

Article

Routing Enhancement in MANET Using Particle Swarm Algorithm

Ohood Almutairi, Enas Khairullah, Abeer Almakky  and Reem Alotaibi * 

Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia; orashedalmutairi@stu.kau.edu.sa (O.A.); ekhairallah@kau.edu.sa (E.K.); aalmakky@kau.edu.sa (A.A.)

* Correspondence: ralotibi@kau.edu.sa

Abstract: A Mobile ad hoc Network (MANET) is a collection of wireless mobile nodes that temporarily establish a network without centralized administration or fixed infrastructure. Designing the routing of adequate routing protocols is a major challenge given the constraints of battery, bandwidth, multi-hop, mobility, and enormous network sizes. Recently, Swarm Intelligence (SI) methods have been employed in MANET routing due to similarities between swarm behavior and routing. These methods are applied to obtain ideal solutions that ensure flexibility. This paper implements an enhanced Particle Swarm Optimization (EPSO) algorithm that improves MANET performance by enhancing the routing protocol. The proposed algorithm selects the stable path by considering multiple metrics such as short distance, delay of the path, and energy consumption. The simulation results illustrate that the EPSO outperforms other existing approaches regarding throughput, PDR, and number of valid paths.

Keywords: mobile ad hoc networks (MANETs); routing protocol; swarm intelligence; particle swarm optimization (PSO)



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1. Introduction

With the development of wireless networks, one of the most prominent areas of research in the modern era is MANETs. Mobile ad hoc Networks (MANETs) are some of the most popular wireless communication networks, consisting of multiple mobile nodes interacting with other nodes using a decentralized infrastructure [1]. This type of network does not rely on a fixed infrastructure. It is highly adoptable in challenging environments, such as emergency management, disaster recovery, border facility sensors, and vehicle networks. Through MANET [2], users can send data without following a definite structure. Furthermore, it is necessary to have an impermanent network with no centralized management or communication structure. During data packet transmission, each node in MANET performs the roles of host and router. Additionally, it has a dynamic topology, and each node has mobility behaviors. Each node is self-configuring and self-healing without the need for human intervention [3]. The mobility nature of MANETs results in constant and unpredictable changes in network topology, leading to complex routing operations [4]. The routing protocol for MANETs contains a routing algorithm with defined rules that are used to monitor the network's operation.

MANET routing protocols are categorized into (i) proactive, (ii) reactive, and (iii) hybrid protocols [5]. In the proactive or Table-driven protocol, each node keeps track of one or more routing tables containing information about the network topology [6]. The reactive protocol depends on the query–reply dialog principle. It does not conserve the up-to-date topology but initiates the process only when a routing path needs to be discovered. The hybrid routing protocol integrates both reactive and proactive routing protocols by dividing the network into zones. The proactive protocol is used when both the source and destination are in the same zone. There are several issues with the routing protocols

that are used in MANETs [7]. Proactive routing, initially, reduces the network's actual data communication capacity. A significant amount of routing table data is exchanged, which takes a lot of the network's capacity as mobile nodes continuously update their routing tables. Moreover, it does not work for large networks since the entries in the routing become too large. Applications that use real-time data and multimedia communication are not proper in on-demand hybrid routing protocols. Hybrid routing protocols are more complex, difficult to configure, and require more memory and processing power.

Traditional routing protocols cannot overcome challenges in MANET because of its limited energy resources, changing topology, and limited link capacity. When routing becomes a critical issue in a challenging network scenario and conventional routing strategies break down, SI is an appealing solution. SI involves a group of agents that interact with each other and with their surroundings [8]. Particle Swarm Optimization (PSO) is an effective optimization technique that relies on mobility and swarm intelligence [9]. It employs agents to spread out in the search area to locate the optimal solution. Particles adjust their positions based on their own experiences and the experiences of other particles. PSO evaluates each particle using a fitness function to determine the position that provides the best evaluation of the fitness function.

In this paper, we propose an EPSO algorithm to find the best routing path in MANETs. It uses a modified fitness function that takes into account the distance, energy consumption, and delay of the network. These modifications are aimed at improving the MANET performance. In this paper, a literature review is provided in Section 2. The EPSO algorithm is presented in Section 3. Evaluation metrics, simulation results, an ablation study, and an analysis of the EPSO are given in Sections 4, 5, and 6, respectively. Section 7 concludes the paper.

2. Literature Review

Particle Swarm Optimization is a search technique that is inspired by flocks of birds. The population-based algorithm was proposed in 1995 by Eberhart [1]. The traditional PSO algorithm contains many populations of particles, and each of them is a candidate solution. The particle moves in a search space and the position of the particle is adjusted depending on its own experience and other particles' experience. The PSO algorithm aims to balance exploration and exploitation by combining local search techniques with global search techniques.

The concept of fitness is used, and potential problem solutions are termed particles. Each particle modifies its search based on both its own experiences and those of its companions. The particle experience is the optimal location that the particle finds; it is represented as P_{best} . The social environment experienced G_{best} is the location that the particle group determines to be optimal.

In each iteration, the particle observes its fitness and the fitness of other particles and tries to imitate the successful particles and move toward them. The position and velocity of particle i in each iteration are represented in the following equations:

$$V_i(t+1) = W \times V_i(t) + C_1 r_1 (P_{best(i)} - X_{i(t)}) + C_2 r_2 (G_{best} - X_{i(t)}) \quad (1)$$

$$X_{i(t+1)} = X_{i(t)} + V_{i(t+1)} \quad (2)$$

where V_i is the current velocity of the particle and W is the inertia weight; it is a positive constant used to balance the exploration and explosions. The cognitive constant C_1 is a positive constant used to weigh the importance of the previous experience of the particle. r_1 and r_2 are random variables. The social constant C_2 weighs the importance of the global learning of the swarm. P_{best} is the best position of the particle and X_i is the current position of the particle and it must be increased to attract the particle to its best own position. G_{best} is the global best position of particles. The particles are initially distributed randomly in the search space. The velocity of each particle is a random value at the beginning and is updated using the particle's experience and the experience of other particles.

