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Effects of Population Size for Location-aware Node Placement in WMNs: Evaluation by a Genetic Algorithm Based Approach

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Abstract Wireless Mesh Networks (WMNs) are cost-efficient networks that have the potential to serve as an infrastructure for advanced location-based services. Location service is a desired feature for WMNs to support location-oriented applications. WMNs are also interesting infrastructures for supporting ubiquitous multimedia Internet access for mobile or fixed mesh clients. In order to efficiently support such services and offering *QoS*, the optimized placement of mesh router nodes is very important. Indeed, such optimized mesh placement, can support location service managed in the mesh and keep the rate of location updates low. This node location-based problem has been shown to be NP-hard and thus is unlikely to be solvable in reasonable amount of time. Therefore, heuristic methods, such as Genetic Algorithms are used as resolution methods. In this paper, we deal with the effect of population size for location-aware node placement in WMNs. Our WMN-GA system uses Genetic Algorithm (GA) to determine the positions of the mesh routers and mesh clients in the grid area. We used a location-aware node placement of mesh router in cells of considered grid area to maximize network connectivity and user coverage. We evaluate the performance of the proposed and implemented WMN-GA system for low and high density of clients considering different distributions and considering giant component and number of covered users parameters. The simulation results show that for low density networks, with the increasing of the population size, GA obtains better result. However, with the increase of the population size, the GA needs more computational time. The proposed system has better performance in dense networks like hotspots for Weibull distribution when the population size is big.

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Keywords Wireless Mesh Networks · Genetic Algorithms · Selection Operators · Size of Giant Component · Number of Covered Users

1 Introduction

WMNs are showing their applicability in deployment of medical, transport and surveillance applications in urban areas, metropolitan, neighboring communities and municipal area networks. WMNs are also interesting infrastructures for supporting ubiquitous multimedia Internet access for mobile or fixed mesh clients. Ubiquitous computing have the ability to determine where people are, what objects and software services can be used at those locations, and how people can move from place to place [1].

At the heart of WMNs are the issues of achieving network connectivity and stability as well as QoS in terms of user coverage. These issues are very closely related to the family of node placement problems in WMNs, such as mesh router nodes placement. One of the biggest challenge in deploying a WMN is to meet the requirements of users with minimal cost. Usually, we have only a limited number of selected places that may have ac power and many locations may not be appropriate for mesh routers deployment. In order to efficiently support such services and offering *QoS*, the optimized placement of mesh router nodes is very important. Indeed, such optimized mesh placement, can support location service managed in the mesh and keep the rate of location updates low. Thus, the problem is to choose some of the locations for mesh routers deployment so as to achieve the best cost performance ratio. A good location of mesh routers not only can provide high network throughput but also can lead to minimum number of mesh for meeting users‘ demand in the WMN design [2].

Node placement problems have been long investigated in the optimization field due to numerous applications in location science (facility location, logistics, services, etc.) and classification (clustering). In such problems, we are given a number of potential facilities to serve to costumers connected to facilities aiming to find locations such that the cost of serving to all customers is minimized. In traditional versions of the problem, facilities could be hospitals, polling centers, fire stations serving to a number of clients and aiming to minimize some distance function in a metric space between clients and such facilities.

Facility location problems are thus showing their usefulness to communication networks, and more especially from WMNs field. WMNs [3,4] are currently attracting a lot of attention from wireless research and technology community due to their importance as a means for providing cost-efficient broadband wireless connectivity [5]. Indeed, such optimized mesh placement, can support location service managed in the mesh and keep the rate of location updates low. This node location-based problem has been shown to be NP-hard and thus is unlikely to be solvable in reasonable amount of time. WMNs infrastructures are currently used in developing and deploying medical, transport and surveillance applications in urban areas, metropolitan, neighboring communities and municipal area networks [6]. WMNs are based on mesh topology, in which every node (representing a server) is connected to one or more nodes, enabling thus the information transmission in more than one path. The path redundancy is a robust feature of this kind of topology. Compared to other topologies, mesh topology needs not a central node, allowing networks based on such topology to be self-healing. These characteristics of networks with mesh topology make them very reliable and robust networks to potential server node failures. In WMNs mesh routers provide network connectivity services to mesh client nodes. The good performance and operability of WMNs largely depends on placement of mesh routers nodes in the geographical deployment area to achieve network connectivity, stability and user coverage. The objective is to find an optimal and robust topology of the mesh router nodes to support connectivity services to clients.

