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Combined Genetic and Fuzzy Approach for Shortest Path Routing Problem in Ad hoc Networks

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Abstract   Shortest path (SP) routing problem for static network has been addressed well in the recent past using different intelligent optimization techniques such as artificial neural network, ant colony optimization, particle swarm optimization, genetic algorithms (GA) etc. However, advancements in the wireless communication result in more and more wireless mobile networks such as mobile ad hoc network, wireless mesh network, etc. for which static path routing algorithms will not work well due to the dynamic nature of the mobile networks whose environmental conditions change over time. In this paper, we present a new method to address the SP routing problem for dynamic wireless sensor networks using well known optimization technique called GA. In this method, different paths which are formed randomly by the nodes between source and destination are modeled as chromosomes in the GA. Then, these chromosomes are undergone various genetic process such as selection, crossover and mutation to get new chromosomes. Every time the topology changes, network parameters such as sent packets, received packets, transmission time and dropped packets are estimated for each path and the optimized route is selected using fuzzy based fitness function applied to each chromosomes.

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1 Introduction

A mobile ad hoc network (MANETs) can be operated on multi hop wireless networks that comprises of self assembling autonomous nodes and these are dynamic temporary networks. MANETs does not use any centralized or existing infrastructure and when nodes are mobile, it can change its topology in a frequent manner. This network consists of freely moving hosts which can travel around the network and it holds each transmitting packets on the sake of every other nodes. In our paper, we look into the troubles in shortest path (SP) routing that is used to discover the routes between sources to particular destination with minimum cost related to the network. Perhaps, the cost factor depends on some factors: network throughput, reliability of the network and round trip delay. Thus, the network algorithms are used to develop, co-ordinate and disseminate the information regarding network states. In order to attain high performance, it renders executable routes among the nodes and it sends traffic by the selected path. This method has a problem called combinatorial optimization which grown in every planning and design circumstances [1, 2].

Generally, so many algorithms are available to yield solutions for SP problem such as Bellman-Ford algorithm, Dijkstra's algorithm [3] and breadth-first search algorithm etc. Polynomial time complexity is the major retreat in above mentioned algorithms. So, in fixed infrastructure network the effectiveness of these algorithms provides better performance. In case of real time communications which has a property of frequently changing topologies that shows high computational complexities. Hence, these algorithms cannot provide suitable solution for computational complexity which presents in real time communication systems using SP. Since, some of the researches have been carried out to solve the computational complexity present in SP algorithms using artificial intelligence techniques like particle swarm optimization (PSO) [4], Artificial Neural Networks (ANNs) [5] and genetic algorithms (GA) [6].

However, these algorithms primarily concentrate on the static SP problem and while the topology change occurs in the network, it can consider this as a new network. Then, the solving procedure will be restarted for this new topology network. Because of the characteristics of MANETs like mobile nodes and battery exhaustion, the rapid topology change takes place and in MANETs, dynamic SP solving algorithms [7, 8] cannot give good performance and also it cannot satisfy the real time requirements since it needs frequent restart. So, there is a new approach is needed to meet the drawbacks in dynamic SP using mobile environment.

In this paper, a novel fuzzy based GA is used which can give the solution for dynamic network problem. In this proposed method, the paths between source and destination nodes have been represented with appropriate number of populations in GA. After certain time, these populations will be evolving to split into small populations and by exploiting the solution space it can precede its searching process. When the topology changes at once, the entire populations in a network will be processed in a way and then SP will be found.

We organize our paper as follows: in Sects. 2 and 3, we talk about the related work describes the basics of GA as existed in the literature. While in Sect. 4 the GA can be improved to find the SP. Simulation results are shown and discussed in Sect. 5. Finally, in Sect. 6 the conclusion is given.

2 Related Work

There are so many approaches have been introduced to solve the SP problem in Wireless Sensor Networks (WSNs). At first, the throughput optimal routing is proposed in [9] and then analyzed in various networks like cooperative relay networks [10, 11], multi hop wireless networks [12–14] and cellular networks [15]. Joint scheduling and joint power control based algorithms have been addressed in and [16]. Optimal scheduling which is used in multicast routing is considered in [17]. The SP information are used in back pressure algorithm and their performance has to be enhanced are studied in [18]. Low complexity routing algorithms are studied in [19]. To minimize the number of hops an alternate algorithm is used which is given in [20–24].

