International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Hybrid Optimization of OLSR Routing Protocol in MANETs: Uniting Genetic Algorithm and Particle Swarm Optimization

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Submitted: 24/04/2023 **Revised**: 26/06/2023 **Accepted**: 04/07/2023

Abstract: The acronym MANET stands for Mobile Ad-hoc Network, which describes a network of mobile nodes that may connect to one another and operate together even in the absence of a central server or other permanent location. Since MANETs are not dependent on any one specific infrastructure for their operation, the nodes that make up these networks are free to migrate anywhere they like. This mobility of the nodes makes routing a difficult task. It also drains the energy of the nodes which affects the performance as well as the lifetime of the network. Hence, MANETs are challenging due to frequent dynamically changing network topology and frequent route breakage. To achieve this compromise between natural selection and appropriate knowledge sharing, we proposed a hybrid approach that integrates the advantages of GA and PSO to conduct a more absolute and effective search of the solution space. To modify the OLSR performance, the adjustable hybrid model makes use of two driving factors, one of which gives precedence to PSO and the other to GA. To avoid having to rebuild the path whenever there is a change in the path due to a node/link failure, the suggested technique is used in conjunction with an effective dynamic component. The result of the simulation indicates that the suggested hybrid methodology enhances the quality-of-service performance of the OLSR routing protocol. The research results indicate that the hybrid model is superior to the PSO and GA models that are often used because of the hybrid model's greater flexibility in parameter selection.

Keywords: *Manets, PSO, GA, NS2, Routing Protocols, Optimization, OLSR.*

1. Introduction

A MANET is a wireless network in which no permanent structures are used. It is made up of many nodes that talk to each other. In this network, each node acts as a server that takes care of and finds a way to reach every other node. A method called routing will be used to send a data file through a network to its target. Routing is used to figure out how data will get from the source node to the target node. To set up a MANET, you need a rule or protocol that helps you keep track of the way to be used [1].

Three basic types of protocols may be used in MANETs: reactive protocols, proactive protocols, and hybrid protocols [2]. Any time a request is made to set up a new route or modify an existing one, the reactive protocol may be put into action. Reactive protocols include but are not limited to, those with names like ADOV(Ad Hoc on-Demand Distance Vector), AOMDV (Ad Hoc On-Demand Multipath Distance Vector), DSR(Dynamic Source Routing), and TORA(Temporally Ordered Routing Algorithm). The proactive routing protocol necessitates numerous refreshes of the routing table. The proactive routing protocol was developed by Cisco Systems. Proactive protocols include Optimised Link State Routing (OLSR), Destination-Sequenced Distance Vector (DSDV) and BATMAN (Better Approach to Mobile Ad-hoc Networking). Hybrid routing protocols incorporate the most advantageous characteristics of proactive and reactive protocols, such as the Zone Routing Protocol (ZRP) [3].

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Routing protocols are used to determine the best paths across a network and set up connections between nodes so that data may be sent. The proactive OLSR routing protocol was utilised in this investigation because of its ability to provide constant exchange of topological information between network nodes. Each node chooses its nearest neighbours to act as multipoint relays (MPRs). The MPR in OLSR is the node responsible for propagating the signal to the rest of the network [4].

The performance of a MANET might be hindered by the higher likelihood of connection failures between nodes due to the mobility of the network's nodes [5]. Several options exist for enhancing the performance of the MANET routing infrastructure. Such algorithms have been implemented in a variety of fields, and some well-known examples include ACO(Ant Colony Optimisation), ABC(Artificial Bee Colony) Optimisation, ANN(Artificial Neural Networks), BOFA(Bacterial Foraging Algorithm), GA(Genetic Algorithm), and PSO(Particle Swarm Optimization). The author plans to improve on previous studies by fusing the OLSR protocol with the GA, the PSO, and a hybrid PSO-GA.

The research article is divided into five parts with the following structure: Part 1 is an introduction; Part 2 is a summary of the general survey of papers published. In Section 3, the suggested technique is laid out in full. Setup of the Environment, data analysis, and results are presented in Section 4. The debate and final conclusion make up Section 5.

2. Literature Review

Mobile Ad-hoc Networks (MANET) have become more common in analytical practice as a consequence of a large body of recent research into the topic.

Tsapna et al. [6] found that routing is the process of identifying and modifying the best route between two nodes. Quality of service parameters including performance metrics are used to evaluate MANET performance under varying network circumstances, such as mobility speed. In this study, they evaluate and contrast many different MANET routing protocols, including AODV, DSDV, OLSR, and DSR.