The fitness function is used to examine the quality of each solution. The fitness function can be formed in different ways; one of the approaches is a calculation model based on the problem domain. Most traditional PSOs do not consider important parameters that affect the network performance. Furthermore, designing an effective fitness function is an important aspect of improving the quality of solutions in PSO.

The authors of [10] presented a hybrid Extended Particle Swarm Optimization (EPSO) model. The proposed model enhances MANET performance by determining the best node mobility and number of hubs to choose the best path. The proposed model used the EPSO algorithm, which relies on population distribution and a particle searching methodology. The EPSO enhanced the traditional PSO by dividing particles into two groups; this division encourages better exploration and reduces the stagnation of the search space. It reduces the discarded packets and reduces the packet delay. The effectiveness of the EPSO was tested on a very small network (a network with less than 20 nodes), which was insufficient to demonstrate the algorithm's effectiveness.

A cross-layer routing protocol that used the PSO algorithm was suggested in [11]. The fitness metrics consider both the success data rate and the remaining energy. The PSO algorithm uses network information to generate the energy-efficient path. It uses the Contention Window measured from the MAC layer. The remaining power adjusts the CW to decrease the energy consumed. However, the proposed algorithm should consider the distance to find the best path. At long transmission distances, the nodes dramatically consume more power.

An optimized particle swarm algorithm (OPSO) integrated into the location-aided routing (LAR) protocol to enhance the energy consumption in MANET was proposed in [12]. The OPSO improves the exploration and exploitation process in the energy-aware location-aided algorithm (EALAR) protocol by replacing a nonuniform mutation with a uniform mutation using PSO. Network performance including packet delivery rate and power consumption was enhanced by combining the OPSO algorithm into the LAR protocol, while a high E2E delay was achieved.

Hadi and Makki in [13] used a hybrid swarm optimization model (CPSO) to improve routing protocols in MANET. They combined PSO with cat swarm optimization (CSO). The model tried to enhance the locally optimal solution known as stagnation by expanding the possibilities of the metaheuristic algorithm. The hybrid model offered proposed solutions for populations. The proposed method first searches for a local solution; if it has an unsuccessful search, it will use the PSO immediately. If the PSO is already at the local optimal and the possible solution did not achieve any enhancement, it will use the cat swarm optimization. The objective function considers latency and packet loss, and PDR increases the network performance.

The authors of [14] introduced a clustering and routing protocol using PSO (CRPL) to select the appropriate next-hop relay nodes of CHs to decrease the consumption power and increase the network lifetime. The system used sensor nodes in a target area to form clusters managed by Cluster Heads (CHs). It used PSO to set the cluster head members (CHs) and select the best path for CHs. The network functions under assumptions like static and homogeneous nodes, symmetric communication links, and a transmission power that is modified according to distance. It employs different energy models for different distances to enhance network efficiency and lifetime. The CRPL reduced the energy consumption during routing. However, its fitness function with the CRPL considers only CHs and their associated relay nodes, decreasing energy efficiency.

The authors of [15] proposed a Binary Particle Swarm Optimization algorithm (BPSO) to improve the energy in the TORA protocol. They developed a new fitness function based on node energy among all possible routing nodes and hops numbers in the selected path. BPSO maximized network lifetime and enhanced network performance. However, the evaluation did not consider energy efficiency and its important parameters.

Saravanan et al. in [16] integrated an expected transmission count (ETX) with PSO. To choose the appropriate paths with the minimum number of hops, the proposed method

employs the ETX to determine the number of transmissions required for a packet to be properly transmitted over a connection. Moreover, the PSO algorithm prioritizes paths based on fitness values to reduce the packet transmission cost. The proposed PSO-ETX achieved high efficiency in delivering the packet but did not work effectively with a greater number of hops.

A Particle Swarm Optimization model dependent on On-Demand Multicast Routing Protocol (PSO-ODMRP) was proposed in [17]. The PSO-ODMRP was intended to enhance the multicast routing optimization algorithm in MANETs. The PSO-ODMRP builds a multicast tree periodically through flooding control packets, and nodes that want to join the multicast group respond accordingly. The algorithm achieved high performance in low mobility, but under a high mobile density, the performance decreased.

The authors of [18] suggested a stable routing method using PSO and centrality betweenness-based stability (CBS) to select a proper network path. The PSO-CBS determines the stable path by choosing nodes based on link quality, remaining energy, and node degree. The proposed method increases the packet delivery ratio and decreases the network delay and the congestion rate.

A Predictive Energy Efficient and Reliable Multicast Routing method utilizing the PSO algorithm was introduced in [19]. The PEERMAR builds an energy-efficient multicast tree using PSO. This approach builds an energy-efficient multicast tree by evaluating a fitness function that takes into account the delay, energy efficiency, and path stability during simultaneous data transmission to multiple destinations. The study assumes a planar Poisson distribution for node deployment within a defined area and focuses on metrics such as residual energy, delay, and link expiration time for routing decisions. The PEERMAR maintained a higher delivery ratio and lower latency than existing methods. However, compared to other nodes, a significant drawback is the overloading of large root nodes.

The study in [20] suggested a Fixed-PSO route selection technique using PSO for MANETs. The algorithm focuses on minimizing the distance from source to destination node. The Fixed-PSO approach allows for effective route discovery in dynamic networks where nodes can join or leave unexpectedly. Parameters considered in the fitness function are the total distance from the source node to the destination and the distance between the last node in the path to the destination node. Two simulation scenarios were conducted: one under the normal situation (all nodes connected) and another under the abnormal condition (some nodes disabled). In normal conditions, the minimum distance for route selection was achieved. According to the results in abnormal situations, additional relay nodes were required.

