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RESEARCH ARTICLE

Deft Particle Swarm Optimization-Based Routing Protocol (DPSORP) for Energy Consumption Minimization in Mobile Ad-Hoc Network

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Abstract – Rapid technological development in the wireless communication sector has improved mobile ad hoc networks (MANETs) to serve a variety of domains, such as military activities, emergency operations, civilian settings, and disaster management. Self-organizing mobile nodes in MANET work together to create a dynamic network architecture to make connections. Before reaching its destination node in a MANET, data must pass through several intermediate nodes. For the creation and maintenance of routes, local link connection is crucial. This paper proposes the Deft Particle Swarm Optimization-based Routing Protocol (DPSORP) to reduce delay, which minimizes energy consumption. DPSORP gives precedence for local and global optimal routes. Before using a route for data transmission, DPSORP assesses its quality using two distinct kinds of rules. DPSORP uses a multi-path for data transmission rather than relying on a single path. Using the NS3 simulator and common network performance metrics and parameters, DPSORP is evaluated. The findings demonstrate unequivocally that the proposed routing protocol, DPSORP, outperforms existing routing protocols in terms of reducing delay and energy consumption.

Index Terms – MANET, Routing, PSO, Optimization, Energy, Swarming.

1. INTRODUCTION

A network of wireless portable devices is referred to as a mobile ad-hoc network (MANET). A laptop, PDA, mobile phone, or any other device that can connect with other devices is a “node” in this context. As nodes relocate, new nodes join, or old nodes leave, the network’s topology changes because there are no central servers or fixed infrastructure, and the whole network is self-managed and self-created [1]. As a result, the foundation of this network is built on the collaboration of its nodes. A node communicates with other nodes throughout the network and helps the network run smoothly by completing routing tasks. It requires the aid of intermediaries to communicate with a node that is beyond its communication range. Due to the lack of tethering, MANETs are more flexible than traditional networks and can be put up and taken down easily [2]. A MANET is an appealing and cost-effective approach for delivering communication in places where fixed infrastructure is unavailable or not dependable. Building a fixed infrastructure is not feasible due to geographical location and economic considerations. In the case of ad hoc networks, deployment may be accomplished with minimal user participation because of their self-organization and self-management [3]. Additionally, ad hoc networks can be linked to the Internet or other networks to provide connection and coverage in places where no fixed infrastructures exist. Ad hoc networks can also operate independently.

MANET applications span a wide range of industries and applications. It is still difficult to secure the MANET, even though the technology is used in many fields. MANET is more prone to data and physical security breaches than permanently fixed wired networks. Mobile wireless networks can’t just use fixed wired network security solutions. Batteries are not the primary source of power for MANET devices. Therefore, saving energy in these networks is essential if the network’s services are to be maintained. When a node runs out of energy, it can no longer participate in the network’s collective effort [4].

Additionally, MANETs have a dynamic topology due to mobility and other factors, such as signal quality change, node

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depletion, or new network members joining and re-entering. Network professionals and experts can benefit from monitoring activities in these networks since they provide them with useful knowledge that can be utilized to develop protocols or systems that focus on the findings of collected monitoring data [5]. User traffic is routed and transmitted via the network using a routing protocol from one node to another [6]. Two main goals are to enhance network performance from the perspective of application needs while reducing network costs in line with its capacity. Cost, jitter, stability, loss rate, throughput, latency and hop count are all factors to consider while evaluating such applications.

Path maintenance, data forwarding, path selection and path creation are the four pillars of MANET routing. Ad-hoc routing protocols have the additional advantages of being quick to set up, flexible in route selection, energy and bandwidth-efficient, and quick to adjust to network changes. Changes in the connection and user traffic conditions are taken into account by nearly all routing systems in some fashion. But routing systems adapt in different ways and at different speeds to different kinds of state changes. In multi-path routing systems, redundant and alternative paths are identified as capable of transmitting data packets successfully [7]. Two additional benefits are reduced power usage and a solution to the network partitioning problem caused by these nodes' energy exhaustion. The QoS of MANETs may be improved by using multi-path routing protocols, which ensure stable communication and load balancing. Using these multi-path protocols, you may decrease latency, increase dependability, lower costs, and extend the life of your network while also hybridizing your routing. In multi-path routing systems, redundant information is sent to the target through other channels to ensure fault tolerance. This will lower the risk of communication interruption in the event of a link failure. Source coding is employed in more advanced algorithms to decrease traffic overhead due to excessive redundancy while retaining the same level of dependability. Metrics like path variety (or disjointness) improve route resilience. Multi-path routing technologies have struggled to find and maintain many pathways [8].

1.1. Problem Statement

A key issue with MANETs is congestion, which harms network performance. Using congestion management over a routing system and mobility at the network layer helps decrease the packet loss caused by this. Throughput, packet delivery ratio, end-to-end latency, and other measures of quality of service (QoS) are among the QoS objectives of congestion management techniques. As a result of MANET congestion, packet loss may be minimized by using congestion management at the network layer in conjunction with mobility and failure-adaptive routing protocol. Many factors may contribute to congestion in MANET, such as poor load distribution or imbalance. Multi-path routing in ad hoc networks reduces congestion by distributing the load evenly. Load balancing, congestion avoidance, and fault tolerance are often independent features in current protocols. When congestion occurs, as in multi-path routing, packets that are lost due to this congestion have to be retrieved. There should be a lot of information and a lot of throughput in the loss recovery method.

