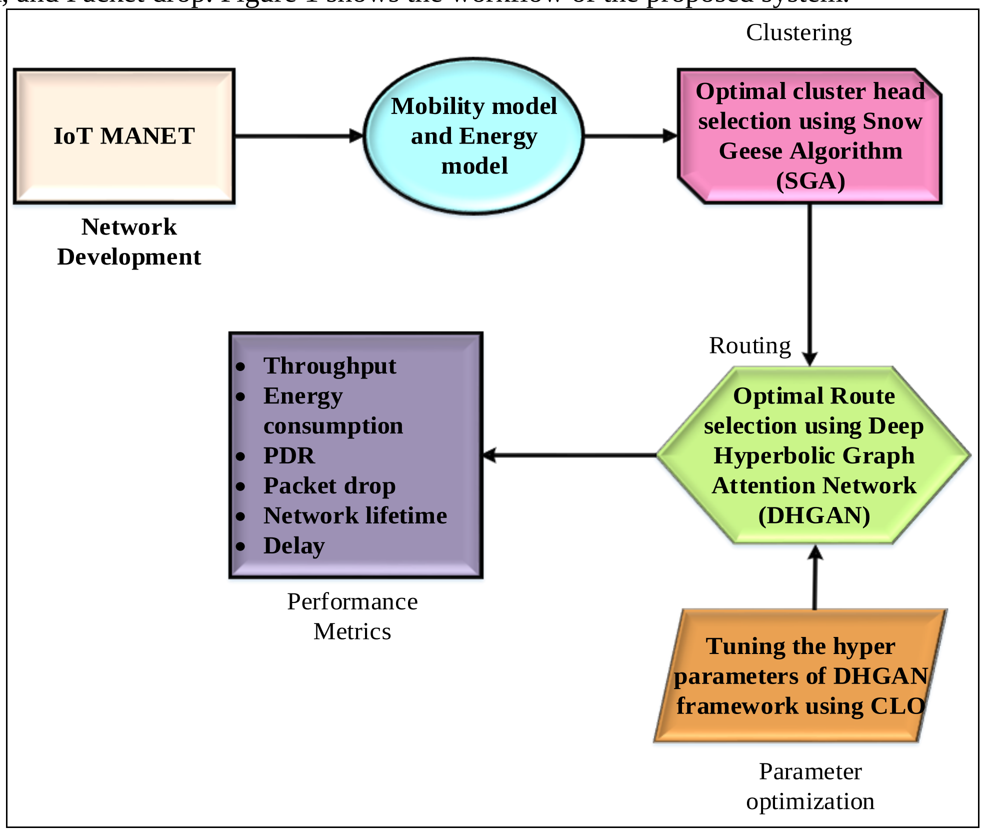

Figure 1: Workflow of the proposed approach

3.1 Network Development

The proposed model involves two rounds of implementation. In the first round, each heterogeneous sensor node is randomly placed in the field, and their distance from the Cluster Manager (CM) to Sensor Nodes (SN) is determined using the received signal strength (RSS). All residual energy values are included in the same control packet, along with the distance to the S.N. Each deployed node calculates its distance during the same round. In the second round, the Cluster Formation (CF) is used to test cluster formations, with the choices of Cluster Head (CLH), Cluster Gateway (CLG), and Cluster Node (CN) being made based on the control and work of C.F. The model assumes that most events, such as sensor deployment and initialization, adhere to IoT-based MANET standard practices. The Euclidean distance equation is utilized to determine the distance between nodes and S.N., and a first-order model is used to calculate energy ingested during data broadcast or reception. A Wireless Harvesting Energy (WHE) unit is installed in each node. The model uses a three-tier approach to aid in load balancing and energy conservation due to high energy usage in long-distance communication.

3.1.1 Deployment of sensors

To process field data, 200 sensors are first placed in two dimensions (2D) over a predetermined area. These nodes vary widely in terms of their capacity, sizes, and other attributes. The positions of the sensors are terrestrial, immovable, and arbitrary. We will select 200 of these deployed nodes for CLG, CLH, and CN. Since the function of the CLH, CLG, or CN changes to another MN when EL falls below a specific level, requiring some calculation to revalidate CF, each SN has a WHE unit to extend the life of the network and reduce computational expenses.