There are different Artificial intelligence (AI) algorithms used to enhance MANET routing. Deep reinforcement learning (DRL) is one of the popular artificial intelligence methods that combines deep neural networks and reinforcement learning. DRL contains states, actions, and rewards. The agent interacts with its environment to assess its state and produce the best action that maximizes the reward. The DRL does not need prior knowledge of the mathematical models; it learns by interacting with its environment. It allows agents to learn complex strategies by interacting with their environment iteratively and making decisions that maximize the rewards.

The authors of [21] present a routing protocol called DeepCQ+ integrating multi-agent deep reinforcement learning techniques with Q-learning-based routing protocols for MANETs. The proposed routing algorithm optimizes next-hop selection while using acknowledgment (ACK) packets to share limited information between network nodes and to encourage minimal overhead in networks. The proposed algorithm achieves better end-to-end throughput with lower overhead compared to traditional Q-learning-based protocols.

The authors of [22] integrated an Artificial Neural Network (ANN) with the Link State Routing Protocol (LSR) to optimize the LSR.

The Optimized Link State Routing Protocol (OLSR) works on limited variable attributes in the MANET. Since MANETs are dynamic environments, the default variables

of the attribute are not proper. Therefore, the authors integrated the OLSR with an ANN to adjust the OLSR's configuration attributes. The proposed method decreases power consumption and maximum PDR. However, the proposed algorithm is inefficient in large networks due to the high computational process.

Most previous studies are not efficient in large networks and do not perform well with a greater number of hops. Additionally, they do not consider important parameters that affect network performance, such as delay. To overcome these limitations, we propose a new particle swarm optimization algorithm that can improve routing in MANETs and enhance their performance. The EPSO algorithm selects the stable path by considering multiple metrics such as short distance, path delay, and energy consumption. Metrics such as throughput, PDR, number of valid paths, and E2E delay are utilized for analyzing the performance of the proposed PSO against the other existing algorithms.

3. The Proposed Method

EPSO proposes a routing algorithm that uses traditional PSO to select the most appropriate path. In MANETs, routes are updated dynamically due to frequent position and velocity updating. EPSO is used in the MANET protocol to maximize the performance by enhancing the path selection in MANET. The following EPSO methodology is applied in this study to enhance the performance of the MANET routing protocols:

1. Initialize the parameters of the PSO algorithm.
2. Look for the best parameters for the MANET routing protocols.
3. Select the best routing path for the MANETs.
4. Evaluate the MANET performance.

In EPSO, each particle represents a potential routing path from a source node to a destination. Each particle is represented as a sequence of nodes from the source to the destination. For instance, a particle might be [S, B, C, D], where S is the source, D is the destination, and B and C are intermediate nodes. The fitness function evaluates the selection path; it is calculated for each particle based on its position and velocity. The proposed model enhances the PSO algorithm by modifying the fitness function as seen in Algorithm 1. The fitness function in the EPSO takes into account the distance between nodes, in the case of various paths, the path that has the least distance will be selected. It also considers energy consumption and the delay in path selection to increase the network performance. Energy consumption is the total energy consumed along the selected path. The delay is the total time needed to move data between the source and destination.

The modified fitness function is calculated using the following equation:

$$Fitness = \sum_{i=1}^N (P_i + D_i + Dis) \quad (3)$$

where N is the number of nodes in the path, P_i is the total consumed power from source node to the i th node, and D_i is the total delay from source node to the i th node.

Dis is the total distance between the source S and destination D, calculated using the Euclidean distance formula represented in Equation (4).

$$Dis = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} \quad (4)$$

Algorithm 1 Pseudocode of proposed PSO**Input:**

$Max_{iter} \leftarrow$ Maximum number of iteration
 $u_b, l_b \leftarrow$ Upper bound and lower bound
 $c_1, c_2 \leftarrow$ Cognitive parameter and Social parameter
 $I \leftarrow$ Population size
 $S \leftarrow$ Source node
 $D \leftarrow$ Destination node

Output:

The path from the source node S to the destination node D that achieves the minimum fitness value.

Begin:

Randomly initialize particle position X and particle velocity V vectors.

Initialize the personal best solution (P_{best}) to its initial position for each particle.

Initialize the global best solution (G_{best}) to the position with the minimum fitness value.

$i = 1$

while $i < Max_{iter}$ **do**

 Set the first node in the path X1 to the source node S.

for $j = 2$ to I **do**

 Update particle velocity using Equation (1).

 Update particle position using Equation (2).

if $f(X_i) > f(P_{best})$ **then**

$P_{best} = X_i$

end if

if $X_i = D$ **then**

 Destination is reached; exit the for loop.

end if

end for

 Update the global best solution (G_{best}) to the position with the minimum fitness value using Equation (3).

$i = i + 1$

end while

End

An Illustrative Example

Figure 1 shows a demo network used to describe the proposed PSO algorithm used to find a route. Consider that node 8 is the source and node 2 is the destination. At the beginning of PSO, we defined particles, where each particle is the problem solution. In our algorithm, each particle is a potential route. For instance, we have three particles; the first particle takes a position in the source node. At the beginning, the particle's velocity is zero. The algorithm checks the neighbors of the source node and chooses a random node from the neighbor's list. First, it selects node 5 from the neighboring list and checks whether it has reached the destination node; node 5 is not the destination. The algorithm takes another random node from the neighbors, takes node 10, and checks if it has reached the destination node. Node 10 is not the destination. It will take node 2 from the neighboring list and reach the destination. Table 1 explains the path selection steps.