1.2. Objective

The primary intention of this research work is to propose a bio-inspired optimization-based routing protocol for MANET to (i) utilize the optimum route available both in the local and global network, (ii) avoid congestion by identifying the better-quality routes which do not face route failure, and (iii) utilize multi-path routing instead of single-path routing that leads a way to minimize delay and energy consumption.

1.3. Organization of the Paper

Overview of MANET, Routing, problem statement and this work's objective were covered in the present portion of the article. In Section 2, the relevant literature is reviewed. The Deft Particle Swarm Optimization-based Routing Protocol is proposed in Section 3. (DPSORP). The simulation's environment and the metrics used to measure the performance are described in Section 4. Further, it discusses the outcomes of the simulation. The conclusion and future dimensions are discussed in Section 5.

2. LITERATURE REVIEW

For sink node placement, route building, and route optimization in sensor networks, the "Routing-Aware Network Coding Protocol" [9] has been developed. This protocol's inspiration is from natural processes. Opportunistic coding is employed at prospective relays to limit the number of transmissions. It takes the best of both worlds and uses them to improve data transfer greatly. Particle swarm optimization is used to put the sink node, a minimal Wiener spanning tree is used to build a route between sensors and the sink, and artificial bee colony techniques are used to optimize this route further. Finally, packets are combined before transmission to neighbors. "Enhanced OLSR Routing" [3] approach uses multi-beam transmissions but also picks the most appropriate multipoint relays to reach all nodes with minimal message broadcasts. It primarily focuses on airborne networks equipped with the newest antenna technology, which enables simultaneous packet delivery in various directions without the interference of RF beams. MPRs are selected using a novel technique based on the social network notion in the multi-beam OLSR.

In MANETs, "Decision-Related Event Occurrence Times" [10] are suggested to understand the intricacies of context-aware strategic planning in identifying the routes. This

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paper's approach has examined the lower and upper constraints for tail probabilities. Its performance is demonstrated by a thorough application that analyses a previous routing system that uses the position and mobility of surrounding nodes to determine its subsequent hop forwarding choices. In the "Fungi-based Routing" [11] system, data flows via nodes and connections with a larger abundance of immobilized biomass, which suggests lower costs and better availability. With each successful delivery of data, the routes are strengthened, and the concentration of immobilized biomass is determined by the efficiency of the route between target and target. The route selection algorithm favors the most visually appealing routes. As part of the "Cognitive Radio Routing Protocol" [12] important challenges in routing are highlighted. Two approaches comprise the core of this protocol: Smart Spectrum Selection and Succeeding Hop Selection. The relay node may pick from various spectrum options in a single step, simplifying establishing a route and lowering the overall routing overhead. Aside from allowing for faster spectrum selection, this reduces the amount of overhead required for the system. Optimization strategies [13]–[15] are applied in networking to find better quality routes to destinations.

For Flying Ad-Hoc Networks, an "improved Q-learning based routing protocol" [16] is presented to solve the network latency caused by the selection of routes remains a significant difficulty due to the high mobility of nodes. Q-Learning algorithms have been modified to decrease network delays in high-mobility situations. For Mobile Wireless Sensor Networks, "Dynamic Directional Routing" [17] has been suggested to adjust the mobility of sensor nodes and establish a dependable and energy-efficient route. As a result of this protocol, the paths to the sink are optimized. When determining the best path, it considers a variety of parameters, including the data routing, scalability, topology, mobility, and amount of remaining energy. According to the paper, combining the advantages of quantum genetics with OLSR, "Quantum Genetic Optimized Link State Routing" [18] is suggested for MANETs. End-to-end optimization in MANET is a big task, but the Q-Learning strategy can dynamically adapt the identified route via contact with the social environment. The approach of quantum genetics was improved to include a new Q-Learning technique. This paper demonstrates the global optimization and convergence properties while optimizing the choice of MPR. Issues present in scheduling intra-cluster and inter-cluster links in multi-channel ad hoc networks are attempted to solve by applying Control and User Plane Separation architecture. "Intra and Intercluster Link Scheduling" [19] is the name of the suggested solution. A non-linear optimization issue is first transformed to a linear form by reducing non-linearities, improving optimizer performance while responding to immediate communication requests. An optimizer's output shows a dramatic rise in run-time costs as a parameter size grows. An approach called "Yet Efficient Routing Protocols" [20] has been presented to deal with the frequent hand-off and reactivation failure issues in IoT-based ad hoc networks. As part of the Route Request Packet (RRQP) delivery, this routing protocol supports multi- and single-cast transmissions. At first, only Half-Duplex data transfer is used for testing. However, it uses Full-Duplex data transfer to allocate a channel. To broadcast the RRQP, it either senses or transmits the information. It enables wireless nodes to simultaneously receive and send data sweepingly.