3.1.2 Initialization

During this previous communication phase, the S.N. uses a distribution initiation hello packet $(Init - Hello_{pkt})$ to establish a connection with each organized node. Once the S.N. sends the $(Init - Hello_{pkt})$, each field node considers the mechanism and replies with a reply packet $(\mathrm{Re}\,ply_{pkt})$ S.N. verifies that the message was successfully received by replying with an acknowledged packet (Ack_{pkt}) as soon as it receives $(\mathrm{Re}\,ply_{pkt})$ from nodes. Information about S.N., including the sink node's identification (SN id), is provided in this (Ack_{pkt}) from S.N. to field nodes. It is a centralized control tool that makes node clustering and MANET startup and initialization possible. Furthermore, at this point, SN collects vital data about field nodes such as node individuality N_{id}, residual energy is denoted as (R_E), link quality is indicated as (L_Q), distance ($d_{\tan ce}$) from/to SN.

SN has stored these data for future use. Furthermore, SN evaluates the LQ of every node by using these received P_{kts}. It will also use the Euclidean Equation to get the distance to SN given in equation (1).

$$d_{\tan ce}(n, SN) = \sqrt{(Y_n - Y_{SN})^2 + (X_n - X_{SN})^2}$$
(1)

Where, $d_{\tan ce}(SN)$ represents the node n coolness in relation to the SN. The node coordinates are SN, Y_n, and X_n, in that order.

The nodes will be arranged into many clusters from source to destination, with a unique CH acting as the cluster's local coordinator. Moreover, cluster-based MANETs improve network management since course construction is restricted to clusters, which reduces the size of each node's routing table and takes the LEACH protocol into account. To improve the adaptability and vitality of the network model, CH is chosen using the unique fitness method of the Geyser Inspired Algorithm (GIA) strategy. The two main issues facing the MANET are choosing a C.H. and its energy, which is why mobility energy proficient systems (ME-PS) were created. A C.H. selection method is required to select the best nodes from a group of nodes that sustain their network with other nodes for an extended duration to function as CH. Therefore, creating a clustering process with the least amount of overhead is a helpful way to increase the MANET's network lifespan.

3.1.3 Mobility model

The mobility of the nodes influences the number of regularly associated pathways and thus the performance of the routing method. Increased CH reflection and interface refreshing brought on by mobility have a detrimental effect on cluster stability. The method specifically aims to minimize control overhead by using data.

3.1.4 Energy model

A routing protocol's primary objective should be to maintain the network's functionality for as long as possible, rather than only creating precise and effective paths between groups of nodes. While max-min routing chooses the path with the highest bottleneck residual node energy, ME routing chooses the route with the lowest total energy usage for packet transmission. This energy node is supplied with energy at predefined intervals by equation (2).

$$E_{energy}(t_i, \Delta t) = E_{residual}(t_i, k_0) - E_{residual}(t_i, k_1)$$
(2)

Here, $E_{residual}$ in this case denotes the energy node at periods 0 and 1, respectively.

3.2 Clustering Mechanism Perfect for MANET using Snow Geese Algorithm (SGA)

The flying patterns of snow geese, in particular their characteristic herringbone and straight-line formations, can serve as an inspiration for the clustering process in MANETs, which can be used to optimise network effectiveness in terms of scalability, efficiency, and dependability.