For most formulations, node placement problems are shown to be computationally hard to solve to optimality [7–10], and therefore heuristic and meta-heuristic approaches are useful approaches to solve the problem for practical purposes. Several heuristic approaches are found in the literature for node placement problems in WMNs [11–15].

Using the mesh network as a medium to distribute or query location-based informations requires a location-based communication primitive to send messages to one or all hosts at a certain location. In order to realize such a service efficiently, WMNs have to be extended to support location-based addressing and routing [16].

Genetic Algorithms (GAs) have been recently investigated as effective resolution methods. Mutation operator is one of the GA ingredients. Mutation operators usually make some small local perturbation of the individuals, which could be beneficial, for instance, to keep diversity of the population. In this work, we present the simulation results on the effect of population size in GA for mesh router nodes placement problem for low and high density of clients. For evaluation, we have used different distributions of mesh node clients (Exponential, Uniform and Weibull).

The rest of the paper is organized as follows. In Section 2 is presented GA template and its application to mesh router nodes placement. The proposed and implemented WMN-GA system is presented in Section 3. The simulation results are given in Section 4. We end the paper in Section 5 with conclusions.

2 Genetic Algorithms

GAs [17] have shown their usefulness for the resolution of many computationally combinatorial optimization problems. For the purpose of this work, we have used the *template* given in Algorithm 1.

We present next the particularization of GAs for the mesh router nodes placement in WMNs (see [18] for more details).

Algorithm 1 Genetic Algorithm Template

Generate the initial population P^0 of size μ;
Evaluate P^0;
while not termination-condition **do**
  Select the parental pool T^t of size λ; $T^t := Select(P^t)$;
  Perform crossover procedure on pairs of individuals in T^t with probability p_c; $P^t_c := Cross(T^t)$;
  Perform mutation procedure on individuals in P^t_c with probability p_m; $P^t_m := Mutate(P^t_c)$;
  Evaluate P^t_m ;
  Create a new population P^{t+1} of size μ from individuals in P^t and/or P^t_m ;
  $P^{t+1} := Replace(P^t; P^t_m)$
  $t := t + 1$;
end while
return Best found individual as solution;

2.1 Encoding

The encoding of individuals (also known as chromosome encoding) is fundamental to the implementation of GAs in order to efficiently transmit the genetic information from parents to offsprings.

In the case of the mesh router nodes placement problem, a solution (individual of the population) contains the information on the current location of routers in the grid area as well as information on links to other mesh router nodes and mesh client nodes. This information is kept in data structures, namely, `pos_routers` for positions of mesh router nodes, `routers_links` for link information among routers and `client_router_link` for link information among routers and clients (matrices of the same size as the grid area are used). Based on these data structures, the size of the giant component and the number of users covered are computed for the solution.

It should be also noted that routers are assumed to have different radio coverage, therefore to any router could be linked to a number of clients and other routers. Obviously, whenever a router is moved to another cell of the grid area, the information on links to both other routers and clients must be computed again and links are re-established.

2.2 Selection Operators

In the evolutionary computing literature, we can find a variety of selection operators, which are in charge of selecting individuals for the pool mate. The operators considered in this work are those based on *Implicit Fitness Remapping* technique. It should be noted that selection operators are generic ones and do not depend on the encoding of individuals.

- *Random Selection*: This operator chooses the individuals uniformly at random. The problem is that a simple strategy does not consider even the fitness value of individuals and this may lead to a slow convergence of the algorithm.

- *Best Selection*: This operator selects the individuals in the population having higher fitness value. The main drawback of this operator is that by always choosing the best fitted individuals of the population, the GA converges prematurely.
- *Linear Ranking Selection*: This operator follows the strategy of selecting the individuals in the population with a probability directly proportional to its fitness value. This operator clearly benefits the selection of best endowed individuals, which have larger chances of being selected.
- *Exponential Ranking Selection*: This operator is similar to Linear Ranking but the probabilities of ranked individuals are weighted according to an exponential distribution.
- *Tournament Selection*: This operator selects the individuals based on the result of a tournament among individuals. Usually winning solutions are the ones of better fitness value but individuals of worse fitness value could be chosen as well, contributing thus to avoiding premature convergence. Some cases of this operator are the *Binary Tournament* and $N-$*Tournament Selection*, for different values of N.

2.3 Crossover Operators

The crossover operator selects individuals from the parental generation and interchanging their *genes*, thus new individuals (descendants) are obtained. The aim is to obtain descendants of better quality that will feed the next generation and enable the search to explore new regions of solution space not explored yet.