Using a two-hop relay method with packet replication, the "Markov Chain Theoretical Framework" [21] is developed for 3D MANETs." Source nodes may send packets using this process to an unlimited number of relays, each of which helps the packet reach its final destination. Because of the algorithm's flexibility, it is possible to regulate the packet delivery process by altering the number of nodes. 3D MANET packet transport is simulated using a generic Markov chain theoretical framework. For Delay Tolerant Networks, "Multi-Hop Large Data Routing" [22] is suggested to overcome the problem of limited connection and brief contacts between network nodes. This protocol divides huge amounts of data into smaller units and then transmits them through a series of connections in a chunked fashion. Inter-contact time, frequency of contact, and duration are all integrated into a probabilistic model. Network nodes' multi-hop delivery probability is calculated using the model's edge weights. To address the present demands and requirements of safe routing for IoT applications, "Secure Multipath Reactive Protocol" [23] has been suggested. Trust management and multi-path routing are integrated into a lightweight and secure system that may be used for various IoT applications. "QoS-aware Routing Protocol" [24] is developed for Cognitive Radio Ad Hoc Networks to solve the current issues in allocating spectrum schemes. It makes a dynamic assessment of the licensed spectrum instead of following the traditional assessment (i.e., static spectrum assessment). As a result, unregulated wireless spectrum congestion moved to previously unlicensed bands to create room for additional wireless subscribers. A wide range of quality-of-service needs is involved in wireless services. Service needs dictate which channels and routes are used at every point along the path. The mathematical formulas calculate each spectrum band's connection latency and interference ratio.

The concept of "Gradient Assisted Routing (GAR)" [25] has been presented for adaptive mesh networks to create a virtual coordinate system (VCS) that may be utilized for geo-like routing. The traditional geographic routing techniques depend on external location information, but this one utilizes two-hop neighbors' information shared in beacons. Approximating the real network nodes' coordinates creates a VCS that may be utilized for geo-like routing. In contrast to standard

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geographic routing protocols that depend on external location information, it is based on information transmitted in beacons between two-hop neighbors. An algorithm based on the foraging Behavior of ants called the "Energy-Efficient Multipath Routing Algorithm (EEMRA)" [26], has been presented for the AODV protocol. EEMRA aims to enhance network longevity by considering numerous effect variables while making routing decisions by extending the standard ant colony-based routing algorithm. It incorporates a slew of meta-heuristic impact variables to provide reliable routes from source to destination while conserving battery power. Analysis of individual impact factors helps to demonstrate their significance when it comes to routing effectiveness. Energy and statistical analysis are used to support the claim of multi-path routing.

3. DEFT PARTICLE SWARM OPTIMIZATION BASED ROUTING PROTOCOL (DPSORP)

3.1. AODV Routing Protocol

To establish routes, the AODV protocol requires that source nodes request them. In other words, because it only communicates when data is needed, AODV is termed an on-demand algorithm. There are no restrictions on how long pathways can be kept open. Trees are also formed to connect the members of a multicast group. AODV relies on sequence numbers to preserve the freshness of its routes. In addition to scalability to many mobile nodes, they are self-starting and loop-free. Until a link is formed, AODV networks remain silent. Requests for connections are disseminated by network nodes that require them. After that, any surviving AODV nodes pass it forward and note which one requested a link-up. These temporary routes lead back to the node that requested them. Receiving such messages and maintaining a route to the desired node causes the receiving node to send a backward message through temporary routes. When a node makes a request, it takes the shortest possible path across other nodes. After a period of time, the routing table entries that are no longer needed are recycled. The transmitting node receives the routing error if a link fails.

3.2. Particle Swarm Optimization

Eberhart and Kennedy invented PSO in 1995, an optimization technique based on natural inspiration from birds. Birds and other swarming creatures were used as inspiration for PSO's social structure. Each individual in PSO, or "particles," act as a possible solution. Like birds seeking food in the wild, swarms of particles fly across the search area, looking for the best solution. Let $P_s(f) = \left(p_{s1}(f), p_{s1}(f), \ldots\ldots, p_{st}(f)\right)$ and $R_s(f) = \left(r_{s1}(f), r_{s2}(f), \ldots.., r_{st}(f)\right)$ be the coordinates of the particle m_s time f in an t -dimensional hyperspace, respectively. Since the best solution between all particles is recognized as the overall best solution. Each m_s retains a detail of its previously identified best solutions, i.e., designated by $pbest_s$. Several factors contribute to an organism's evolution. These factors include both its own experience $pbest_s$ as well as information on its position and velocity from its global leader.

$$R_s(f+1) = \pi R_s(f) + u_1 r_1 \left(P_{pbesti} - P_s(f)\right) + u_2 r_2 \left(P_{gbest} - P_s(f)\right) \quad (1)$$

$$P_s(f+1) = P_s(f) + R_s(f+1) \quad (2)$$

where π is the parameter, f is the count of generation, u_1 and u_2 represents the factors applied to learn local and global solutions, and b_1, b_2 represents the random variable having values between 0 and 1.

Foreach $D_s \ni D$

Calculate the Euclidean distance between D_s and D_w as Y_{sw}

$DAN_s^1 = \min(Y_s)$;

$TT_s = \{w | Y_{sw} = DAN_s^1\}$;

$D_s = TT_s + DAN_s^1$

End Foreach

Algorithm 1 Pseudocode for Calculating Local Neighbor's Distance

While most previous PSO algorithms update the particles alone, it is based on a single search strategy. The current strategies determine the leadership at each iteration for the entire swarm.