3.2.1 Cluster formation

Every MANET node is compared to a single snow goose in the suggested clustering process, signifying a possible cluster member. The parameters of the clustering issue are correlated with the nodes' spatial placements in the network. Like snow geese constructing flight patterns, the nodes dynamically modify their positions and create clusters based on specific parameters. The nodes' spatial coordinates are indicated by a position matrix (N), while their network speeds are indicated by a velocity matrix (Y) given in equation (3).

$$N = \begin{bmatrix} n_{1,1} & n_{1,2} & .....n_{1,v} \\ n_{2,1} & n_{2,2} & .....n_{2,v} \\ \vdots & \vdots & \vdots \\ n_{x,1} & n_{x,2} & .....n_{x,v} \end{bmatrix} \qquad Y = \begin{bmatrix} y_{1,1} & y_{1,2} & .....y_{1,v} \\ y_{2,1} & y_{2,2} & .....y_{2,v} \\ \vdots & \vdots & \vdots \\ y_{x,1} & y_{x,2} & .....y_{x,v} \end{bmatrix}$$

(3)

Where v is the count of dimensions in the search space and x is the total count of nodes. In order to create clusters, the nodes shift places, decreasing intra-cluster distances and improving inter-cluster distances.

3.2.2 Cluster Head selection

Cluster management efficiency is largely dependent on the cluster head (CH) selection procedure. Chosen based on their capacity to oversee and maintain the cluster, the CHs are motivated by the cooperative behaviour of snow geese, in which leading geese minimise air resistance for the flock. A fitness function that takes into account variables including residual energy, connection, and distance to neighbouring nodes is used to assess each node's suitability as a CH. A vector FR contains the fitness values is given in equation (4).

$$FR = \begin{bmatrix} f_{r1} \\ f_{r2} \\ \vdots \\ f_{rx} \end{bmatrix} \tag{4}$$

The locations, velocities, and fitness values are generated by the function S given in equation (5).

$$S : \theta \rightarrow \{N, Y, FR\} \tag{5}$$

Higher fitness nodes have a higher chance of being chosen as cluster leaders (CHs), guaranteeing that the CHs have enough energy and are positioned optimally to manage the cluster.

3.2.3 Optimal Cluster Head Selection

The SGA-inspired method is used to iteratively modify the placements of CHs and optimise the overall network performance in order to improve the effectiveness and resilience of the clustering mechanism. What controls the velocity updating process is given in equation (6).

$$Y^{t+1} = c.Y^{t} + a$$

(6)

where \(a\) is the acceleration and \(c\) is a weighting factor that indicates the impact of past and present velocities. The dynamic behaviour of snow geese modifying their flight routes to reduce energy consumption is reflected in the velocity adjustment process. The location update equations pertaining to distinct node categories guarantee that the optimisation procedure takes into account fluctuating node situations. For the nodes that perform best is given in equation (7).

$$N_i^{t+1} = N_i^{t+1} + b.(N_b^t - N_i^t) + Y_i^{t+1}$$

(7)

For the mid-performing nodes give in equation (8)

$$N_i^{t+1} = N_i^{t+1} + b.(N_b^t - N_i^t) - d.(N_c^t - N_i^t) + Y_i^{t+1}$$

(8)

For the remaining nodes is given in equation (9)

$$N_i^{t+1} = N_i^{t+1} + b.(N_b^t - N_i^t) - v.(N_c^t - N_i^t) - e.(N_x^t + P_i^t) + Y_i^{t+1}$$

(9)

Where the weakest node's position is N_x^t, the centre position is N_c^t, and the optimum position is N_b^t. Effective position updates are ensured by the empirically derived values of the coefficients b, x, and e. The central position N_c is given in equation (10).

$$N_c^t = \frac{\sum_{i=1}^{x} N_i^t . f(N_i^t)}{x.\sum_{i=1}^{x} f(N_i^t)}$$

(10)

Phases of the clustering process change from exploration to exploitation. To create the first clusters, nodes first investigate the search space (herringbone pattern). Nodes use the local optima, or straight-line pattern, to fine-tune cluster formations as the iteration goes on, guaranteeing ideal network performance in equation (11)

$$N_i^{t+1} = \begin{cases} N_i^t + (N_i^t - N_b^t).r, & r > 0.5 \\ N_b^t + (N_i^t - N_b^t).r \oplus Brownian(v), & r \le 0.5 \end{cases}$$

(11)

Brownian motion is used to help the algorithm break free from local optima, guaranteeing robust clustering and global convergence. By following these steps the optimal cluster head has been selected

3.4 Routing Mechanism using deep hyperbolic graph attention network-clouded leopard Routing Algorithm

To apply the principles of the Hyperbolic Graph Attention Network (HAT) for optimal path selection in routing within IoT-MANETs, combine analogies between the graph nodes and network nodes, and between the graph edges and communication links. The goal is to find the best path for data transmission by leveraging hyperbolic geometry and attention mechanisms.

