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Analysis of Mesh Router Placement in Wireless Mesh Networks Using Friedman Test

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***Abstract*—In this paper, we deal with connectivity and coverage problem in Wireless Mesh Networks (WMNs). We used Friedman test to compare Genetic Algorithm (GA) and Tabu Search (TS). We found out that GA and TS have difference in their performance. Then, we used the implemented systems WMN-GA and WMN-TS to evaluate and compare the performance of the system for different distributions of mesh clients in terms of giant component and covered mesh clients. The simulation results shows that for big radius of communication distances WMN-GA performs better than WMN-TS for Uniform, Normal and Weibull distributions of mesh clients. For Exponential distribution WMN-TS performs better than WMN-GA for all radius of communication distances.**

***Keywords*-Wireless Mesh Networks, Friedman test, Genetic Algorithm, Tabu Search Algorithm, Connectivity, Coverage.**

I. Introduction

The wireless networks and devices are becoming increasingly popular and they provide users access to information and communication anytime and anywhere [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. Wireless Mesh Networks (WMNs) [12] are a subclass of wireless networks that are attracting a lot of research attention recently. WMNs are important networking infrastructures. These networks are made up of wireless nodes, organized in a mesh topology, where mesh routers are interconnected by wireless links and provide Internet connectivity to mesh clients.

WMNs distinguish for their low cost nature that makes them attractive for providing wireless Internet connectivity. Moreover, such infrastructure can be used to deploy community networks, metropolitan area networks, municipal and, corporative networks, and to support applications for urban areas, medical, transport and surveillance systems.

The main issue of WMNs is to achieve network connectivity and stability as well as QoS in terms of user coverage [13]. This problem is very closely related to the family of node placement problems in WMNs [14], [15], [16], [17], among them, the mesh router mesh nodes placement. Here, we consider the version of the mesh router nodes placement problem in which we are given a grid area where to deploy a number of mesh router nodes and a number of mesh client nodes of fixed positions (of an arbitrary distribution) in the grid area. The objective is to find a location assignment for the mesh routers to the cells of the grid area that maximizes the network connectivity and client coverage. As node placement problems are known to be computationally hard to solve for most of the formulations [18], [19], [20], Genetic Algorithms (GAs) and local search methods like Tabu Search (TS) have been recently investigated as effective resolution methods. However, GAs require the user to provide values for a number of parameters and a set of genetic operators to achieve the best GA performance for the problem [21], [22], [23], [24], [25], [26], [27].

In this paper, we deal with connectivity and coverage problem of WMNs. First, we used Friedman test to check if we can compare GA and TS. Then, we used the web interface to evaluate and compare the performance of the system for GA and TS for different distributions of mesh clients in terms of giant component and covered mesh clients. The simulation results shows that system performs better for Normal distribution of mesh clients.

The rest of the paper is organized as follows. The mesh router nodes placement problem is defined in Section II. We give a brief introduction of GAs and TS algorithms and Web Interface system in Section III. The simulation results are given in Section IV. In Section V, we give some conclusions and future work.

II. Mesh Router Node Placement Problem

In this problem, we are given a grid area arranged in cells where to distribute a number of mesh router nodes and a number of mesh client nodes of fixed positions (of an arbitrary distribution) in the grid area. The objective is to find a location assignment for the mesh routers to the cells of the grid area that maximizes the network connectivity and client coverage. Network connectivity is measured by the size of the giant component of the resulting WMN graph, while the user coverage is simply the number of mesh client nodes that fall within the radio coverage of at least one mesh router node.

An instance of the problem consists as follows.

- N mesh router nodes, each having its own radio coverage, defining thus a vector of routers.
- An area $W \times H$ where to distribute N mesh routers. Positions of mesh routers are not pre-determined, and are to be computed.
- M client mesh nodes located in arbitrary points of the considered area, defining a matrix of clients.

It should be noted that network connectivity and user coverage are among most important metrics in WMNs and directly affect the network performance. Nonetheless, network connectivity is usually considered as more important than user coverage.

