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Performance Evaluation of WMN-GA System in Node Placement in WMNs for Different Distributions of Mesh Clients and Different Selection and Mutation Operators

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Abstract. Wireless Mesh Networks (WMNs) have become an important networking infrastructure due to their low cost for providing broadband connectivity. Issues for achieving the network connectivity and user coverage are related to the node placement problem. Several optimization problems are showing their usefulness to the efficient design of WMNs. These problems are related to optimizing network connectivity, user coverage and stability. In this paper, we formulate the optimization problems using a multi-objective optimization model. For the mesh router nodes placement, the bi-objective optimization problem is obtained consisting in the maximization of the size of the giant component in the mesh routers network (for measuring network connectivity) and that of user coverage. We evaluate the performance of WMN-GA system for node placement problem in WMNs. For evaluation, we consider Normal, Exponential and Weibull Distribution of mesh clients and different selection and mutation operators. The population size is considered 64 and the number of generation 200. The simulation results show that WMN-GA system performs better for Single Mutation, Linear Ranking selection and Normal distribution of mesh clients.

Key words: WMNs, GAs, population size, number of generations, connectivity, coverage.

1. Introduction

Wireless Mesh Networks (WMNs) (Akyildiz *et al.*, 2005; Nandiraju *et al.*, 2007; Chen and Chekuri, 2007) are an important networking infrastructure for providing cost-efficient

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broadband wireless connectivity. In WMNs there are two types of nodes: mesh routers and mesh clients. Mesh routers are similar to normal routers but incorporate some additional functions in order to support mesh networking, and are usually equipped with multiple interfaces to work with different wireless technologies. Mesh routers provide the same coverage with much less transmitter power through multi-hop communications compared with normal routers. Also, mesh routers can be installed on a dedicated machine or on a general purpose machine. On the other hand, mesh clients have the necessary functions for mesh networking and could also be able to act as routers but do not have the functionality of a gateway or bridge and their single wireless interface with the hardware and software platform is much simpler than in the case of mesh routers. In WMNs mesh routers provide network connectivity services to mesh client nodes. The good performance and operability of WMNs largely depend 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.

There are many more scenarios for which WMNs can be used. We mention some of them in following: Transportation Systems (provide information services to passengers, remote monitoring of vehicle safety and communications by the driver), Automatic Control Buildings (in buildings there are several electrical devices to be controlled, including light, elevator, air conditioning, and so on), Medical and Health Systems (in a hospital information monitoring and diagnosis must be transmitted from one room to another), Surveillance (corporate buildings, shopping malls and stores need broadband data transmission).

The main issues in WMNs are achieving network connectivity, stability and QoS in terms of user coverage. These issues are related to mesh router node placement problems in WMNs. Node placement problems have been long investigated in the optimization field due to numerous applications in facility location, logistics, services and also clustering.

In most formulations, node placement problems are shown to be computationally hard to solve to optimality (Garey and Johnson, 1979; Lim *et al.*, 2005; Amaldi *et al.*, 2008; Wang *et al.*, 2007), 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 (Muthaiah and Rosenberg, 2008; Zhou *et al.*, 2007; Tang, 2009; Franklin and Ram Murthy, 2007; Vanhatupa *et al.*, 2007; Xhafa *et al.*, 2010).

In this work, we use GA for optimizing node placement in WMNs. Our study aims to identify the mutation and selection types that work best for instances of different characteristics. We formulate the optimization problems using bi-objective optimization models. Thus, for the mesh router nodes placement, the bi-objective optimization problem is obtained consisting in the maximization of the size of the giant component in the mesh routers network (for measuring network connectivity) and that of user coverage.

