# Social Group Optimization-based New Routing Approach for WMN's

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***Abstract*—Wireless Mesh Networks (WMNs) are hop-to-hop communication networks that are quickly deployable, dynamically self-organizing, self-configuring, self-healing, self-balancing, and self-aware. In WMNs, a node can leave or join the network at any time. Due to the mobile nature of nodes, the routes between source and destination can change frequently. Computing the shortest path under dynamic conditions for a given time constraint imposed due to node mobility can also be placed in the class of highly complex problems. However, as the network size grows, the performance of the nodes decreases. As a result, we require Soft Computing approaches to handle this problem. This article proposes a Social Group Optimization (SGO) based routing approach to wireless mesh networks. The proposed approach was implemented in MATLAB and tested on different dynamic nodes network scenarios. We compare the performance of the proposed approach with Ant Colony Optimization (ACO), Ad-hoc On-demand Distance Vector (AODV), Dynamic Source Routing (DSR), BAT, Biogeography-based optimization (BBO), and Firefly Algorithm based routing approaches. We observe that the proposed approach outperformed all other approaches on the more than 1000 node network scenarios.**

***Keywords*—ACO; AODV; DSR; BAT; BBO; wireless mesh network; social group optimization**

## I. Introduction

A mesh network is a rising era that can provide broadband Internet access, wi-fi nearby area coverage, and network connectivity to operators and customers at a low cost. Wireless Mesh Network is a network that consists of n number of nodes that help in communication within a network structure. Because of its characteristics like self-healing, fault-tolerant and self-organizing, WMNs make the communication process more reliable. There are three types of components in Wireless Mesh Network: Mesh Clients, Wireless Mesh Routers, and Wireless Mesh gateways. Mesh clients, also known as Wireless Mesh clients, are the end-user devices that access the network to run applications like email, games, tracking location, etc. Examples of these clients are mobile, laptops, smartphones, etc. They have limited resources, and sometimes they might not be connected to the network. Client WMNs consists of routers with no cabling connecting the nodes and can work using inbuilt radios in network nodes. Unlike traditional wireless access points, every node consists of inbuilt hardware gateways to connect it with neighbor nodes.

Routing in WMNs is a challenging issue due to the dynamic nature of networks. In WMNs, any node can move anywhere without informing other nodes. Due to the mobile nature of nodes, the routes are frequently changing. Computing the shortest path under dynamic conditions for a given time constraint imposed due to node mobility can also be placed in the class of highly complex problems. So, for efficient communication, there is a need for routing approaches that can discover the new routes quickly before the network structure changes again. It is a well-known fact that the probability of finding the best solution is significantly less for the highly nonlinear and complex problems falling under the class of NP-hard or NP-complete problems. The computational cost for such cases may be so high that the best solutions may not be affordable. Under such circumstances, wherever best can be replaced with reasonable solutions, soft computing approaches perform better than their hard computing counterparts. Thus, suggesting that soft computing-based approaches to dynamic shortest path route evaluation shall provide better results than the hard computing-based approaches such as AODV, DSR, etc. The hard computing-based algorithms work well on WMNs with less than 1000 nodes. This article proposes a new soft computing-based routing approach for WMNs. The proposed approach works upon the social learning behavior of humans. The proposed algorithm worked very well on large nodes network scenarios.

We divide our paper into 5 sections. Section 1 of the paper presents the motivation for the paper. Section 2 discusses the overview of the SGO (Social Group Optimization) Algorithm. Section 3 presents the SGO based approach for shortest route evaluation in WMNs. Section 4 discusses the implementation and performance analysis of the proposed approach for WMNs. Section 5 concludes the paper.

## II. Social Group Optimization Algorithm

Social Group optimization group is the nature-inspired computing approach that is based on the human decision-making process. This algorithm is based on peer learning and increasing an individual's knowledge. The SGO algorithm works in two phases: The Improving Phase and Acquiring Phase. Here each person in the group is considered as a candidate solution. Each candidate tends to acquire knowledge and possess to increase fitness value. On the other hand, the one with the highest expertise or the best person tries to distribute the knowledge among all the candidate solutions, resulting in upgrading the knowledge level of the entire group members.

### A. Improving Phase

In the improving Phase, each candidate solution communicates/interacts with the best person present in the group. As a result, an individual's knowledge shall upgrade with the help of the one with the highest fitness value. The pictorial representation of this Phase can be seen in Fig. 1.

