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Original Article

Cascaded ANN Based Clustering and Optimized Routing Path Selection in Mobile Adhoc Networks

K. Paul Joshua[1], D. Srinivasa Rao[2], Govinda Patil[3], Mohit Kadwal[4], Jitendra Choudhary[5]

[1]*Department of Electronics and Communication Engineering, St. Peter's College of Engineering and Technology, Chennai, Tamil Nadu, India.*
[2]*Department of Computer Applications, Medi-Caps University, Indore, Madhya Pradesh.*
[3, 5]*Department of Computer Science, Medi-Caps University, India.*
[4]*Department of Computer Applications, Govindram Seksaria Institute of Management and Research (GSIMR), Indore, India.*

[1]*Corresponding Author : k.pauljoshua@gmail.com*

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Abstract *- Mobile Ad Hoc Networks (MANETs) permit wireless communication terminals that establish communication networks at any time and from any location because they do not require any established infrastructure. As a result, MANETs have a high application potential and have become a popular study area in recent years. However, MANETs continue to confront many hard issues that significantly impact their performance and use in real-world scenarios. The two problems involved in handling MANET topology are scalability and energy limitation. In this proposed system, clustering and routing mechanism are employed to resolve these issues. The novel clustering algorithm based on Cascaded Artificial Neural Network and routing path selection uses hydridized Ant Colony Optimization (ACO), and Salp Swarm Optimization (SSO) is proposed to support massive mobile ad hoc networks. A novel clustering technique assists in solving routing protocol issues and improving scalability. Clustering in MANETs offers a robust technique that optimally deploys resources while ensuring network architectural integrity. To examine the proposed system, MATLAB software is used to run simulations. According to the simulation results, the MANET network performance factors such as throughput, Packet delivery ratio, delay, and Average energy have improved.*

Keywords *- Cascaded Artificial Neural Network (CANN), Ant Colony Optimization (ACO) and Salp Swarm Optimization (SSO).*

1. Introduction

MANET is one of the confidential network topologies that enable a collection of wireless devices to communicate without any supporting facilities. Due to its quick expansion, this technique is frequently utilised in many sectors, including the industrial and education sectors. Moreover, it is also used in the field of military and civil. The nodes in MANET are portable, and the connections are made in a wireless topology. Nonetheless, there are several restrictions on the network, such as the nodes' transmission capabilities, limited energy, erratic node connections, bandwidth, and so many others. To boost the data transmission capacity of MANET and extend its lifespan, it is essential to choose an optimal routing and node for information processing and transmission. Commonly, MANET structures are classified into two categories, distributed and cluster network structures. Each node's obligations are fair in a distributed network structure, and the network layout can be flexibly altered based on node mobility. However, in a clustering network, choosing the cluster-head node is a critical issue as cluster-head nodes perform superior to regular nodes, which calls for more powerful processing power and greater energy. Therefore, choosing cluster-head nodes are crucial in a clustering network. Clustering can solve issues with routing protocols, enhance the calibre of data transmission, and increase network scalability [1], [2]. In a MANET, clusters offer a dependable way to link mobile nodes and effectively distribute resources, as well as a network-layered basis to ensure the integrity of the MANET structure. A MANET's primary characteristic is that it may be joined using a cluster-based hierarchy and the division of a more extensive network into smaller subgroups.

Clusters are the divisions of nodes into separate groupings. Data collection from one cluster's members and transmission to another cluster are the responsibility of a cluster leader. In network administration as well as control, cluster heads are crucial. By performing clustering, the essential three issues are solved (a) network expansion, (b) communication staying within the cluster such that other neighbouring clusters are oblivious of the communication, and (c) routing maintenance becoming much more straightforward, are all solved by clustering of mobile nodes [3]. To attain this, different algorithms are employed. One among the technique is Artificial intelligence. The benefits of this strategy include minimum time consumption in the re-selection of cluster heads, which minimizes communication overhead and better cluster head node selection. However, the downfall involved is more energy consumption [4], [5]. Hence, the fuzzy logic system is used while choosing a cluster head for a wireless sensor network. It optimizes routing efficiently, whereas it limits the effective communication range of the sensor nodes [6], [7].

Hence, in this proposed system, an effective clustering technique is employed, which sorts out these issues and helps in efficient transmission, which in turn, to perform routing, an influential novel hybridized technique is used after performing the clustering approach. Routing is vital in different sorts of networks [8]. There are two primary methods for routing packets. The first is unicast, whereas the second is multicast. One-to-one communication between a source and a destination is referred to as unicast. Multicast is a one-to-many communication method in which the same source delivers the same packets to several destinations. Finding the shortest path between two network nodes is often the goal of the unicast routing issue, while the multicast routing problem entails finding the best tree that connects the source and all destinations [9]. Currently, both these routing approaches are addressed using intelligent optimization techniques.

The SP routing problem seeks to minimize the overall cost of the path while determining the shortest route connecting two nodes at different points in a network. Several deterministic search algorithms exist to find the shortest path, such as the bellman Ford algorithm, Dijkstra's algorithm, etc. They function well in wireless or wired networks with fixed infrastructure. However, they have an unacceptably high computational complexity for instantaneous communication with rapidly changing network topologies [10, 11]. Hence, in a dynamic network context, numerous effective methods were utilised to tackle the dynamic shortest path routing issue, including Particle Swarm Optimization (PSO), Salp Swarm Optimization Genetic Algorithm (GA), Ant Colony Optimization (ACO), [12].

PSO determines the optimum solution; however, dealing with conditions such as boundaries is exceedingly difficult [13-15]. As a result, GA is utilized, which has the finest routing solution, but it operates on its own rules and is inapplicable to dynamic data sets [16-18]. To address all of these issues, ACO is established. ACO stores numerous travel paths in the routing table based on pheromone information and has minimal communication costs in wired and wireless networks [19-23]. However, in a network outage, the planned path becomes unsuitable in the optimal path. So, to solve this problem, the salp swarm algorithm [24], [25] is combined with ACO to determine the optimum route that causes the least time to travel between the origin and the node it will reach.