Every node in an IoT-MANET has a variety of characteristics, including processing capacity, battery life, and connection. In order to apply the HAT model, we first use the exponential map to project these node attributes into hyperbolic space, which allows us to capture intricate hierarchical interactions between nodes. The feature vector f_e for node e is projected into hyperbolic space by the exponential map $\exp_0^c(f_e)$. When $if \in H_x D_c^d \setminus \{0\}$, where x indicates point in hyperbolic space and D_c indicates tangent space at x, and tangent space at x, the exponential map is as follows in equation (12).

$$\exp_0^c(f_e) = x \oplus_c \left(\tanh\left(\sqrt{c} \frac{\lambda_x^c \| f_e \|}{2} \right) \frac{f_e}{\sqrt{c} \| f_e \|} \right)$$

(12)

Where, $\lambda_x^c : \dfrac{2}{1 - c \| x \|^2}$ represents the conformal factor, and $\oplus_c$ indicates the Mobius addition. For $x = 0$, the exponential map simplifies to equation (13)

$$\exp_0^c(f_e) = \tanh\left(\sqrt{c} \frac{\lambda_x^c \| f_e \|}{2} \right) \frac{f_e}{\sqrt{c} \| f_e \|}$$

(13)

Then use a shared linear transformation parameterised by a weight matrix T to turn the projected feature p_f into a higher-level latent representation h_l given in equation (14)

$$h_l = M \otimes_c p_f = \frac{1}{\sqrt{c}} \tanh\left(\frac{\| T_{p_f} \|}{\| p_f \|} \tanh^{-1}(\sqrt{c} \| p_f \|) \right)$$

(14)

Here, the Möbius matrix-vector multiplication is indicated by the symbol $\otimes_c$. By taking this step, you can be sure that the representation has enough power to accurately depict the node's place in the network. Use a hyperbolic attention mechanism to calculate the importance of each nearby node j to node i in order to discover the ideal path. Based on the hyperbolic distance d c between latent representations h_i and h_j, the attention coefficient α_{ij} is calculated in equation (15).

$$d_c(h_i, h_j) = 2\sqrt{c} \tanh^{-1}(\sqrt{c} \| -h_i \oplus_c h_j \|)$$

(15)

The attention coefficient α_{ij} is then given in equation (16)

$$\alpha_{ij} = -d_c(h_i, h_j)$$

(16)

Closer nodes in the hyperbolic space have a higher coefficient, indicating greater similarity or connectedness. Then, to make sure the attention coefficients are equivalent, normalize them using the softmax function is given in equation (17).

$$w_{ij} = \frac{\exp(\alpha_{ij})}{\sum_{k \in N_i} \exp(\alpha_{ik})}$$

(17)

Where, N_i indicates the set of neighbours of nodes i. To obtain the final aggregated representation h_i' compute a linear combination of the latent representations of all neighbours using the normalized attention coefficients w_{ij} is given in equation (18)

$$h_i' = \sigma\left(\sum_{j \in N_i}^{\oplus_c} w_{ij} \otimes_c h_j\right) \tag{18}$$

Where Möbius addition accumulation is indicated by $\oplus_c$, and σ is a nonlinearity function similar to ELU. When it comes to routing, the best path selection criteria are contained in the final aggregated representation h_i' of every node. It may train the model to anticipate the optimal paths for data transmission in the network by applying a loss function that is specific to the routing target like minimizing latency or energy consumption.

By following these procedures, DHGAN to understand complex IoT-MANET node relationships, aiding in data transmission optimal paths by projecting features, computing attention, normalizing coefficients, and aggregating representations.