There exist many types of crossover operators explored in the evolutionary computing literature. It is very important to stress that crossover operators depend on the chromosome representation. This observation is especially important for the mesh router nodes problem, since in our case, instead of having strings we have a grid of nodes located in a certain positions. The crossover operator should thus take into account the specifics of mesh router nodes encoding. We have considered the following crossover operators, called *intersection operators* (denoted `CrossRegion`, hereafter), which take in input two individuals and produce in output two new individuals (see Algorithm 2).

2.4 Mutation Operators for Mesh Routers Nodes Placement in WMNs

Mutation operator is one of the GA ingredients. Unlike crossover operators, which achieve to transmit genetic information from parents to offsprings, mutation operators usually make some small local perturbation of the individuals, having thus less impact on newly generated individuals.

Crossover is "a must" operator in GA and is usually applied with high probability, while mutation operators when implemented are applied with small probability. The rationale is that a large mutation rate would make the GA

Algorithm 2 Crossover Operator

1: **Input**: Two parent individuals P_1 and P_2; values H_g and W_g for height and width of a small grid area;
2: **Output**: Two offsprings O_1 and O_2;
3: Select at random a $H_g \times W_g$ rectangle RP_1 in parent P_1. Let RP_2 be the same rectangle in parent P_2;
4: Select at random a $H_g \times W_g$ rectangle RO_1 in offspring O_1. Let RO_2 be the same rectangle in offspring O_2;
5: Interchange the mesh router nodes: Move the mesh router nodes of RP_1 to RO_2 and those of RP_2 to RO_1;
6: Re-establish mesh nodes network connections in O_1 and O_2 (links between mesh router nodes and links between client mesh nodes and mesh router nodes are computed again);
7: **return** O_1 and O_2;

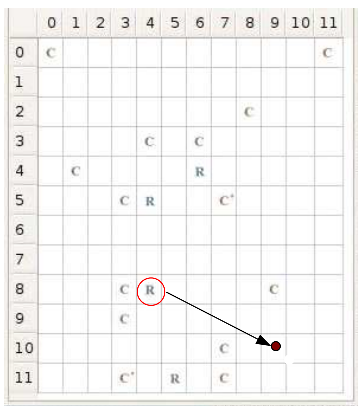


Fig. 1 Single mutate operator.

search to resemble a random search. Due to this, mutation operator is usually considered as a secondary operator.

In the case of mesh routers node placement, the matrix representation is chosen for the individuals of the population, in order to keep the information on mesh router nodes positions, mesh client positions, links among routers and links among routers and clients. The definition of the mutation operators is therefore specific to matrix-based encoding of the individuals of the population. Several specific mutation operators were considered in this study, which are move-based and swap-based operators.

SingleMutate This is a move-based operator. It selects a mesh router node in the grid area and moves it to another cell of the grid area (see Fig. 1).

RectangleMutate This is a swap-based operator. In this version, the operator selects two “small” rectangles at random in the grid area, and swaps the mesh routers nodes in them (see Fig. 2).

SmallMutate This is a move-based operator. In this case, the operator chooses randomly a router and moves it a small (*a priori* fixed) number of cells in

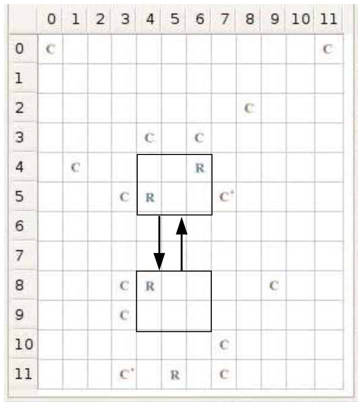


Fig. 2 Rectangle mutate operator.

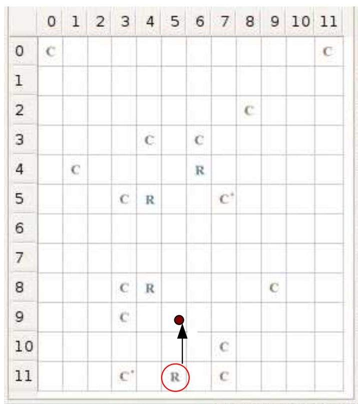


Fig. 3 Small mutate operator.