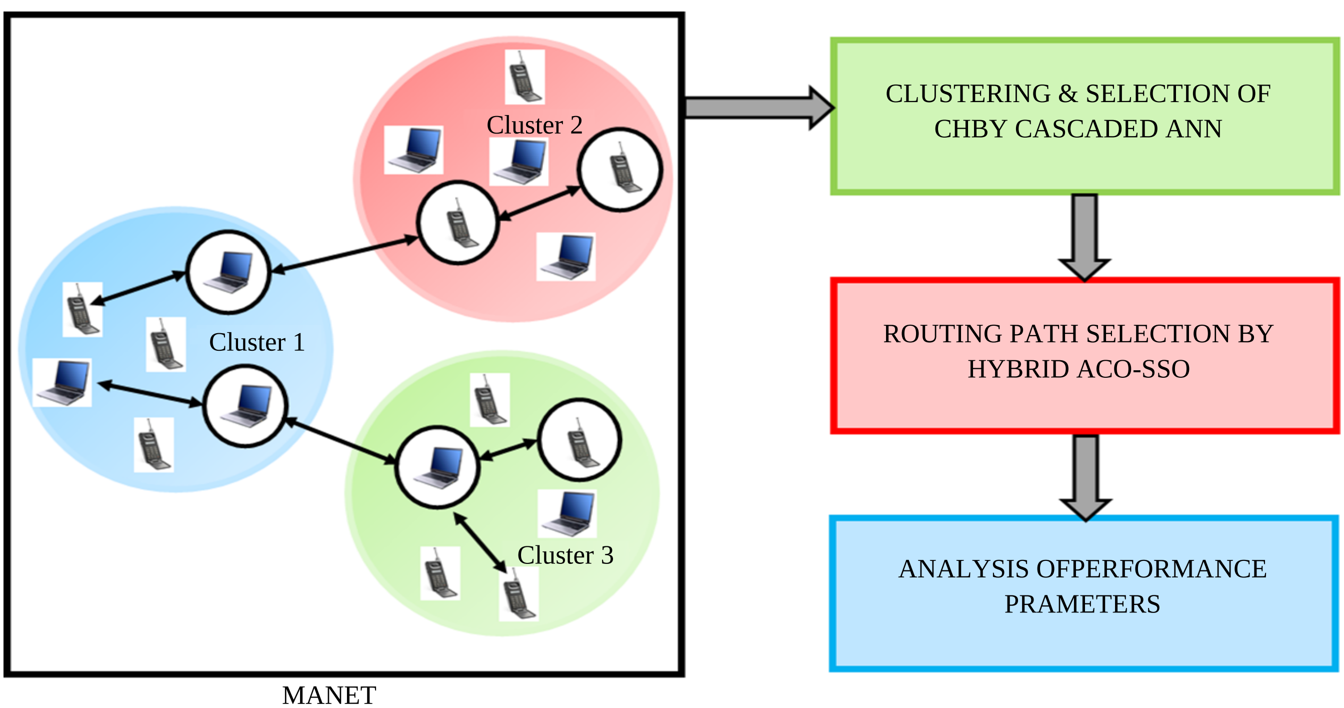

Fig. 1 Proposed diagram

This proposed system aims to develop a new clustering approach where the cluster head is chosen based on the most crucial mobile ad hoc network characteristics, such as distance and received signal strength (RSS). A cascaded Artificial Neural Network (ANN) is employed to create a secure, reliable and energy-efficient routing method to perform clustering. The best channel for data transmission is then chosen, which decreases network latency and lengthens network lifetime using less energy. To choose the best route for data transfer, a hybridized optimization technique combines Ant colony and salp swarm optimization.

The remaining sections are arranged as follows, a brief note about the proposed system is discussed in section 2, In part 3, and the clustering and optimum shortest path routing techniques are thoroughly presented. In section 4, the results and their discussion are completed. Finally, section 5 concludes.

2. Proposed System

Due to the increased mobility in multimedia wireless networks, the network topology in MANET becomes more dynamic, which causes network congestion. An excess of communications inside a network also brings on congestion. Since routing is closely related to the internet and customer service quality, creating a more effective dynamic routing method is imperative. Hence, in this proposed system, clustering is performed using a cascaded Artificial Neural Network to perform efficient routing, as indicated in Figure 1. In clustering, mobile nodes are gathered into clusters. A cluster head is chosen for each cluster, which makes routing maintenance easier.

The routing path selection is carried out using a novel hybrid ACO-SSA method which assists to determine the shortest data transfer path between the source and the destination node. The hybridized approach reduces network latency and increases network lifetime using less energy. The efficacy of this proposed system is evaluated based on measures including throughput, end-to-end delay, average latency, energy consumption and packet loss.

2.1. Clustering

Clustering is a technology that organises nodes to simplify network management. Each cluster in the network has a cluster head responsible for managing it. Nodes serve distinct functions in clustering algorithms, and three different types of nodes exist such as

- Cluster head nodes
- Cluster gateway nodes
- Cluster member node

Cluster head nodes: A node that oversees cluster operations is known as the cluster head. There will be one cluster head node per cluster. It is mainly used to perform routing, which makes it more accessible.

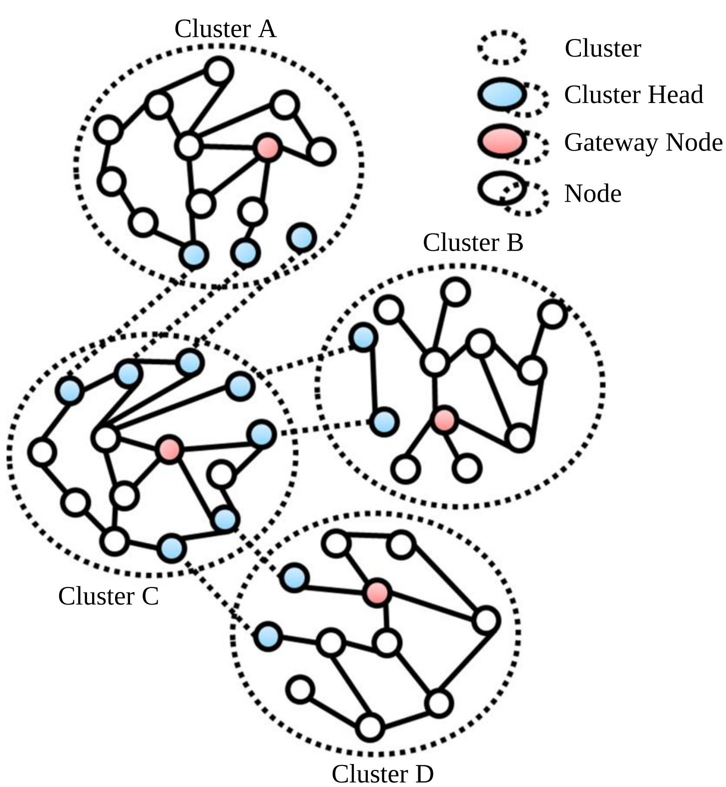

Fig. 2 Clustering

Cluster gateway nodes: A node is referred to as a gateway if two or more cluster heads can reach it.