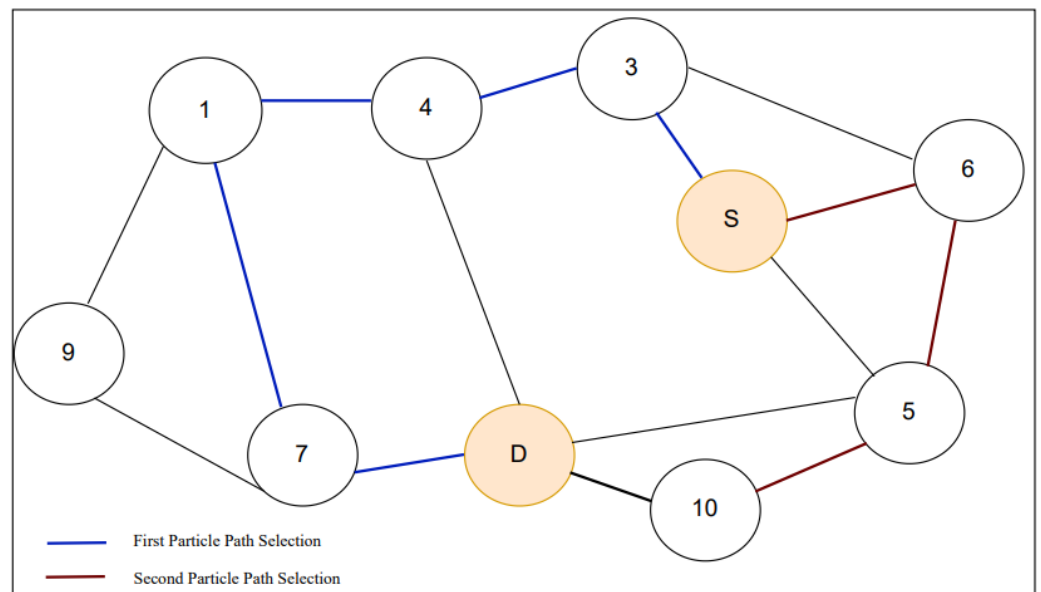


Figure 1. Demo network.

The path obtained by the first particle is [8, 3, 4, 1, 7, 2] and its fitness value is 703.39. The global best is the path with the minimum fitness value. After the particle initialization, updating takes place. Equations (1) and (2) will update the position and velocity, respectively. The second particle tries to find its route path; it selects [8, 6, 5, 10, 2], and its fitness value is 457.02. The third particle tries to find a new route with a minimum fitness. It will obtain [8, 5, 10, 2], and its fitness value is 457.02; Table 2 shows the path evaluation. The next step is to evaluate the selected path. The PSO algorithm calculates the fitness value for each path and attempts to select the global best that achieves the minimum fitness. Therefore, the best path obtained is [8, 5, 10, 2] since it achieves the minimum fitness value. Figure 2 shows the network after the third particle is updated.

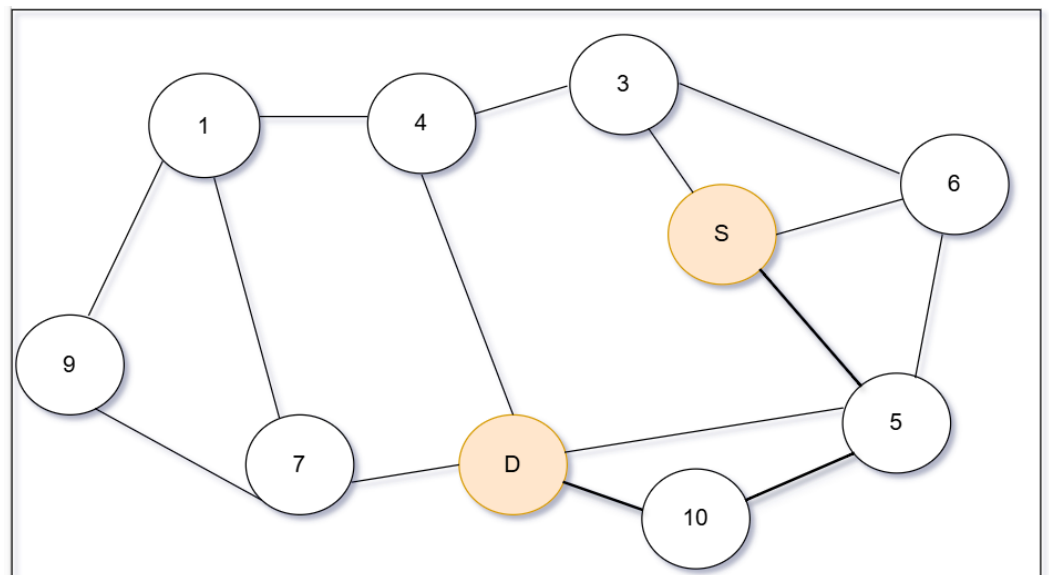


Figure 2. Network after the third particle is updated.

Table 1. Path selection.

Nodes	Neighbors	Next Node	Current Path	Destination Reached?
8	3, 5, 6	5	[8, 5]	No
5	6, 8, 10, 2	10	[8, 5, 10]	No
10	2, 5	2	[8, 5, 10, 2]	Yes

Table 2. Path evaluation.

Iteration	Path	Distance	Consumed Power	Delay	Fitness Value	Global Best
1	[8, 3, 4, 1, 7, 2]	83.39	236	384	703.39	[8, 3, 6, 5, 10, 2]
2	[8, 6, 5, 10, 2]	77.57	229.00	350.00	656.57	[8, 6, 5, 10, 2]
3	[8, 5, 10, 2]	38.02	168	251	457.02	[8, 5, 10, 2]

4. Evaluation Metrics

To evaluate the performance of the EPSO algorithm, we used the throughput, packet delivery ratio, end-to-end delay, and number of valid paths.

1. Packet Delivery Ratio (PDR)

This is the ratio between data packets successfully reaching a destination and the total number of packets sent by the source. A higher PDR demonstrates the reliability and performance of the protocols, suggesting most packets reach the destination without being lost. In contrast, a lower PDR indicates potential issues in the network causing packet loss. PDR is determined using the formula below:

$$PDR = \frac{\text{number of packets received}}{\text{number of packets sent}} * 100 \quad (5)$$

2. Throughput

Throughput refers to the actual data packets that can be processed over time. Throughput reflects the actual performance of the routing mechanism; it assesses the ability of the routing protocol to successfully transmit the data over the network. Throughput is calculated using the following formula:

$$\text{Throughput} = \frac{\text{number of packets received}}{\text{Time period}} \quad (6)$$

3. Number of Valid Paths

The number of valid paths refers to the number of active, usable routes that connect a source node and destination node. It is a critical factor in the routing protocol that affects its performance. More paths help in load balancing and fault tolerance.