3.3. Deft Particle Swarm Optimization

The DPSORP algorithm is discussed in detail in this section. In the beginning, the algorithm generates a first archive D depending on Pareto dominance by randomly initializing all particles. All the solutions present in D are compared to their neighbor who is nearby to create D_s for each response in D. Each solution has a value for its smallest route to other answers DAN_s^1 and the score of the associated neighbour TT_s as indicated in Algorithm 1. The leaders (i.e., P_{gbest}) are picked to lead the hunt in the subsequent generation when velocity and location are updated either by using Eq.(1) or Eq.(2).

3.3.1. Identification of Local and Global Best-Position

The ideal position P_{pbesti} in DPSORP is modified when the velocity and location are continuously synchronized using Eq.(1) and Eq.(2). P_{pbesti} may be replaced by P_{newi}, if it is more effective than the present role. If P_{pbesti} is now in a stronger position, it will remain in the same position.

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DPSORP will choose a better position based on the chance if neither position has a clear advantage. Particle learning, pair-wise selection, and elite particle choosing are all default components of enhanced PSO. Selection of P_{gbest} leaders for each particle are discussed below.

Input:

D(archive),

M(position),

R(vector),

μ (elite particles size)

Output:

M' (new position)

Procedure:

Distance all particles present in D in descending order based on DAN_s^1;

Choose head μ to build the elite particle set from D particles and it is represented as H;

Foreach $M_s \in M$ **do**

From H, randomly choose d and v (i.e., elite particles)

Using d and m_s, calculate ρ_1

Using v and m_s, calculate ρ_2

If $\rho_2 > \rho_1$ **then**

$d \rightarrow P_{gbest}$;

Else

$v \rightarrow P_{gbest}$;

End if

Using Eq.(1), synchronize the velocity of m_s with r_s';

Using Eq.(2), synchronize the velocity of m_s with M_s';

$M' \leftarrow M_s' \cup \{M_s'\}$;

End foreach

Algorithm 2 Pseudocode for Identifying New Position

All D solutions are ranked according to their DAN_s^1 in DPSORP. It is necessary to choose an exact number μ from the upper particles in the archive D before assembling the H. By directing the search to less populated areas. This phase is specifically meant to conserve variety. A pair-wise contest is used to choose a chief for every particle in the swarm. For this competition, two particles, d and v, are selected at random from the set of elite particles. There is a calculation of the angle among d, v, and m. A particle having minimum angler wins the contest and serves as the guide for m number of particles. d and v are two distinct elite particles picked for the pair-wise contest, whereas m is the particle that will be upgraded. ρ_1 across d and m is less than the angle ρ_2 among v and m, the elite particle d is employed as a leader for m particles. By utilizing Eq.(1) and Eq.(2), elite particles are updated, where P_{gbest} is the winning particle's current position in m. Algorithm 2 fully explains particle selection, competition, and updating.

3.3.2. External Archive Synchronization

There is a finite amount of non-dominated solutions in the external archive, and each generation adds an c number of non-dominated Pareto solutions i.e., $E = (e_1, e_2, \ldots\ldots, e_c)$ to D. In the swarm-based search, the exploration and exploitation phases are separated by the generation index with a threshold value δ. The threshold value δ can maintain a high balance of convergence and the different number of suitable solutions. Archive updates are handled differently in each step. Initially, the solutions in the archive are compared using the proximity distance measure, which is beneficial in the discovery phase to retain variety. Step two involves balancing convergence and variation during exploitation using (i) peak rule, and (ii) overall cost rule.

3.3.2.1. Distance of Neighborhood

The Euclidean distance metric is used to give each solution in D, i.e., a distance value, DAN_a^1, to its nearest neighbour. Due to the symmetry of the metric, there are always two ways to find the shortest DAN_a^1 in D that has the same distance value. In other words, let D_a be the a-th answer in D, DAN_a^1 be the distance present to reach the neighbor nearby and AN_a indicates the nearby neighbor's index. So, the distance between D_a and D_{AN_a} will be the same, which is DAN_a^1. To identify the crowd in D_a and D_{AN_a}, a comparison is carried out by utilizing the distance metric that reflects the distance present between neighbor nearby (i.e., DAN_s^2) and individual solutions. Eq.(3) provides the DPSORP's formal definition for calculating the neighborhood distance.

$$RY_s = \prod_{a=1}^{c} DAN_s^a \tag{3}$$

where RY_s is the distance between particle s and its neighbours, DAN_s^a is the Euclidean distance between particle s and its ath neighbour, and c represents the count of neighboring particles. If the distance of particle aRY_a is smaller than the distance of its nearby neighbor RY_{AN_a}, then DPSORP considers D_a to be the high-level solution, and it is eliminated from D. The remaining distances of D_a neighbors will be impacted by removing of D_a from$D$. The distances

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value DAN_s^1 and the associated indices of the extreme nearby neighbors AN_s must be modified continuously until the proposed solutions in D equal the maximum length of the archive tD. It is necessary to synchronize DAN_c^1 and AN_c if the associated nearby neighbor index AN_c of another solution D_c is identical to the index of the deleted solution a. Algorithm 3 showcases the steps involved in the distance of neighborhood.