Common node: It is said to be a cluster member and serves no specific purpose.

In MANET, source nodes that want to interact with the target nodes send or receive command messages, such as requests for routing and replies, to linked neighbour nodes. This operation is repeated until a path to the target node is discovered. The traditional routing technique produces a lot of control overhead in networks with many nodes or that are congested. To address the extra overhead, clusters are created by a collection of a few nodes, with routing begun by cluster head instead of standard nodes. As seen in Figure 2, when routes have been created, information transmission will now occur via cluster nodes rather than individual nodes. Once grouped into clusters, a cluster leader is chosen from among the moveable nodes. A cascaded artificial neural network performs clustering in this proposed system. Clustering in MANET is represented in Figure 2

This work's main objective is effective cluster head determination in challenging instances where nodes dynamically change their positions with their neighbours. The cluster head node has optimum characteristics such as throughput, energy, and strong cooperation between each cluster's participants. The cluster head is selected after analysis of the cluster head nodes' properties. This system's goals include locating the appropriate cluster head, reducing the chance of overcrowding inside a cluster, and effortlessly creating other cluster heads.

2.1.1. Cluster Head Selection using Cascaded ANN

Based on the distance between nodes, mobile nodes are grouped. The nodes that have the least distance difference are grouped. After grouping, the cluster head is chosen to perform routing efficiently. The cluster head plays a vital role in routing path selection. Clustering in MANET using Cascaded ANN is represented in Figure 3; a cascaded artificial neural network is used to perform the cluster head selection. A simple artificial neural network's performance is not much efficient for wide area network. Hence, the cascaded structure is employed to increase wireless communication's transmission effectiveness. The cascaded ANN structure is as follows: cluster head is chosen for each cluster. The highest output value is taken to choose a cluster head and to find whether the model was trained adequately with minimum error; the chosen one is combined with the target output to determine the optimal result with high accuracy.

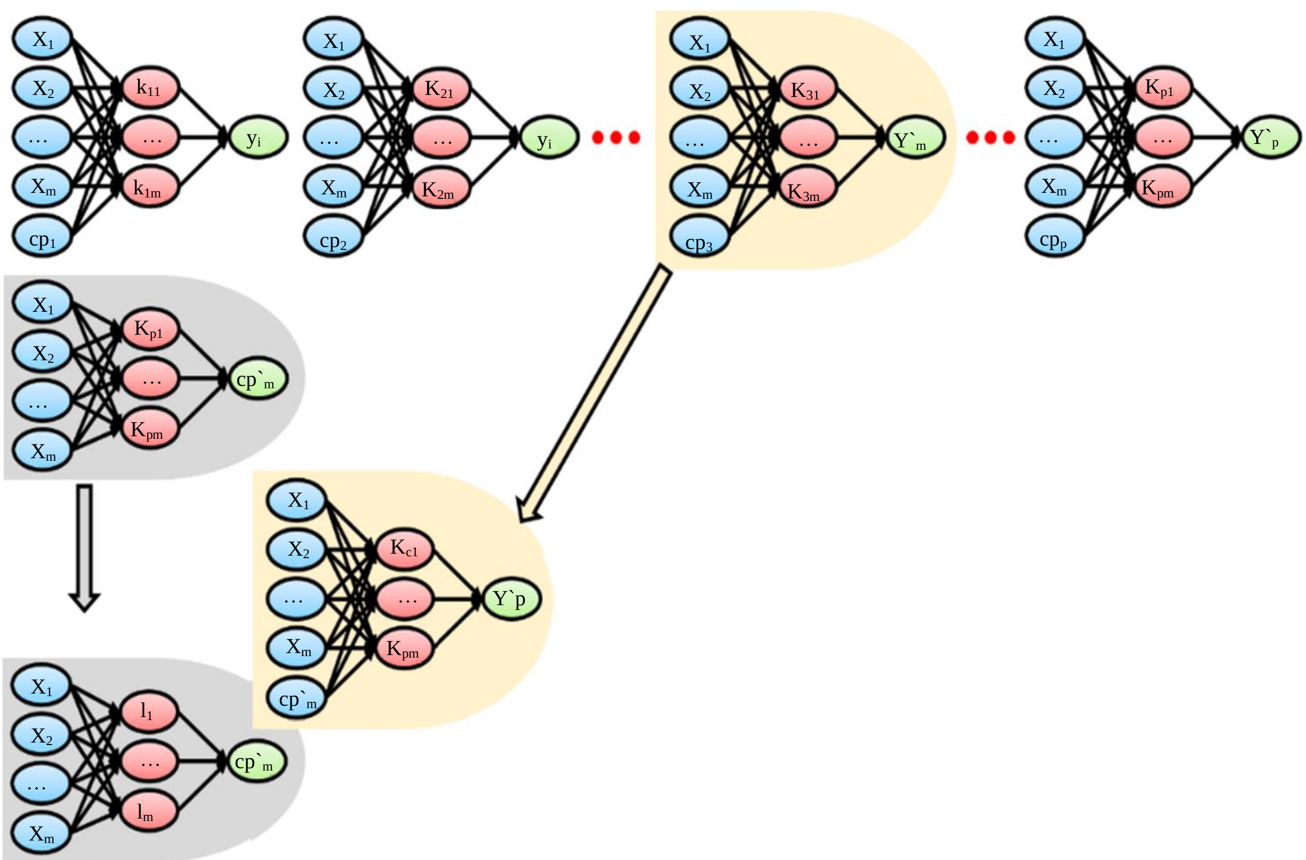

Fig. 3 Structure of cascaded ANN

Table 1. Input parameter values

Parameters	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8	N_9	N_{10}	MAX
Energy	50	45	80	70	60	75	95	40	85	55	100 J
Node degree	5	4	3	2	2	7	8	9	6	10	10 nodes
Mobility	20	9	8	12	13	19	8	16	14	7	20 m/s
Packet drop	200	150	120	180	170	175	125	100	160	140	200 packets