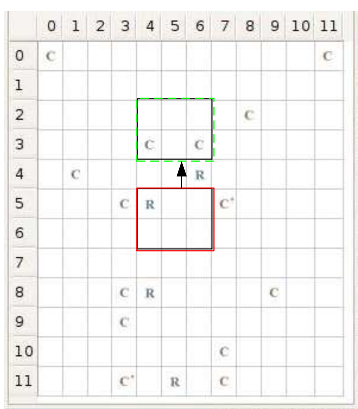


Fig. 4 Small rectangle mutate operator.

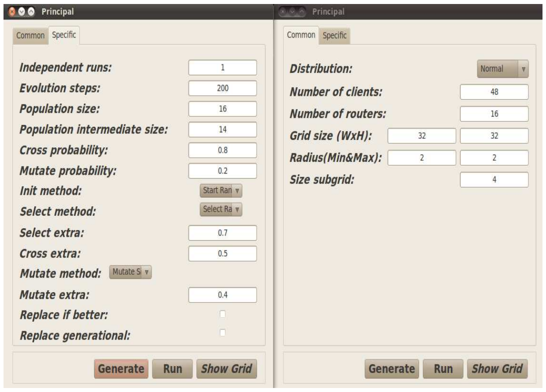


Fig. 5 GUI tool for WMN-GA system.

one of the four directions: up, down, left or right in the grid (see Fig. 3). This operator could be used a number of times to achieve the effect of SingleMutate operator.

SmallRectangleMutate This is a move-based operator. The operator selects first at random a rectangle and then all routers inside the rectangle are moved with a small (*a priori* fixed) numbers of cells in one of the four directions: up, down, left or right in the grid (see Fig. 4).

3 Proposed and Implemented WMN-GA System

In this section, we present WMN-GA system. Our system can generate instances of the problem using different distributions of client and mesh routers.

The GUI interface of WMN-GA is shown in Fig. 5. The left site of the interface shows the GA parameters configuration and on the right side are shown the network configuration parameters.

For the network configuration, we use: distribution, number of clients, number of mesh routers, grid size, radius of transmission distance and the size of subgrid.

For the GA parameter configuration, we use: number of independent runs, GA evolution steps, population size, population intermediate size, crossover probability, mutation probability, initial methods, select method.

4 Simulation Results

We carried out many simulations to evaluate the performance of WMNs using WMN-GA system.

In this work, we consider the population size (n). We consider two parameters, m and n and the relation between them is:

$$n \triangleq 2^m, m \triangleq \{m \in Z \mid 0 \leq m \leq 12\}, 1 \leq n \leq 4096. \quad (1)$$

The grid size is considered 32 x 32. There are many distribution methods, but we take in consideration the Exponential, Uniform and Weibull distributions. As selection method we used linear ranking and as mutation method we used single mutation. The crossover rate is considered 0.8 and the mutation rate 0.2. This selections are done by many simulations.

We used box plots to analyze the range of data values. The bottom and top of the box are the 25th and 75th percentile (the lower and upper quartiles, respectively), and the band near the middle of the box is the 50th percentile (the median). The ends of the whiskers represent the minimum and maximum of all data.

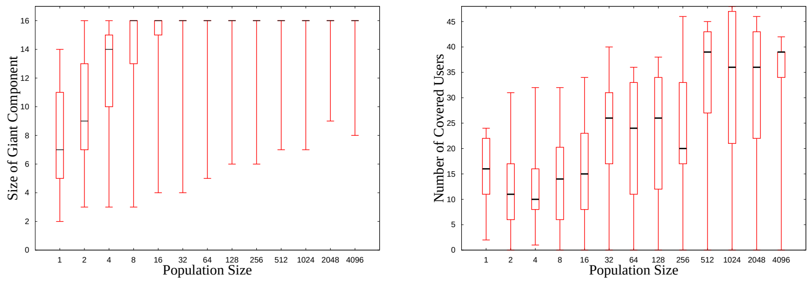
We used a bi-objective optimization, maximizing first the size of the giant component in the network (for measuring connectivity between routers) and then the user coverage. The location of the mesh routers should be aware of the location of mesh clients in order to offer better coverage.

In Fig. 6, Fig. 7 and Fig. 8 are shown the simulation results for low density of clients for Exponential, Uniform and Weibull distributions, respectively.

In Fig. 6 are shown the simulation results for Exponential distribution. In Fig. 6(a) is shown the size of giant component vs. population size. The number of mesh routers is considered 16. In Fig. 6(b) is shown the number of covered users vs. population size. The number of clients is considered 48. From these figures, we can see that with the increase of the population size, the size of giant component and the number of covered users is increased.