An enhanced CS algorithm, NNCS was suggested by Lijiang et al. [7], combining the closest neighbour method with the probabilistic mutation technique. The suggested method was able to develop new solutions by learning from their nearby neighbour solutions rather than the best solution so far found, thanks to the nearest neighbor's approach. Similar measures, such as solution quality and fitness, were used in the selection of closest neighbour solutions in the nearest neighbour method. Unlike traditional CS, which uses all possible solutions, this method uses the probabilistic mutation approach to regulate the answers and learn from the closest neighbour solutions in partial dimensions. Furthermore, experimental evidence suggested that both the closest neighbour technique and the probability mutation strategy might be improved upon in terms of their efficacy and efficiency.

An approach for route recovery in MANET based on lifespan prediction using PSO(particle swarm optimization) was proposed by Devi M et al. [8]. This method estimates how long a given connection and node will last within the available bandwidth by considering factors such as the nodes' relative mobility and the pace at which their energy is being used. Predictions are used to "fuzzify" the parameters, and then fuzzy rules are developed to determine the node's actual state. All of the nodes are able to freely share this data with one another. As a result, the health of each node is checked before any information is sent. The concerned routes are redirected to the effective nodes even if the ineffective node is performing the route recovery technique. The PSO prediction is used to minimise data loss and communication overhead with the help of the simulated outcomes.

To decrease the amount of network overhead, Fadlallah Chbib et al. [9] recommended that OLSR use the idea of MPR to lessen the frequency with which the Link State messages are sent. Another technique has been developed to decrease the overhead while simultaneously improving the throughput and packet delivery ratio. By introducing a novel idea called backup MPR and a Routing table mechanism, the suggested protocol has updated the traditional OLSR to reduce the number of executions. In terms of performance metrics, the acquired results have shown to be superior to those of the original OLSR routing system.

MPR selection in the OLSR network was considered to be an NP-Complete issue by Tami et al. [10]. The BEST method improves performance over the Greedy approach by ensuring that the OLSR network has the fewest possible MPR nodes. TC communications that flood the network are guaranteed to be secure by the security algorithms implemented on the chosen MPR nodes. Threshold cryptography is also used to give a measure of safety.

Desai et al. [11] proposed routing attacks, such as the Link Spoofing Attack and the Routing Table Overflow Attack, with a focus on evaluating their numerous implementations. In order to implement these attacks, NS2 makes use of the OLSR protocol. Packet loss due to congestion and, finally, successful delivery are negative outcomes of a routing table overflow assault. Results from simulations indicate that the OLSR protocol's performance suffers more from a Link Spoofing Attack than from a Routing Table Overflow Attack.

By including pertinent route data in the routing decision strategy to counteract the effects of the factors that cause greater energy use, Sahnoun et al. [12] proved the effectiveness and efficiency of the power-aware proactive MANET routing protocol OLSR. Residual energy, traffic, and the structure of the network all have a role. By creatively including the willingness variable into MPR selection criteria, the lifetime of the network may be extended. To improve the energy efficiency of the OLSR routing protocol, Paraskevas et al. [13] proposed a new multi-metric energy-efficient routing technique. There are three cross-layer characteristics that can be used to determine the cost of routing through this node; they are all indicators of energy depletion. Periodically, the network receives TC packets with revised node weights to account for changes in traffic load and mobility patterns.

In terms of PDR, the improved OLSR increases network longevity by 5-20% without impacting performance. This paper [14] proposes FF-AOMDV, an innovative energy-efficient multi-path routing technique, and evaluates it in three scenarios with varying node velocities, packet sizes, and simulation durations. Simulations employing the proposed FF-AOMDV algorithm showed considerable improvements in performance metrics to those using AOMR-LM and AOMDV. Energy efficiency and network life were both improved over AOMDV. More resources for the network may be used to increase service quality and prolong the network's lifespan.

For downlink OFDMA HetNets with coordinated scheduling CoMP, this research [15] established the EE maximization issue. As the population grows, so does the GA's computing complexity. When the population is twice the variables, more than 80% of the optimal values for energy efficiency and total throughput can be attained, and more than 95% when the population is negative times the variables. For the simulations used in this study, the GA-based technique converges in under a hundred iterations. The simulation results showed, however, that energy efficiency and total throughput are not mutually exclusive. Based on the impact of node mobility utilising a variety of performance criteria, OLSR is defined in this research [16] as a routing protocol with improved network performance and safe and encrypted bit data. This study reveals the optimisation of OLSR control data, which outperforms the conditions of the target wireless node and is analysed using realistic agility models to obtain optimal protocol performance. If two wireless network components are within range of one another, a connection has been established. Transmission range management is the essence of topology control in this scenario. MANET security vulnerabilities may compromise the network's safety and effectiveness. A black hole attack in a MANET is a denial-of-service attack that results in inadequate network performance.