Input:

$\boldsymbol{D}$ (archive),

$\boldsymbol{E}$(non-dominant solutions)

Output:

D' (current archive)

Procedure:

$D \cup E \rightarrow D'$

Foreach $D' \ni D_s$ **do**

Synchronize DAN_s^1 and AN_s for D';

End Foreach

While $D < D'$ **do**

Identify D'_a having least DAN_a^1;

Assume w as the index for the nearby neighbor, $w \leftarrow AN_a$

Identify DAN_a^2 and DAN_w^2;

Calculate the distance of neighborhood RY for D_a and D_w;

If $RY_a \geq RY_a$ **then**

From D' remove D_a

Identify the closest neighbor TT_c as a from D_c

Synchronize DAN_w^1, DAN_c^1, AN_w and AN_c;

Else

Analyze D' for abnormal values D_w

If D_w is present, then delete it

Identify the closest neighbor AN_c as w from D_c

Synchronize DAN_a^1, DAN_c^1, AN_a and AN_c;

End if

End while

Algorithm 3 Pseudocode for Calculating Distance of Neighborhood

The Euclidean distance of the removed solution is determined only after removing a solution from the non-dominant set.

3.3.2.2. Overall Cost Estimation Rule

After incorporating fresh nondominated solutions S in the archive, the second strategy is employed to avoid losing better candidates. DPSORP don't have a criterion for comparing non-dominant solutions, whether it removes them from the archive randomly or uses the crowding length as a metric to eliminate additional solutions. Because of this, the additional new solutions may be less convergence-friendly than the previously deleted solution. During the exploitation phase, each objective's fitness values for all incoming nondominated solutions are compared to the objective's maximum cost value before being added to the archive. The better values of the newly added solution e_s are $G_s = (g_{s1}, g_{s2}, \dots g_{sc})$ in a c-objective minimization problem, and $G_{max} = [g_{max1}, g_{max2} \dots, g_{maxc}]$ is a vector consisting of the highest fittest of each object in the archive D. Only if G_s falls below or equals G_{max} for all c number of objectives is G_s and it is added to D.

3.3.2.3. Aggregation Cost Rule

The external archive's non-dominant solution count may surpass the allowed quantity when the aggregation cost rule is applied to all new non-dominant solutions. The aggregation cost rule is another strategy for keeping the number of non-dominant solutions inside the archive while maintaining convergence across the diversity. Let D_s and D_w be the two solutions that are closest to each other in Euclidean terms (i.e. $DAN_s^1 = DAN_w^1$), and let G_s and G_w be their respective fitness values. If D_s is retained then D_w is deleted from an c-objective reduction problem. Eq.(4) mathematically expresses the aggregation cost rule.

$$\sum_{a=1}^{c} G_s \leq \sum_{a=1}^{c} G_w \tag{4}$$

$$G_s = (g_{s1}, g_{s2}, \dots g_{sc}), G_w = (g_{w1}, g_{w2}, \dots g_{wc})$$

Similarly, until the number of solutions in D equals the required size of tD, the rank DAN_s^1 and the associated nearest neighbours' indices AN_s must be synchronized repeatedly. Algorithm 4 highlights the rules of Overall Cost Estimation and Aggregation Cost.

Insert:

D (archive),

E (fresh, non-dominant approaches)

Output:

D'(following archive)

Procedure:

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/*Overall Cost Estimation Rule*/

Begin

From the synchronized archive D, identify G_{max}

Foreach $E \ni e_s$ **do**

If $g_{maxw} \geq g_w(e_s)$ and $c > w > 1$, where w represents the objective index

$D \cup \{e_s\} \rightarrow D'$

Else

Eliminate e_s;

End Foreach

End

/* Aggregation Cost Rule*/

Begin

While $tD < D'$ **do**

With the least value of DAN_a^1 identify D_a'

$TT_a \rightarrow w$, where w indicates the nearby neighbor's solution D_a'

Compute $\sum_{a=1}^{c} G_s$ and $\sum_{a=1}^{c} G_w$;

If $\sum_{a=1}^{c} G_w \geq \sum_{a=1}^{c} G_s$ **do**

Eliminate D_w from D';

Identify D_c i.e., the closest neighbor

Synchronize DAN_s^1, DAN_c^1, AN_s and AN_c;

Else

Eliminate D_w from D';

Identify D_c and Synchronize YTT_w^1, YTT_c^1, TT_s and TT_c;

End if

End while

End

Algorithm 4 Pseudocode of Rules Followed in DPSORP

3.3.3. Algorithm for Complete DPSORP

The two aspects of DPSORP mentioned in the preceding sections are highly significant. Algorithm 5 highlights the complete flow of DPSORP, where T denotes population size and δ denotes a predefined value that regulates the exploration and exploitation phases. DPSORP initializes its operation by randomly initializing the random number of swarms with T particles, removing the external archive. As soon as all particles' fitness functions have been evaluated, non-dominant sorting is performed. Its main intention is to choose the initial non-dominant solution stored for future usage. Termination criteria are met when the DPSORP its development cycle.

To make an elite particle set, Euclidean distance is used to figure out how far apart each particle in the archive is from its closest neighbor. As described in Algorithm 1, this is accomplished by assigning a number to every particle in the archive representing the distance and the index of the closest particle. Afterwards, the archive's particles are sorted by distance from the nearest ones in descending manner. It is possible to choose a group of the best μ particles from the archive using the pair-wise competition method.

Using Eq.(1) and Eq.(2) established in Algorithm 2, the particles are then recalculated. There are two approaches to synchronizing the archive after analyzing the swarm particles, both of which are dictated by the chosen user-defined values. The archive is modified using the nearby neighborhood distance metric shown in Algorithm 3 during the exploration phase. The iteration value equal to or greater than δ is used to update non-dominant solutions in the archive, as stated in Algorithm 4. The final estimated Pareto fronts in the exterior archive are presented as a result of the method. Overall architecture diagram of the proposed protocol is provided in Figure 1.