In Fig. 7 are shown the simulation results for Uniform distribution. In Fig. 7(a) is shown the size of giant component vs. population size and in Fig. 7(b) is shown the number of covered users vs. population size. As can be seen from the figures, for big population size, the size of giant component arrives its maximum. The number of covered users is almost stable with the increasing of the population size. The maximum number of covered users is 25 and it is achieved for population size 4096.

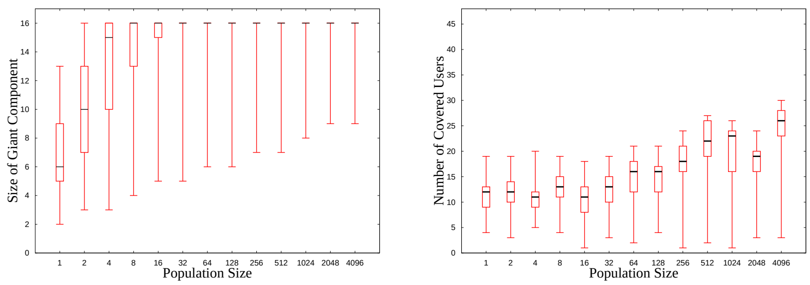
In Fig. 8 are shown the simulation results for Weibull distribution. In Fig. 8(a) is shown the size of giant component vs. population size and in Fig. 8(b) is shown the number of covered users vs. population size. As we can see from the results, with the increase of the population size, the size of giant component is increased. The maximum number of covered users is 45 and it is reached for the population size 2048. For big population size this distribution offers good user coverage. For population size smaller than 8, the size of giant component is small for all the distributions. This means that the connectivity between routers is small and the user coverage is small. With the increasing of the population size, GA obtains better result. However, with the increase of the population size, the GA needs more computation time.



(a) Size of giant component vs. population size (16 mesh routers)

(b) Number of covered users vs. population size (48 clients)

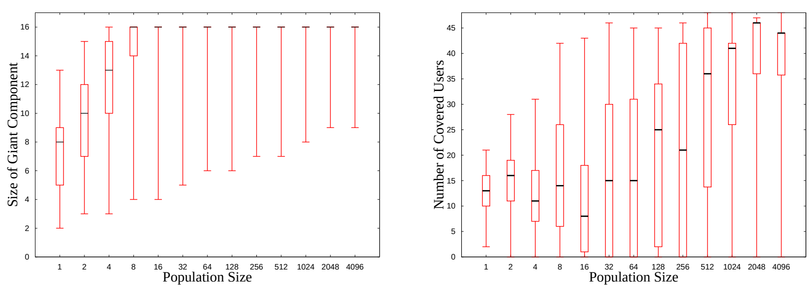
Fig. 6 Simulation results for low densities of clients, Exponential distribution.



(a) Size of giant component vs. population size (16 mesh routers)

(b) Number of covered users vs. population size (48 clients)

Fig. 7 Simulation results for low densities of clients, Uniform distribution.



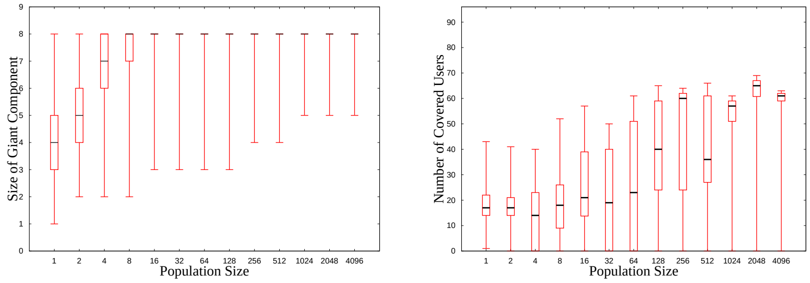
(a) Size of giant component vs. population size (16 mesh routers)

(b) Number of covered users vs. population size (48 clients)

Fig. 8 Simulation results for low densities of clients, Weibull distribution.

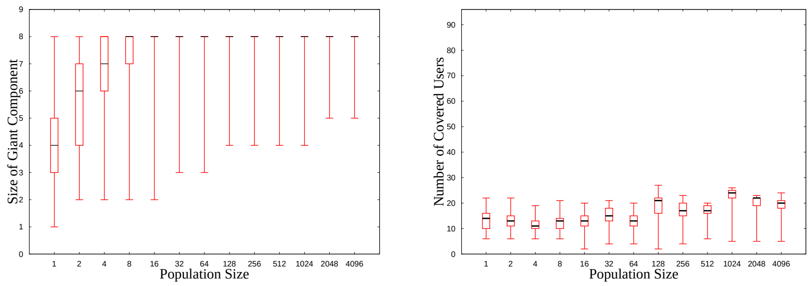
From these simulation results we can see that Weibull distribution have better performance in dense networks. This distribution offers a good coverage to the users in hotspot scenario.