Notice from the above definition that mesh client nodes can be arbitrarily situated in the given area. For evaluation purposes, it is, however, interesting to consider concrete distributions of mesh client nodes such as Uniform, Normal, Exponential and Weibull distributions.

In fact, we can formalize an instance of the problem by constructing an adjacency matrix of the WMN graph, whose nodes are router nodes and client nodes and whose edges are links between nodes in the mesh network. Each mesh node in the graph is a triple $v = < x, y, r >$ 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. It should be noticed here that the deployment grid area is partitioned by cells, representing graph nodes, where we can locate mesh router nodes. We assume that in a cell, both a mesh router node and a mesh client node can be placed.

Optimization setting: For optimization problems having two or more objective functions, two settings are usually considered: the hierarchical and simultaneous optimization. In the former, the objectives are classified (sorted) according to their priority. Thus, for the bi-objective case, one of the objectives, say f_1, is considered as a primary objective and the other, say f_2, as secondary one. The meaning is that we first try to optimize f_1, and then when no further improvements are possible, we try to optimize f_2 without worsening the best value of f_2. In the case of WMNs, the hierarchical approach is used due achieving network connectivity is considered more important than user coverage. It should be noted that due to this optimization priority, some client nodes may not be covered due the user coverage is less optimized. For example, in Fig. 1, we can see that all mesh router nodes are connected, establishing a mesh network; however, a few clients remain disconnected from the network.

III. Optimization Resolution Methods and Web Interface

Purely random placements would produce poor performance due to far from optimal router placement as a result. Therefore, using more efficient methods is crucial for node placement nodes in WMNs. Due to computational intractability of the problem, exact methods can only solve to optimality small size instances, and therefore heuristic and meta-heuristic approaches are the de facto approach to solve the problem for practical purposes.