Input:

T (the population)

Output:

D (Non-dominant solutions archive)

Procedure:

Randomly initialize M, R and D

Identify the distance of nearby neighbors all solutions in D (Algorithm 1);

While termination criteria are not met,

Synchronize particles (D, M, R, μ) based on the strategy of Elite particle selection (Algorithm 2);

Check Dominance Rate(M');

If the current generation's index count falls below a threshold value, i.e., $f < \delta$**do**

Synchronize (D, E) based on neighborhood distance (Algorithm 3);

Else

Synchronize (D, E) based on the Overall Cost Estimation Rule and Aggregation Cost Rule (Algorithm 4);

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End If

End while

Algorithm 5 Pseudocode of Overall DPSORP

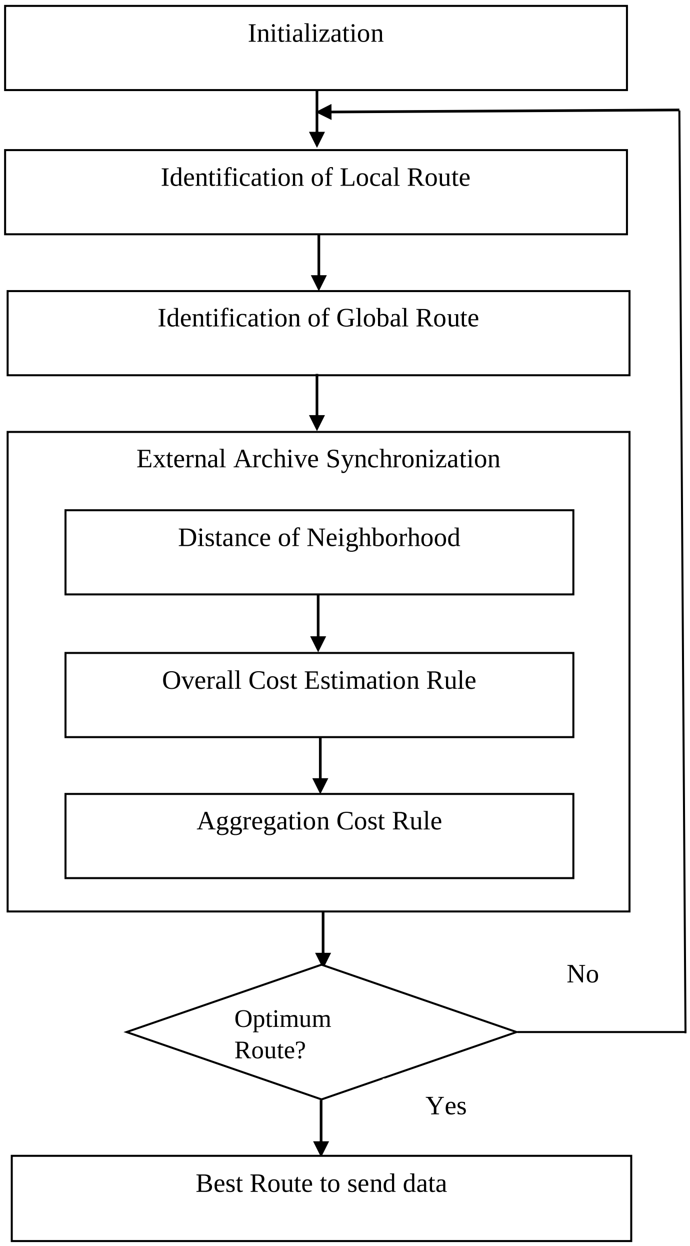

Figure 1 Architecture Diagram of the Proposed Routing Protocol

4. SIMULATION RESULTS

4.1. Simulation Setting

Settings used in the simulator while experimenting are provided in Table 1.

Table 1 Settings Used to Conduct Simulation

Simulation specification	Value
Simulator Name	Network Simulator 3
Version	NS-3.36
Distribution of Node	Random
MAC	802.11
Node Count	200
Simulation Duration (in seconds)	300
Size of data packet (in bytes)	1475
Type of traffic	UDP
Simulation Size	1200m × 1500m
Mobility Model	Randomway Point
Total Number of Packets	1300

4.2. Performance Metrics

- Throughput measures how much information a protocol can process over time.
- Energy consumption measures the energy consumed by a packet to travel from source to destination.
- Packet Delivery Ratio measures the proportion of packets transmitted from the source to those received at the destination
- Packet Loss Ratio compares lost packets against the total transmitted packets.
- Delay represents the time a packet takes from the source network node to its destination.

4.3. Discussion of Results

4.3.1. Throughput

In Figure 2, the throughput of DPSORP is contrasted with the current routing protocols (i.e., GAR and EEMRA). The number of nodes is indicated on the x-axis, while the throughput in kbps is indicated on the y-axis. It is clear from Figure 2 that DPSORP performs better than the current routing protocols. Fine-tuned optimization in identifying local and global best-position plays a significant role in DPSORP where it identifies the local and global best-position before selecting it for routing the data to the destination, and it makes to achieve better throughput than the current routing

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protocols. The strategies followed by the current routing protocols are not efficient enough to identify better routes and result in minimum throughput. Table 2 provides the Figure 2 outcome values.

