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A COMPARISON STUDY OF SIMULATED ANNEALING AND GENETIC ALGORITHM FOR NODE PLACEMENT PROBLEM IN WIRELESS MESH NETWORKS

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One of the key advantages of Wireless Mesh Networks (WMNs) is their importance for providing cost-efficient broadband connectivity. There are issues for achieving the network connectivity and user coverage, which are related with the node placement problem. In this work, we compare Simulated Annealing (SA) and Genetic Algorithm (GA) by simulations for node placement problem. We want to find the optimal distribution of router nodes in order to provide the best network connectivity and user coverage in a set of randomly distributed clients. From the simulation results, both algorithms converge to the maximum size of GC. However, according to the number of covered mesh clients SA converges faster.

Keywords: Simulated Annealing, Genetic Algorithm, WMN, Node Placement Problem

1 Introduction

With the emerging of several new networking paradigms, optimization, modeling and resolution turn out to be crucial to achieve optimized performance networks. One such networking paradigm that is requiring the resolution of optimization problems is that of Wireless Mesh Networks (WMNs).

WMNs [1–3] are an important network infrastructure for providing cost-efficient broadband wireless connectivity. They are showing their applicability in deployment of medical, transport and surveillance applications in urban areas, metropolitan, neighboring communities and municipal area networks. The main issues of WMNs consist 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.

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).

Facility location problems are thus showing their usefulness to communication networks, and more especially from WMNs field. WMNs are currently attracting a lot of attention from wireless research and technology community for providing cost-efficient broadband wireless connectivity.

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 does not need 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 [4–7], 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 [8–12].

In this work, we use our proposed and implemented WMN simulation systems, which are based on Simulated Annealing (SA) and Genetic Algorithm (GA) to deal with the node placement problem in WMNs. For simulations, we consider different number of mesh routers and mesh clients in different grid sizes. We apply two algorithms, respectively, initially to maximize the size of Giant Component (GC). Finally, we maximize the number of covered mesh clients, and compare the performances for both approaches.

The rest of the paper is organized as follows. The definition of node placement problem is presented in Section 2. The proposed and implemented simulation systems are presented in Section 3. The simulation results and comparison are discussed in Section 4. Finally, conclusions and future work are given in Section 5.

2 Node Placement Problem in WMNs

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 GC 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.

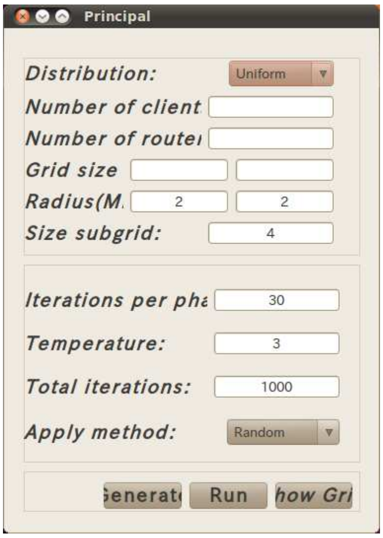


Fig. 1. GUI tool for WMN-SA system.

- 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.

In this work, we have considered a bi-objective optimization in which we maximize the network connectivity of the WMN (through the maximization of the size of the GC) and then maximize the number of covered mesh clients.

3 Implemented Simulation Systems

We have implemented SA and GA algorithms in the simulation system to create WMN-SA and WMN-GA simulation systems, respectively. Our systems can generate instances of the problem using different distributions of client. We set the network configuration parameters as distribution, number of clients, number of mesh routers, grid size, radius of transmission distance and the size of subgrid through a Graphical User Interface (GUI). For WMN-SA, we set SA parameters as number of iterations per phase, total number of iterations. Also for WMN-GA, we set initial population size, crossover and mutation probability and so on. The GUIs for WMN-SA and WMN-GA systems are shown in Fig. 1 and Fig. 2, respectively.