3.5 Optimize the hyperparameters of DHGAN using Clouded Leopard Optimization (CLO)

Clouded Leopard Optimization (CLO) will be used to optimize a Deep Hyperbolic Graph Attention Neural Networks (DHGAN) hyperparameters in order to minimize latency and energy consumption and choose the best path in an IoT MANET. Figure 2 shows the step by step procedure of the CLO.

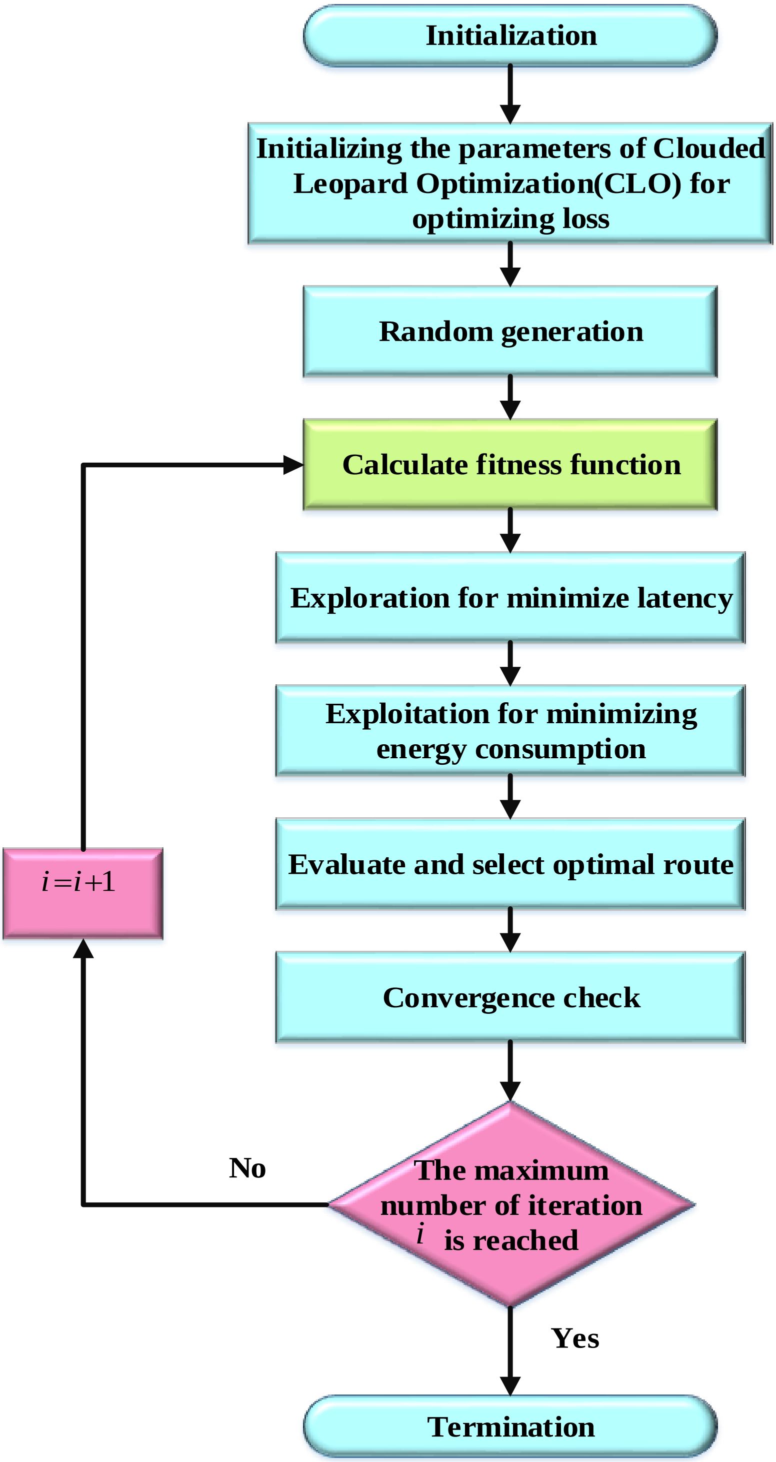

Figure 2: the step by step procedure of the CLO.