A. Population-based Methods: Genetic Algorithms

GAs have shown their usefulness for the resolution of many computationally hard combinatorial optimization problems. They are, of course, a strong candidate for efficiently solving mesh router nodes placement problem in WMNs. For the purpose of 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; t = 0.
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 indi-
    viduals 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;
```

As can be seen from the template, several parameters intervene in the GAs: population size, intermediate population size, number of evolution steps, crossover probability, mutation probability and parameters for replacement strategies. On the other hand, there are the (families of) genetic operators: crossover operators, mutation operators, selection operators and replacement operators. As there are

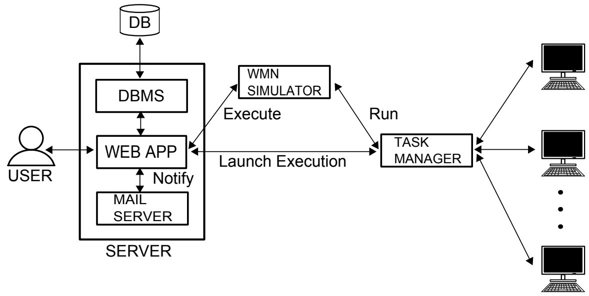


Figure 1. System based on Web Interface

potentially large range values for parameters and different versions of operators, their tuning becomes crucial to the GA's performance.

B. Local Search Method: Tabu Search Algorithm

Tabu Search (TS) method was introduced by Glover [28] as a high-level algorithm that uses other specific heuristics to guide the search; the objective is to perform an intelligent exploration of the search space that would eventually allow to avoid getting trapped into local optima. The objective is thus to remedy one of the main issues of local search methods, namely the useless search in neighborhood of local optima without further improvements due to re-visiting solutions or paths of solutions already explored. This is achieved by giving the tabu status to solutions visited in the recent search. TS is also designed to be a flexible method, so that the tabu status of solutions can be waived, in case they have been prohibited for a long while or if they satisfy some aspiration criteria. The classification of some solutions as tabu is achieved through the intelligent use of adaptive memory, which is allowed to evolve and eventually change the status of tabu solutions. The main features of the TS method are that of adaptive memory and responsive exploration. Again, the adaptive memory is the basis to guide the search in taking intelligent decisions. This gives the TS method advantages with regard to other memoryless methods, being these local search methods (Hill Climbing, Simulated Annealing, etc.) or population based methods (Genetic Algorithms, Memetic Algorithms, etc.). On the other hand, the responsive exploration enables the method to select some solutions which though not so good at the current search iteration might at long run lead to promising areas of good solutions in the search space (see Algorithm 2).

C. Web Interface

The Web application [29] follows a standard Client-Server architecture and is implemented using LAMP (Linux + Apache + MySQL + PHP) technology (see Fig. 1). Remote users (clients) submit their requests by completing first the parameter setting. The parameter values to be provided by the user are classified into three groups, as follows.

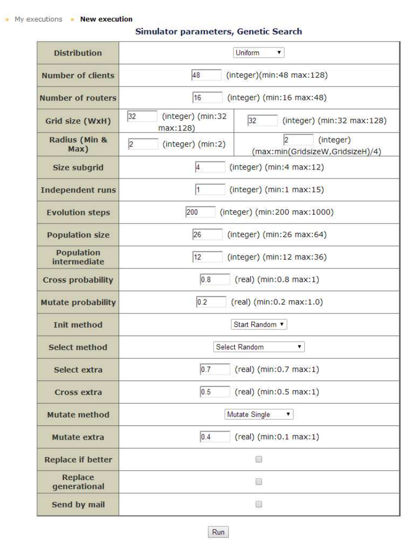
- Parameters related to the problem instance: These include parameter values that determine a problem instance to be solved and consist of number of router nodes, number of mesh client nodes, client mesh distribution, radio coverage interval and size of the deployment area.
- Parameters of the resolution method: Each method has its own parameters. In Fig. 2 is shown the the GUI of Web Interface for the parameter setting of Genetic Algorithm and Tabu Search.
- Execution parameters: These parameters are used for stopping condition of the resolution methods and include number of iterations and number of independent runs. The former is provided as a total number of iterations and depending on the method is also divided per phase (e.g., number of iterations in a exploration). The later is used to run the same configuration for the same problem instance and parameter configuration a certain number of times.

Algorithm 2 Tabu Search Algorithm

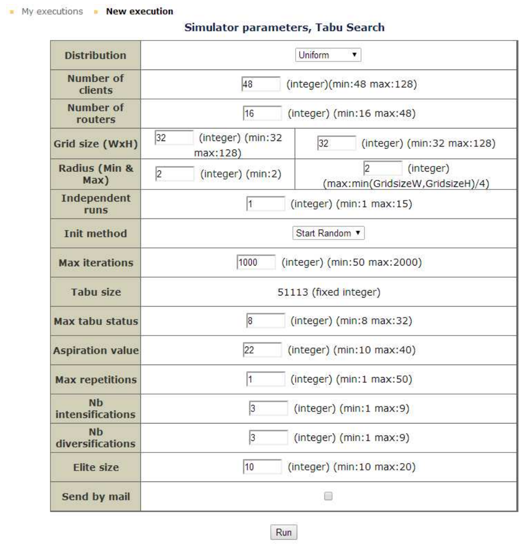
begin
Compute an initial solution s;
let $\hat{s} \leftarrow s$;
Reset the tabu and aspiration conditions;
while not termination-condition **do**
  Generate a subset $N^*(s) \subseteq N(s)$ of solutions such that:
  (none of the tabu conditions is violated) or (the aspiration criteria hold)
  Choose the best $s' \in N^*(s)$ with respect to the cost function;
  $\hat{s} \leftarrow s'$;
  if improvement(s' , $\hat{s}$) **then**
    $\hat{s} \leftarrow s'$;
  end if
  Update the recency and frequency;
  if (intensification condition) **then**
    Perform intensification procedure;
  end if
  if (diversification condition) **then**
    Perform diversification procedures;