In [17], proposed and implemented several alternative routing protocols to avoid and detect various forms of mobile ad hoc network attacks. The most significant downside occurs during network data transfer when the host delivers updated data through an overflow in the OLSR protocol. When using OLSR, valuable network bandwidth is wasted on the control overhead that is produced. This study [18] presents an optimised technique for enhancing MANET network performance between nodes. In IEEE 802.11 MANETs, this introduces effective routing. In this study, they provide methods for dealing with the most pressing issues in MANETs. To obtain the optimal path, the Ad hoc On-Demand Multipath Distance Vector (AOMDV) is united with a GA with a modified fitness function (FFn). This is reflected in the method's name: (AOMDV-FFn). The authors successfully combined the AOMDV routing protocol with GA (AOMDV-GA). In comparison to other routing protocols, AOMDV-GA performs poorly in terms of routing overhead ratio, despite its superior performance in other metrics.

In [19], an evolutionary multi-objective (EMGA) optimisation approach is described. In an attempt to reconcile the divide between the EMA and the GA, the EMGA was established. The merger of the GA and EMA has resulted in the formation of the EMGA. EMGA is a powerful technique for determining the exact value of the optimal solution with the fewest possible iterations; this is one of its primary applications. The simulation results indicate that EMGA is capable of determining the optimal solution in a minimal time and with the least amount of effort. The simulation results demonstrated that EMGA is a dependable algorithm that is effective, precise, and quick. In addition, It can find the global optimal solution for a variety of discrete and continuous functions. Linear, nonlinear, mixed-integer linear, and mixed-integer nonlinear problems are all within the scope of EMGA's applicability as a strong computing tool.

Scaling multiple constraint functions and a comparison mechanism are introduced in this paper [20] to help efficiently handle constraints in swarm-based meta-heuristic optimisation algorithms. In this study, they examined and evaluated nine more meta-heuristic optimisation techniques to the constraint-handling enhanced cuckoo search approach. Finally, the highly restricted challenge of reducing drag on a transonic airfoil may be addressed with success using the constraint-handling modified cuckoo search approach. The novel method has a faster convergence rate and a lower drag coefficient than the standard cuckoo search based on the penalty strategy. For quicker exchanges in VANET, they proposed a routing algorithm constructed on the Hybrid Genetic Firefly Algorithm (HGFA). Using the Firefly algorithm and the GA method, the authors of this paper [21] suggest a productive routing protocol. The technique took inspiration from fireflies' ability to work together and communicate to accomplish the goal. The suggested algorithm's novel goal function was developed using GA's specific properties. Comparisons were made between the planned HGFA and the industry-standard Firefly and PSO. OLSR is a method of routing that was developed by MANET, particularly for use in wireless mobile ad hoc networks. The authors of this study discovered that, across a range of node velocities and delay durations, the UL-OLSR obtained the highest throughput and latency results.

In [22], the authors proposed a modified variation of particle swarm optimisation with effective guides (MP-SOEG) to better the search performance of the algorithm when confronted with diverse types of optimisation problems. When comparing the overall optimisation performances of each evaluated PSO version, MPSOEG is shown to perform best across three parameters known as search accuracy, search reliability, and search efficiency. Both qualitative and quantitative assessments of the proposed MPSOEG's complexity are possible with the help of theory.

Computer network researchers have studied network routing for years. Manets are popular now. Due to node mobility, MANET communication requires excellent routing methods. The suggested system incorporates research from several research articles and information resources. Hybrid algorithms are needed to improve the OLSR routing protocol.

3. Methodology

3.1. Optimization Link State Routing Protocol

An OLSR network uses an improved protocol to route data across links. It's a protocol based on a proactive system of tables. In this scenario, the connection statuses of all nodes are continuously broadcast. When a node receives data on the status of a link from another node, it stores that data locally. Each node determines the subsequent hop to each destination using the preceding data. Every node relays the connection status data it has learned from its neighbours. A spanning tree grows from each node. The whole topology of the network is available to every node. MultiPoint Relaying (MPR) is a crucial idea in this method.

Advantages

- Applications that require the least amount of delay feasible can benefit from OLSR's lower end-to-end average latency.
- OLSR implementation is simpler to use and operates with fewer problems than other protocols.
- It's a simple routing protocol as well.
- The routing procedure does not need a centralised administration system.
- It enhances the protocol's suitability for use in an ad hoc network, where source-to-destination connections are continuously changing.
- The connection reliability in managing messages is not required since messages are delivered on a periodic basis and delivery is not required to be consecutive.

Disadvantages

- It keeps track of all the potential routes in a routing table.
- The control messages add more and more overhead as the number of mobile hosts grows.
- Locating a lost connection may be a time-consuming process.
- When compared to other protocols, it needs more processing resources to choose a different path.