In order to extend the network life-time, an energy aware routing is used and it attracts the interest of everyone. Minimize maximum node cost and maximize time to partition are some of the energy aware quantities and SP algorithms mainly focus on such quantities are mentioned in [25]. To balance the energy consumption in every node in the network, there are two algorithms are employed such as flow argumentation algorithm and flow redirection algorithm that are explained in [26]. Extensions along this approach were addressed in [27]. Power aware routing that reduces most former times while a packet cannot be sent are studied by the author in online were described in [28]. A usage of geographical locations of wireless nodes for energy managements are given in [29]. When the unnecessary nodes are turned off, we can save the energy are designed in GAF algorithm was proposed in [30]. The conventional protocols like DSR and AODV protocols which haven't any awareness on energy are re-imposes to take for energy-aware metrics.

3 Genetic Algorithm

Genetic algorithms are optimization techniques based one group of closely related algorithms that draw upon ideas of Darwinian evolution and genetics. Goldberg [31] defines GA are stochastic search algorithms based on the mechanism of natural selection and natural genetics. They are highly parallel and adaptive. GAs exploits the idea of the survival of fittest and an interbreeding population to create a novel and innovative search strategy. They are a form of randomized search, in that way in which strings are chosen and combined is stochastic process. This is radically different approach to the problem solving methods used by more traditional algorithms, which tend to be more deterministic in nature, such as gradient methods used to find the minima in graph theory.

GA has been quite successfully, applied in machine learning and optimization problems. For a given problem to be solved, GA maintains a population of individuals called strings or chromosomes. These strings then are probabilistically modified by some genetic operators such as selection, crossover and mutation to get close optimal solution to the problem.

3.1 GA Working Methodology

In GA, the variables are represented as genes on a chromosome. A population of strings, representing solutions to a specified problem, is maintained by the GA. The GA then iteratively creates new populations from the old by ranking the strings and interbreeding the fittest to create new strings, which are closer to the optimum solution to the problem at

hand. So I each generation, the GA create a set of strings from the bits and pieces of the previous string, occasionally adding random new data to keep the population from stagnating. The end result is a search strategy that is tailored for vast, complex, multimodal search spaces. The working method of GA involves several key genetic components: genetic representation, population initialization, fitness function, crossover, and mutation.

The following Fig. 1 shows the various steps in GA's working principle.

4 Proposed Algorithm

Our proposed genetic based SP routing algorithm is addressed for MANET operating within a fixed geographical region. This network is modeled as a network with undirected and connected topology graph *G0 (N0, E0)*, where *N0* are the set of wireless nodes (i.e. routers) and *E0* represents the set of communication links connecting two nearby routers which are falling within the radio transmission range.

The following notations are used throughout this paper to represent the network and its components:

$G (N_0, E_0)$—Initial MANET topology graph;
$G (N_i, E_i)$—MANET topology after *i*th change;
s—Source node;
d—Destination node;
Pi(s,r)—Path from s to d in graph *G*;
DS—Total amount of packet sent from source node to destination node;
DR—Total amount of packet received at the destination node;
DD—Total amount of packet dropped throughout the network;
TT—Total packet transfer time.

1. *[Start]* Generate random population of *n* chromosomes (suitable solutions for the problem)
2. *[Fitness]* Evaluate the fitness *f(x)* of each chromosome *x* in the population.
3. *[New Population]* Create a new population by repeating following steps until the new population is completed.
   1. *[Selection]* Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected).
   2. *[Crossover]* With a crossover probability, cross over the parents to form new offspring (children). If no crossover is performed, offspring is the exact copy of parents.
   3. *[Mutation]* With a mutation probability, mutate new offspring at each locus (position in chromosome).
   4. *[Accepting]* Place new offspring in the new population.
4. *[Replace]* Use new generated population for a further run of the genetic algorithm.
5. *[Test]* If the end condition is satisfied, **stop** and return to the best solution in current population
6. *[Loop]* Go to step **2**.

Fig. 1 GA's working principle

In our approach, the network under consideration is represented as graph with 10 nodes (represented with integers 0, 1…9 corresponding to nodes in the route, whereas 0th node is called source node and 9th node is called as destination node). Excluding these source and destination nodes, the remaining eight nodes are undergone for GA process.

