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Sakamoto, S. [et al.] (2016) Investigation of fitness function weight-coefficients for optimization in WMN-PSO simulation system. *2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems, CISIS 2016, Fukuoka Institute of Technology (FIT), Fukuoka, Japan 6-8 July 2016: proceedings*. IEEE. Pp. 224-229. Doi: <http://dx.doi.org/10.1109/CISIS.2016.55>.

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Investigation of Fitness Function Weight-Coefficients for Optimization in WMN-PSO Simulation System

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Abstract—With the fast development of wireless technologies, Wireless Mesh Networks (WMNs) are becoming an important networking infrastructure due to their low cost and increased high speed wireless Internet connectivity. In our previous work, we implemented a simulation system based on Particle Swarm Optimization for solving node placement problem in wireless mesh networks, called WMN-PSO. In this paper, we use Size of Giant Component (SGC) and Number of Covered Mesh Clients (NCMC) as metrics for optimization. Then, we analyze effects of weight-coefficients for SGC and NCMC. From the simulation results, we found that the best values of the weight-coefficients for SGC and NCMC are 0.7 and 0.3, respectively.

Keywords-Wireless Mesh Networks, Particle Swarm Optimization, Node Placement, SGC, NCMC, Replacement Method.

I. INTRODUCTION

The wireless networks and devices are becoming increasingly popular and they provide users access to information and communication anytime and anywhere [1]–[11]. Wireless Mesh Networks (WMNs) are gaining a lot of attention because of their low cost nature that makes them attractive for providing wireless Internet connectivity. A WMN is dynamically self-organized and self-configured, with the nodes in the network automatically establishing and maintaining mesh connectivity among them-selves (creating,

in effect, an ad hoc network). This feature brings many advantages to WMNs such as low up-front cost, easy network maintenance, robustness and reliable service coverage [12]. 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.

Mesh node placement in WMN can be seen as a family of problems, which are shown (through graph theoretic approaches or placement problems, e.g. [13], [14]) to be computationally hard to solve for most of the formulations [15]. In fact, the node placement problem considered here is even more challenging due to two additional characteristics: (a) locations of mesh router nodes are not pre-determined (any available position in the considered area can be used for deploying the mesh routers) and (b) routers are assumed to have their own radio coverage area. 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.

Node placement problems are known to be computationally hard to solve [16]–[18]. In some previous works,

intelligent algorithms have been recently investigated [19]–[27].

In this work, we present our simulation system based on Particle Swarm Optimization (PSO) to solve the problem of mesh router placement problem in WMNs, called WMN-PSO. The metrics used for optimization are the Size of Giant Component (SGC) and the Number of Covered Mesh Clients (NCMC). In this paper, we analyze the effect of fitness function weight-coefficients for SGC and NCMC.

The rest of the paper is organized as follows. The mesh router nodes placement problem is defined in Section II. We present our proposed and implemented WMN-PSO simulation system in Section III. The simulation results are given in Section IV. Finally, we give conclusions and future work in Section V.

II. NODE PLACEMENT PROBLEM IN WMNS

For this problem, we have a grid area arranged in cells we want to find 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 area that maximizes the network connectivity and client coverage. Network connectivity is measured by SGC 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 and is measured by NCMC.

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.

In this work, we have considered a bi-objective optimization in which we first maximize the network connectivity of the WMN (through the maximization of the SGC) and then, the maximization of the NCMC.

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 $\mathbf{v} = \langle x, y, r \rangle$ representing the 2D location point and r is the radius of the transmission range. There is an arc between two nodes \mathbf{u} and \mathbf{v} , if \mathbf{v} is within the transmission circular area of \mathbf{u} .

III. PROPOSED WMN-PSO SYSTEM

A. PSO

In PSO a number of simple entities (the particles) are placed in the search space of some problem or function and each evaluates the objective function at its current location. The objective function is often minimized and the exploration of the search space is not through evolution [28]. However, following a widespread practice of borrowing from the evolutionary computation field, in this work, we consider the bi-objective function and fitness function interchangeably. Each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function.

Each individual in the particle swarm is composed of three \mathcal{D} -dimensional vectors, where \mathcal{D} is the dimensionality of the search space. These are the current position \vec{x}_i , the previous best position \vec{p}_i and the velocity \vec{v}_i .