3.2. OPTIMIZATION ALGORITHMS

3.2.1. Genetic Algorithm

Natural selection, which favours the healthiest and most adaptable members of a population, is the basis for the genetic algorithm. Darwin's "Survival of the Fittest" theory provides the foundation for this idea. People are encouraged to have children in genetic algorithms so that the population may continue to grow. Gene, chromosome, parent, offspring, and fitness function are employed in this method, and their respective definitions are as follows [23], [24]:

- Genes are optimisation variables that have their encoding encoded in DNA.
- Chromosomes: The set of DNA molecules that make up an individual's chromosomes
- Natural selection determines which individuals will become parents in a given population.
- A child is a person who is the product of this operation.
- Fitness Function: An individual's fitness function value represents how well they adapt to their environment.

Implementation

Step-1: Establishing the GA's parameters is part of the initialization process. These GA parameters are as follows:

- A path's gene count is equivalent to the sum of its node counts.
- The "Pop Size" is the sum of all possible paths from any given set of origins to any given set of destinations.
- The likelihood of a route pair being crossed, denoted as Pc, is roughly between 0.61 and 1.
- Pm is the mutation probability of a node along a path.
- SurvivorSel is the command that will determine the optimal path with the highest score.
- The termination metric is denoted by GensNoChange and is the maximum number of generations that may elapse without the elite path changing.

Step-2: The method is used to do calculations on the fitness of each route that is produced. Here three component values are calculated:

1. Calculating Residual Energy
2. Calculating Shortest Distance
3. Calculating Congestion between links

1. **To calculate residual energy:**

$$f_e = {Een}/{Ean} \quad (1)$$

— where $\mathbf{F_e}$ represents the Fitness Function dependent on Energy and

— $\mathbf{E_{en}}$ stands for the Residual Energy at Each Node

— The total amount of unused energy in the network is referred to as $\mathbf{E_{an}}$.

2. **To calculate the shortest distance:**

$$f_d = {Dn,n}/{Dsd} \quad (2)$$

— Where $\mathbf{F_d}$: The fitness function of a node, Fd, is described as being based on the intra-distance,

— **Dn,n,** The distance between two nodes along a path, denoted by the notation Dn,n.

— The distance from the source to the destination, abbreviated as $\mathbf{D_{sd}}$.

3. To calculate congestion between links, we first need to calculate two values:

- TCP CERL measures channel congestion. CERL and queue length L may approximate connection congestion.

$$L = (RTT - T)\ BW \quad (3)$$

- o Each time a new round-trip-time (RTT) value is obtained, L is redefined as the value based on the most recent RTT measurement.
- o The shortest Round-Trip-Time (RTT) recorded by a TCP Sender is denoted by T. Round-Trip Time (RTT) is the standard for measuring the duration of a complete circuit between two points. The shortest round-trip time (RTT) recorded by the TCP Sender is denoted by T.
- o BW is defined as the Band Width
- In specifically, CERL decided to adopt the dynamic queue length barrier described below for N.:

$$N = A * L_{max} \quad (4)$$

- o where N is defined as the dynamic queue threshold
- o A is defined as a constant between 0 and 1.
- o L_{max} is defined as the largest value of L detected by the transmitter.

Thus, the fitness value due to congestion is:

$$F_c = 1–(L/B) \quad (5)$$

The overall fitness function value for each node is:

$$F = F_e + F_d + F_c \quad (6)$$

Step 3: In Step 3, we will delete the routes that have the lowest fitness values, and we will continue with the routes that are left.

Step 4: All of the paths are coupled together in the crossover, except for the elite path, and then they are crossed over into one another with probability Pc. The likelihood of a crossing will range from 0.6 to 1 at various points.

Step 5: In the fifth and final stage, named "Mutation," every node on the routes is mutated except for the best route. Therefore, there is a Pc% chance that the order of the nodes along the same path will be altered.

Step 6: After all of the crossovers and mutations have been completed, the Survivor Selection Process is then used to once again analyse the pathways. At this point, the newly produced kid (route) is given an evaluation based on the equation:

$$F = F_e + F_d + F_c \quad (7)$$

If the newly created route's fitness is higher than that of the parent routes, it is chosen as a good way to send the packet. If the new kid route does not increase fitness, it is included in the list of ideal routes. This array will be sorted descending using the fitness values, starting with the greatest value.