3.1 Simulated Annealing

SA algorithm [13] is inspired by the cooling process of metals by which a material is heated and then cooled in a controlled way to increase the size of its crystals and reduce their defects. The heat causes the atoms to leave their initial positions (a local minimum of energy) and move randomly; the slow cooling gives them more likelihood to find configurations with lower

Algorithm 1 : Pseudo-code of SA.

```
t := 0
Initialize T
s0 := Initial_Solution()
v0 := Evaluate(s0)
while (stopping condition not met) do
  while t mod MarkovChainLen = 0 do
    t := t+1
    s1 := Generate(s0,T)    //Move
    v1 := Evaluate(s1)
    if Accept(v0,v1,T) then
      s0 := s1
      v0 := v1
    end if
  end while
  T := Update(T)
end while
return s0
```

energy than the previous one. In each iteration, it considers some neighbors of the current state s, and probabilistically decides.

SA algorithm [13] is a generalization of the metropolis heuristic. Indeed, SA consists of a sequence of executions of metropolis with a progressive decrement of the temperature starting from a rather high temperature, where almost any move is accepted, to a low temperature, where the search resembles HC. In fact, it can be seen as a hill climber with an internal mechanism to escape local optima (see pseudo-code in Algorithm 1). In SA, the solution s' is accepted as the new current solution if $\delta \leq 0$ holds, where $\delta = f(s') - f(s)$. To allow escaping from a local optimum, the movements that increase the energy function are accepted with a decreasing probability $\exp(-\delta/T)$ if $\delta > 0$, where T is a parameter called the "temperature". The decreasing values of T are controlled by a *cooling schedule*, which specifies the temperature values at each stage of the algorithm. This represents an important decision for its application (a typical option is to use a proportional method, like $T_k = \alpha \cdot T_{k-1}$). SA usually gives better results in practice, but uses is very slow. The most striking difficulty in applying SA is to choose and tune its parameters such as initial and final temperature, decrement of the temperature (cooling schedule), equilibrium detection, etc.

3.2 Genetic Algorithm

GA has shown their usefulness for the resolution of many computationally hard combinatorial optimization problems. Their main features are briefly described next (see Algorithm 2 for a template).

Population of individuals: Unlike local search techniques that construct a path in the solution space jumping from one solution to another one through local perturbations, GA use a population of individuals giving thus the search a larger scope and chances to find better solutions. This feature is also known as "exploration" process in difference to "exploitation" process of local search methods.

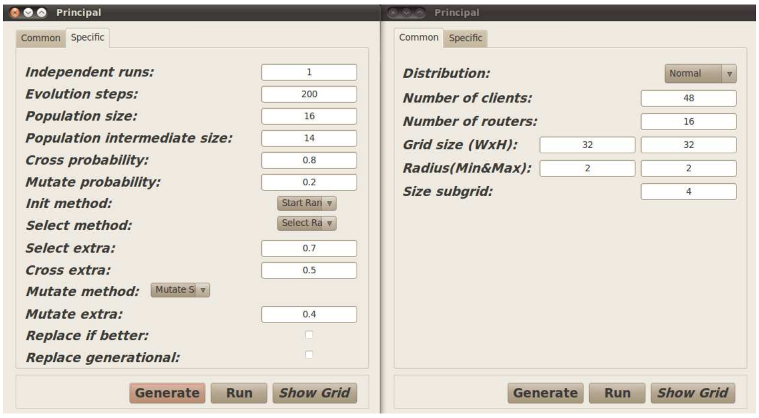


Fig. 2. GUI tool for WMN-GA system.

Algorithm 2 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; $P^t_c := Cross(T^t)$;
  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;

Fitness: The determination of an appropriate fitness function, together with the chromosome encoding are crucial to the performance of GA. Ideally we would construct objective functions with "certain regularities", i.e. objective functions that verify that for any two individuals which are close in the search space, their respective values in the objective functions are similar.