Table 2. Value of normalized input

Parameters	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8	N_9	N_{10}
Energy	0.52	0.47	0.84	0.73	0.63	0.78	1	0.42	0.89	0.57
Node degree	0.5	0.4	0.3	0.2	0.2	0.7	0.8	0.9	0.6	1
Mobility	1	0.45	0.4	0.6	0.65	0.95	0.4	0.8	0.7	0.35
Packet drop	1	0.75	0.6	0.9	0.85	0.87	0.62	0.5	0.8	0.7
Target value	0.306	0.421	0.121	0.142	0.349	0.48	0.736	0.266	0.547	0.661

To perform cluster head selection, the steps are as follows

Step 1 : Initially, the input parameters are taken into consideration. The input parameters are

- Packet drop (PD_N)
- Mobility (M_N)
- Energy (E_N)
- Neighbour of node (ND_N)

Step 2 : After considering the input, the weights are allocated to each parameter. Weighting the input variables when choosing the cluster head will ensure the maximum final goal value. Such input values imply that although access and packet loss should be reduced, energy and neighbour nodes should be increased.

Step 3 : Assume an example data set of 10 nodes, and equation 1 shows the weights for the input parameters,

$$W_1(E_N) = 0.3, W_2(ND_N) = 0.3, W_3(M_N) = 0.2, W_4(PD_N) = 0.2 \quad (1)$$

Here, $W_1 + W_2 + W_3 + W_4 = 1$

Step 4 : Table 1 displays the values of the input parameters for the five nodes.

Step 5 : The input values are normalized, and it is shown in Table 2.

Step 6 : After normalizing, the target value is computed for given inputs by the below formula.

Target value = Energy*W_1 + Node degree*W_2+ (1-Mobility) *W_3+ (1-packet drop)*W_4 (2)

Step 7 : By step 6, the target values are computed, represented in Table 2.

Step 8 : The neural network works based on the given parameters and automatically trains and optimizes the network. Nodes, which are synthetic neurons, are created from these factors. Input, hidden, and output layers are the three components that make up a neural network. The total of concealed layers can vary depending on the optimization needed. Nodes in each layer represent the artificial neurons. The input layer's nodes are chosen based on the number of inputs provided. Four nodes will be chosen for the input layer if four inputs are present. Figure 4 depicts the training paradigm between the three layers is shown in Figure 4.

Step 9 : Forward pass: The neural network predicts an output after receiving inputs (xi) and weights from the input layer. The total net input is determined using the formula shown in the equation.

$$net_{input} = \sum w_i * x_i \quad (3)$$

$$net_{input} = w1 * E_{Ni} + w_3 * ND_{Ni} + w_5 * M_{Ni} + W_7 * PD_{Ni} \quad (4)$$

$$net_{input} = w_2 * E_{Ni} + w_4 * ND_{Ni} + w_6 * M_{Ni} + w_8 * PD_{Ni} \quad (5)$$

Step 10 : To produce the output, the logistic function simplifies the input.

$$out_{output1} = \frac{1}{1+e^{-net_{input1}}} \quad (6)$$

$$out_{output2} = \frac{1}{1+e^{-net_{input2}}} \quad (7)$$

Step 11 : The outcomes from the hidden layer neurons are supplied into output layer neurons as inputs in a subsequent iteration of this process.

Step 12 : A squared error function is used to calculate the error of each outcome neuron, and the combined errors are then totalled to determine the total error. Providers of the squared error function include,

$$E_{total} = \sum \frac{1}{2} (target - output)^2 \quad (8)$$

Step 13 : The neural network's total error is computed by adding up all the errors shown in equations 9, 10 and 11

$$E_{total} = E_{output1} + E_{output2} \quad (9)$$

$$E_{output1} = \frac{1}{2} \left(target_{01} - out_{output1}\right)^2 \quad (10)$$

$$E_{output2} = \frac{1}{2} \left(target_{02} - out_{output2}\right)^2 \quad (11)$$

Step 14 : Substituting equations 10 and 11 in equation 9, the yielded equation is provided below,

$$E_{total} = \frac{1}{2} \left(target_{01} - out_{output1}\right)^2 + \frac{1}{2} \left(target_{02} - out_{output}\right)^2 \quad (12)$$

Step 15 : Backward pass: The network's loads are adjusted via backpropagation when determining the overall error to make the actual output more closely resemble the target value. This minimizes error for both the network as a whole and for each output neuron. Backpropagation takes partial derivative of E_{total} With respect to the supplied weights.

Step 16 : Chain rule application at the output level denoted below,

$$\frac{\partial E_{total}}{\partial W_9} = \frac{\partial E_{total}}{\partial E_{total}} * \frac{\partial Out_{output}1}{\partial net_{input1}} * \frac{\partial net_{input1}}{\partial w_9} \quad (13)$$

Repeat the same to find the weight W_{10}

Step 17 : Similarly, the chain rule is applied at the hidden layer as given in equation 14.

$$\frac{\partial E_{total}}{\partial W_n} = \frac{\partial E_{total}}{\partial E_{total}} * \frac{\partial Out_{output1}}{\partial net_{input1}} * \frac{\partial net_{input1}}{\partial w_n} \quad (14)$$

The same equation is used to find other weights in the hidden layer where n=1to8.

Step 18 : The overall error change is computed with respect to the output is,

$$E_{total} = \frac{1}{2} \left(target_{01} - out_{output1}\right)^2 + \frac{1}{2} \left(target_{02} - out_{output2}\right)^2 \quad (15)$$

The output (o1) fluctuates in proportion to its overall net intake, as shown by the computation below.

$$Out_{output1} = \frac{1}{1+e^{-net_{input1}}} \quad (16)$$

$$Out_{output2} = \frac{1}{1+e^{-net_{input2}}} \quad (17)$$

After performing partial differentiation in equation 13 concerning outoutput1 yields equation (18).

$$\frac{\partial E_{tota;}}{\partial net_{output1}} = -(target_{01} - out_{output1}) \quad (18)$$

In the same way, the differentiation is applied in equation 6 in relation to net_{input1}, which is provided in equation 19.

$$\frac{\partial out_{output1}}{\partial net_{input1}} = out_{output1}(1 - out_{output1}) \quad (19)$$

Overall net input of output1 alters in relation to weights.