4. RESULT AND DISCUSSION

The clustering-based routing technique is employed by the NS2 simulation tool. The simulations' limits are shown in Table 1. The MAC type for the Omni Antenna model is 802_11. This section offers a thorough analysis of the results of the proposed method. This method outperforms existing approaches and reduces the overall EC of the network by decreasing the lifetime in MANET.

Table 1: Execution parameters

Entity	Description
Time obligatory for simulation	168 h
The density of the network	Default
Area mandatory for simulation	10,000 m2
Node type	Mobile
Specification of router	Selecting automatically
Number of nodes	100 to 500
Radiofrequency spectrum	0.5 km
Nodes placement	Distribution at random
Frequency spectrum	4G

4.1 Performance analysis

Using the required node, the proposed SGA-DHGAN-CLRA technique is tested on the NS3 platform and in a wireless sensor network. Numerous parameters including throughput, delay, packet drop, packet delivery ratio, network lifetime and EC are used to confirm the effectiveness of the SGA-DHGAN-CLRA method. Compare these metrics with the existing approach to prove the performance improvement of the SGA-DHGAN-CLRA approach. The existing methods are SN-TOCRP [8], FPSOR [9], Bi-GRU-DM [10], and ADR-MTS [11].

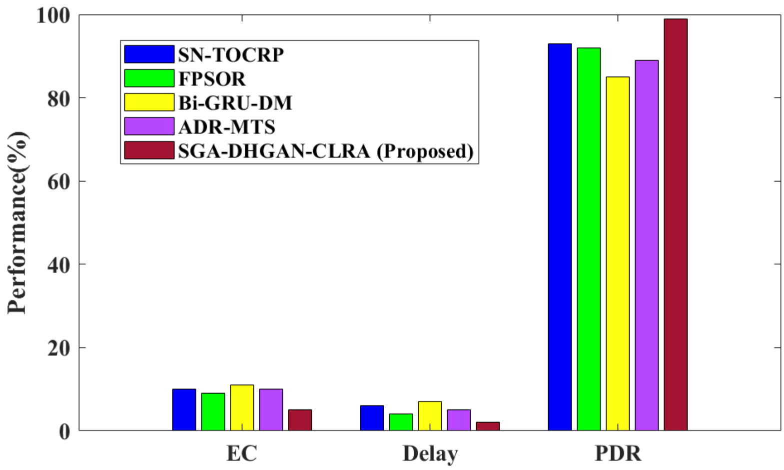

Figure 3: Overall comparative analysis of EC, Delay and PDR

The performance of several algorithms (SN-TOCRP, FPSOR, Bi-GRU-DM, ADR-MTS, and SGA-DHGAN-CLRA) in terms of EC, Delay, and PDR is compared in figure 3. Out of all three metrics, SGA-DHGAN-CLRA regularly performs the best, followed by SN-TOCRP and FPSOR.