In this paper, by considering Normal, Exponential and Weibull distributions we improve our implemented WMN-GA system and carry out comparison evaluation for different selection and mutation operators. The Mesh client nodes can be arbitrarily situated in the given area. For evaluation purposes, it is interesting, however, to consider concrete distributions of clients. For instance, it has been shown from studies in real urban areas or university campuses that mobile users tend to cluster to hotspots. In our previous work (Barolli *et al.*, 2013), we considered Weibull distribution of mesh clients and evaluated the performance of WMN-GA for different selection operators. In this work, we extended our experimental study by considering different distribution of mesh clients in order to find better combinations of operators and parameters. The population size is considered 64 and the number of generations 200. For evaluation, we consider the giant component and the number of covered users metrics. The simulation results show that the WMN-GA system performs better for Normal distribution of mesh clients.

The rest of the paper is organized as follows. In Section 2, we present different optimization problems and mesh router node placement. The proposed and implemented WMN-GA system based on GA is presented in Section 3. The simulation results are given in Section 4. We give some concluding remarks and future work in Section 5.

2. Optimization Problems and Mesh Router Nodes Placement

Different optimization problems can be formulated based on the objectives to optimize and a set of different constraints, such as topological restrictions, battery restrictions, QoS requirements, etc. Some optimization problems are related to minimize the cost of the WMN, such as minimizing the number of mesh router nodes to deploy, while others focus on the WMN performance, such as computing optimal placement of an a priori fixed number of mesh router nodes. The presence of many objectives is in fact a main challenge. These objectives include minimizing the number of mesh routers, maximizing network connectivity, maximizing user coverage, minimizing energy consumption (especially in wireless and mobile networks), minimizing communication delay, maximizing throughput, minimizing deployment cost, etc. And, additionally, there could be certain constraints to take into account such as topological restrictions of the geographical area, interference model, etc. It should also be noted that some of the objectives are contradicting, in the sense that trying to optimize some objective goes in detriment to the optimization of another objective.

2.1. *Mesh Router Nodes Placement*

In the mesh node placement problem we are given a 2D area where to distribute a number of mesh router nodes and a number of stationary mesh client nodes. Positions of the mesh client nodes can follow any arbitrary distribution (Normal, Exponential, Weibull). The objective is to find a position for the mesh routers that maximizes the network connectivity that is measured in terms of size of the giant component and client coverage. An instance of the problem consists of: (a) N mesh router nodes, each having its own radio coverage, defining thus a vector of routers; (b) an area with size $W \times H$ where to distribute N mesh routers and we need to compute the positions of mesh routers. The 2D area is divided in square cells of a priori fixed length and mesh router nodes are to be deployed in the cells

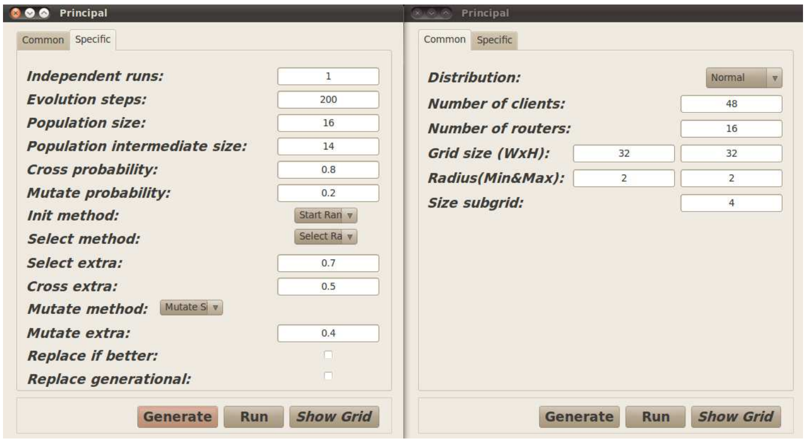


Fig. 1. GUI tool for WMN-GA system.

of the grid area; and, (c) M client mesh nodes located in arbitrary cells of the considered grid area, defining a matrix of clients. An instance of the problem can be formalized by an adjacency matrix of the WMN graph, whose nodes are of two types: router nodes and client nodes and whose edges are links in the mesh network (there is a link between a mesh router and a mesh client if the client is within radio coverage of the router). Each mesh node in the graph is a triple $v = \langle x; y; r \rangle$ representing the 2D location point and r is the radius of the transmission range. There is an arc between two nodes u and v, if v is within the transmission circular area of u. The deployment area is partitioned by grid cells, representing graph nodes, where we can locate mesh router nodes. In a cell, both a mesh and a client node can be placed. The objective is to place mesh router nodes in cells of considered area to maximize network connectivity and user coverage.