3.2.2. Particle Swarm Optimization

- Particle swarm optimization is a metaheuristic method; it is a stochastic search strategy that employs a population to discover the optimal solution [25].
- The cooperative behaviour of birds in flocks served as inspiration for PSO, a population-based search method. In its pursuit of Optimum, PSO continually improves its generational data.
- PSO is the computational approach that we are using to address issues related to optimisation.
- Problems were addressed using PSO's Population of Candidate Solutions (also known as Swarms), which were named Particles.
- o Representation of Potential Answers
- o Each particle's velocity is affected by its best-known location.
- The value will be re-initialized if any optimal control value of any particle surpasses the searching space. This will cause the value to be reset.

Advantages

- PSO is simple to implement.
- PSO has a limited number of parameter options.
- Effectively used in the training of neural networks, also known as artificial neural networks, fuzzy control systems, and function optimisation.

PSO Initialization

- In Particle Swarm Optimisation, each node is a particle, and the population is a swarm.
- We will begin by determining the population's initial positions, which correspond to the initial population, and the particles can move in any direction at random.
- To find what it's looking for, each particle traverses three tiers of the seeking area and keeps track of its location concerning itself and its neighbours at all times.

Algorithm steps for PSO

STEP-1: **Initialization**

- Initialise Parameters
- Initialise the Population
- Determine the initial location (xi) of each particle in random order.
- Determine the initial velocity (vi) of each particle in a random fashion.

STEP-2: Evaluate fitness f(x_i^t)

- Determine the optimality of each particle.

- if the event that fitness exceeds the optimal value (gBest), then.
- Change the old value to the new one (gBest)
- Pick the particle with the highest fitness and label it gBest.

STEP-3: Find the velocities and position of each particle.

- find the position of particles by:

$$x_i^{t+1} = x_i^t + v_i^t * t \tag{8}$$

- Calculate velocity by:

$$\dot{v}_{k+1}^i = wv_k^i + C_1 r_1((xBest_i^t) - x_i^t) + C_1 r_1((gBest_i^t) - x_i^t) \tag{9}$$

STEP-4: calculate fitness $f(x_i^t)$

Calculate current best [gBest]

STEP-5: increment t=t+1

STEP-6: Output gBest & x_i^t

3.2.3. The proposed method of Hybrid PSO-GA

It has been shown that population-based algorithms, such as PSO and GA are capable of successfully resolving very challenging optimisation issues [26]. Both of these approaches have some benefits as well as drawbacks. To put its straightforward concept into action, the PSO algorithm needs just a few lines of programming code. PSOs, as opposed to GAs, can keep information even if a person is not chosen to take part in the study. In contrast to GAs [27], which have difficulties finding a precise response but are excellent at reaching a global area, PSOs profit from the cooperative group interactions of its members in order to discover the ideal solution. This is in contrast to GAs, which excel in reaching a global region. Nevertheless, in the absence of a selection operator, PSOs face the risk of allocating resources to a disadvantaged node that is located in an area of the search space that is inefficient. Eberhart [28] and Angeline et al. [29] compared GAs and PSOs, and the findings of both studies demonstrated that a composite model that incorporates the traditional GA and PSO models would result in a particularly effective search strategy.

We provide a hybrid PSO-GA method to speed up the QoS issue search process. This strategy incorporates the most beneficial aspects of PSO and GA in a single solution. We'll be able to solve the problem much quicker if we do this. The hybrid algorithm takes the best features of PSOs and GAs and combines them. These features are position and velocity updates and crossover and mutation, respectively [30].

The fundamental goal of the method that has been described is to offer a flexible approach that enables optimisation of the performance of a PSO-GA hybrid [31]. This purpose will be met if the methodology is successful in doing what has been stated above. The hybrid algorithm makes use of two novel driving components in order to determine which of PSO and GA yields the best results in terms of finding the optimum solution. The following is the suggested algorithm for the hybrid PSO-GA that has been developed.

Pseudo code for Hybrid PSO-GA

1. **for** each node do
2. Initialize the position and velocities;
3. Evaluate the fitness value;
4. **end for**
5. **set** Local best fitness as current fitness;
   Local best position as current position;
   Global best fitness as min (Local best fitness);
6. **for** each node do
7. update the velocity and position;
8. **end for**
9. **set** i=0;
10. **repeat**
11. **for** each node do
12. Evaluate the fitness value;
13. **end for**
14. **incr** i;
15. choose the node with one of the fitness values
16. **set** P=randomly initializing the vector with $swarm_{max}$
17. P(i) = chose the fitness value
18. Set Gen_i=0
19. **repeat**
20. **incr** Gen_i;
21. apply crossover & mutation operation;
22. **until** Gen_i<=$swarm_{max}$ is not attained
23. **if** current fitness > Local best fitness then **Goto Step10**
24. Set Local best fitness as current fitness;
25. **if** current fitness > Global best fitness then G**oto Step10**
26. Set Global best fitness as current fitness;
27. **until** maximum iterations or minimum error criteria is not attained;

4. Simulation Environment

Designing Manet protocols requires performance analysis. It assesses Manet procedures' efficacy under diverse scenarios. Simulating Manet protocol performance is typical. Using network simulators like NS-2 and NS-3, researchers may test MANET protocols in various environments. Traffic patterns, mobility, and device density are just a few factors that might impact a network's behaviour, making Manet protocol performance evaluation challenging.