Step 19 : Apply partial differentiation in (6) and (7) with regards to the corresponding weights yields the (20)

$$\frac{\partial net_{input1}}{\partial w_n} = out_{output1} \quad (20)$$

The total error is computed by applying the values of 17, 18 and 19 in equation 8, which gives,

For each weight, $\frac{\partial E_{total}}{\partial W_n}$ is computed. Where n=1to10.

Step 20 : Next, to reduce the error, $\frac{\partial E_{total}}{\partial W_n}$ partial total is deduced from the actual weight results which yields the equation 21.

$$\text{New weights are: } W_n^+ = W_n + \mu * \frac{\partial E_{total}}{\partial W_n} \tag{21}$$

In the algorithm above, in the hidden layer and output layer, the sigmoid function is used to activate. Neural networks train themselves and update weight following calculating errors in output neurons using a backpropagation algorithm based on the input samples. Here, the N8 node is selected as the head of the cluster for this analysis. The cluster head node is the node (sample) with the highest output value. When the final output closely resembles the node's goal value, it is deemed that the model was correctly trained and the error was minimal.

2.2. Shortest Path Routing using Hybridized Approach

The Ant Colony and Salp Swarm optimization algorithms are coupled in the proposed work to find the best routes in MANET routing. The two algorithms are the most effective and competent in swarm intelligence. All of the parameters of both the ACO and SSA algorithms are used in the presented technique. The suggested strategy takes advantage of SSA to improve the qualities of the ACO algorithm. A novel swarm intelligence approach named SSA is inspired by the swarm foraging behaviour of sea salps, and the distinct chain structure of SSA has a beneficial impact on enhancing the algorithm's accuracy, speed of convergence and strong searchability, which these benefits assist in improving the ACO method to discover the shortest path or route. Not only does the suggested approach reduce the number of paths in the ACO, but it also discovers the shortest path among the wide network. The hybrid algorithm outperforms the standalone ACO and SSA algorithms. The hybrid ACO-SSA technique's flowchart is shown in Figure 6, and the steps to choose a routing path are listed below.

1. Initialize the ACO parameters.
2. Construct Ant solutions utilizing pheromone testing based on bandwidth and residual node energy after initialization.
3. Update the number of pheromones.
4. If the maximum number of iterations is attained, move on to step 5; otherwise, move on to step 2.
5. A set of routes that the Ant agents have discovered is produced.
6. The salp chain population is initialized after the set of paths is discovered.
7. Evaluate the fitness function to find the optimal solution
8. Identify an ideal search agent
9. Revise the ranking of the most prominent salp and followers.
10. Adjust the salps based on the variable's upper and lower boundaries.
11. Repeat the steps from 7 to 11 until the optimum solution is found to determine the shortest path selection.
12. Terminate.

2.2.1. Ant Colony Optimization

ACO is a metaheuristic method created to address challenging combinatorial optimization issues. Pheromone is left behind by real ant colonies on the trails they travel as they look for food sources. A path will likely be reinforced if other ants in quest of food detect the pheromone along it and follow it rather than wandering off in random directions. A path's pheromone concentration will rise as more ants travel it, increasing the likelihood that other ants will choose it over others. Conversely, fewer ants will likely follow the trail when the pheromone wears off over time. The pheromone dissipates more quickly the farther the distance is between the food source and its home.

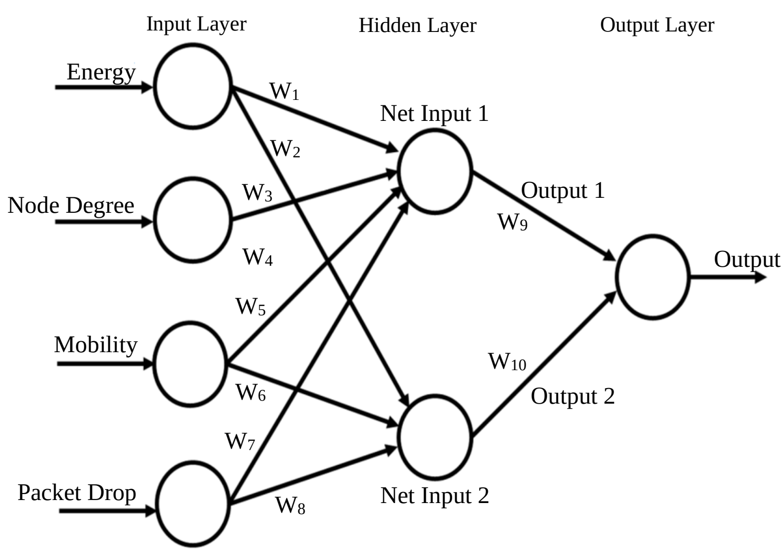

Fig. 4 Workflow of ANN

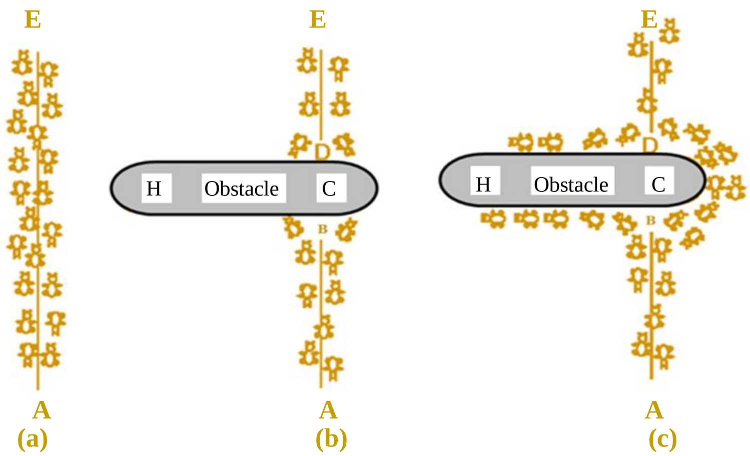

Fig. 5 Set of routes discovered by ants

The pheromone concentrations, therefore, stay higher on the shorter pathways. As a result, the journey's length and the food supply's calibre largely determine the degree of pheromone laid. The experimental setup shown in Fig. 5 exemplifies how ants would behave in the abovementioned situation. In Figure 5(a), an ant-made trail between the hive (E) and an energy supply (A) is shown. On the passage being blocked by a barrier, as in Figure 5(b), The location B ants travel from point A to E while the ants at D location travelling along point E-A must decide between the paths that go through points C or H. Since neither of the two other pathways has ever had a pheromone trail, it is equally probable that the first ants to arrive at these spots will choose either way. As route BCD is faster than path BHD, the ant which picked the road via point C will arrive at point D before the ant that chose the road through point H. The track on path DCB will be more robust for an ant travelling from point D to point E. As a result, path DCB will have a higher selection chance than path DHB. The number of pheromones on path BCD will rise more quickly than the number of pheromones on road BHD because more ants will follow path BCD per unit of time and because of the evaporation factor.