Initial population with two chromosomes is taken first, and their corresponding genes values are randomly selected from the 8 routing nodes without any repetition within the chromosomes. This step is illustrated in Fig. 2. In Fig. 2:

S, D source and destination nodes,
C1N1, C1N2…C1N10—Genes (nodes) in chromosome 1,
C2N1, C2N2…C2N10—Genes (nodes) in chromosome 2

Then, single bit crossover between chromosome 1 and chromosome 2 is carried out in which half of the gene values are exchanged across the chromosomes. This step is illustrated in the Figs. 3 and 4. In Fig. 3, the genes marked with double brackets are swapped across chromosome 1 and chromosome 2 respectively. Figure 4 shows the results of genes position after crossover. Followed the crossover, single bit mutation is done in which gene values are interchanged within the chromosomes itself. Figures 5 and 6 shows the gene position before and after the mutation process.

At the end of the crossover and mutation process, we arrive at two new chromosomes with altered gene values that vary from initial population. Now we have four chromosomes equivalent to four different routing paths for which fitness values should be estimated. For each chromosome, DS, DR, DD and TT values are measured and the optimum chromosome to carry into the next generation is selected based on the fitness function computed using fuzzy logic.

The fitness function using fuzzy logic is designed in such a way that any one of the following fuzzy conditions should be met by the route in order to say that this is the optimum path. Let us consider, are the minimum values required to transmit a packet through the network via the selected route. Then the required fuzzy sets are:

(DS> & DR> & DD< & TT<) ‖
(DS> & DD<) ‖
(DS> & DR>) ‖
(DS> & TT<) ‖
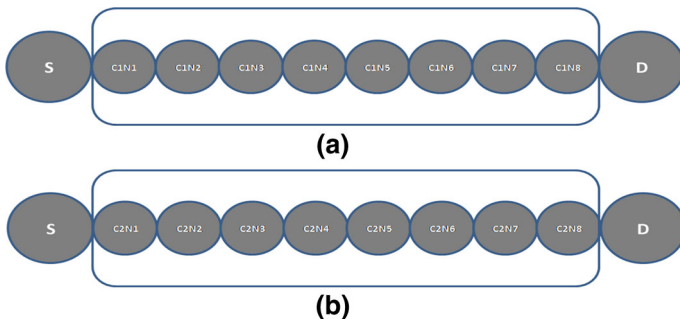(DS> & DR> & TT<) ‖
(DR> & DD<) ‖

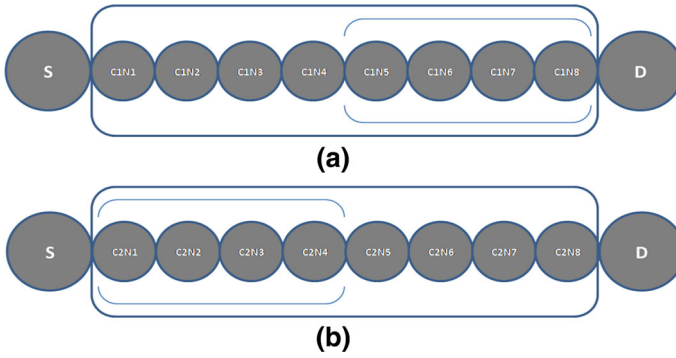**Fig. 2** Initial population (**a**) Chromosome 1 (**b**) Chromosome 2

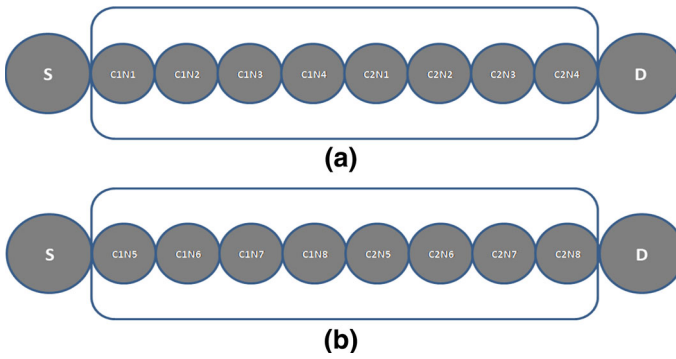**Fig. 3** Genes position before crossover (**a**) Chromosome 1 (**b**) Chromosome 2