3. Proposed and Implemented WMN-GA System

3.1. *WMN-GA System*

The GUI interface of our WMN-GA system (Barolli *et al.*, 2013) is shown in Fig. 1. Our system can generate instances of the problem for different distributions of client and mesh routers.

On the left side of the interface are shown the GA configuration parameters and on the right side are shown the network configuration parameters.

For the GA parameter configuration, the following are used: number of independent runs, GA evolution steps, population size, population intermediate size, crossover probability, mutation probability, initial methods, select method. For the network configuration, the following are used: distribution, number of clients, number of mesh routers, grid size, radius of transmission distance and the size of subgrid.

3.2. *Genetic Algorithms*

Genetic Algorithms (GAs) are based on the evolution of a population of individuals over a number of generations. Each individual of the population is assigned a fitness value whose determination is problem dependent. At each generation, individuals are selected for reproduction based on their fitness value. Such individuals are crossed to generate new individuals, and the new individuals are mutated with some low mutation probability. The objective of GAs is to find the optimal solution to a problem. However, since GAs are heuristics, the solution found is not always guaranteed to be optimal. Nevertheless, experience in applying GAs to a great deal of problems has shown that often the goodness of the solutions found by GAs is sufficiently high. GAs (Holland, 1975) have shown their usefulness for the resolution of many computationally combinatorial optimization problems. In this work we have used the *template* given in Algorithm 1.

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; $P_c^t := Cross(T^t)$;
  Perform mutation procedure on individuals in P_c^t with probability p_m; $P_m^t := Mutate(P_c^t)$;
  Evaluate P_m^t ;
  Create a new population P^{t+1} of size μ from individuals in P^t and/or P_m^t ;
  $P^{t+1} := Replace(P^t; P_m^t)$
  $t := t + 1$;
end while
return Best found individual as solution

A basic GA comprises:

- *Encoding*: the encoding of individuals is fundamental to the implementation of GAs in order to efficiently transmit the genetic information from parents to offsprings.
- *Selection*: individuals are selected from the population to be parents to crossover. The problem is how to select these individuals. According to Darwin's evolution theory, the best ones should survive and create a new offspring. The fitter the individual, the higher its probability of being selected for reproduction. The selection operators are generic ones and do not depend on the encoding of individuals.
  - *Random Selection*: it chooses the individuals uniformly at random.
  - *Best Selection*: it selects the individuals with higher fitness value.
  - *Linear Ranking Selection*: it selects the individuals in the population with a probability directly proportional to its fitness value.
  - *Exponential Ranking Selection*: is similar to Linear Ranking but the probabilities of ranked individuals are weighted according to an exponential distribution.

  - *Tournament Selection*: it selects the individuals based on the result of a tournament among individuals. Two particular cases of this operator are the *Binary Tournament* and *N-Tournament Selection*.
- *Crossover*: after selection of pairs of parents, the crossover operator is applied to each of these pairs. The crossover operator involves the swapping of genetic material between the two parents. This operator randomly chooses one or more locuses and exchanges subsequences based on these locuses between two chromosomes to create two offsprings. Crossovers are deterministic operators that sometimes capture the best features of two parents and pass it to a new offspring.
- *Mutation*: the two individuals resulting from each crossover operation will be subjects of the mutation operator in the final step of forming the new generation. This operator randomly alters one or more alleles at randomly selected locuses. Mutation can occur with some probability and in accordance with its biological equivalent, usually this is very small. Starting from an initial population of strings (representing possible solutions), the GA uses these operators to calculate successive generations. First, pairs of individuals of the current population are selected to mate with each other to form the offspring, which then forms the next generation.