In Fig. 9, Fig. 10 and Fig. 11 are shown the simulation results for dense networks for Exponential, Uniform and Weibull distributions respectively.



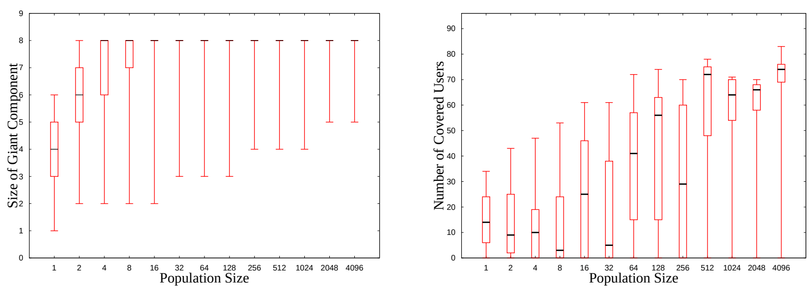
(a) Size of giant component vs. population size (8 mesh routers)
(b) Number of covered users vs. population size (96 clients)

Fig. 9 Simulation results for dense networks, Exponential distribution.



(a) Size of giant component vs. population size (8 mesh routers)
(b) Number of covered users vs. population size (96 clients)

Fig. 10 Simulation results for dense networks, Uniform distribution.



(a) Size of giant component vs. population size (8 mesh routers)
(b) Number of covered users vs. population size (96 clients)

Fig. 11 Simulation results for dense networks, Weibull distribution.

In Fig. 9 are shown the simulation results for Exponential distribution. In Fig. 9(a) is shown the size of giant component vs. population size. The number of mesh routers is considered 8. In Fig. 9(b) is shown the number of covered users vs. population size. The number of clients is considered 96. From these figures, we can see that with the increase of the population size, the size of giant component and the number of covered users is increased. For this distribution, the maximal number of covered users is 65 and is reached for population size 2048.

In Fig. 10 are shown the simulation results for Uniform distribution. In Fig. 10(a) is shown the size of giant component vs. population size and in Fig. 10(b) is shown the number of covered users vs. population size. As can be seen from the figures, for big population size, the size of giant component achieves its maximum. The number of covered users is almost stable with the increasing of the population size. The performance of this distribution is not good because the maximum number of covered users is 20.

In Fig. 11(a) is shown the size of giant component vs. population size and in Fig. 11(b) is shown the number of covered users vs. population size. From the value of population size 4, the routers achieve maximum connectivity. As we can see from the results, for small values of population size, the number of covered users is small. But, when the population size increases, the number of covered users is increased. The maximum number of covered users is 70 clients and it is reached for the population size 4096.

5 Conclusions

In order to offer *QoS*, the optimized placement of mesh router nodes is very important in WMNs. The optimized mesh placement, can support location service managed in the mesh and keep the rate of location updates low.

In this work, we used GAs to solve the connectivity and coverage problems in WMNs. We used our proposed and implemented WMN-GA system for simulations. We used a location-aware node placement of mesh router in cells of considered area to maximize network connectivity and user coverage.

We made many simulations using different genetic operators and different distributions of router nodes considering giant component and number of covered users parameters in order to check the effect of population size for node placement in WMNs.

From the simulations, for low density networks we found the following results.

- For population size smaller than 8, the size of giant component is small for all distributions but for big population size it has good values.
- With the increase of the population size, number of covered users is increased for the Exponential and Weibull distributions but for Uniform distribution is low.
- With the increasing of population size, the GA obtains better result. However, with the increase of the population size, the GA needs more computation time.

We made extensive simulation to see the performance of the system also for dense networks and we found the following results.

– For Exponential distribution, the maximal number of covered users is 65 and is reached for population size 2048.
– For Uniform distribution, the number of covered users is almost stable with the increasing of the population size. The performance of this distribution is not good because the maximum number of covered users is 20.
– For dense networks like hotspots, the Weibull distribution has better performance in terms of connectivity and user coverage for big population size.

In the future work, we would like to evaluate the performance of WMN-GA system for different distributions of router nodes.

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