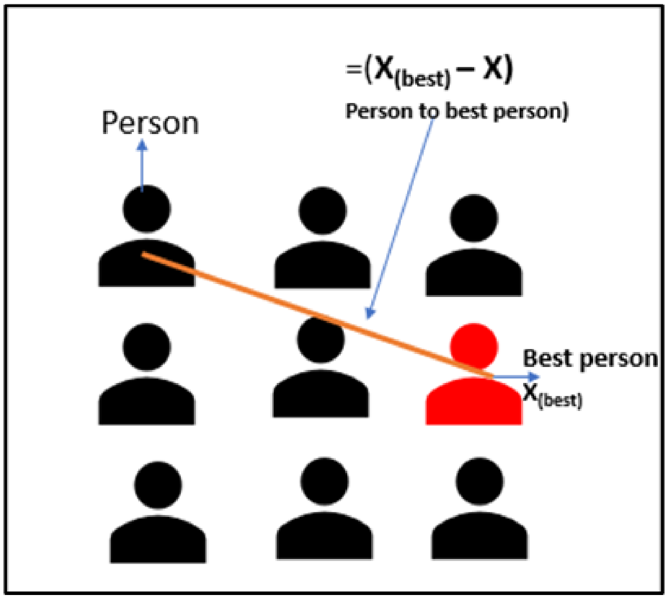


Fig. 1. Shows the Improving Phase Working.

$$X_{new} = cX + r(X_{best} - X) \quad (1)$$

The new solution computed with c, a self-introspection parameter, is here $X_{new}$, r is the random number between (0,1), and X is the previous solution. $X_{best}$ represents the one with the highest fitness value. With ($X_{best}$, X), the individual interacts with the best person in the group, which helps them enhance their expertise. The focus will be on the acquisition phase once the new solution has been produced. This entire process works in two steps: Improving and acquiring Phases. Previously the improving Phase has been discussed. Once the communication between the partner and the best person occurs, the algorithm moves to the next phase, i.e., acquiring.

### B. Acquiring Phase

Now this Phase works in two steps:

Step 1: Mutual interaction with the other partners in the group.

Step 2: Mutual Interaction with the other people in the group + considering the best person from Phase 1 (Fig. 2).

In the case of Step 1, each person interacts with other people in the group by using the following Eq 2:

$$Person\ to\ partner\ or\ peer\ = X - X_p \quad (2)$$

Where $X$ is the person and $X_p$ are their colleagues. In Step 2, communication will be done with the best person in the group. Here each member interacts with the best person only, which is calculated using the following Eq calculates. 3.

$$Person\ to\ Best\ person = (X_{best} - X) \quad (3)$$

Here $X_{best}$ represents the person with the highest fitness value or with the best knowledge. Once the acquiring completes, each person's ability in the group is updated using the following Eq. 4.

$$X_{new} = X + r1(X - X_p) + r2\,(X_{best} - X) \quad (4)$$

With the help of these two steps, a new solution is generated by $X_p$(partner solution). The obtained solution could be used to solve different types of optimized problems. Here if the knowledge of the person $X$ is greater than the partner $X_p$. The objective function for Maximization is given by equation 5. Similarly, if the knowledge of the person $X$ is less than the partner $X_p$ , then the objective function is given by following (Eq. 6)

$$X_{new} = X + r1(X - X_p) + r2\,(X_{best} - X)$$
$$if\ X > X_p \quad (5)$$

$$X_{new} = X - r1(X - X_p) + r2\,(X_{best} - X)$$
$$if\ \ X < X_p \quad (6)$$

and for the same condition, the objective function for Minimization is shown below in (Eq. 7 and Eq. 8)

$$X_{new} = X + r1(X - X_p) + r2\,(X_{best} - X)$$
$$if\ \ X < X_p \quad (7)$$

$$X_{new} = X - r1(X - X_p) + r2\,(X_{best} - X)$$
$$if\ \ X > X_p \quad (8)$$

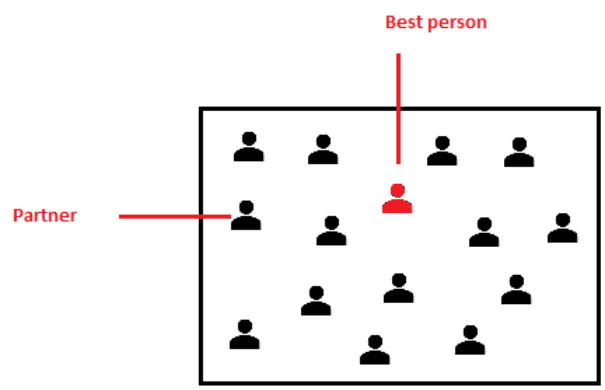


Fig. 2. SGO with the Best Person and the Partner.