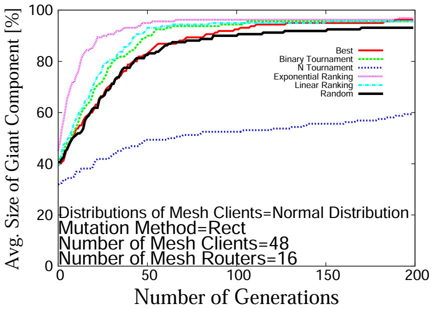
In this work, we have considered *intersection operator*, which takes in input two individuals and produces in output two new individuals as shown in Algorithm 2.

Algorithm 2 Crossover Operator

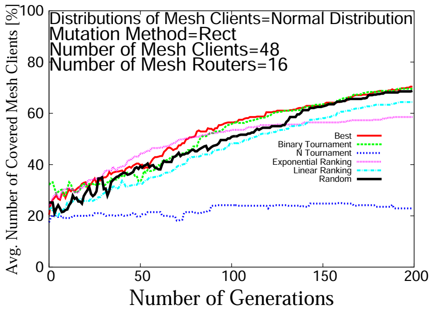
1: **Input**: Two parent individuals P_1 and P_2; values H_g and W_g for height and width of a small grid area;
2: **Output**: Two offsprings O_1 and O_2;
3: Select at random a $H_g \times W_g$ rectangle RP_1 in parent P_1. Let RP_2 be the same rectangle in parent P_2;
4: Select at random a $H_g \times W_g$ 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

4. Simulation Results

In this work, we will present an experimental study on the effect of mutation and selection operators in GA for mesh router nodes placement problem. To evaluate the performance of WMNs we used our WMN-GA simulation system. In this simulation scenarios, grid

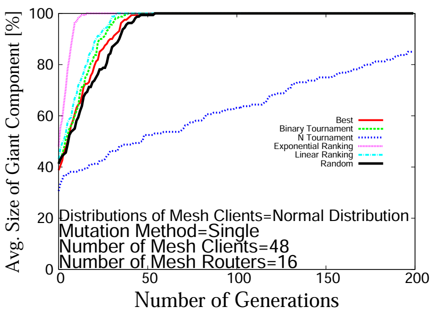


(a) Avg. size of giant component vs. number of generations

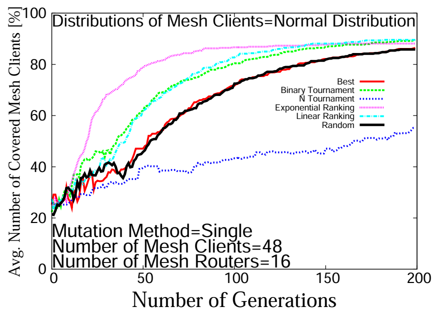


(b) Avg. number of covered mesh clients vs. number of generations

Fig. 2. Results for Normal distribution and Rectangle Mutate.



(a) Avg. size of giant component vs. number of generations



(b) Avg. number of covered mesh clients vs. number of generations

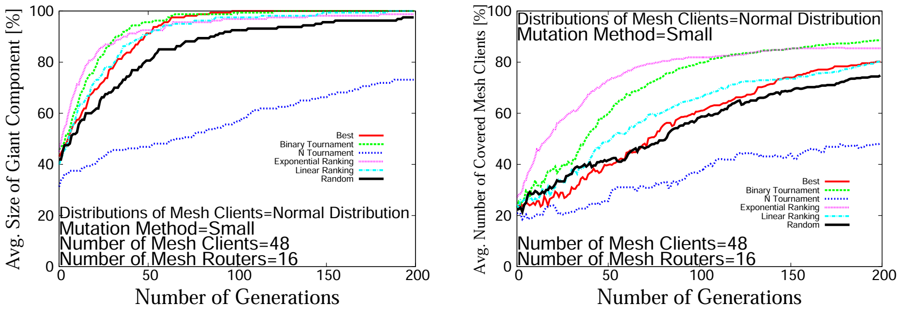
Fig. 3. Results for Normal distribution and Single Mutate.

size is considered (32×32). The number of mesh routers is considered 16 and the number of mesh clients 48. For evaluation, we considered Normal, Exponential and Weibull Distribution of mesh clients and six different selection operators (Best, Binary Tournament, N Tournament, Exponential Ranking, Linear Ranking and Random) and four mutation operators (Rectangle Mutate, Single Mutate, Small Mutate, Small Rectangle Mutate). The population size is considered 64 and the number of generation 200. As evaluation metrics, we consider the giant component and the number of covered users.

