Routing in Wireless Mesh Network: A New Metaheuristic Based Routing Approach

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Abstract
Routing is a challenging issue of WMNs due to the dynamic nature of the network. In WMNs, a node can leave or join the network at any time. So, there is a need for an efficient routing algorithm in WMNs that should quickly discover the path. The development of different networking environments has a significant effect on WMNs routing. This paper proposes a new Butterfly Optimization algorithm (BOA) based routing approach for Wireless Mesh Networks. The proposed BOA routing approach was implemented using MATLAB, and its performance was compared with Ad Hoc On-Demand Distance Vector(AODV), Ant Colony Optimization(ACO), BAT optimization algorithm, Dynamic Source Routing(DSR), and Biogeography-based optimization(BBO) based routing approaches on 500, 1000, 1500, and 2000 dynamic node scenarios. From the results, We observe that the proposed Butterfly based routing approach outperforms the existing five routing approaches.

Keywords: Wireless mesh network; ACO; AODV; DSR; BBO; Butterfly Optimization Algorithm

1. Introduction
Wireless Mesh Networks are multihop networks that are quickly deployable, dynamically self-organizing, self-configuring, self-healing, self-balancing, and self-aware. Each node (stationary or mobile) in these networks can join or leave the network at any time. So, there is the need for some new approaches which can discover or maintain the route quickly. Wireless Mesh Networks (WMNs) have been designed to provide better services to stable and portable clients. There are three different categories of WMNs: 1. Infrastructure Wireless Mesh Networks 2. Client Wireless Mesh Networks 3. Hybrid Wireless Mesh Networks Akyildiz et al. (2005).

Some more interesting study on WMN’s with routing can be seen in Perkins et al. (2003), Ogier et al. (2004,Johnson et al. (2001). The current MAC and routing protocols for WMNs are insufficiently scalable Huang and Lai (2002). The routing path selection is heavily influenced by resource distribution, interference avoidance, and rate adaptation across multiple hops Akyildiz et al. (2008).

Butterflies are classified as Lepidoptera in the Animal Kingdom’s Linnaean classification scheme. There are over 18,000 butterfly species worldwide. Their senses are responsible for their long-term existence after millions of years Sacheri (1998). Butterflies employ their senses of smell, sight, taste, touch, and hearing to find food and a partner. These abilities come to be handy while moving from one site to another, avoiding predators, and laying eggs in difficult places. The smell is the most essential of these senses, helping butterflies discover food, generally nectar, from long distances. Blair and Launer are two of the most influential people in the world (1997) who carried out their research in this field. Butterflies can locate meals and friends regionally and globally. When thinking about bodily proximity and different factors (consisting of rain, wind, and different climate conditions), foraging can constitute an vital part of butterfly mating or foraging activities. To transfer from general worldwide seek to dense nearby seek, BOA makes use of a various possibility. Some related work with the hybridized monarch approach is done by Strumberger et al. (2019). Arora et al. (2018) modified the mechanical design problems by using the enhanced
bovine algorithm. The binary bovine optimization algorithm modifies a hybrid feature selection in Sadeghian et al., (2021). Chen et al., (2017) explored the dynamic vehicle routing problem by using monarch butterfly optimization. The butterfly optimization algorithm for optimum shape design is presented by Yildiz et al., (2020) in automobile suspension components.

In the proposed algorithm, when a butterfly detects the odor of another butterfly, the process of moving toward that butterfly is called global navigation. If the odor cannot be detected around the butterfly, the proposed algorithm will move randomly, called a local quest. The terms scent and scent are used interchangeably in this document. This paper proposes a new soft computing (BOA) based routing approach for wireless mesh network.

2. Fragrance power of Butterfly

To distinguish scent/fragrance in BOA is generated as a characteristic of the bodily energy of the stimulus Arora and Anand (2019):

\[
f = cI^a
\]

where \( f \) explains the cognitive intensity of the scent, or the intensity of the scent of other butterflies, \( c \) is the sensory mode, and \( I \) is the intensity of the power exponential stimulation according to the mode. Other types of intensity can be explained in the same way as the fitness function of the Firefly algorithm (Yang 2010b), genetic algorithm or bacterial collection approach (Gazi and Passino 2004).

2.1 Working of Butterflies

The following characteristics of butterflies are idealized to illustrate the above discussion in terms of search algorithms:

- All butterflies are expected to emit a fragrance that makes them attractive to each other.
- Each butterfly flies in a random direction, or towards the best butterfly that emits the most fragrance.
- The landscape influence of the target feature may determine the intensity of butterfly stimulation.