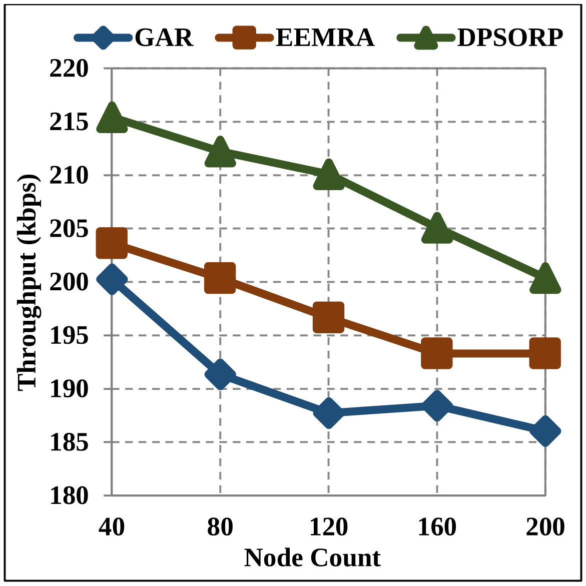

Figure 2 Throughput

Table 2 Throughput Outcomes

Node Count	GAR	EEMRA	DPSORP
40	200.250	203.620	215.430
80	191.340	200.360	212.220
120	187.710	196.650	210.090
160	188.420	193.290	205.080
200	186.050	193.301	200.380

4.3.2. Energy Consumption

In Figure 3, the energy consumption of DPSORP is contrasted with the current routing protocols (i.e., GAR and EEMRA). The number of nodes is indicated on the x-axis, while the energy consumption in percentage is indicated on the y-axis. Figure 3 clearly shows that DPSORP outperforms the current routing protocols by consuming minimum energy for transmitting data from source to destination. The strategy used for calculating the neighbour's distance plays a major role in the routing process of DPSORP. Even though the closest neighbors are identified in DPSORP, it is evaluated for utilization in routing, achieving less energy consumption than current routing protocols. No strategies are used in current routing protocols to evaluate the neighbor to utilize in the routing process. Table 3 provides the Figure 3 outcome values.

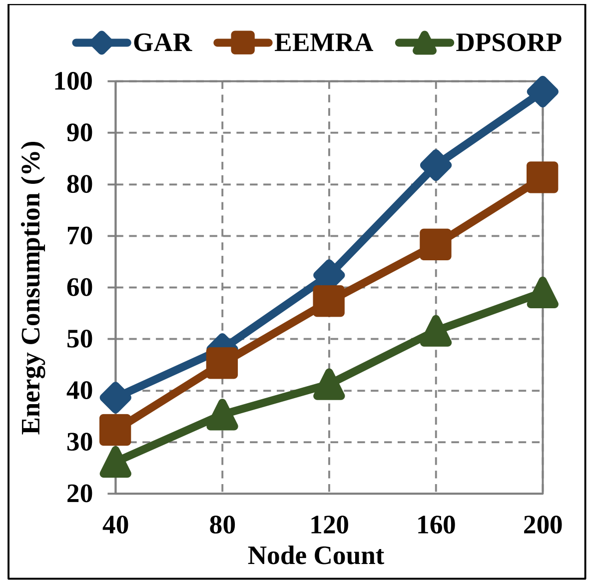

Figure 3 Energy Consumption

Table 3 Energy Consumption Outcomes

Node Count	GAR	EEMRA	DPSORP
40	38.630	32.320	26.180
80	48.070	45.260	35.350
120	62.410	57.330	41.240
160	83.750	68.270	51.610
200	98.020	81.280	59.050

4.3.3. Packet Delivery Ratio and Drop Ratio

Figure 4 and Figure 5 contrast the packet delivery and drop ratio of DPSORP with the current routing protocols (i.e., GAR and EEMRA). The number of nodes is indicated on the x-axis of Figures 4 and 5. In Figure 4, the packet delivery ratio in percentage is indicated on the y-axis, and in Figure 5, the packet drop ratio is indicated on the y-axis. The performance of DPSORP surpasses that of the present routing protocols, as seen in Figures 4 and 5. DPSORP identifies the route by applying the two rules, namely the Overall Cost Estimation Rule and Aggregation Cost Rule. These two rules assist in identifying the route quality before sending the data, resulting in increased delivery of packets and vice-versa drop ratio. The current routing protocols attempt to select a route without analyzing its quality, which affects the delivery of packets and increases the drop ratio of packets. Table 4 provides the Figure 4 outcome values, and Table 5 provides the Figure 5 outcome values.