2.2.2. Salp Swarm Algorithm

SSA mimics the swarming and navigation behaviours of oceanic salps to find meals. There are two tiers of hierarchy in a salp chain: leaders and followers. The swarm is led by the leader, who is in the lead as they navigate across a multidimensional search space in search of the optimum food source for the optimization issue. SSA begins using arbitrary responses and iterative analysis to ascertain each salp's optimal fitness by scouring and using the search space. The mathematical modelling of the salp swarm algorithm is represented below,

The following equation is used to update the leader's salp location following the distance between the salp and food supply

$$x_i^1 = \begin{cases} F_i + r_1\big((ub_i - lb_i) * r_2 + lb_i\big) r_3 \geq 0 \\ F_i + r_1\big((ub_i - lb_i) * r_2 + lb_i\big) r_3 < 0 \end{cases} \tag{22}$$

X_i^1 indicates the position of leader in i^{th} place.

F_i indicates the position of food sources in i^{th} place.

ub_i, lb_i represents the position of the upper and lower bound in i^{th} place.

r_1, r_2 *and* r_3 are the random numbers.

In search space, the parameter $r_1$stabilizes exploration and exploitation where r_1 is given by,

$$r_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{23}$$

L and l denote the most iterations and the most recent iteration, respectively.

By using Newton's law of motion, the follower's position is updated by,

$$x_i^j = \frac{1}{2}at^2 + V_0 t \tag{24}$$

x_i^j represents the follower of j in i^{th} dimension.

The initial speed is represented by V_0

t represents the time of iterations.

The flowchart of the hybrid ACO-SSA algorithm is presented below.