BOA is divided into 3 stages: (1) initialization, (2) is repeated (iteration), and (3) final stage. Each BOA runs the next iterative search that completes the initialization step first, and finally finds the best solution to finish the algorithm. It defines the objective function along with solution space during the first phase. The total number of butterflies in the BOA simulation has not changed, so a fixed amount of memory is reserved to store the data. Butterfly positions are randomly generated from the search space, and the butterfly scent and fitness values are calculated and stored. Now that the initialization process is complete, the algorithm goes into a repetitive step where the search is performed. The algorithm performs multiple iterations in the second phase of the algorithm. Each butterflies in optimal area travel to new positions in each iteration, and their fitness values are then evaluated. Then, using Eq (1), these butterflies produce fragrance at their respective locations. The Algorithm has two main steps: a global search phase and a local search phase. The Butterfly moves closer to the fittest butterfly/solution \( g^* \) in the global search process, which can be interpreted using Eq (2)

\[
x^{t+1}_i = x^t_i + (r^2g^* - x^t_k) \times f_i
\]

where \( x^{t+1}_i \) is the solution vector \( x_i \) in ith iteration number \( t \). The current best solution found among all the solutions in the current iteration is denoted by \( g^* \). The ith butterfly’s fragrance is expressed by \( f_i \), and \( r \) is a random number in the range \([0,1]\). Local search phase can be represented as

\[
x^{t+1}_i = x^t_i + (r^2x^t_j - x^t_k) \times f_i
\]

\( x^t_i \) and \( x^t_j \) are the jth and kth butterflies in the solution vacuum, respectively. Eq. (3) becomes a local random walk if \( x_i \) and \( x_k \) belong to the same swarm and \( r \) is a random number in the range \([0,1]\).

3. Proposed Butterfly Optimization Algorithm (BOA) based routing approach

In this section, we propose a Butterfly Optimization-based Routing approach that can quickly discover the optimum route and provides seamless communication between network nodes. The working of the proposed approach is shown in Algorithm 1. In the BOA Algorithm, we generate the random routes initially. After that, the optimum route is discovered by the BOA algorithm. The termination criteria to discover the route is the timing constraints. The shortest route is not most frequently calculable. So to delivered a route under the present dynamic conditions, the shortest one
must be replaced with the lowest cost one. We call the nearest shortest route the least-cost route Singh et al. (2017).

**Proposed BOA based Routing Approach for Wireless Mesh Network’s**

```plaintext
Begin
/* Adjacency Matrix: Matrix of Neighbor nodes of each node */ /* SE: Number of nodes in best Butterfly, Path Matrix: Collection of butterflies, N = Number of Butterflies/routes, Path nodes: Number of Nodes in a route. */
Generate N butterflies. Every Butterfly consists of NG genes;
iter = 1
while iter ≤ termination criteria do
for i = 1: N do
Compute the fitness of each Butterfly;
Sort the population from best to worst based on fitness (cost) value;
End for
Compute the best Butterfly from the population using equation 1.
For each butterfly bf in the population do
Generate a random number R between 0 to 1
If R < p then
Move towards best butterfly/Route
Else
Generate the network route on a random basis.
Endif
End for
Iter = iter + 1;
End while
Return Best Butterfly
```

This BOA routing approach may find the shortest route or the minimum route to select the optimal route in WMNs. One of the wide variety of metrics is used to analyze the distance/cost of a particular route. The literature has several different routing metrics.

Metrics play an essential role in WMN’s routing, both for path discovery and route optimization. ETX stands for Expected Transmission Count as described in the literature Nelakuditi et al. (2005, September), which are needed when transmitting data from a source node to a destination node. To calculate ETX, each node distributes an inquiry packet containing the total number of received inquiries from each node. Route EXT sums up the ETX connections that come in between the path. The Local on-Demand Connection State (LOLS) protocol Drave’s et al. (2004, September). Exe-

cutes the route-discovery mechanism using source routing and ETX/ETT metrics. WCETT Koksal et al. (2006) suggested reducing the number of nodes on a flow’s route that transmits data over the same channel. End-to-end delay and channel diversity are combined to create this effect. With the support of the WCETT metric, the MR-LQSR (Multi-Radio Connection Quality Source Routing Protocol) Yang et al. (2005) extends LQSR to multiple channels and interfaces. By considering the variations in connection transmission speeds, ETT solves the poor performance that ETX has. ETT adapts ETX to various PHY rates and data-packet sizes. Some more are Expected Transmission on a Path (ETOP) Liu, T et al. (2006, June), Effective Number of Transmissions (ENT) and Modified Expected Number of Transmissions (mETX) Karbaschi et al. (2005, November), Metric of Interference and Channel Switching (MIC) Liu, et al. (2006, June), Bottleneck Link Capacity (BLC) path metric Karbaschi et al. (2005, November), cross-layer link quality and congestion aware (LQCA) metric L. Ma et al. (2005), per-hop Round Trip Time (RTT) Adya et al. (2004, October), Per-Hop Packet Pair Delay (PktPair) Shakti Kumar et al. (2013). An interference aware low overhead routing metric was proposed by Liran Ma et al. (2005). Our work calculated the cost of a path using the Fuzzy-based integrated link cost (ILC) technique. The architecture of ILC is shown in Figure 1.