Thus, Manet protocol performance should be assessed under various settings. Real-world measurements and tests are used to verify a protocol's performance in a deployment situation [32]. Performance analysis helps choose the optimum Manet protocol for a job while building and developing them.

Table 1. Simulation Setup

Parameter Type	Parameter Value
Simulation time	30s
No of nodes	50,100,150.200
Area of simulation	1216m x 768m
Transportation protocol	UDP
Packet type	CBR
Packet size	512 bytes
Rate of packets	4 Packets / sec
Maximum packets	Constant Bit Rate
Propagation model	TwoRayGround
Initial energy	1000J
TxPower	1.3 w
RxPower	1.4 w

4.1. Performance Metrics

Performance metrics in Mobile Ad hoc Networks (MANETs) are used to review and measure the efficiency, effectiveness, and quality of many elements of the network's operation. These metrics are used to evaluate and quantify performance. Researchers and network designers are able to analyse and compare various protocols, algorithms, and optimisation approaches for the purpose of improving network performance with the assistance of these performance measures, which give insights into many elements of the functioning of a MANET. The following are some performance measures that are often used in MANETs:

4.1.1. Throughput(t)

$$t = \frac{\sum Received\ packet\ size}{Stop\ time - Start\ time} \quad \text{bytes / sec or bit / sec} \quad (10)$$

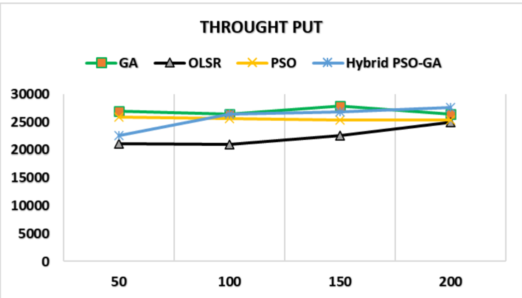

Fig 1. Analysis of Performance Regarding Throughput

4.1.2. Delay (End-To-End Delay)

$$Delay = \frac{\sum Packet\ Received\ \ Time - Packet\ Sent\ Time}{Packet\ Received\ Successfully} \quad (11)$$

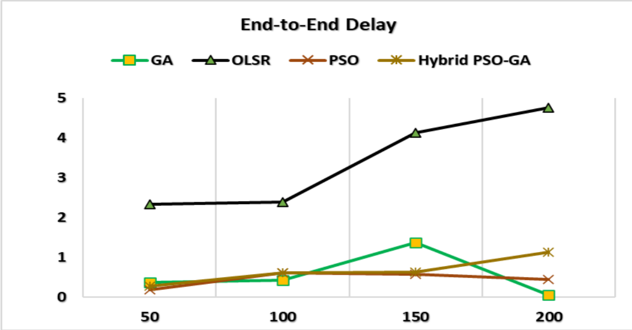

Fig 2. Analysis of Performance Regarding Delay

4.1.3. PDR (Packet Delivery Ratio)

$$PDR = \frac{Total\ number\ of\ packets\ receievd}{Total\ number\ of\ packets\ sent}\ X\ 100 \quad \text{----(10)}$$

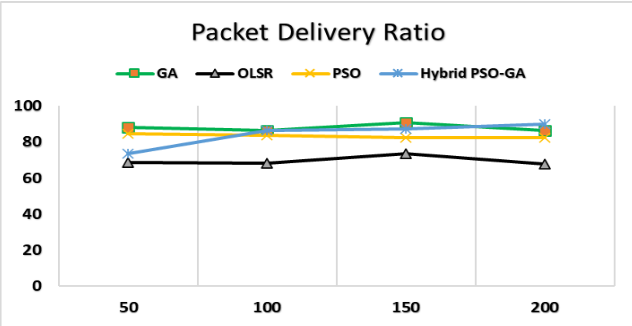

Fig 3. Analysis of Performance Regarding PDR

4.1.4. Average Energy Consumption (AEC)

$$\text{Average Energy consumption} = \frac{i-r}{N} \quad (12)$$

The energy consumption of MANET can be computed with Equation (12). The energy consumption of each node is computed the difference between the initial value (i) of energy at each node and the quantity of energy remaining (r) and dividing the result by the number of nodes (N).