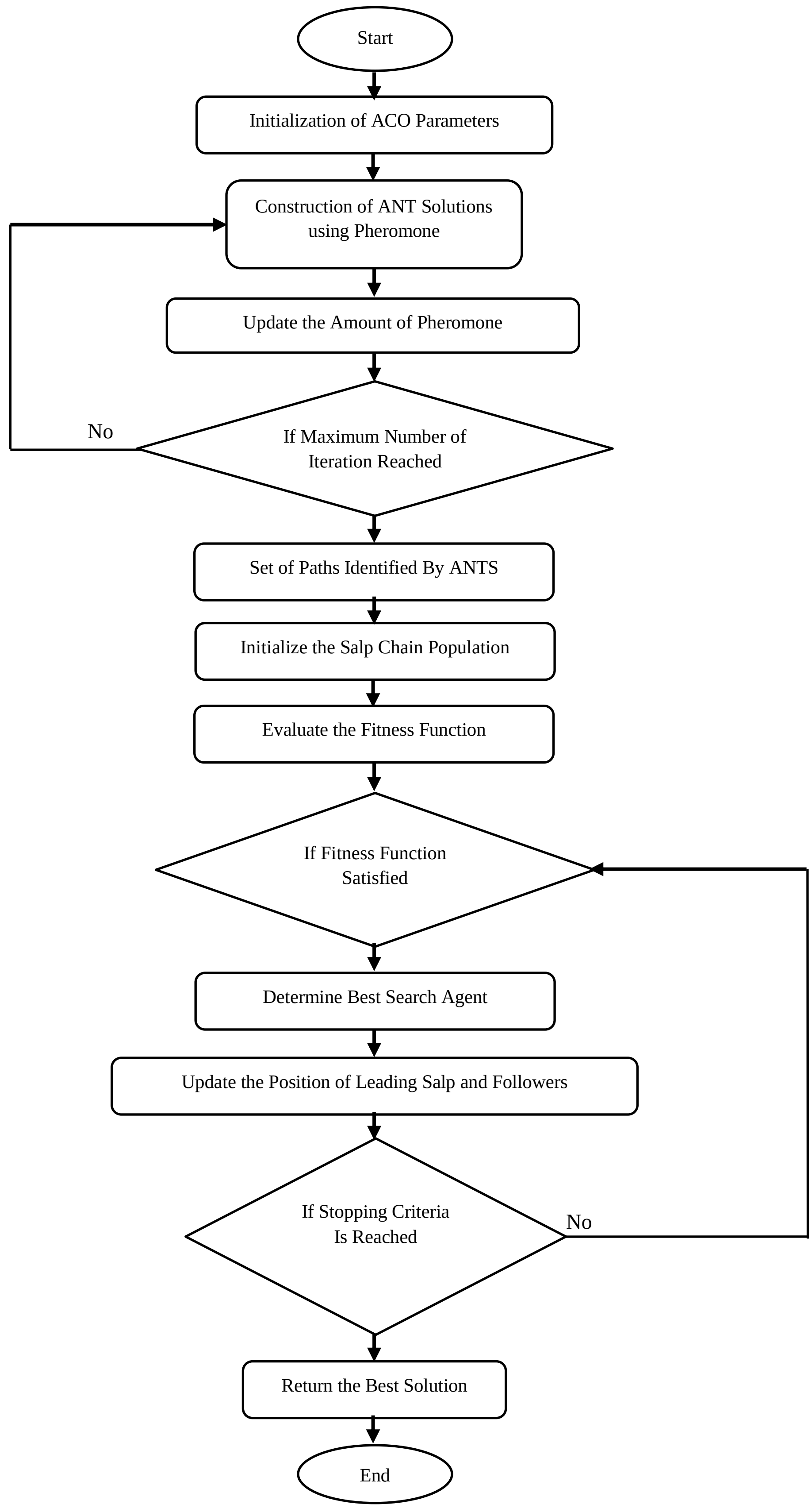

Fig. 6 Flowchart of hybrid AC0-SSA

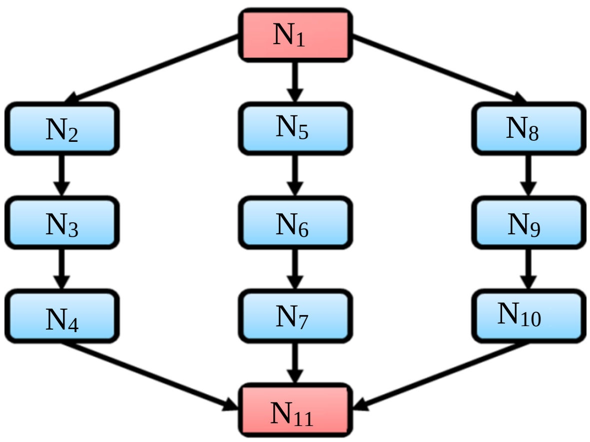

Fig. 7 Possible routes from source node to target node

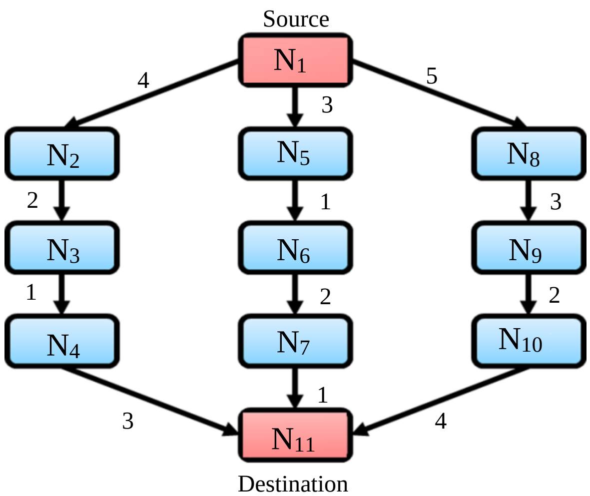

Fig. 8 Delay in each node between the source and destination

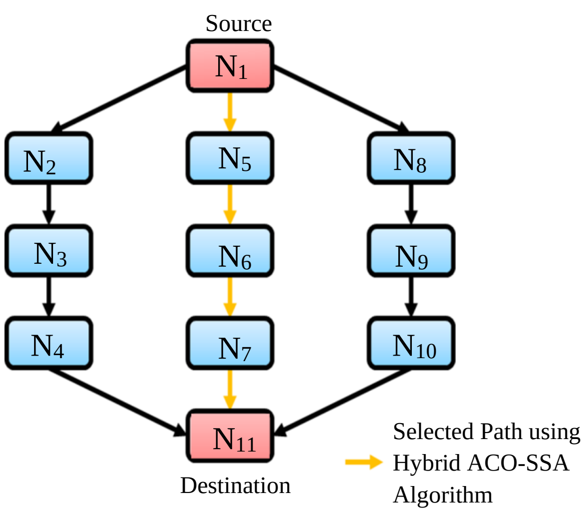

Fig. 9 Selected path from source to destination

N1 is the source node, and N11 is the destination node in the sample topology shown in Figure 7. It outlines the potential route the ACO algorithm picks. Initial populations for SSA are created using these paths. The delay among the origin and the final point is shown in every node in Figure 8.

The SSA algorithm calculates these delays to choose the path with the least delay between the source and the destination. The SSA method chooses the best path by calculating the fitness function, which includes metrics like delay and the hop count between the source and destination nodes.

In Figure 9, N1 transmits data to the N11 destination node utilizing the N5, N6, and N7 pathways. The ACO algorithm chooses the pathways between N1 and N11 nodes. The SSA algorithm receives a population that is a chosen path from the ACO algorithm. Each chosen pathway has the same hops between the source and destination nodes.

The SSA algorithm calculates the latency between the hop and the destination node to address this issue. The SSA algorithm updates the node's position and velocity in addition to computing fitness functions utilizing latency and hop count as metrics. The SSA approach selects the route with the least amount of time between the source and destination nodes.

3. Results and Discussion

Due to the increased mobility in wireless networks, the network topology in MANET becomes more dynamic, which causes network congestion. Since routing is directly related to internet and consumer service quality, improving dynamic routing strategies for multimedia wireless networks is critical. Therefore, a novel hybrid ACO-SSA and cascaded ANN clustering are used to achieve an efficient dynamic routing approach in wireless networks. Matlab software is used to implement the simulation.

3.1. Energy Dissipation of Cluster Heads

The graphical depiction of Cluster Heads' energy dissipation is shown in Figure 10. It is clear from the graph that the energy levels of the nodes serving as Cluster Heads are not dropping off quickly. In the network, Cluster Heads are in charge of the majority of the tasks being carried out, i.e., Network administration uses more energy than regular nodes perform. Thus, it can be inferred from the preceding graph that less energy dissipation results in a longer network life. The proposed novel hybrid algorithm is empirically evaluated and compared to several optimization methods in many aspects, detailed below. Table 1 shows the parameters utilized for simulation in the MATLAB software.

3.2. Latency

Latency is the time taken to reach the data to its destination across the network. In Figure 11, the proposed hybrid algorithm's latency is analogized with other algorithms such as Particle Swarm Optimization (PSO), Ant colony optimization (ACO) Genetic Algorithm (GA), and Salp Swarm Algorithm (SSA). The graph demonstrates that other optimization strategies lag behind the hybrid ACO-SSA approach. This hybridized method is more effective than other methods because it takes less time to transmit packets to their destination.

3.3. Jitter

Jitter is defined as intermittent delays during data transmission. It is caused by network congestion, poor queuing, or delays between packet transfers. The minimum number of jitter results in the best network performance. In Figure 12, a Comparison is made between proposed hybrid algorithm with other optimization approaches to measure the network performance. The graph shows that the hybrid algorithm outperforms the other methods as it takes the least intermittent delays during data transfer.