In Figs. 2, 3, 4 and 5 the simulation results of Normal distribution for Rectangle Mutate, Single Mutate, Small Mutate and Small Rectangle Mutate operators, respectively, are shown. In Figs. 2(a), 3(a), 4(a), 5(a) the simulation results for avg. size of giant component vs. number of generations for six different selection methods, are shown. In Figs. 2(b), 3(b), 4(b), 5(b) the results for avg. number of covered mesh clients vs. number of generations, are shown.

In Figs. 2(a), 4(a) and 5(a), for all the selection operators the size of giant component is not maximized (this means that all 16 mesh routers cannot be connected to each other).

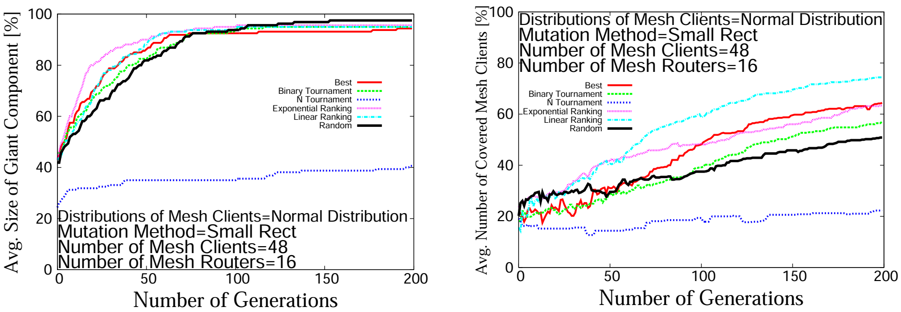
In all the scenarios, N Tournament has a poor performance (the avg. size of giant component and the avg. number of covered mesh clients is very small). Good results are



(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

Fig. 4. Results for Normal distribution and Small Mutate.



(a) Avg. size of giant component vs. number of generations

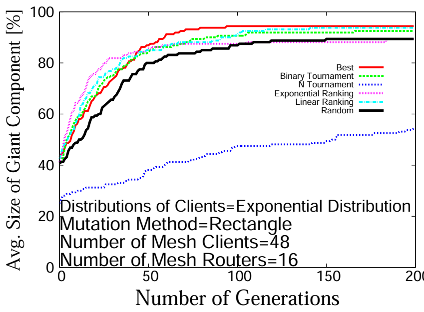
(b) Avg. number of covered mesh clients vs. number of generations

Fig. 5. Results for Normal distribution and Small Rectangle Mutate.

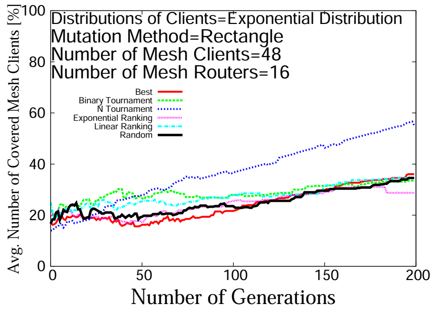
obtained for Single Mutate (see Fig. 3). In this scenario, the avg. size of giant component is maximized for all selection operators except for the N Tournament case, and the avg. number of covered mesh clients is higher than in all other scenarios. The best results are obtained for Single Mutate and Linear Ranking where the avg. number of covered mesh clients is 90%.

In Figs. 6, 7, 8 and 9 the simulation results of Exponential distribution for Rectangle Mutate, Single Mutate, Small Mutate and Small Rectangle Mutate operators, respectively, are shown. In Figs. 6(a), 7(a), 8(a), 9(a) the simulation results for avg. size of giant component vs. number of generations for six different selection methods, are shown. In Figs. 6(b), 7(b), 8(b), 9(b) the results for avg. number of covered mesh clients vs. number of generations, are shown.