Selection: The selection of individuals to be crossed is another important aspect in GA as it impacts on the convergence of the algorithm. Several selection schemes have been proposed in the literature for selection operators trying to cope with premature convergence of GA.

Crossover operators: Use of crossover operators is one of the most important characteristics. Crossover operator is the means of GA to transmit best genetic features of parents to offsprings during generations of the evolution process.

Mutation operators: These operators intend to improve the individuals of a population by small local perturbations. They aim to provide a component of randomness in the neighborhood of the individuals of the population.

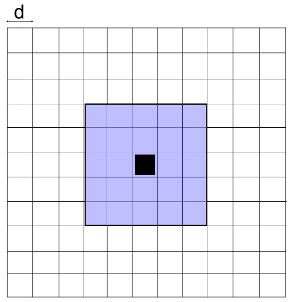


Fig. 3. Mesh router coverage distance.

Table 1. Common parameters of Simularions.

Parameters	Values
Client distribution	Weibull
Area size	320[m] × 320[m]
	640[m] × 640[m]
	1280[m] × 1280[m]
Number of mesh router nodes	4, 16, 64
Number of mesh client nodes	12, 48, 192
Coverage of mesh router nodes	50[m]
Size of GC priority	0.7
Covered mesh clients priority	0.3

Escaping from local optima: GA has the ability to avoid falling prematurely into local optima and can eventually escape from them during the search process.

Convergence: The convergence of the algorithm is the mechanism of GA to reach to good solutions. A premature convergence of the algorithm would cause that all individuals of the population be similar in their genetic features and thus the search would result ineffective and the algorithm getting stuck into local optima. Maintaining the diversity of the population is therefore very important to this family of evolutionary algorithms.

4 Simulation Results

4.1 Simulation Settings

We carried out many simulations to evaluate the performance of WMNs using WMN-SA and WMN-GA simulation systems. In these simulation scenarios, we consider grids with 16×16, 32×32, 64×64 size. One grid unit is 20m × 20m (d=20m). In Fig. 3, we show the coverage area of a mesh router, which has a radius of 50m. We consider the router to be positioned in the middle of a grid unit. In Tables 1 to 3, we show the simulation parameters. The

Table 2. Simulation Settings for WMN-SA.

Parameters	Values
SA temperature	1
Iteration per phase	64
Applied method	Combination

Table 3. Simulation Settings for WMN-GA.

Parameters	Values
Selection method	Linear ranking
Mutation method	Single mutation
Crossover rate	0.8
Mutation rate	0.2

number of mesh routers are 4, 16, 64 and the number of mesh clients are 12, 48, 192, which are positioned in the simulation area by Weibull distribution. For each phase of calculations, SA runs a number of 64 iterations. In GA, we consider the population size to be 64.

4.2 Results Discussion

In Figs. 4 to 6 are shown the results for the size of GC for different area sizes and both algorithms. As the size of the area increases, the performance for each case decreases. For the area size 64×64, there are more routers than in previous cases and it takes more calculation phases to reach the maximum size of GC. SA shows more oscillations than GA, when the area size increases. However GA is slower when converging to the maximum size of GC.