4. End-to-End (E2E) delay

End-to-end (E2E) delay refers to the number of hops involved in a routing path.

$$E2E \text{ delay} = M \quad (7)$$

where M is the total number of hops in the selected path.

5. Simulation Results

The performance of the proposed algorithm is tested in a MANET simulation environment using the MATLAB 2021a programming tool on a system with 8 GB random access memory, an i7 intel core processor, and the Windows 10 operating system.

First, the MANET was used to set the simulation environment including the network size and node number. Secondly, we implemented the algorithm using MATLAB software. In addition, the proposed PSO algorithm performance was analyzed by evaluating its results with the other algorithms. The performance was analyzed by varying the node size

such as 50, 100, 150, 200, 250, and 300. Each experiment was repeated 10 times, and the average was taken. Table 3 shows the simulation parameters used in the experiment.

This section presents an overall comparison of the proposed PSO against the Fixed-PSO [20] and the existing Ad Hoc On-Demand Distance Vector (AODV) protocol. The Fixed-PSO aims to minimize the distance from the source to the destination node. Two parameters considered in the fitness function are the total distance from the source node to the destination and the distance between the last node in the path and the destination node.

Table 3. Simulation parameters.

Parameters	Value
Number of Nodes	50–300
Mobility Model	Random waypoint
Network Dimension	100 × 100
Node Distribution	Random

The Packet Delivery Ratio (PDR) is a major metric for the performance of any routing protocol. In Figure 3, the proposed PSO achieves high PDR across all network sizes, starting at 50 nodes and continuing up to 300. The PDR in the proposed PSO is better than the other two algorithms as the number of nodes increases. The AODV and Fixed-PSO start lower and scale with an increasing number of nodes. The Fixed-PSO generally shows better results than the AODV in large networks but it achieved lower values in small networks. The proposed PSO is more effective in ensuring the successful delivery of packets in a network, especially in large networks. In Figure 3, it is obvious that the PDR in the proposed PSO was better than the PDR in the AODV as the number of nodes increased. Furthermore, the network connectivity was high due to the high number of nodes, which minimized the probability of packet loss. The proposed PSO protocol consistently achieved a higher Packet Delivery Ratio (PDR) than the AODV protocol. The proposed PSO was more effective in ensuring the successful delivery of packets in a network, especially in large networks.

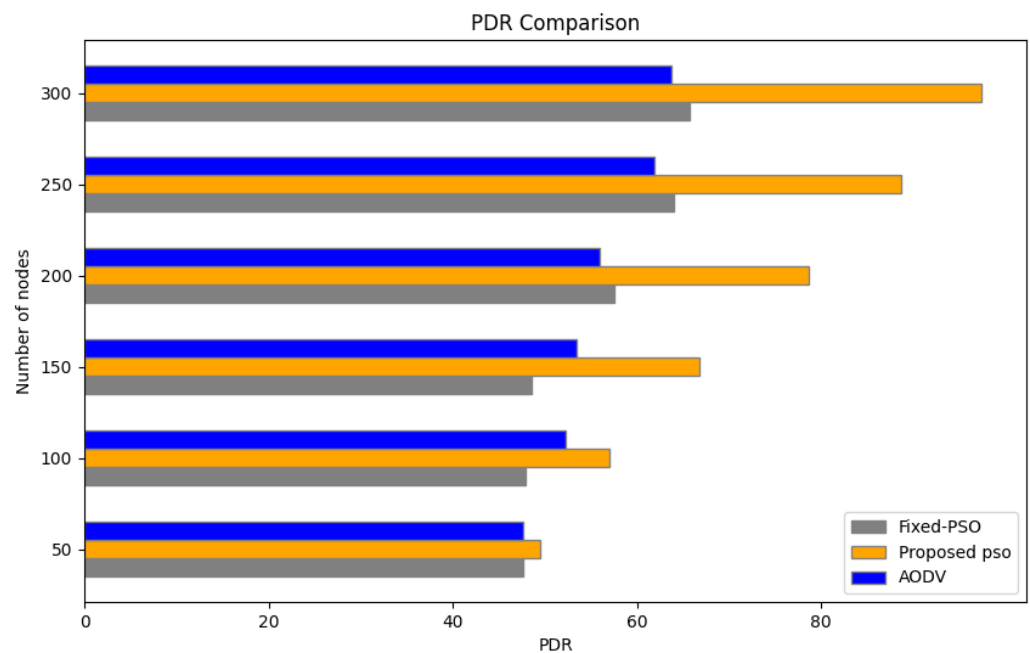


Figure 3. Packet delivery ratio for proposed PSO, Fixed-PSO, and AODV.

Throughput represents the efficiency of the routing method in receiving the data packets. A higher average throughput indicates a more effective and efficient routing protocol. In Figure 4, throughput is measured in different network sizes for three different algorithms:

Fixed-PSO, proposed PSO, and AODV. The proposed PSO algorithm outperforms other algorithms and consistently shows the highest throughput across all networks, indicating it is the most efficient protocol among the three in handling larger numbers of nodes. The Fixed-PSO generally shows better results than the AODV, especially as the number of nodes increases. The throughput for the three algorithms increases as the number of nodes increases. However, the proposed PSO consistently outperforms the other algorithms as the network size scales up.