Fig. 4 Genes position after crossover (**a**) Chromosome 1 (**b**) Chromosome 2
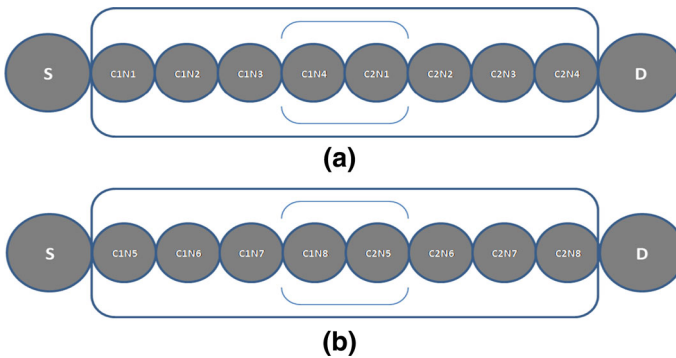

Fig. 5 Genes position before mutation (**a**) Chromosome 1 (**b**) Chromosome 2

(DD< & TT<) ||
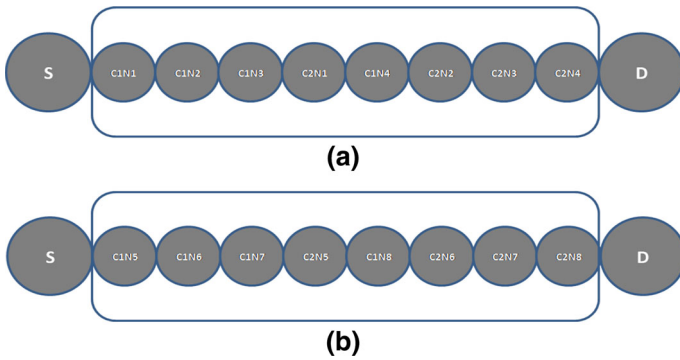(DR> & TT<) ||
(DR> & DD<) ||
(DR> & TT<)

Fig. 6 Genes position after mutation (**a**) Chromosome 1 (**b**) Chromosome 2

The chromosome which gives optimum result based on the above fuzzy conditions is taken to the next generation and other chromosomes are discarded. Now, along with the current one, one more chromosome is formed with new randomly selected genes (nodes). Then the above mentioned genetic operators will be repeated for these two new chromosomes that will undergo further offspring procedure. This procedure is repeated up to particular iterations until an optimum solution is achieved. Once achieved, the chromosome which has been selected finally is considered the shortest route.

5 Simulation Work

The proposed algorithm was applied to network topology shown in Fig. 7. The objective is to find the SP for the source node 1 to reach destination node 10. The network in Fig. 7 is simulated using NS2 simulator to find the SP. The initial population consists of 2 chromosomes with 10 genes of each. The best results are obtained using single points of crossover. The simulation result for various iterations is given in the Tables 1, 2, 3 and 4.

Table 1 shows the results obtained for four network parameters by applying the proposed method with different number of iterations. From the table, it is very clear that as the number of iterations increases, the amount of packet sent and amount packet received

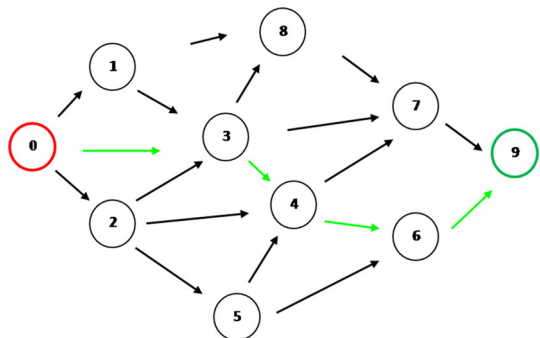**Fig. 7** Network topology for simulation

Table 1 Simulation results for all measures

Iteration	DS	DD	TT	DR
100	358964	2135	2.32	356829
200	358964	2008	2.02	356956
300	358964	1952	1.94	357012
400	358964	1851	1.82	357113
500	358964	1811	1.62	357153
600	358964	1625	1.52	357339
700	358964	1432	1.23	357532
800	358964	1326	1.15	357638
900	358964	1012	1.01	357952