## III. Social Group Optimization-Based Dynamic Shortest Path Route Evaluation in Wireless Mesh Network

This section proposes an SGO based approach for least-cost route evaluation in WMNs. Routing is the process of establishing a communication link between a source and a destination node. The cheapest path in WMNs is challenging to determine due to the dynamic nature of network nodes. Routing techniques for WMNs are often divided into two phases. The first Phase is the route discovery phase. The source nodes should discover the best route within the specific time frame. Once the route is discovered, data communication is performed in the second Phase. In the second phase, source and destination nodes can communicate. Data transfer continues until a specified time interval or network structure changes.

When estimating a minimal or near-cost route, these dynamic scenarios and time constraints complicate the routing process. In most cases, the exact shortest path cannot be calculated, so the shortest path must be replaced with the least cost path so that the path can be served as an input to the existing dynamic environment [1]. Due to the complexity of this in Wireless Mesh Network, A soft computing approach is preferred over hard computing. Soft computing techniques provide an optimized route instead of the best route within a given time constraint.

In WMN's routing, matrices play a crucial role in path selection and route optimization. As defined in the literature, ETX [2] is termed as the "expected no of transmission nodes," which are required when transmitting the information from a source node to a destination node. To calculate ETX, each node spreads an inquiry packet which is having the number of received inquiries from every neighbor. The Route EXT sums up all the ETX links which come in between the route. With the help of source routing and ETX/ETT metrics, the Local On-Demand Link State (LOLS)[3] protocol executes the route-discovery process. WCETT was proposed [4] to minimize the number of nodes on the route of a flow that transmits information on the same channel. It is a combination of end-to-end delay and channel diversity. The MR-LQSR (Multi-Radio Link Quality Source Routing Protocol) [5] follows LQSR to work over multiple channels and interfaces with the help of the WCETT metric. ETT (Expected Transmission Time) [6] tackles the problem of low performance presented in ETX by considering the differences in link transmission rates. ETT adjusts ETX to different PHY rates and data-packet sizes. Apart from all these, we have some more metrics like Per-Hop Packet Pair Delay (PktPair)[7], Expected Transmission on a Path (ETOP) [8], Effective Number of Transmission (ENT)[9], and Modified Expected Number of Transmissions (mETX) [10], Metric of Interference and Channel Switching (MIC) [11], Bottleneck Link Capacity (BLC) path metric [12], cross-layer link quality and congestion aware (LQCA) metric [13]. A novel interference aware low overhead routing metric was proposed [14]. In our proposed approach we use the fuzzy-based integrated link cost (ILC) method [15].

Some more interesting study on Soft computed based WMN’s can be seen in [16]-[20].

Integrated link cost (ILC) = f(throughput, delay, jitter, node residual energy)

**Proposed SGO Approach in Routing in Wireless Mesh Network for Dynamic Optimal Cost Route Evaluation**

**Begin**
/* SGO starts
Initialize the SGO parameter. Generate N populations each with randomly generated NC candidate Solutions, Dimension D of each population, termination criteria self-introspection parameter c.
while! = T C **do**
/* TC is a termination criterion */
**for** i = 1: N **do**
Calculate ILC of every link of the network.
Using ILC to evaluate the fitness calculate the fitness value of each person in the population
Sort the ith populations from best to worst based on the values of ILC;
The best-fit individual of the ith population is chosen as the gbest of the person;
End **for**
Record the best route from amongst all available routes. The best fit is called elite;
Initiate an improving Phase to update the knowledge of persons with the help of the best route
**for** i = 1: N **do**
Update the $i^{th}$ route by integrating it with the best route in populations.
End for
%Acquiring Phase
**Select a route 'r' randomly from the available population of routes**
**Compute fitness of 'r'**
**for** i = 1: N **do**
if r is better than the ith route
Update the $i^{th}$ route by integrating it with the 'r' route in populations.
**End for**
Compute fitness of the entire route population.
**Calculate the best fit route from the current population and call it temp_fit**
**Update elite with temp_fit (if required)**
**Stop**

## IV. Architectural Details of Various Client WMN Scenario

For implementation purposes, we consider different client WMN scenarios. The architectural detail of each scenario is shown in Table I.