  end if
end while
return $\hat{s}$;
end

IV. Simulation Results

The Friedman test [30] is a nonparametric statistical test of multiple group measures. It can be used to approve the null hypothesis that the multiple group measures have the same variance to a certain required level of significance. On the other hand, failing to approve the null hypothesis shows that they have different variance values. We analyze the difference in performance between GA and TS using Friedman test in MATLAB. We considered as null hypothesis H_0 that there is not difference in the performance between GA and TS. And as alternative hypothesis we considered H_1 that there is difference in the performance of GA and TS. As value of the hypothesis testing we took



(a) GA



(b) TS

Figure 2. GUI of Web Interface

Table I
INPUT PARAMETERS OF WMN-TS.

Parameters	Values
Number of clients	48
Number of routers	16
Grid width	32 [units]
Grid height	32 [units]
Communication Distance (min:max)	2×2:n×n (n=2, 4, 6, 8) [units]
Independent runs	10
Initial Router Placement Method	HotSpot
Max Iterations	2000
Max Tabu Status	9
Aspiration Value	15
Max Repetitions	15
Number of Intensifications	4
Number of Diversifications	4
Elite Size	10
Distribution of Clients	N, U, E, W

Table II
INPUT PARAMETERS OF WMN-GA.

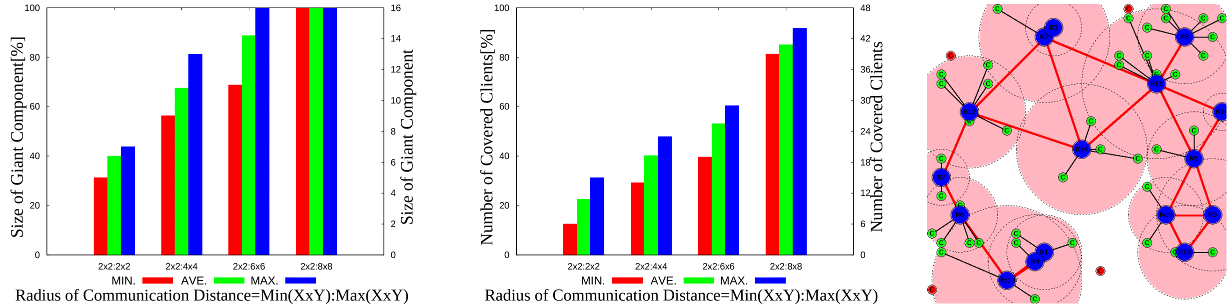
Parameters	Values
Number of clients	48
Number of routers	16
Grid width	32 [units]
Grid height	32 [units]
Communication Distance (min:max)	2×2:n×n (n=2, 4, 6, 8) [units]
Independent runs	10
Initial Router Placement Method	HotSpot
Number of Generations	200
Population size	32
Selection Method	Linear Ranking
Crossover rate	80 %
Mutate Method	Single
Mutate rate	20 %
Distribution of Clients	N, U, E, W

the maximum value of number of covered mesh clients and size of giant component. The significance level in this testing hypothesis is $\alpha = 0.05$. We reject H_0 for $p < \alpha$ (p-value is the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true). Further, since there is a correspondence between GA and TS, we used Friedman test. The results of Friedman test show that p-value for the giant component is 0.0027 and H_0 is rejected because $p < 0.05$. In this case we adopted H_1. For covered mesh clients p-value was 0.6171, and we adopt H_0 since $p > 0.05$. But, since our study is a bi-objective optimization we used both giant component and covered mesh clients parameters.