In Figs. 10, 11, 12 and 13 the simulation results of Weibull distribution for Rectangle Mutate, Single Mutate, Small Mutate and Small Rectangle Mutate operators, respectively, are shown. In Figs. 10(a), 11(a), 12(a), 13(a) the simulation results for avg. size of giant component vs. number of generations for six different selection methods, are shown. In Figs. 10(b), 11(b), 12(b), 13(b) the results for avg. number of covered mesh clients vs. number of generations, are shown.

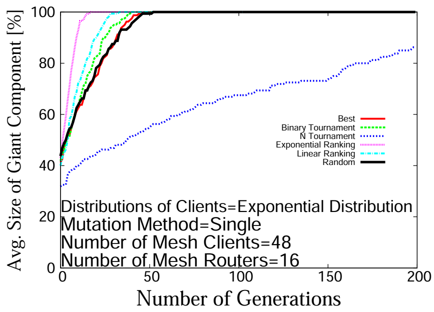


(a) Avg. size of giant component vs. number of generations

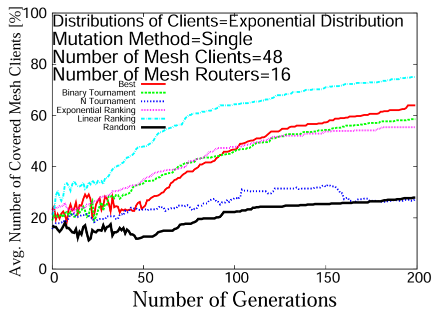


(b) Avg. number of covered mesh clients vs. number of generations

Fig. 6. Results for Exponential distribution and Rectangle Mutate.

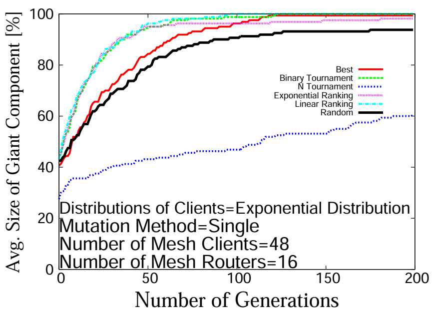


(a) Avg. size of giant component vs. number of generations

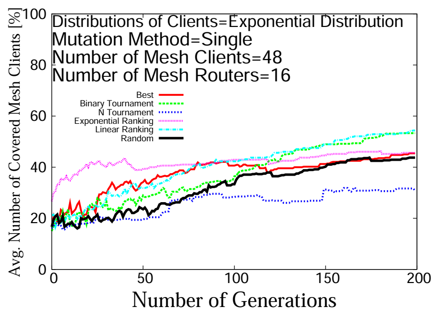


(b) Avg. number of covered mesh clients vs. number of generations

Fig. 7. Results for Exponential distribution and Single Mutate.



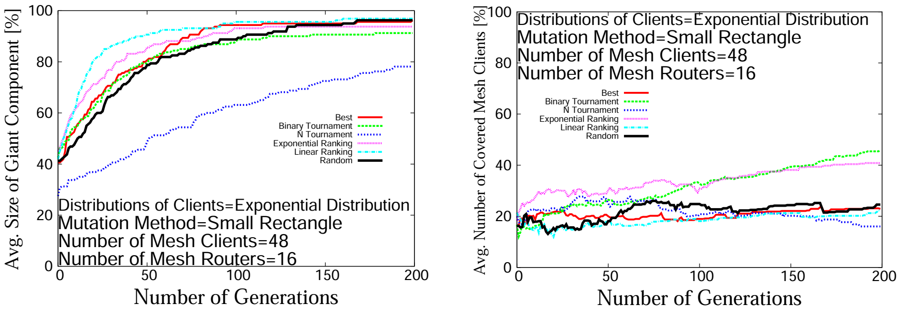
(a) Avg. size of giant component vs. number of generations



(b) Avg. number of covered mesh clients vs. number of generations

Fig. 8. Results for Exponential distribution and Small Mutate.