TABLE I. NETWORK ARCHITECTURE OF CLIENT MESH NETWORK

| No. of Nodes Area | Area(m×m) | Radio Range | Timing Constraint (in Seconds) |
|---|---|---|---|
| 500 | 1000 *1000 | 250 | 1.3,1.5,1.7,2.1,2.3,2.5,2.7,3.1,3.3,3.5 |
| 1000 | 1000*1000 | 250 | 1.2,1.4,1.6,1.8,2.0,2.2,2.4,2.6,2.8,3.0 |
| 2000 | 2000*2000 | 250 | 2.0,2.2,2.4,2.6,2.8,3.0,3.2,3.4,3.6,3.8 |
| 3000 | 3000*3000 | 250 | 4.0,4.5,5.0,5.5,6.0,6.5,7.0,7.5,8.0,8.5 |
| 4000 | 4000*4000 | 250 | 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, 8.0, 8.5, 9.0, 9.5, 10.0 |

## V. Result and Discussion

To assess the appropriateness of the suggested SGO-based approach to route evaluation in WMNs, we implemented it in MATLAB along with 6 other algorithms and ran simulations using dynamic scenarios. We evaluated 500, 1000, 2000,3000, and 4000 node client WMN designs for simulation purposes. For simplicity, we have eliminated the findings from WMNs with up to 1000 nodes because the proposed SGO technique performs better on larger networks. Table I shows the architectural design of several Client WMN node scenarios.

### *A. Comparative Performance of 2000 Node Client Wireless Mesh Networks*

The performance of the Social Group Optimization-based new routing approach for the Wireless Mesh Network approach is evaluated along with other 6 algorithms on the 2000 node client WMN scenario. We have considered 2.0, 2.2,2.4,2.6,2.8,3.0,3.2,3.4,3.6, and 3.8 seconds timing constrain for performance analysis purpose. For each timing constrain, we conducted 10 trials. For testing purposes, we conducted a total number of 100 trials.

The performance of each approach with different time intervals on the 2000 nodes scenario is presented in Table II. For all time limits and given trials, the results achieved by SGO based routing approach outperformed ACO, DSR, AODV, BAT, BBO, and Firefly algorithms 56 times out of 100 trials. The optimal route generated by Firefly is 32 times and BAT 8 times. BBO generated better results 4 times in some time constraints including equal optimal route cost with BAT, Firefly, and SGO. With the given timing constraints, no route was discovered by ACO, DSR, and AODV. For the time constraints 2.0, 2.6 3.4, and 3.8, BAT and BBO were able to discover routes but were unable to produce optimal route cost. For the time constraints 2.4,3.0, and 3.2 BAT, BBO, and Firefly generated similar route costs. SGO came out as a winning approach with the highest route discovery and minimal route cost in the entire analysis. Fig. 3 shows the pictorial representation of the best performance of SGO with the other 6 algorithms.

TABLE II. ARCHITECTURAL DETAILS OF 2000 NODES CLIENT WMN SCENARIOS

| Time Constraints | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Algo** | **2.0** | **2.2** | **2.4** | **2.6** | **2.8** | **3.0** | **3.2** | **3.4** | **3.6** | **3.8** |
| **ACO** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **AODV** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **DSR** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **BBO** | 0 | 0 | 1+A | 0 | 0 | 1+A | 1+A | 0 | 1+A | 0 |
| **BAT** | 0 | 2 | 1+A | 0 | 2 | 1+A | 1+A | 0 | 1+A | 0 |
| **Firefly** | 4 | 3 | 2 | 3 | 4 | 1+A | 2 | 4 | 5 | 4 |
| **SGO** | 6 | 5 | 6 | 7 | 4 | 7 | 6 | 6 | 3 | 6 |
| A=1 represents equal results generated | | | | | | | | | | |

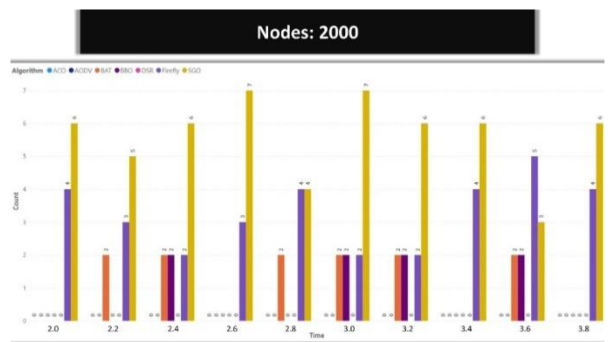


Fig. 3. Graphical Presentation of 2000 Nodes in Client Wireless Mesh Networks.