Table 2 Simulation results DS and DR

Iteration	DS	DR
100	358964	356829
200	358964	356956
300	358964	357012
400	358964	357113
500	358964	357153
600	358964	357339
700	358964	357532
800	358964	357638
900	358964	357952

Table 3 Simulation results for TT and DR

Iteration	TT	DR
100	2.32	356829
200	2.02	356956
300	1.94	357012
400	1.82	357113
500	1.62	357153
600	1.52	357339
700	1.23	357532
800	1.15	357638
900	1.01	357952

reaches high, while the amount of packet dropped goes low with decrease in transmission time which shows the potential of our proposed method.

The following figures illustrate the results obtained for various iterations.

In Fig. 7, the path marked in green color ($0 \rightarrow 3 \rightarrow 4 \rightarrow 6 \rightarrow 9$) indicates the SP found by our proposed method.

In order to prove the effectiveness of our proposed algorithm further, our algorithm is compared with different existing algorithms for various network parameters with different network nodes and the comparison results are given as follows (Figs. 8, 9, 10, 11).

Table 4 Simulation results for TT and DD

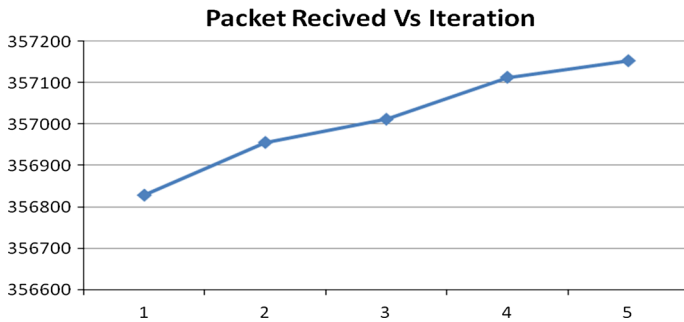| Iteration	TT	DD
100	2.32	2135
200	2.02	2008
300	1.94	1952
400	1.82	1851
500	1.62	1811
600	1.52	1625
700	1.23	1432
800	1.15	1326
900	1.01	1012

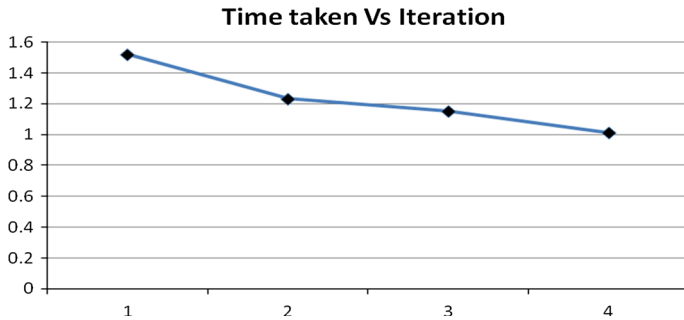**Fig. 8** DR versus Iterations

Fig. 9 TT versus Iterations

Table 5 contain the comparison results for the network parameter "Data received" for the networks of 100, 300 and 600 nodes respectively. From these tables, it is very clear that our proposed method delivers highest data to the destination comparing to others. Comparison result for "Data send", "Data received" and "Data dropped" for the network consists of 100 nodes is given in the Table 6. Our proposed method is computationally less cost than others.