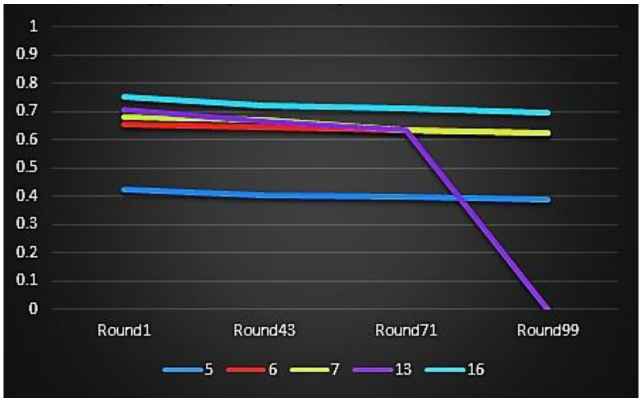

Fig. 10 Energy dissipation graph of cluster heads

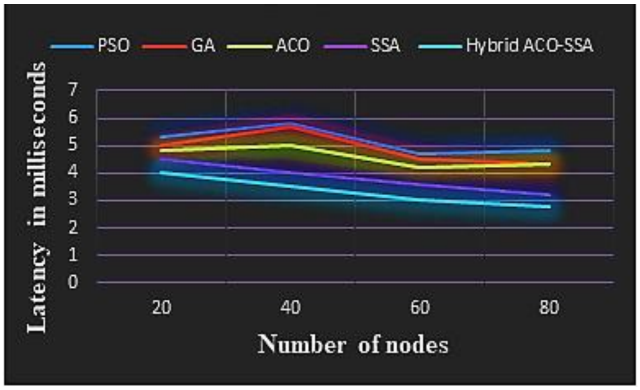

Fig. 11 Latency

3.4. Packet Delivery Ratio

It measures the number of packets transmitted by the source to the number of packets obtained by the destination. A comparison of the packet delivery ratio is represented in fig. 13. The graph shows that the proposed hybrid algorithm attains the topmost position in the packet delivery ratio compared to other approaches. Hence it is more effective than other algorithms.

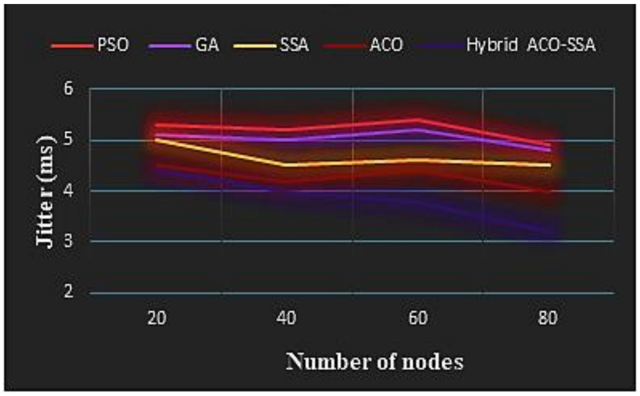

Fig. 12 Jitter

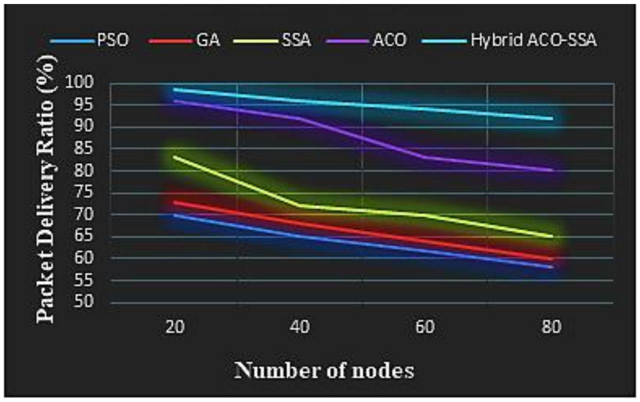

Fig. 13 Packet delivery ratio

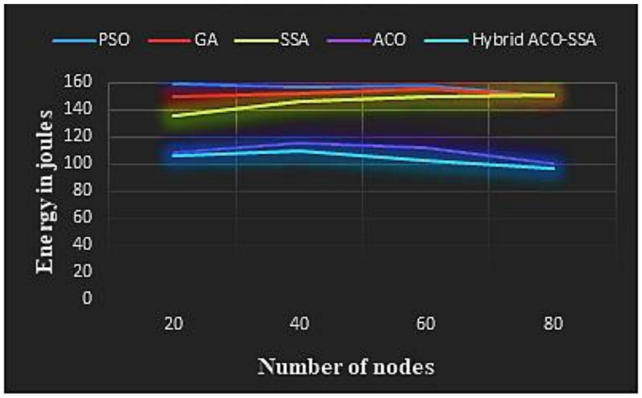

Fig. 14 Average energy

Table 3. Energy dissipation of cluster heads

Cluster Head Node ID	5	6	7	13	16	22
Round 1	0.4218	0.6552	0. 6782	0.7075	0.7514	0.9141
Round 43	0.4035	0. 6421	0. 6671	0.6664	0.7216	0.9005
Round 71	0.3980	0. 6345	0. 6543	0.6321	0.7105	0.8875
Round 99	0.3876	0.6249	0. 6421	0.0000	0.6934	0.8765

Table 4. Throughput comparison

Number of Nodes	PSO	GA	SSA	ACO	Hybrid ACO-SSA
20	210	215	225	236	250
40	198	208	216	220	236
60	186	198	204	210	228
80	180	185	196	199	204

3.5. Throughput

The throughput analysis of the proposed hybrid algorithm is analogized in Table 4. Throughput is the number of packets reaching the destination within a given interval. It is measured in Kbps. The graph shows that the proposed hybrid algorithm's clustering behaviour significantly increases its throughput over the other techniques.

3.6. Average Energy

One of a network's properties is its energy usage. Maintaining the node's energy level throughout the transmission is a challenging task. The average energy of the proposed hybrid ACO-SSA is compared with other approaches, such as PSO, GA, ACO and SSA, represented in Figure 14. The graph shows that energy consumption is reduced by using a proposed hybrid algorithm. As a result, the hybrid strategy outperforms the other alternatives. The efficacy of the proposed system is calculated based on latency, jitter, packet delivery ratio, throughput and Average delay. The hybrid approach generates the best output in all these metrics to convey data from the source to the destination.

4. Conclusion

The suggested study aims to create an efficient dynamic routing strategy for wide-area networks. In order to accomplish effective routing, clustering and cluster head selection are formed using cascaded ANN. Following clustering, hybrid ACO-SSA is used to find the best path to perform routing. Network Simulator (NS2) is used to implement a simulation. Regarding several variables, the suggested model is empirically evaluated and contrasted with PSO, GA, SSA, and ACO. Based on the findings, other optimization algorithms have a higher delay than the hybridized approach. The hybrid ACO-SSA algorithm is faster than the other protocols at delivering packets to their intended locations. Utilizing a hybrid method reduces the routing protocol, packet loss, and energy usage to some extent. The suggested unique hybrid algorithm's throughput is higher than conventional protocols due to its clustering characteristic, and its average delay is the least packet forwarding latency. The proposed method is, therefore, more effective than other protocols.

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