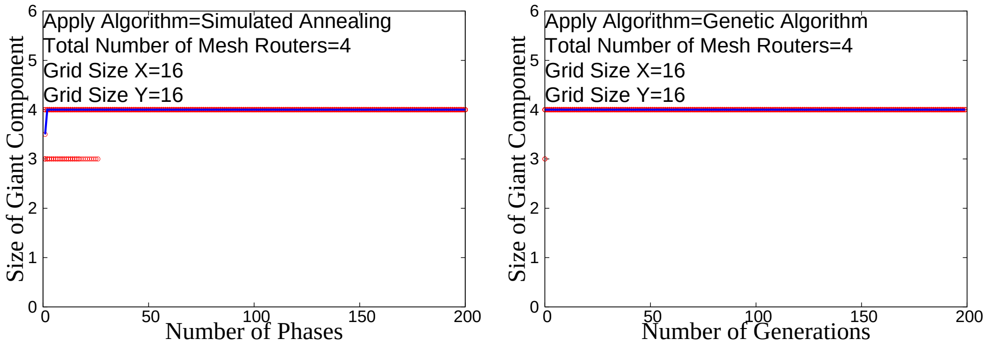
We show the results for the number of covered mesh clients, in Figs. 7 to 9. We notice also here that, the best performance is for the smallest area size (Fig. 7), where the number of mesh clients is also smaller. It is easier to cover 12 mesh clients, and both algorithms have a good performance, converging in less than 20 calculation phases. When the area size increases, SA and GA need more calculations phases to reach 47 and 28, respectively. On the other hand, using GA, the number of covered mesh clients is lower and it does not cover all clients.

5 Conclusions

In this paper, we compared the performances of SA and GA for node placement problem in WMNs. We conducted simulations for 3 cases when grid size is 16×16, 32×32 and 64×64, when we deployed 12, 48 and 192 mesh clients and 4, 16 and 64 mesh routers. From the simulation results we conclude that:

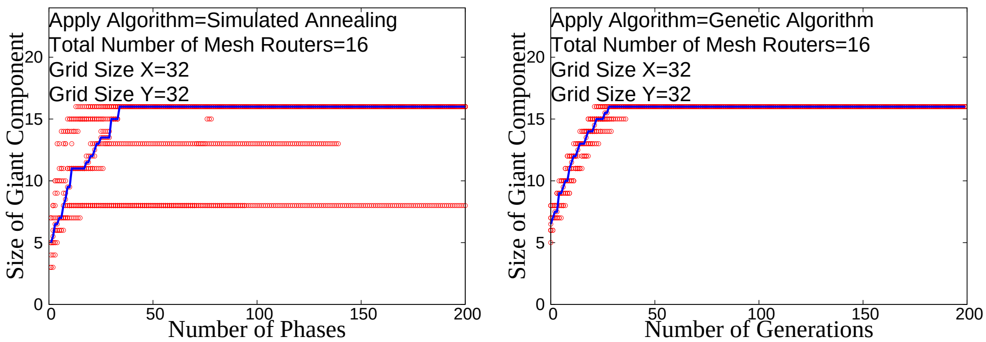
- The size of GC, in most cases, is about 100%.
- For covered mesh clients, SA has a better performance than GA.

In our future work, we would like to evaluate the performance of both algorithms for different cases and patterns. Also, we would like to implement other search optimization algorithms in our simulation system.



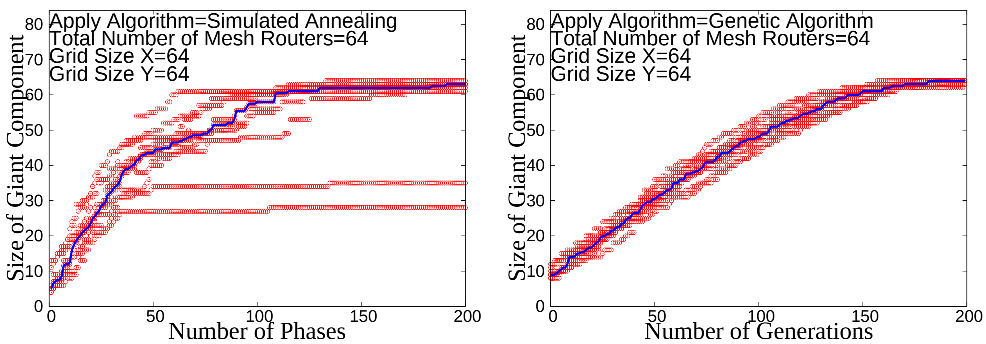
(a) Simulated Annealing (b) Genetic Algorithm

Fig. 4. Size of GC for area size = 16 × 16.