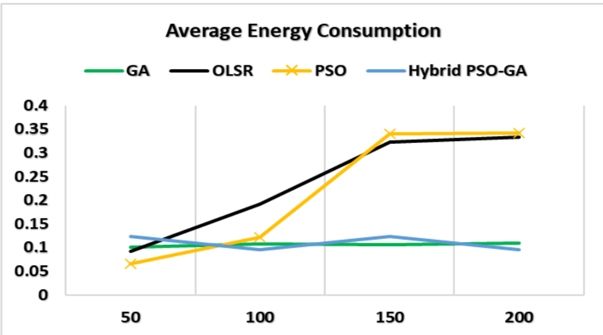

Fig 4. Analysis of Performance Regarding AEC

4.1.5. PLR (Packet Loss Ratio)

$$PLR = \frac{Total\ number\ of\ packets\ lost}{Total\ number\ of\ packets\ sent}\ X\ 100 \quad (13)$$

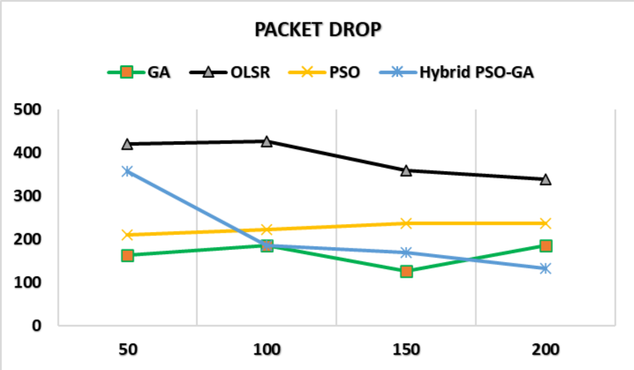

Fig 5. Analysis of Performance Regarding packets Drop

4.1.6. Goodput

Goodput in MANETs is the quantity of usable data transmitted from source to destination in a specific period.

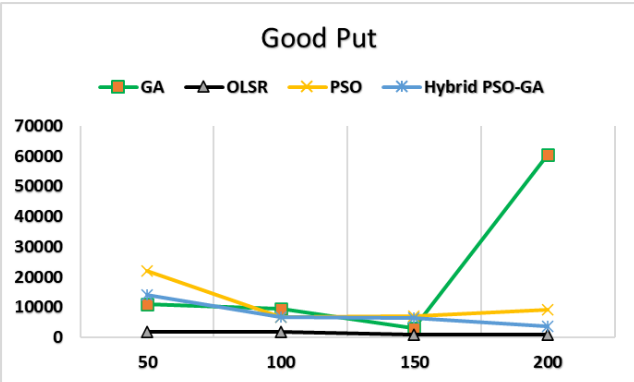

Fig 6. Analysis of Performance Regarding goodput

4.1.7. Jitter

In MANETs, jitter is the difference between when packets are sent and when they arrive.

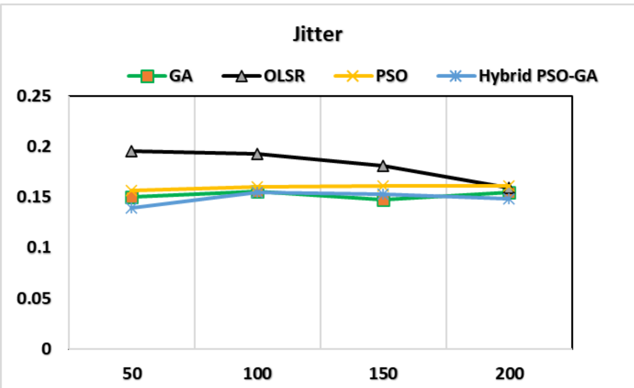

Fig 7. Analysis of Performance Regarding Jitter

4.1.8. Network Lifetime

The Lifetime Ratio is a metric used to ensure that vital data packets may always be sent over the network without interruption. An algorithm's effectiveness is measured in part by its Lifetime ratio.

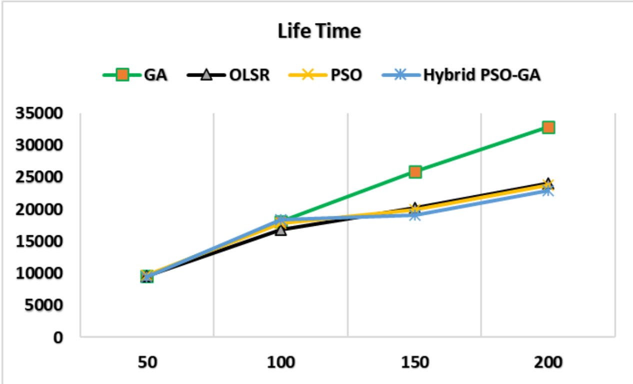

Fig 8. Analysis of Performance Regarding Network Lifetime

4.1.9. Remaining Energy

$$RE = \frac{\text{Initial\_Energy} - \text{Total\_Consumed\_Energy}}{Total\ number\ of\ Nodes} \quad (14)$$