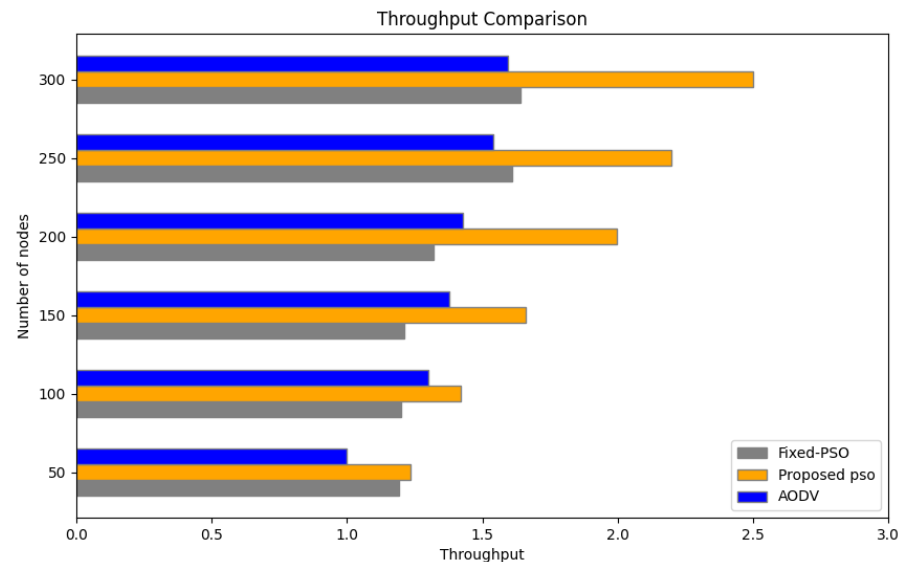


Figure 4. Throughput of proposed PSO, Fixed-PSO, and AODV.

In Figure 5, the E2E delay of AODV consistently maintains a slightly lower delay in different network sizes. The proposed PSO algorithm seems to offer an improvement over the fixed PSO, while AODV routing appears to perform best in terms of minimizing delay. The proposed PSO achieves a slightly higher delay because of the occurrences of the frequent route discovery process.

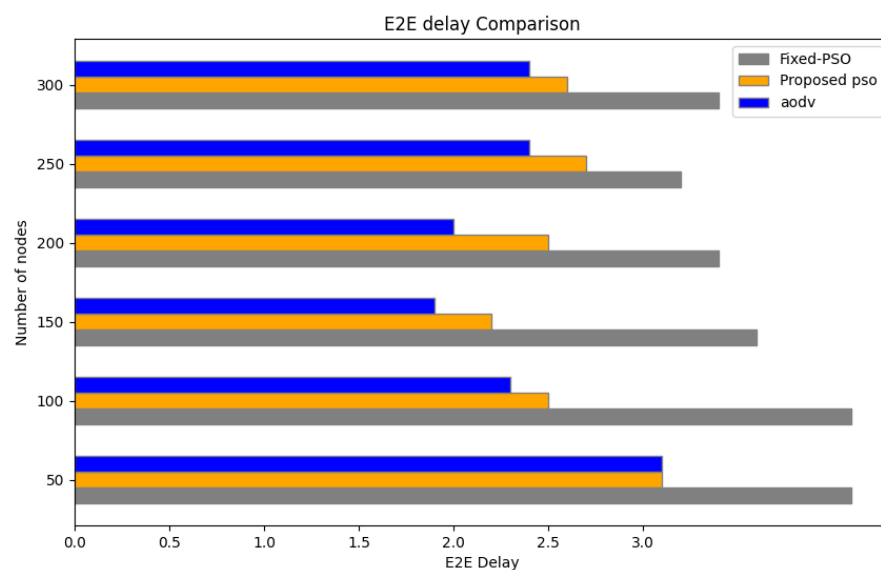


Figure 5. E2E delay of proposed PSO, Fixed-PSO, and AODV.

The number of valid paths in a routing protocol is a critical factor that affects its performance. More paths help in load balancing and fault tolerance. Various routing systems protocols manage paths differently, often balancing between complexity, efficiency,

and redundancy. Figure 6 shows the number of valid paths of AODV, Fixed-PSO, and the proposed PSO algorithm as the network size increases. AODV discovers a single valid path while PSO discovers multiple valid paths simultaneously; PSO is more suitable for large-scale networks where different criteria needed be balanced. AOOV finds a path on demand, and PSO continuously enhances paths. The proposed PSO consistently outperforms the AODV, and Fixed-PSO as the network size scales up.

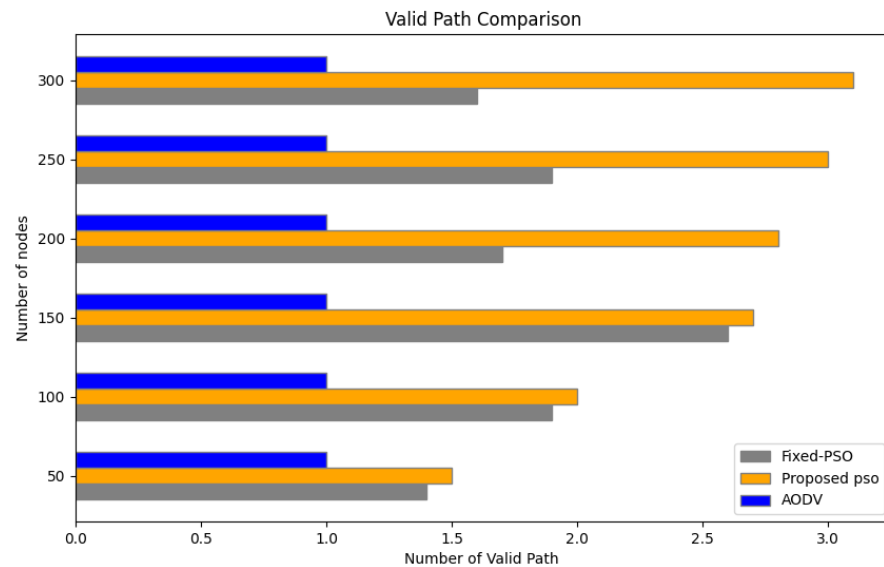


Figure 6. Number of valid paths for proposed PSO, Fixed-PSO, and AODV.

Figure 7 shows a comparison between the proposed PSO and Fixed-PSO in terms of their average execution time across different network sizes. In both algorithms, the execution time increases as the number of nodes increases. The lines are very close to each other, suggesting similar performance. There is a slight divergence between the two algorithms at higher node counts (250–300). The proposed PSO has marginally higher execution times at the maximum node count. The nearly overlapping lines indicate that algorithms have very similar computational efficiency across different network sizes, with minimal performance differences.