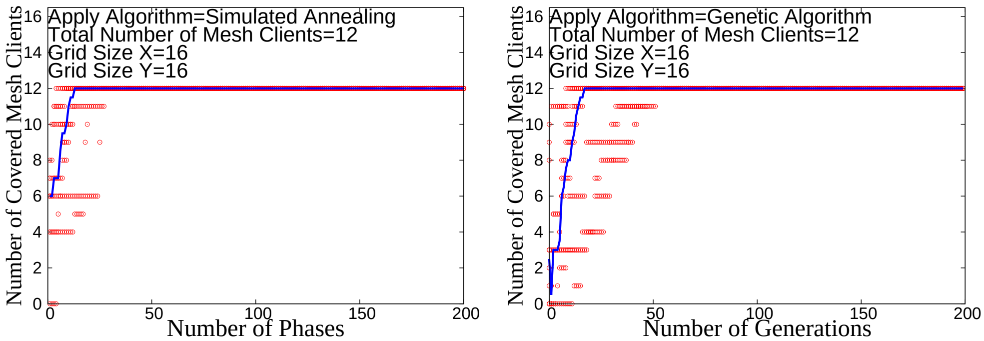
(a) Simulated Annealing (b) Genetic Algorithm

Fig. 5. Size of GC for area size = 32 × 32.



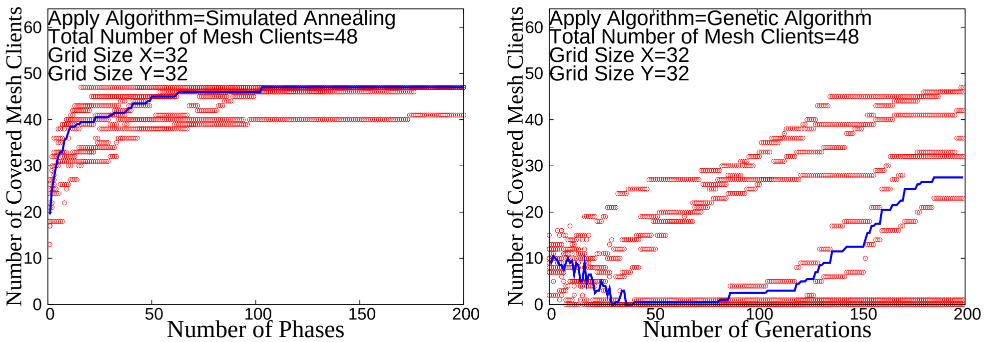
(a) Simulated Annealing (b) Genetic Algorithm

Fig. 6. Size of GC for area size = 64 × 64.



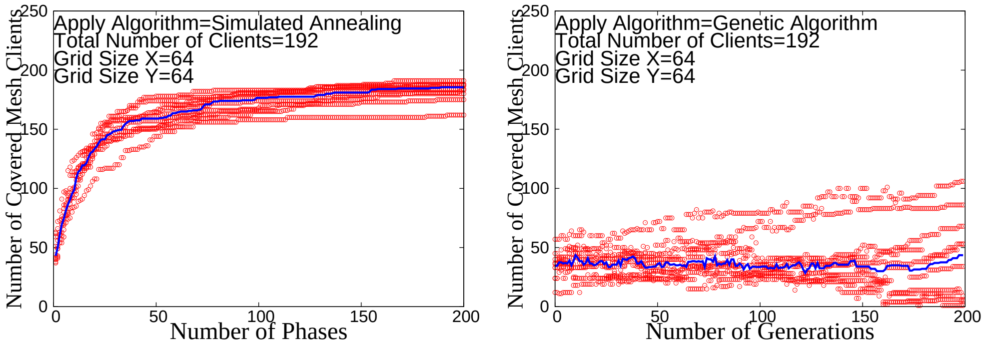
(a) Simulated Annealing (b) Genetic Algorithm

Fig. 7. Number of covered mesh clients for area size = 16 × 16.