### *B. Comparative Performance of 3000 Node Client Wireless Mesh Networks*

From Table III, it is observed that for time constraints of 4.0 seconds BAT and BBO produce minimum route cost and equal results for one time each, Firefly-based approach produced 3 times and SGO generated minimum cost route 5 times. Within time constraint 4.5 BBO and BAT and SGO produced enumerated equal best paths. For 5.0 seconds BAT, BBO and Firefly produced equal results once and generated minimal route path 1 time.

SGO on the other hand generated a minimal route cost path 7 times. For time constraints 6.0, 7.0,8.0, and 8.5 BBO and BAT-based approaches successfully discovered the route but did not produce the shortest path. For the same time constraints, the shortest path discovered by Firefly is 13 times and SGO is 22 times in total. Further, we observe that the overall performance of SGO based routing approach is much better than the other 6 approaches for each timing constraint. For a total of 100 trials, SGO produced a minimum cost path 55 times followed by Firefly 34 times, BAT 6 times, and BBO 5 times. For the given timing constraint all the algorithms except for AODV, ACO, and DSR have produced results. Fig. 4 represents the histogram of the frequency of best performance for each timing constraint.

TABLE III. ARCHITECTURAL DETAILS OF 3000 NODES CLIENT WMN SCENARIOS

| Time Constraints | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Algo** | **4.0** | **4.5** | **5.0** | **5.5** | **6.0** | **6.5** | **7.0** | **7.5** | **8.0** | **8.5** |
| **ACO** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **AODV** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **DSR** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ |
| **BBO** | 1+A | 1+A | 1+A | 1 | 0 | 0 | 0 | 1+A | 0 | 0 |
| **BAT** | 1+A | 1+A | 1+A | 1 | 0 | 1 | 0 | 1+A | 0 | 0 |
| **Firefly** | 3 | 2 | 1+A | 5+A | 7 | 3 | 4 | 2 | 2 | 5 |
| **SGO** | 5 | 6+A | 7 | 3+A | 3 | 6 | 6 | 6 | 8 | 5 |
| A=1 represents equal results generated | | | | | | | | | | |

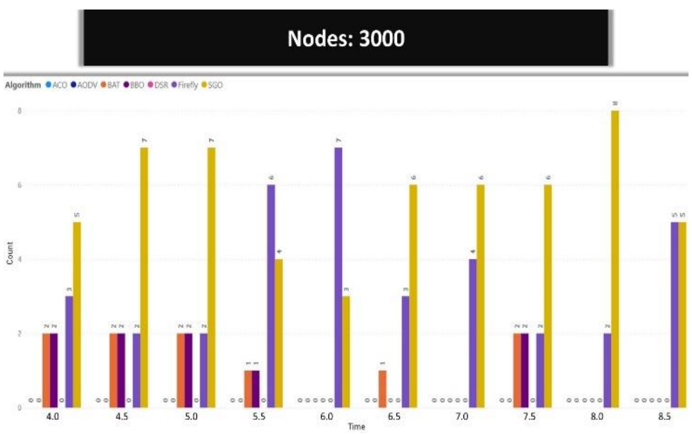


Fig. 4. Graphical Presentation of 3000 Nodes in Client Wireless Mesh Networks.