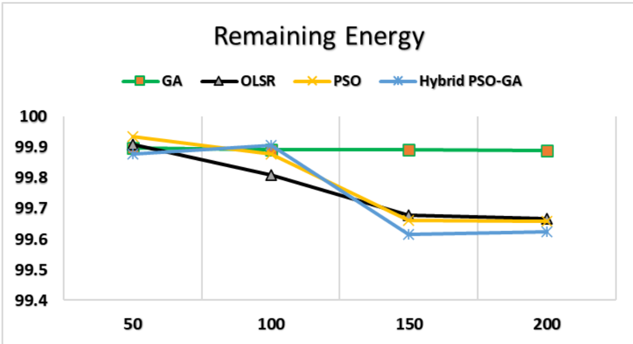

Fig 9. Analysis of Performance Regarding Remaining Energy

4.2. Observations

1. Figure 1 shows that the throughput of a Hybrid PSO-GA network does not significantly vary as the number of nodes in the network increases.
2. The Genetic Algorithm outperforms the PSO, OLSR, and Hybrid PSO-GA in terms of latency, according to the data depicted in Figure 2.
3. In Figure 3, the packet delivery ratio does not fluctuate much; nevertheless, it improves when the number of nodes in a hybrid PSO-GA network increases.
4. Figure 4 shows that the proposed method and the Genetic method have similar Average Energy Consumption, however, the average energy consumption in the Hybrid PSO-GA algorithm decreases with the number of network nodes.
5. In Figure 5, the PLR does not differ substantially between the suggested technique and the Genetic Algorithm. In contrast, the loss ratio of the Hybrid PSO-

GA algorithm decreases as the no. of network nodes grows.

6. In figure 6, indicates that the GA better than the PSO, the OLSR, and the Hybrid PSO-GA algorithms in terms of Goodput.
7. As the network size increases, the volatility does not significantly change, as shown in Figure 7.
8. Figure 8 demonstrates that there is little difference in tenure, but the delivery ratio in GA increases as the number of network nodes increases.
9. In figure 9, GA outperforms other algorithms in terms of remaining energy; however, the genetic algorithm's performance is unaffected by the number of network nodes.

5. Conclusion

In this study, we have effectively implemented a new Hybrid routing strategy that incorporates an enhanced version of the Optimised Link State Routing (OLSR) protocol with the integration of Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA) to produce optimal routing results. In the hybrid strategy, the selection between PSO and GA is based on a combination of two distinct criteria, allowing for a dynamic selection mechanism. We have demonstrated through exhaustive simulations that the proposed hybrid algorithm outperforms both the PSO and the genetic algorithm in terms of quality of service (QoS) performance. This substantial improvement demonstrates the efficacy of our strategy. The adaptability of the hybrid algorithm's parameter-tuning plays a crucial role in augmenting the evolutionary operators' capacity to generate individuals with rapid convergence while minimising unintended jumps to local minima. The ability of the hybrid algorithm to produce individuals with accelerated development contributes to its superior performance.

We have incorporated a dynamic component into our proposed method to address the challenges posed by dynamic network changes and node and link disruptions. This component minimises network traffic rerouting whenever the network topology changes. By preventing frequent rerouting, the proposed method increases the overall efficacy and stability of the network. To evaluate the effectiveness of the proposed techniques, simulations utilising networks with varying capacities were conducted. The experimental results demonstrate the algorithm's usefulness and effectiveness in obtaining optimal routing solutions. In addition, the hybrid algorithm's ability to rapidly converge while avoiding local optima enables it to efficiently search for the optimal solution.

Finally, our study highlights the benefits of the new Hybrid routing approach that integrates an improved OLSR with PSO-GA. The proposed method demonstrates superior QoS performance compared to standalone PSO and Genetic Algorithm approaches. The algorithm's parameter-tuning flexibility, combined with an efficient dynamic component, contributes to its effectiveness in handling dynamic network scenarios. Overall, our findings validate the significance and potential of the hybrid algorithm for optimising routing in mobile ad hoc networks.

Acknowledgments The authors acknowledge the help from the GVP College of Engineering for Women faculty.

Author Contributions All listed authors have made substantial, direct, and intellectual contributions to the work and have authorised its publication.

Funding This study received no outside funding.

Compliance with Ethical Standards

Conflict of Interest Every author has confirmed that they do not have any conflicting interests.

Ethical approval None of the authors of this article conducted any research with human subjects or animals, hence there are no examples of such work here.

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