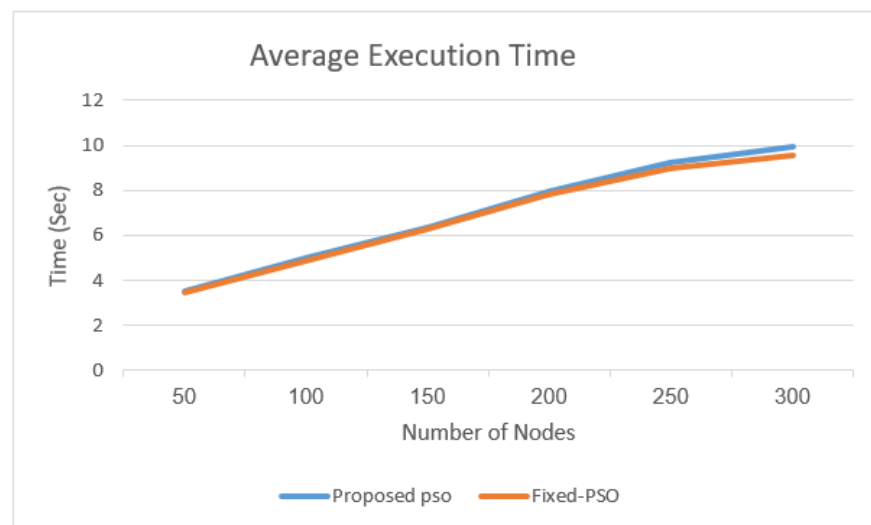


Figure 7. Execution time of proposed PSO and Fixed-PSO.

6. Ablation Study and Analysis

- Applying different fitness functions
 Figure 8 displays the relationship between the number of nodes and average throughput for different fitness functions. Initially, the throughput value for each parameter in the fitness equation was calculated separately, and then the throughput value for all parameters together was calculated. In Figure 8, all four fitness functions show a positive correlation between the number of nodes and the average throughput. The fitness functions consider all parameters achieving high throughput.
- Applying different particle numbers
 Figure 9 represents the relationship between the number of particles and the average fitness for different networks. In all networks, increases in the particles led to a decrease in the average fitness. More particles led to better exploration of the search space, resulting in the discovery of diverse paths with minimum fitness values. However, too many particles can lead to less exploitation of the known paths. In addition, increasing the number of particles will increase the algorithm's computational complexity, as the position and velocity need to be updated for each particle in each iteration. To successfully apply PSO to optimization problems, balancing between exploration and exploitation is needed.

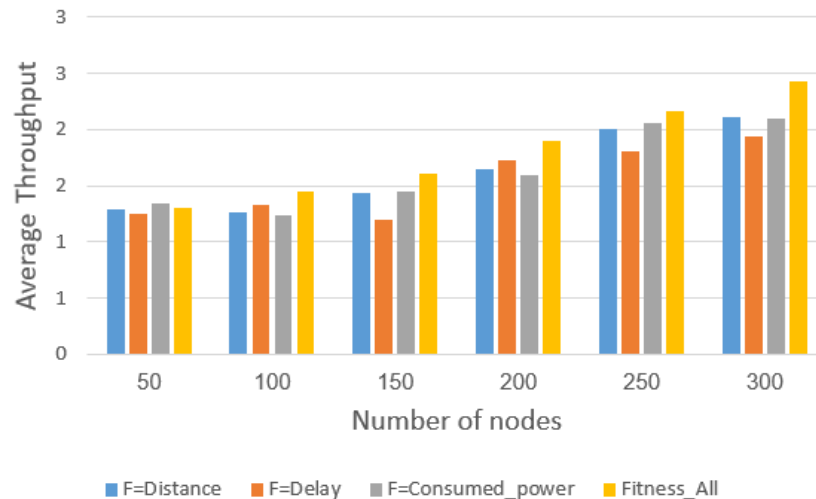


Figure 8. Average different fitness functions comparison.

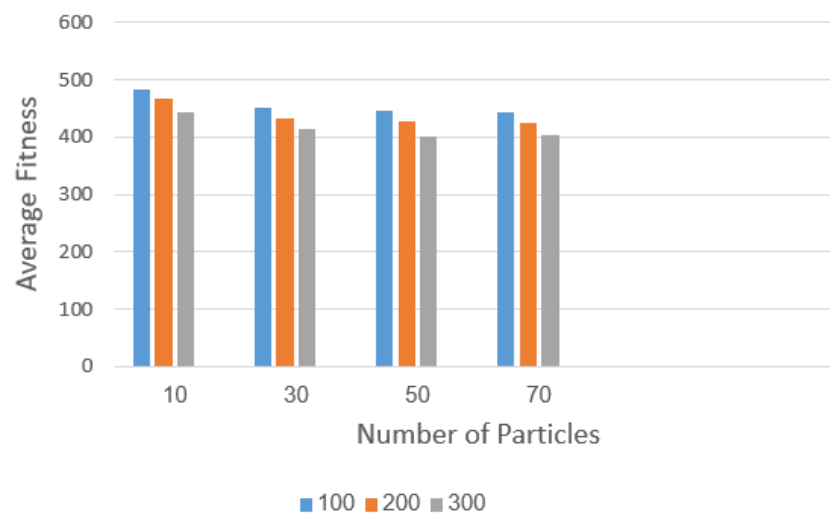


Figure 9. Average different particles number comparison.

7. Conclusions

Particle Swarm Optimization (PSO) was employed in MANET routing, resulting in a promising solution. The PSO algorithm consists of particles that move in the search space looking for the appropriate solution. The PSO algorithm evaluates each solution using a fitness function to find the best solution. In this paper, an improved PSO routing algorithm was proposed to enhance MANET routing. The proposed algorithm improves MANET performance by considering additional metrics for finding the optimal path. The metrics considered in this work were short distance, path delay, and energy consumption. Therefore, results show the proposed EPSO performs better than traditional PSO; the comparison considered network throughput, the PDR, and the number of valid paths. The results show the proposed algorithm is more suitable for large networks. In the future, we will test the potential of EPSO in different network scenarios and applications.