Figure 12 shows that the average end to end delay and it is defined as the time taken to transmit the data between one end user to another end user. The proposed technique has
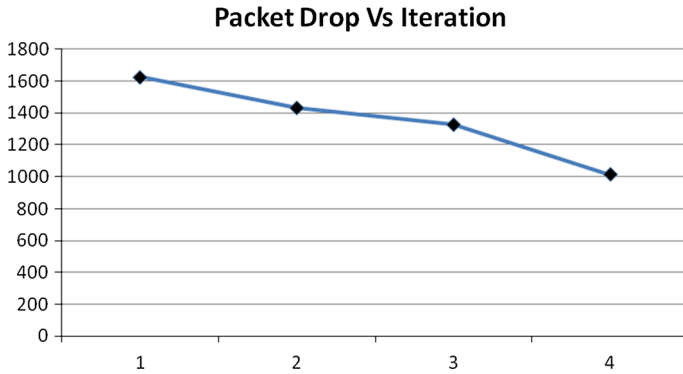
Packet Drop Vs Iteration
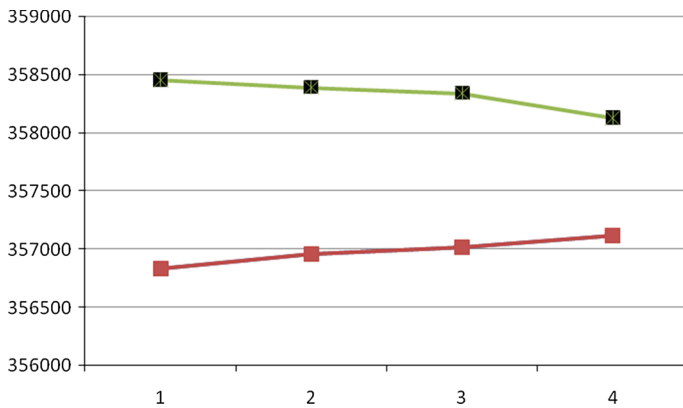

Fig. 10 DD versus Iterations

Fig. 11 DS, DR versus Iterations

lesser end to end delay of 1800 ms. The other techniques of DAWMNet, AntHocNet, ARAWSN and AOMDV has higher delay due to the more number of users in the existing techniques. These existing techniques increases the delay but the proposed scheme reduces the delay with the help of topology maintenance.

Figure 13 shows that the queueing length per node analysis and this has been calculated based on the queuing length of each node. The proposed technique has lesser queuing length compared to other techniques. The traditional algorithm has high queuing length and this analyzed per node. When the queuing interval is high that will increase the queuing length for each node. But the proposed scheme has low queuing interval so that reduces the queuing length per node has reduced. That will increase the network performance.

The average number of hops between the source and destination is calculated using the routing table. Based on that information, proposed technique has lesser average number of hops which is shown in Fig. 14. By reducing the number of hops between the source and destination will reduce the delay and increase the network efficiency. The proposed scheme is used to increase the reliability and scalability and this has to maintain the

Table 5 Comparison of network parameters for 100, 300 and 600 nodes

Number of nodes	Number of iteration			
	200	400	600	800
100				
Proposed	356956	357113	357339	357638
AOMDV	333956	337713	353332	357608
ARAWSN	323952	311713	327331	352630
AntHocNet	313152	306523	312139	350631
DAWMNet	323055	306533	307339	350031
300				
Proposed	346999	347013	347239	347638
AOMDV	313956	327713	333332	337607
ARAWSN	313952	321713	317301	330630
AntHocNet	303152	316523	312039	300631
DAWMNet	313055	326533	307309	309031
600				
Proposed	326906	327213	327399	327639
AOMDV	312056	307713	308332	317607
ARAWSN	310902	311913	317371	310630
AntHocNet	300102	316503	312009	308631
DAWMNet	303055	316533	307329	301031

Table 6 Comparison based on number of iterations

Number of node	Number of iteration			
	200	400	600	800
600				
Proposed	2.02	1.82	1.52	1.15
AOMDV	2.62	1.99	2.33	1.95
ARAWSN	2.32	2.09	2.30	1.99
AntHocNet	2.52	2.82	2.33	2.14
DAWMNet	2.72	2.02	2.52	1.12

topology. Lesser number of hop counts between the source and destination will transmit the data without loss rate and failure rate.