### C. Comparative Performance of 4000 Node Client Wireless Mesh Networks

Table IV shows the architectural design of 4000 nodes of Client Wireless Mesh Network along with 6 algorithms in given time constraints of 5.0,5.5,6.0,6.5,7.0,7.5,8.0,8.5,9.0,9.5, and 10.0 seconds. During implementation and results analysis, SGO outperformed ACO, DSR, AODV, BAT, BBO, and Firefly. ACO, DSR, and AODV failed to identify the path as the number of nodes increased, suggesting that these two approaches cannot perform for bigger networks. For the time constraints 5.0,6.5,8.0 and 9.5 BBO, BAT and Firefly have produced equal minimal route cost paths for once. SGO in the same time constraints produced the best results 30 times. For a time constraint of 5.5 seconds, BBO and BAT were able to discover a route but did not produce the shortest path. On the other hand, the optimal path produced by SGO is 8 times and Firefly 2 times for the same time intervals i.e. 5.5 seconds. For time constraints 6.5 and 7.0 seconds SGO discovered route 9 times, firefly 1 time each. BAT and BBO, on the other hand, were able to discover a route but not an optimal one. For a total of 100 trials, SGO outperforms 76 times, followed by Firefly 28 times, BAT 4 times, and BBO 1 time excluding the same route discovery cost. It illustrates how, as SGO is implemented in a larger network with greater time constraints, its performance improves, yielding the optimal shortest path.

Fig. 5 shows the graphical representation of the simulation results implemented using MATLAB.

TABLE IV. ARCHITECTURAL DETAILS OF 4000 NODES CLIENT WMN SCENARIOS

| Time Constraints | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Algo** | **5.0** | **5.5** | **6.0** | **6.5** | **7.0** | **7.5** | **8.0** | **8.5** | **9.0** | **9.5** | **10.0** |
| **ACO** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | |
| **AODV** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | |
| **DSR** | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | ------ | |
| **BBO** | A | 0 | 0 | A | 0 | 0 | 1+A | 0 | 0 | A | A |
| **BAT** | 1+A | 0 | 0 | A | 0 | 0 | 1+A | 0 | 0 | 1+A | 1+A |
| **Firefly** | 1+A | 2 | 4 | 1+A | 1 | 6 | 2+A | 3 | 3 | 1+A | 4 |
| **SGO** | 8 | 8 | 6 | 9 | 9 | 4 | 6 | 7 | 7 | 7+A | 5 |
| A=1, represents equal results generated | | | | | | | | | | | |

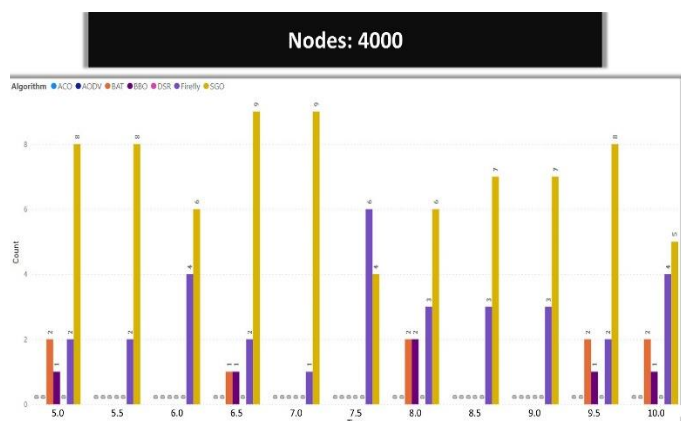


Fig. 5. Graphical Presentation of 4000 Nodes in Client Wireless Mesh Networks.

## VI. CONCLUSION

Wireless Mesh Network is dynamic because nodes are free to move in any direction. As the node's changes, the structure of the network also changes along with them. Due to network changes, there comes a high probability of route variation between source and destination. This route variation causes a loss of information between nodes and however it is difficult to get the optimized results in less time. Thus, there is a need for a routing approach that can discover the optimum route quickly even if there is any fault in a specific path. To overcome this problem some soft computing-based approaches can be integrated into Wireless Mesh networks which can help to get optimal results within the given time constraints. This article proposes a new SGO based new Routing approach for wireless mesh networks. The proposed approach was tested and implemented in MATLAB on different network scenarios. The performance of the proposed approach was compared with 6 other algorithms (ACO, AODV, DSR, BAT, and Firefly) on the bases to calculate a minimal cost path. The result analysis shows that SGO based routing approach outperforms the other 6 algorithms on network architecture greater than 1000 nodes. Thus, with all the computational results and analysis, we conclude that SGO based routing approach is the best-suited dynamic near shortest path approach amongst all 6 algorithms discussed.

## Acknowledgment

I would like to express my very great appreciation to Dr Amar Singh for their valuable and constructive suggestion during the planning and development of the research work. This paper and research behind it would not have been possible without their guidance. His enthusiasm and knowledge have always been an inspiration to me. I wish to acknowledge the help and support provided by Lovely Professional University and my colleagues.

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