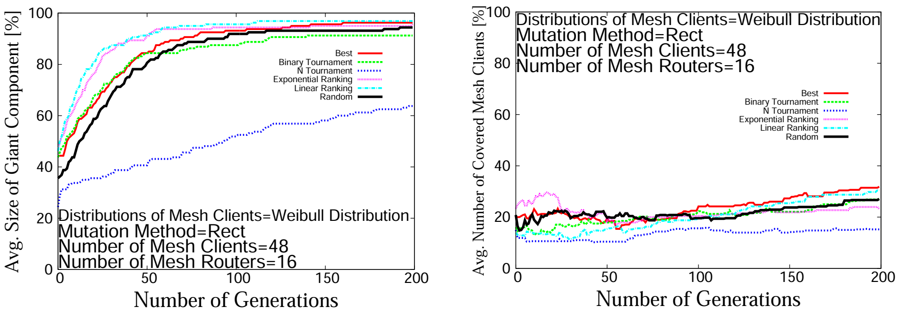
If we compare the simulation result for Rectangle Mutate in Figs. 10 and 7, we can see that for both distribution methods, the performance of the system is not very high and is almost the same except for the N Tournament selection. For Exponential distribution



(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

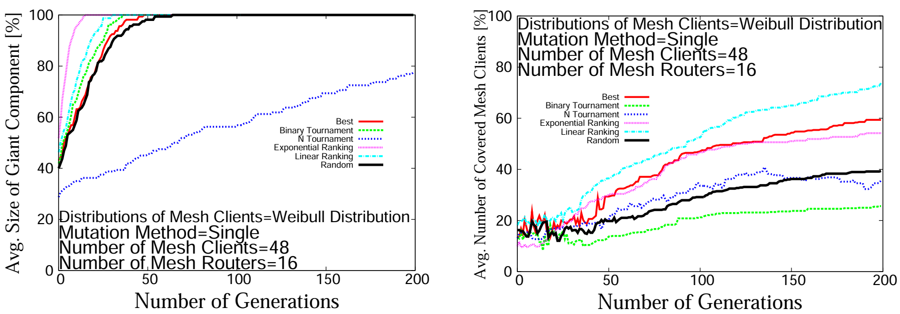
Fig. 9. Results for Exponential distribution and Small Rectangle Mutate.



(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

Fig. 10. Results for Weibull distribution and Rectangle Mutate.

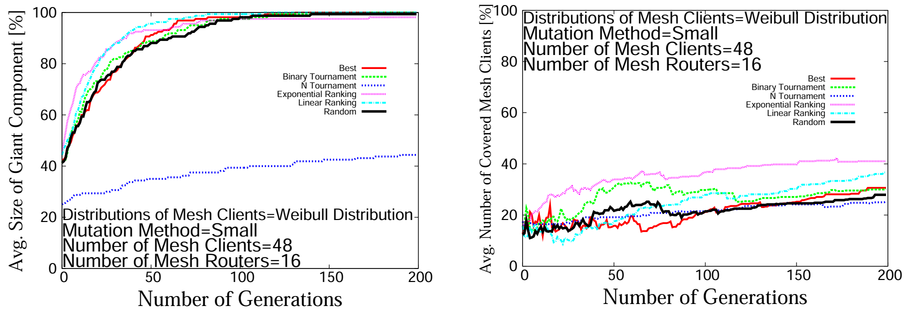


(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

Fig. 11. Results for Weibull distribution and Single Mutate.