The lesser number of hops and hop count has reduced the delay. If the delay decreases the delivery ratio is increased. That delivery ratio increases in the proposed technique which is shown in Fig. 15. Delivery ratio is defined as the ratio of number of packets successfully received with respect to the number of packets transmitted. Compared to other traditional algorithms, proposed scheme increase the delivery rate and decreases the drop rate. When the delivery rate increases that reduces the routing overhead. This proposed algorithm has high reliable communication and balancing the load without flooding and increases the delivery rate.
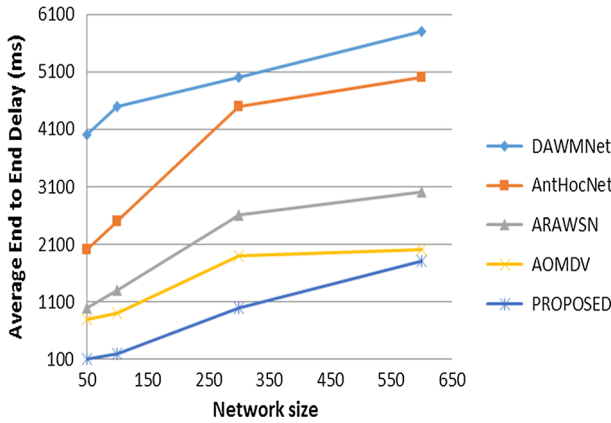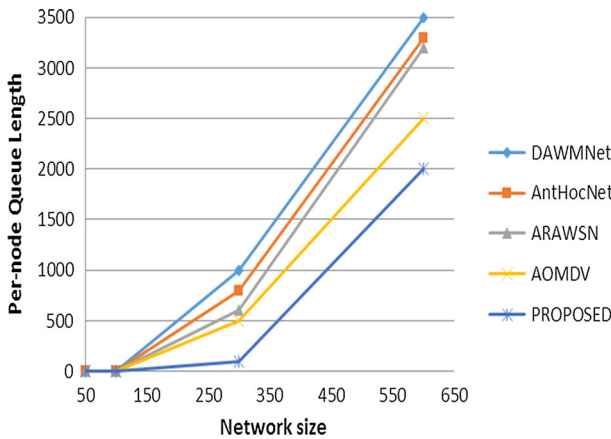
Fig. 12 Average End to End delay

Fig. 13 Per-node Queue length

6 Conclusion

A novel multi-path shortest routing algorithm for wireless networks is proposed in this article. The proposed algorithm uses genetic optimization algorithm to find the SP among the different nodes in the network. The simulation results demonstrate that the proposed algorithm works well when compared to the traditional algorithms in terms of average data transfer time, data sent, data received, data dropped and routing overhead. Moreover, the proposed algorithm can adapt with topological changes. Therefore, this algorithm achieves deterministic and reliable communication, ensures load balance, and has the ability to adapt with topological changes without high flooding. Several possible lines of work can be studied further on this proposed method. The advantages of this approach in larger number of nodes network are not that evident. Thus, the proposed algorithm should be improved to be made to allow it to adapt to larger network scales. And the proposed
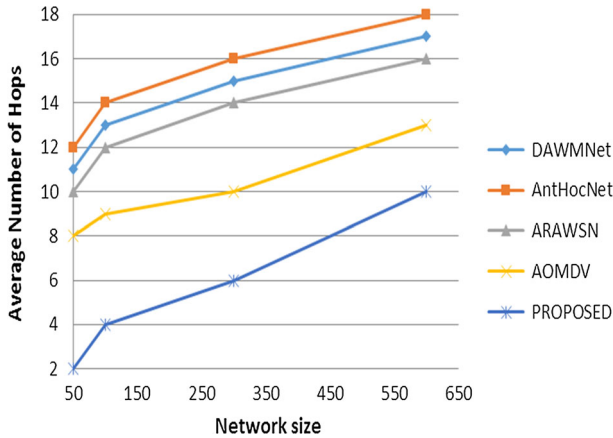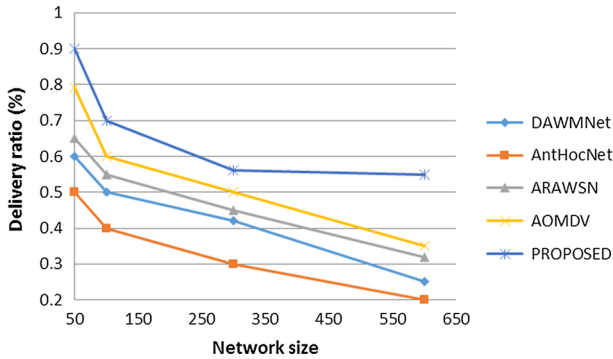
Fig. 14 Average number of Hops

Fig. 15 Delivery Rate Analysis

algorithm will be improved to combine with the Neural Fuzzy System to improve the accuracy in networks with larger number of nodes.

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