In this work, we took in consideration different radius of communication distances and evaluate the performance of WMN-GA and WMN-TS for Uniform (U), Normal (N), Exponential (E) and Weibull (W) distributions. The number of mesh routers for all scenarios is considered 16 and the number of mesh clients 48. The input parameters for WMN-TS are shown in Table I and for WMN-GA are shown in Table II.

In Fig. 3 and Fig. 4 are shown simulation results for Uniform distribution using WMN-GA and WMN-TS, respectively. We used bar graph representation that shows the minimum, average and maximum value. During our analysis we considered only the maximum value. If we compare the results of size of giant component vs. radius of communication distance in Fig. 3(a) and Fig. 4(a), we can notice that for radius of communication distance less than 2×2:4×4 WMN-TS performs better. For number of covered mesh clients GA performs better for radius of communication distance 2×2:8×8. From the visualization of nodes after the placement for 2×2:8×8, the area covered by mesh routers is bigger when WMN-GA is used.

In Fig. 5 and Fig. 6 are shown simulation results for Normal distribution using WMN-GA and WMN-TS, respectively. For distance 2×2:8×8 the size of giant component and number of covered mesh clients (see Fig. 5(a) and Fig. 5(b)) are maximized and WMN-GA have the best performance. In case of Normal distribution mesh clients are concentrated at the grid center. The WMN-GA places the mesh routers in the grid center, but in case of WMN-TS mesh routers are spread on the grid area (see Fig. 5(c)

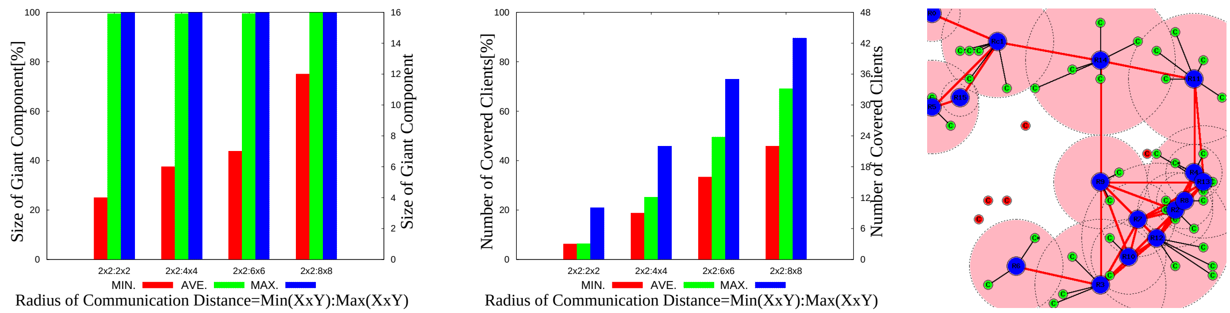


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 3. Simulation results of WMN-GA for uniform distribution.

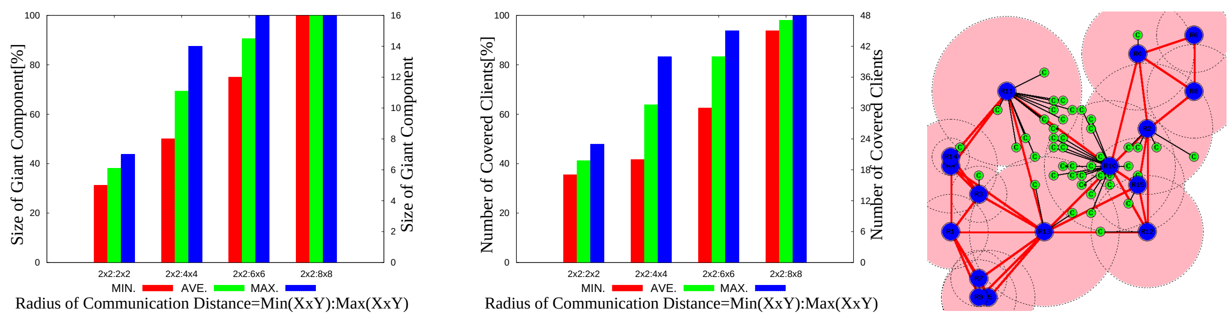


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 4. Simulation results of the WMN-TS for uniform distribution.

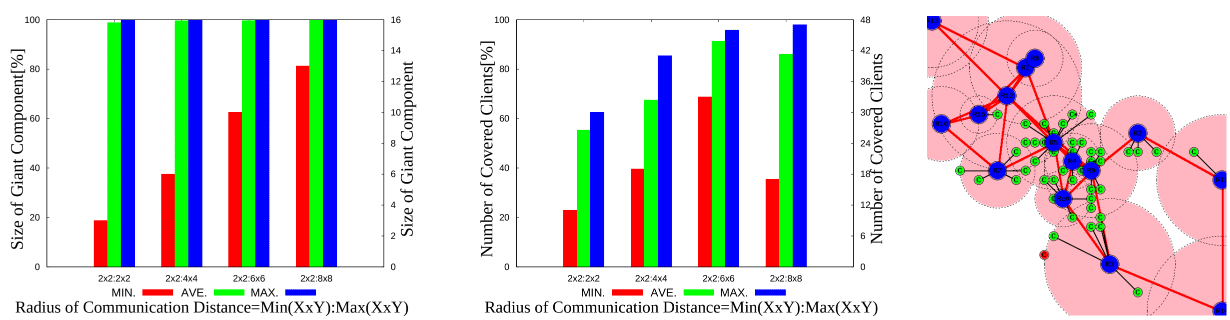


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 5. Simulation results of WMN-GA for normal distribution.

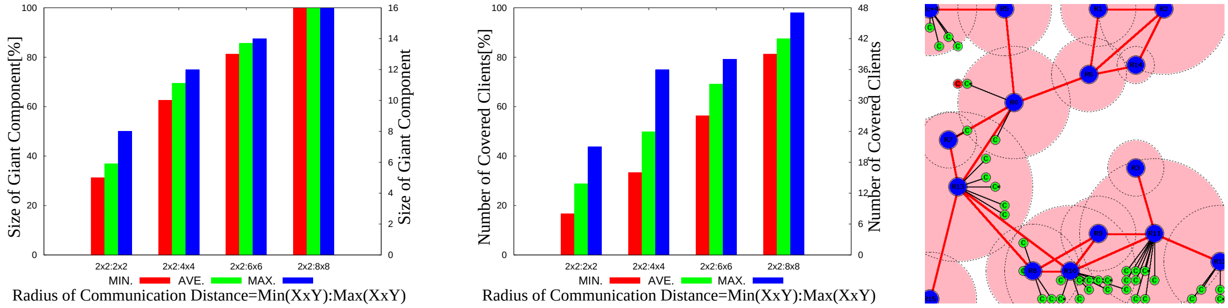


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 6. Simulation results of the WMN-TS for normal distribution.

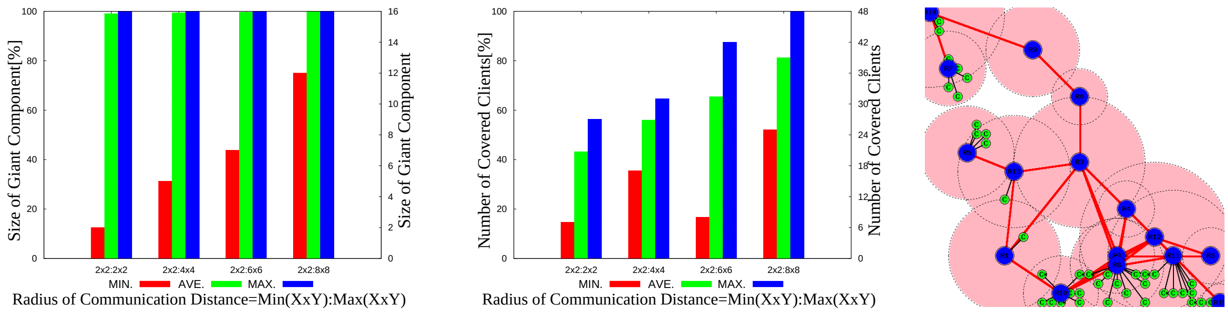


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 7. Simulation results of WMN-GA for exponential distribution.

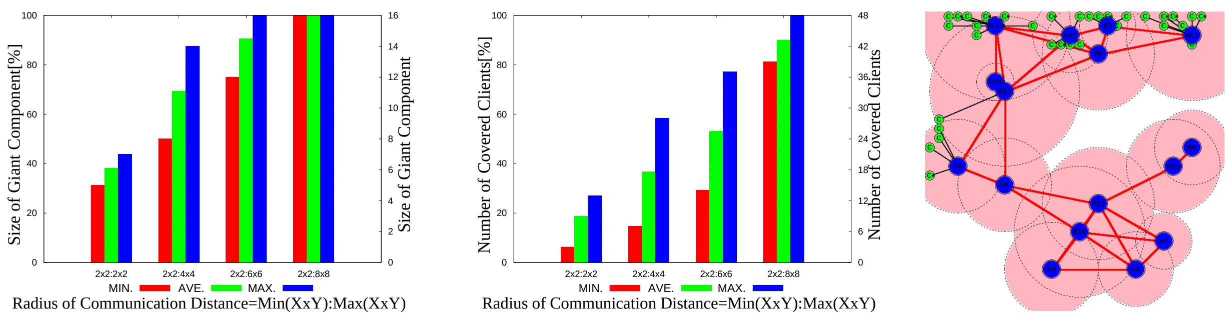