In Wireless Mesh Network, The Integrated Link Cost is calculated as Shakti Kumar et. al (2013, 2014).

\[ \text{integrated link cost (ILC)} = f(\text{throughput, delay, jitter, node residual energy}) \]

We also utilize the same ILC cost route model as Shakti Kumar et al. (August 2015) for evaluation. An algorithm 1 shows the recommended optimal cost route assessment technique.

4. Implementation and performance of the Proposed Approach

To evaluate the performance of the butterfly-based routing approach, we implemented it in MATLAB along with five other routing approaches and performed simulations of different mobile nodes scenarios. For implementation purposes, the architectural detail of each network scenario is shown in Table 1.

The performance of all implemented approaches was assessed under time limitations. To evaluate them, we considered 500, 1000, 1500, and 2000
nodes network scenarios. So, We conducted 200 trials for each network node architecture. In total, we conducted 800 trials to evaluate and compare the performance of all six implemented algorithms.

4.1 Comparative Performance of 500 node Client WMNs

Table 2 shows the comparative performances of all implemented algorithms on different time constraints. From Table 2 we observe that the Butterfly optimization algorithm outperforms other in terms of minimum cost path as compared to ACO, DSR, AODV, BAT and BBO within the stipulated time. ACO and DSR approach failed to produce any result for all the time constraints. AODV does not discover a route for 0.2, 1.6, and 2.0 seconds while for 0.4-time constraint, it gives minimum route cost 6 times but also failed 5 time to produce the results. For 0.6 time constraint it gives minimum route cost 8 times including 12 times failure for route discovery. Similarly, for 0.8, 1.0, and 1.2 seconds it generates 7,12, and 9 times optimal paths with 3.7 and 4-time failure, respectively. As shown in the table for time constraints 1.4 and 1.8 seconds, the AODV approach generates the minimal cost path 6 and 4 times without any failure. BAT algorithm for the 1.2,1.4,1.8 timing constraints successfully discovered the route but did not produce the minimum core route. The BBO based approach discovered the routes in the given time constraints but did not obtain the optimized route path in any timing constraint. It is observed from the table that Butterfly Optimization Algorithm (BOA) outperformed other approaches as it produces a minimum route path 13 times for 0.2,1.8, and 2.0 seconds. It finds the better minimal route path for other remaining timing constraints compared to ACO, AODV, BAT and BBO algorithms, including the same best performance in other given time constraints. Figure 2 shows the graphical representation of the best performance in each timing constraint.

4.2 Comparative Performance of 1000 node Client WMNs

To assess all implemented six approaches on 1000 node scenarios, We considered ten different timing constraints and conducted 20 trials in each
Table 2. Performance of 500 Node Client Network

| Algorithm | Time Constant |
|-----------|--------------|
| ACO       | 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 2 |
| AODV - AODV | 6 + 5 8 + 12 7 + 3 12 + 7 9 + 4 6 - 4 - |
| BAT       | G G A A B 0 0 C 0 A |
| BBO       | 2+G 5 5 + A 1+B 4 3 C 3 6 + A |
| BOA       | 13+G 5+G 7+A 7 + A 5+B 7 11 17+C 13 13 + A |
| DSR       | - - - - - - - - - - |

Table 3 shows the comparative performance of 1000 node client WMN and Figure 3 shows the comparative performance of 1000 node client WMN's.

4.3 Comparative Performance of 1500 node Client WMNs

Table 4 and Figure 4 show the comparative performance of AODV, BAT, DSR, BBO, ACO, and BOA with higher time constraints 1.6,1.8,2.0,2.4,2.8,3.0,3.2 and 3.4 seconds for 1500 nodes architecture. We observe that in the given time constraint, BOA performed better as compared to other algorithms. In the 1500 dynamic nodes architecture, ACO, DSR, and AODV could not discover or generate any route in any timing constraints. BAT and BBO produced equal best routes for stimulated time. For 3.2 and 3.4 seconds, BAT discovered a route but failed to obtain the minimum cost path, whereas, for the same time constraints, BBO discovered optimal routes twice and once. In total, BOA in total 200 trails produced a minimum route cost path 130 times than BBO, which discovered path 40 times.