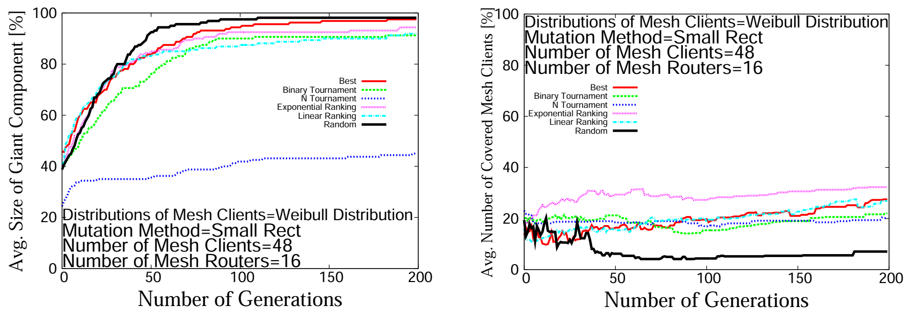
when the N Tournament selection method is used, the size of giant component is less than 60% (only 60% of mesh routers are connected to each other) but this selection offers the better user coverage compared with other selection methods.



(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

Fig. 12. Results for Weibull distribution and Small Mutate.



(a) Avg. size of giant component vs. number of generations

(b) Avg. number of covered mesh clients vs. number of generations

Fig. 13. Results for Weibull distribution and Small Rectangle Mutate.

In the simulation results for Single Mutate, for both distribution methods the best results are achieved for Linear Ranking where more than 75% of mesh clients are covered (see Figs. 4 and 8).

In the simulation results for Small Mutate and Small Rectangle Mutate in Figs. 9, 10, 12 and 13, the performance for Exponential distribution is higher compared with Weibull distribution.

For all distributions, the best results are achieved for single mutation. Among all distributions, WMN-GA system performs better for Normal distribution of mesh clients.

5. Conclusions

In this work, we used GA for optimizing node placement in WMNs. We formulate the optimization problems using bi-objective optimization models. We used our proposed and implemented WMN-GA system to deal with the node placement problem in WMNs.

For evaluation, we took in consideration Normal, Exponential and Weibull Distributions of mesh clients and different selection and mutation methods.

From the simulations we found out the following results.

- For Normal distribution, the avg. size of giant component is maximized for all selection operators except for the N tournament case, and the avg. number of covered mesh clients is higher than in all other scenarios.
- From the simulations we found out that the performance of the system for Exponential distribution is higher compared with Weibull distribution.
- For Exponential distribution, the best results are obtained for Single Mutate and Linear Ranking where all mesh routers are connected to each other and the avg. number of covered mesh clients is 75%.
- For all distributions best results are obtained for Single Mutate and Linear Ranking where all mesh routers are connected to each other and the avg. number of covered mesh clients is 90%.
- N Tournament has a poor performance in almost all scenarios (the avg. size of giant component and the avg. number of covered mesh clients is very small).

In this work, we have considered the bi-objective case. In the future, we plan to extend the model to integrate more objectives resulting in a multi-objective optimization model where different objectives could as well be contradicting ones. We also would like to make extensive simulations to evaluate the performance of WMN-GA system for different scenarios and parameters.

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Sistemos WMN-GA našumo sprendžiant tinklo mazgų lokalizavimo WMN vertinimas esant skirtingam vartotojų pasiskirstymui ir naudojant skirtingus atrankos ir mutacijos operatorius

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Bevieliai junglieji tinklai (angl. Wireless Mesh Networks, WMN) svarbūs dėl mažų plačiajuosčio tinklo tiekimo kaštų. Siekiant gero tinklo junglumo ir padengti daug vartotojų, susiduriama su tinklo mazgų lokalizavimo uždaviniais, kurie gali būti formuluojami kaip optimizavimo uždaviniai. Kai kurie jau suformuluoti tinklo junglumo, vartotojų padengimo ir stabilumo optimizavimo uždaviniai pasitvirtino esą naudingi projektuojant WMN. Šiame straipsnyje formuluojamas dvikriteris optimizavimo uždavinys tinklo maršrutizatorių lokalizacijai, atsižvelgiant į tinklo komponentų skaičių ir vartotojų padengimą. Straipsnyje taikoma tinklo mazgų lokalizavimo sistema WMN-GA, jos našumas vertinamas simuliuojant WMN su skirtingais vartotojų pasiskirstymais ir taikant įvarius algoritmo parametrus.