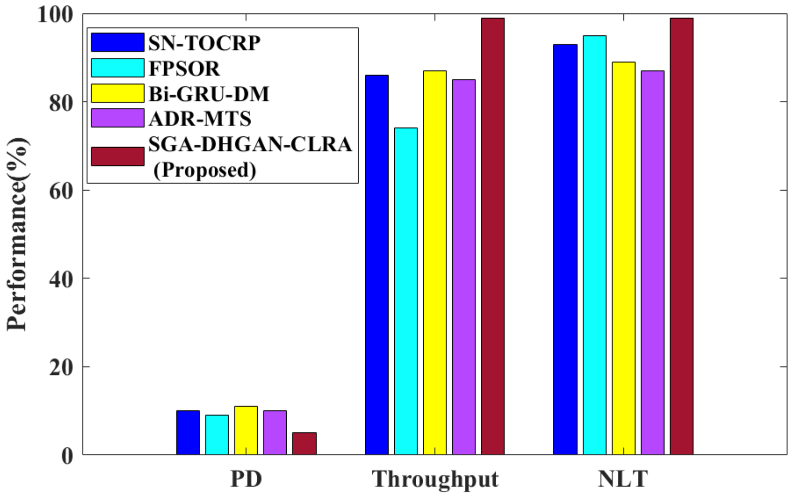

Figure 4: Overall comparative analysis of EC, Delay and PDR

Figure 4 shows the packet drop, Throughput, and Network Lifetime (NLT) are the three metrics used to compare the performance of four alternative algorithms: SN-TOCRP, FPSOR, Bi-GRU-DM, ADR-MTS, and the proposed SGA-DHGAN-CLRA. The results are displayed in a bar chart. There are variances in performance across the remaining methods, but overall the suggested SGA-DHGAN-CLRA performs better than the other algorithms in all three criteria.

Table 2: comparison analysis of throughput, delay, and energy consumption

Metrics	**No of rounds**	**SN-TOCRP**	**FPSOR**	**Bi-GRU-DM**	**ADR-MTS**	**SGA-DHGAN-CLRA (proposed)**
Throughput (kbps)	500	849	780	800	900	955
	1000	620	720	720	850	860
	1500	580	690	568	620	750
	2000	470	590	479	573	600
Delay (sec)	500	0.22	0.25	0.12	0.05	0.01
	1000	0.29	0.29	0.15	0.1	0.1
	1500	0.3	0.31	0.22	0.19	0.2
	2000	0.36	0.37	0.27	0.25	0.23
Energy Consumption (J)	500	0.5	0.5	0.2	0.6	0.12
	1000	0.69	0.9	0.5	0.9	0.31
	1500	0.85	1.2	1	1	0.45
	2000	0.9	1.39	1.2	1.4	0.61

A comparison of existing methods on a network with 2000 rounds an increase from 1000 is shown in Table 2. The recommended SGA-DHGAN-CLRA technique stands out from the others, achieving near-perfect throughput of 955 kbps at 1000 rounds and the lowest delay and energy consumption across all network sizes, while the majority of existing techniques see some performance loss as the network scales.

Table 3: comparison analysis of Network lifetime, PDR, Packet drop

Metrics	No of rounds	SN-TOCRP	FPSOR	Bi-GRU-DM	ADR-MTS	SGA-DHGAN-CLRA (proposed)
Network lifetime (sec)	500	100	110	100	100	200
	1000	200	200	400	200	470
	1500	360	450	570	400	600
	2000	670	610	820	620	950
Packet delivery ratio (%)	500	87.5	90	85	93.5	97
	1000	85	89	80	89	90
	1500	79	80	76	80	85
	2000	72	70	72	72	75
Packet drop (%)	500	80	82	71	73	70
	1000	77	80	70	70	67
	1500	74	75	69	69	65
	2000	70	73	65	63	63

Table 3 compares the network lifetime, packet delivery ratio, and Packet of the proposed approach with the existing approaches for different numbers of rounds (500, 100, 1500, and 2000). The recommended method produces the best results across all metrics for different numbers of nodes.

5. CONCLUSION

The paper presented an Improved Snow Geese Deep Hyperbolic graph Attention Network based Clouded Leopard Routing Algorithm (SGA-DHGAN-CLRA) for clustering, with the goal of optimising the energy-saving performance of the MANET network. Snow Geese optimisation (SGO) has increased the significance of CH selection by choosing nodes that can operate at a time with the least amount of energy usage. Furthermore, Clouded Leopard Routing Algorithm (DHGAN-CLRA), an expanded Deep Hyperbolic graph Attention Network-based algorithm, is used for enhanced routing with the goal of selecting the optimal path for data transmission throughout the network. In order to assess performance and compare it with the current methods, performance measures such as throughput, energy consumption, delay, packet drop rate, and network were employed. The network has 955 kbps throughput and 0.12J energy consumption and the network life time is 200 seconds lower than other methods for 1000 rounds. In future, develop and integrate security mechanisms to protect against various types of attacks, like Sybil attacks, eavesdropping, and denial-of-service (DoS) attacks.

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