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References

1. Raza, N.; Umar Aftab, M.; Qasim Akbar, M.; Ashraf, O.; Irfan, M. Mobile ad-hoc networks applications and its challenges. *Commun. Netw.* **2016**, *8*, 131–136. [[CrossRef](#)]
2. Mirza, S.; Bakshi, S.Z. Introduction to MANET. *Int. Res. J. Eng. Technol.* **2018**, *5*, 17–20.
3. Ahmed, D.E.M.; Khalifa, O.O. An overview of MANETs: Applications, characteristics, challenges and recent issues. *Int. J. Eng. Adv. Technol. (IJEAT)* **2017**, *6*, 128–133
4. Arumugam, S.; Thangavel, R. IRDFPR-CMDNN An energy efficient and reliable routing protocol for improved data transmission in MANET. *Sci. Tech. J. Inf. Technol. Mech. Opt.* **2022**, *22*, 364–375. [[CrossRef](#)]
5. Al Ogaili, R.; Alsaeedi, A.H.; Alkafagi, S.S.; Alfoudi, A.S.D. A critical review of Optimization MANET routing protocols. *Wasit J. Comput. Math. Sci.* **2022**, *1*, 44–54. [[CrossRef](#)]
6. Kanellopoulos, D.; Sharma, V.K. Survey on power-aware optimization solutions for MANETs. *Electronics* **2020**, *9*, 1129. [[CrossRef](#)]
7. Ramphull, D.; Mungur, A.; Armoogum, S.; Pudaruth, S. A review of mobile ad hoc NETWORK (MANET) Protocols and their Applications. In Proceedings of the 2021 5th International Conference on Intelligent Computing And Control Systems (ICICCS), Madurai, India, 6–8 May 2021; pp. 204–211.
8. Slowik, A. Particle swarm optimization. In *Swarm Intelligence Algorithms*; CRC Press: Boca Raton, FL, USA, 2020; pp. 265–277.
9. Dixit, S.; Singhai, R. A survey paper on particle swarm optimization based routing protocols in mobile ad-hoc networks. *Int. J. Comput. Appl.* **2015**, *119*, 1–5. [[CrossRef](#)]
10. Alsaeedi, A.H.; Al-Sharqi, M.A.; Alkafagi, S.S.; Nuijaa, R.R.; Alfoudi, A.S.D.; Manickam, S.; Mahdi, A.M.; Otebolaku, A.M. Hybrid Extend Particle Swarm Optimization (EPSO) model for Enhancing the performance of MANET Routing Protocols. *J. Al-Qadisiyah Comput. Sci. Math.* **2023**, *15*, 127. [[CrossRef](#)]
11. Shivakumar, K.S.; Patil, V.C. An optimal energy efficient cross-layer routing in MANETs. *Sustain. Comput. Inform. Syst.* **2020**, *28*, 100458. [[CrossRef](#)]
12. Abdali, T.A.N.; Hassan, R.; Muniyandi, R.C.; Mohd Aman, A.H.; Nguyen, Q.N.; Al-Khaleefa, A.S. Optimized particle swarm optimization algorithm for the realization of an enhanced energy-aware location-aided routing protocol in manet. *Information* **2020**, *11*, 529. [[CrossRef](#)]
13. Adnan Hadi, A.; Vahab AL-Din Makki, S. Performance improvements for MANET routing protocols using a combination of cat and particle swarm optimization (CPSO). *Int. J. Nonlinear Anal. Appl.* **2023**, *14*, 2821–2829.
14. Hu, H.; Guo, Y.; Zhang, J.; Yin, C.; Gao, D. Cluster routing algorithm for ring based wireless sensor network using particle swarm and lion swarm optimization. *Wirel. Pers. Commun.* **2023**, *128*, 1631–1650. [[CrossRef](#)]
15. Jamali, S.; Rezaei, L.; Gudakahriz, S.J. An energy-efficient routing protocol for MANETs: A particle swarm optimization approach. *J. Appl. Res. Technol.* **2013**, *11*, 803–812.
16. Saravanan, N.; Subramani, A.; Balamurugan, P. Optimal route selection in MANET based on particle swarm optimization utilizing expected transmission count. *Clust. Comput.* **2019**, *22*, 11647–11658. [[CrossRef](#)]
17. Baburaj, E.; Vasudevan, V. An intelligent mesh based multicast routing algorithm for MANETs using particle swarm optimization. *Int. J. Comput. Sci. Netw. Secur.* **2008**, *8*, 214–218.
18. Malarvizhi, P.; Kavithaa, G. Identifying Stable Path in Self Configured Networks Using Particle Swarm Optimization with Centrality Betweenness. *J. Electr. Eng. Technol.* **2024**, *19*, 2701–2713. [[CrossRef](#)]

19. Subramaniam, K.; Tamilselvan, L. Research Article Predictive Energy Efficient and Reliable Multicast Routing In MANET. *Res. J. Appl. Sci. Eng. Technol.* **2015**, *9*, 706–714. [[CrossRef](#)]
20. Aini, Q. A Route Discovery of Dynamic Wireless Network Using Particle Swarm Optimization. *J. Commun.* **2019**, *14*, 368–374. [[CrossRef](#)]
21. Kaviani, S.; Ryu, B.; Ahmed, E.; Larson, K.A.; Le, A.; Yahja, A.; Kim, J.H. Robust and scalable routing with multi-agent deep reinforcement learning for MANETs. *arXiv* **2021**, arXiv:2101.03273.
22. Vikkurty, S.; Setty, P. Artificial Neural Network based Optimized Link State Routing Protocol in MANET. *Int. J. Intell. Eng. Syst.* **2022**, *15*, 65–73.

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