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 8. Simulation results of WMN-TS for exponential distribution.

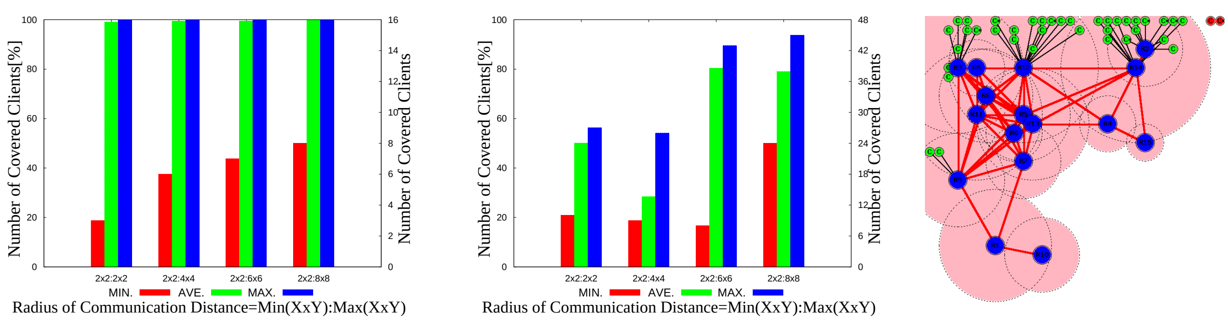


(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 9. Simulation results of WMN-GA for Weibull distribution.



(a) Size of Giant Component vs. Radius of Communication Distance.

(b) No. of Covered Mesh Clients vs. Radius of Communication Distance.

(c) Visualization of nodes after placement for 2×2:8×8

Figure 10. Simulation results of WMN-TS for Weibull distribution.

and Fig. 6(c)).

In Fig. 7 and Fig. 8 are shown simulation results for Exponential distribution using WMN-GA and WMN-TS, respectively. If we compare the results of size of giant component vs. radius of communication distance in Fig. 7(a) and Fig. 8(a), we can notice that WMN-TS performs better than WMN-GA for all radius of communication distance.

In Fig. 9 and Fig. 10 are shown simulation results for Exponential distribution using WMN-GA and WMN-TS, respectively. If we compare the results of size of giant component vs. radius of communication distance in Fig. 9(a) and Fig. 10(a), we can notice that WMN-TS have a good performance for radius of communication distance less than 2×2:6×6, but for 2×2:8×8 WMN-GA performs better.

For all distribution of mesh clients, in case of WMN-TS mesh routers are positioned near mesh clients, but for WMN-GA many mesh routers are located far for mesh clients and there are cases where they do not cover any mesh client (see Fig. 7(c) and Fig. 8(c).

V. Conclusions

In this paper, we deal with connectivity and coverage problem in WMNs. We used Friedman test to compare GA and TS. Then, we used the web interface to evaluate and compare the performance of the system for GA and TS for different distributions of mesh clients in terms of giant component and covered mesh clients. The simulation results shows the following.

- Using Friedman test we found out that GA and TS have difference in their performance.
- For big radius of communication distances WMN-GA performs better than WMN-TS for Uniform, Normal and Weibull distributions of mesh clients.
- For Exponential distribution WMN-TS performs better than WMN-GA for all radius of communication distances.

In the future work, we would like to make extensive simulations to evaluate the performance of WMN-GA and WMN-TS systems for different scenarios and parameters.

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