4.4 Comparative Performance of 2000 node Client WMN’s

To evaluate and compare the performance of 6 algorithms in 2000 node Client Wireless Mesh Network, out of 800 trials( 10 timing set * 20 trials per set), BOA discovered a minimal cost path 150 times along with an equal best performance with BAT and BBO in some time constraints. Table 5 and Figure 5 show the comparative performance of all the six approaches for the higher time. The performance of AODV, BAT, BOA, Butterfly optimizations for 2000 node points are compared. Table 5 and Figure 5 indicate that the Butterfly Optimization algorithm shows a good agreement regarding the minimum cost path compared to DSR, ACO, AODV, BAT, and BBO within the stipulated time. It may be noted that the results of Butterfly’s effec-
Table 3. Performance of 1000 Node Client Network

| Algorithm | 1   | 1.2 | 1.4 | 1.6 | 1.8 | 2   | 2.2 | 2.4 | 2.6 | 2.8 |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ACO       | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |
| AODV      | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |
| BAT       | A   | C   | B   | B   | 0   | 0   | 0   | 0   | 0   | A   |
| BBO       | 11+A| 9+C | 10+B| 5+B | 3   | 6   | 9   | 6   | 0   | 6+A |
| BOA       | 8+A | 8+C | 8+B | 13+B| 17  | 14  | 11  | 14  | 20  | 13+A|
| DSR       | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |

- represents route not discovered 0 represent no minimal cost A=1, B=2, C=3, D=4, E=5, F=6 and G=7

Table 4. Performance of 1500 Node Client Network

| Algorithm | 1.6 | 1.8 | 2.0 | 2.2 | 2.4 | 2.6 | 2.8 | 3.0 | 3.2 | 3.4 |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ACO       | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |
| AODV      | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |
| BAT       | G   | E   | G   | B   | D   | A   | A   | C   | 0   | 0   |
| BBO       | G   | 6+E | 5+G | 8+B | 3+D | 8+A | 7+A | C   | 2   | 1   |
| BOA       | 13+G| 09+E| 08+G| 10+B| 13+D| 11+A| 12+A| 17+C| 18  | 19  |
| DSR       | -   | -   | -   | -   | -   | -   | -   | -   | -   | -   |

- represents route not discovered 0 represent no minimal cost A=1, B=2, C=3, D=4, E=5, F=6 and G=7

Fig. 5. Comparative performance of 2000 node client WMN’s

The effectiveness methods are well consistent with other algorithms in the specified time limit. Here the time constraint is higher than the previous node scenarios. ACO, AODV, and DSR did not perform the given time constraints.

4.5 Overall Comparative performance of all the networks

To compare the performance of 6 algorithms, we have conducted 800 trials. There are various timing limitations for each different network dynamic node architecture. As shown in Table 6 and Figure 6, Out of 800 total trials, the Butterfly Optimization algorithm produced 504 times optimal cost path, BBO produced 160 times, and AODV produced 52 times in total. Multiple algorithms have given the same best performance 56 times. The findings show that the suggested BOA method outperforms the other implemented five available approaches.

5. Conclusion

In this paper we propose, a new BOA routing-based technique for dynamic shortest route evaluation in WMNs. We implemented the proposed approach along with 5 other namely ACO, DSR, BBO, BAT and AODV routing approaches in MATLAB for different time constraint and node scenarios. The performance was compared based on minimal cost path evaluation parameter. BOA based Routing Approach for Wireless Mesh Network’s outperformed all the other approaches in all the client node network scenario i.e 500,1000,1500
Table 5. Performance of 1500 Node Client Network

| Algorithm | 1.6  | 2.0  | 2.5  | 3.0  | 3.5  | 4.0  | 4.5  | 5.0  | 5.5  | 6.0  |
|-----------|------|------|------|------|------|------|------|------|------|------|
| ACO       | -    | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| AODV      | -    | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| BAT       | D    | A    | E    | A    | A    | B    | B    | A    | C    | D    |
| BBO       | 3+D  | 2+A  | 2+E  | 2+A  | 4+A  | 3+B  | 2+B  | 2+A  | 3+C  | 3+D  |
| BOA       | 13+D | 17+A | 13+E | 17+A | 15+A | 15+B | 16+B | 17+A | 14+C | 13+D |
| DSR       | -    | -    | -    | -    | -    | -    | -    | -    | -    | -    |

Table 6. Performance of 1500 Node Client Network

| Number of nodes | No. of trial | ACO | AODV | BAT | BBO | BOA | DSR | No. of equals |
|-----------------|--------------|-----|------|-----|-----|-----|-----|---------------|
| 500             | 200          | 0   | 52   | 0   | 29  | 98  | 0   | 13            |
| 1000            | 200          | 0   | 0    | 0   | 65  | 126 | 0   | 6             |
| 1500            | 200          | 0   | 0    | 0   | 40  | 130 | 0   | 22            |
| 2000            | 200          | 0   | 0    | 0   | 26  | 150 | 0   | 15            |
| Total           | 800          | 0   | 52   | 0   | 160 | 504 | 0   | 56            |

and 2000. As a result, we observed that the current proposal for WMN’s is an outstanding optimization method and can be considered as the best dynamic near shortest path assessment approach routing in Wireless Mesh networks.

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