(a) Simulated Annealing (b) Genetic Algorithm

Fig. 8. Number of covered mesh clients for area size = 32 × 32.



(a) Simulated Annealing (b) Genetic Algorithm

Fig. 9. Number of covered mesh clients for area size = 64 × 64.

References

1. I. F. Akyildiz, X. Wang, and W. Wang, "Wireless Mesh Networks: A Survey", Computer Networks, Vol. 47, No. 4, pp. 445-487, 2005.
2. N. Nandiraju, D. Nandiraju, L. Santhanama, B. He, J. Wang, and D. Agrawal, " Wireless Mesh Networks: Current Challenges and Future Direction of Web-in-the-Sky", IEEE Wireless Communications, pp. 79-89, 2007.
3. Ch. Chen and Ch. Chekuri. "Urban Wireless Mesh Network Planning: The Case of Directional Antennas", Tech Report No. UIUCDCS-R-2007-2874, Department of Computer Science, University of Illinois at Urbana-Champaign, 2007.
4. M.R. Garey and D.S. Johnson, "Computers and Intractability -A Guide to the Theory of NP-Completeness", Freeman, San Francisco, 1979.
5. A. Lim, B. Rodrigues, F. Wang and Zh. Xua, "$k-$Center Problems with Minimum Coverage", Theoretical Computer Science, Vol. 332, No. 1-3, pp. 1-17, 2005.
6. E. Amaldi, A. Capone, M. Cesana, I. Filippini, F. Malucelli. "Optimization Models and Methods for Planning Wireless Mesh Networks", Computer Networks, Vol. 52, pp. 2159-2171, 2008.
7. J. Wang, B. Xie, K. Cai and D.P. Agrawal, "Efficient Mesh Router Placement in Wireless Mesh Networks", MASS-2007, Pisa, Italy, pp. 9-11, 2007.
8. S. N. Muthaiah and C. Rosenberg, "Single Gateway Placement in Wireless Mesh Networks", In Proc. of 8th International IEEE Symposium on Computer Networks, Turkey, pp. 4754-4759, 2008.
9. P. Zhou, B.S. Manoj and R. Rao, "A Gateway Placement Algorithm in Wireless Mesh Networks", Proc. of the Third Annual International Wireless Internet Conference (WICON-2007), pp. 1-9, October 2007.
10. M. Tang, "Gateways Placement in Backbone Wireless Mesh Networks", International Journal of Communications, Network and System Sciences, Vol. 2, No.1, pp. 45-50, 2009.
11. A. Antony Franklin and C. Siva Ram Murthy, "Node Placement Algorithm for Deployment of Two-Tier Wireless Mesh Networks", In Proc. of IEEE GLOBECOM-2007, Washington, USA, pp. 4823-4827, 2007.
12. T. Vanhatupa, M. Hännikäinen and T.D. Hämäläinen, "Genetic Algorithm to Optimize Node Placement and Configuration for WLAN Planning", In Proc. of 4th International Symposium on Wireless Communication Systems, pp. 612-616, 2007.
13. S. Kirkpatrick, C. D. Gelatt and M. P. Vecchi, "Optimization by Simulated Annealing", Journal of Science, Vol. 220, pp. 671-680, 1983.
14. F. Xhafa, C. Sanchez, L. Barolli, R. Miho, "An Annealing Approach to Router Nodes Placement Problem in Wireless Mesh Networks", In Proc. of CISIS-2010, pp. 245-252, 2010.
15. J. Holland, "Adaptation in Natural and Artificial Systems", University of Michigan Press, Ann Arbor, 1975.
16. F. Xhafa, C. Sanchez, L. Barolli, "Genetic Algorithms for Efficient Placement of Router Nodes in Wireless Mesh Networks", Proc. of AINA-2010, pp. 465-472, 2010.