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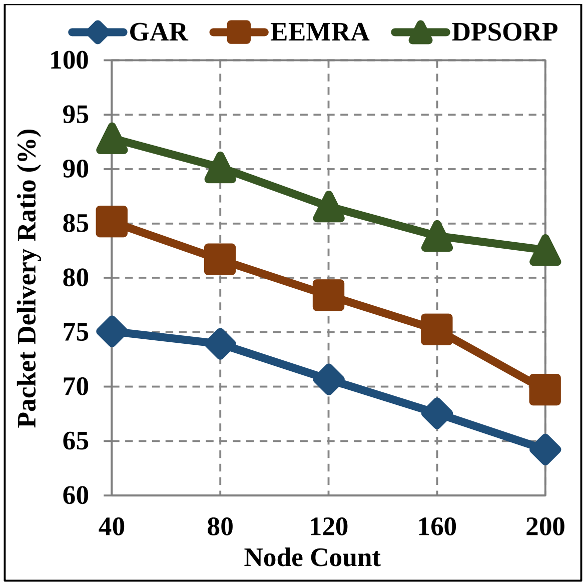

Figure 4 Packet Delivery Ratio

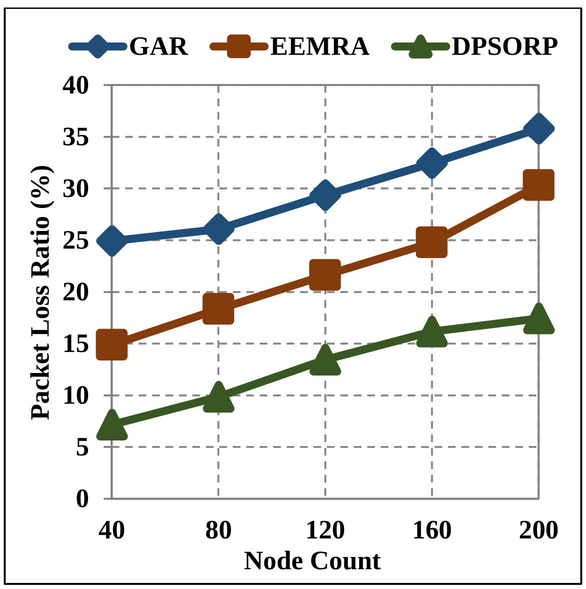

Figure 5 Packet Drop Ratio

Table 4 Packet Delivery Ratio Outcomes

Node Count	GAR	EEMRA	DPSORP
40	75.08	85.14	92.84
80	73.92	81.66	90.16
120	70.66	78.38	86.57
160	67.55	75.23	83.84
200	64.21	69.69	82.56

Table 5 Packet Drop Ratio Outcomes

Node Count	GAR	EEMRA	DPSORP
40	24.92	14.86	7.16
80	26.08	18.34	9.84
120	29.34	21.62	13.43
160	32.45	24.77	16.16
200	35.79	30.31	17.44

4.3.4. Delay

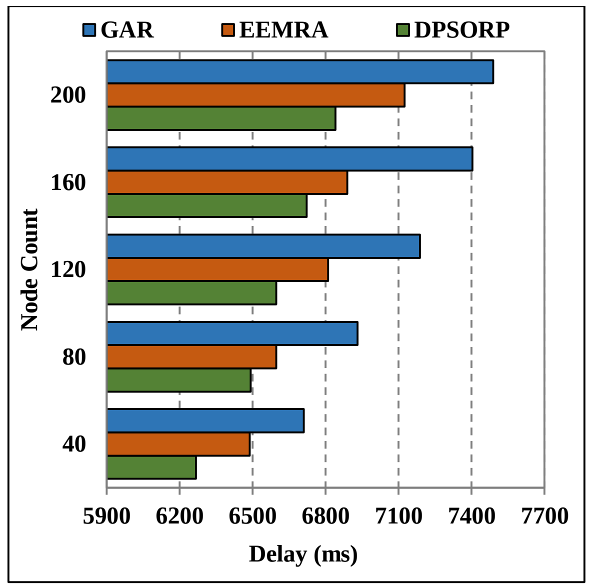

Figure 5 Delay

Table 5 Delay Results

Node Count	GAR	EEMRA	DPSORP
40	6711	6488	6268
80	6932	6597	6492
120	7188	6810	6597
160	7403	6889	6722
200	7489	7125	6841

In Figure 6, the delay faced by DPSORP is contrasted with the current routing protocols (i.e., GAR and EEMRA). The number of nodes is indicated on the x-axis, while the delay measured in milliseconds is indicated on the y-axis. Figure 6 illustrates how DPSORP outperforms current routing

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protocols in terms of delay. The fitness function in DPSORP achieves a lower delay than the current routing protocols. The fitness function is used to check the quality of the route. The routes that do not satisfy the fitness function result are not used in routing to transfer the data. The current routing protocols select the route for transmitting the data without checking its quality and end with route failure and this makes them face more delay and leads to more energy consumption. Table 6 provides the Figure 6 outcome values.

5. CONCLUSION

The major cause for consuming more energy in MANET is congestion and the poor-quality route for data transmission. Deft Particle Swarm Optimization-based Routing Protocol (DPSORP) is proposed in this paper to reduce delay and energy consumption in MANET. The main intention of DPSORP is to avoid congestion in MANET by selecting an available local and global optimum route. The position of nodes has more significance in identifying the optimum route. DPSORP gives one step more priority to node position and calculates the distance of nearby neighbor before utilizing it in routing. The two cost rules present in DPSORP assist in identifying the quality of the selected route before transmitting the data in it. DPSORP is evaluated in NS3 using throughput, energy consumption, packet delivery and drop ratio, and delay. Results indicate that DPSORP consumed 42.68% energy during the simulation and achieved an 87.19% packet delivery ratio with 208.64 kbps of throughput. The future scope of this research can focus on different bio-inspired strategies to minimize delay and energy consumption even more.

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