The particle swarm is more than just a collection of particles. A particle by itself has almost no power to solve any problem; progress occurs only when the particles interact. Problem solving is a population-wide phenomenon, emerging from the individual behaviors of the particles through their interactions. In any case, populations are organized according to some sort of communication structure or topology, often thought of as a social network. The topology typically consists of bidirectional edges connecting pairs of particles, so that if j is in i 's neighborhood, i is also in j 's. Each particle communicates with some other particles and is affected by the best point found by any member of its topological neighborhood. This is just the vector \vec{p}_g for that best neighbor, which we will denote with \vec{p}_g . The potential kinds of population “social networks” are hugely varied, but in practice certain types have been used more frequently.

In the PSO process, the velocity of each particle is iteratively adjusted so that the particle stochastically oscillates around \vec{p}_i and \vec{p}_g locations.

B. WMN-PSO System for Mesh Router Node Placement

We propose and implement a new simulator that uses PSO algorithm to solve the node placement problem in WMNs. We call this simulator WMN-PSO. Our system can generate instances of the problem using different iterations of clients and mesh routers.

We present here the particularization of the PSO algorithm (see Algorithm 1) for the mesh router node placement problem in WMNs.

Algorithm 1 Pseudo code of PSO.

```
/* Generate the initial solutions and parameters */
Computation maxtime:=  $T_{max}$ ,  $t = 0$ ;
Number of particle-patterns:=  $m$ ,  $2 \leq m \in \mathbf{R}^1$ ;
Particle-patterns initial solution:=  $\mathbf{P}_i^0$ ;
Global initial solution:=  $\mathbf{G}^0$ ;
Particle-patterns initial position:=  $\mathbf{x}_{ij}^0$ ;
Particles initial velocity:=  $\mathbf{v}_{ij}^0$ ;
PSO parameter:=  $\omega$ ,  $0 < \omega \in \mathbf{R}^1$ ;
PSO parameter:=  $C_1$ ,  $0 < C_1 \in \mathbf{R}^1$ ;
PSO parameter:=  $C_2$ ,  $0 < C_2 \in \mathbf{R}^1$ ;
/* Start PSO */
Evaluate( $\mathbf{G}^0, \mathbf{P}^0$ );
/* "Evaluate" does calculate present fitness value of each
Particle-patterns. */
while  $t < T_{max}$  do
  /* Update velocities and positions */
   $\mathbf{v}_{ij}^{t+1} = \omega \cdot \mathbf{v}_{ij}^t$ 
     $+ C_1 \cdot \text{rand}() \cdot (\text{best}(\mathbf{P}_{ij}^t) - \mathbf{x}_{ij}^t)$ 
     $+ C_2 \cdot \text{rand}() \cdot (\text{best}(\mathbf{G}^t) - \mathbf{x}_{ij}^t)$ ;
   $\mathbf{x}_{ij}^{t+1} = \mathbf{x}_{ij}^t + \mathbf{v}_{ij}^{t+1}$ ;
  Update_Solutions( $\mathbf{G}^t, \mathbf{P}^t$ );
  /* "Update_Solutions" compares and updates the
  Particle-pattern's best solutions and the global best
  solutions if their fitness value is better than previous.
  */
  Evaluate( $\mathbf{G}^{(t+1)}, \mathbf{P}^{(t+1)}$ );
   $t = t + 1$ ;
end while
Update_Solutions( $\mathbf{G}^t, \mathbf{P}^t$ );
return Best found pattern of particles as solution;
```

Initialization: Our proposed system starts by generating an initial solution randomly, by *ad hoc* methods [29]. We decide the velocity of particles by a random process considering the area size. For instance, when the area size is $W \times H$, the velocity is decided randomly from $-\sqrt{W^2 + H^2}$ to $\sqrt{W^2 + H^2}$.

Particle-pattern: A particle is a mesh router. A fitness value of a particle-pattern is computed by combination of mesh routers and mesh clients positions. In other words, each particle-pattern is a solution as shown in Fig. 1. Therefore, the number of particle-patterns is a number of solutions.

Fitness function: One of most important thing in PSO algorithm is to decide the determination of an appropriate objective function and its encoding. In our case, each particle-pattern has an own fitness value and compares other particle-pattern's fitness value in order to share information of global solution. The fitness function follows a hierarchical approach in which the main objective is to maximize the SGC in WMN. The fitness function of this scenario is

considered as

$$\text{Fitness} = \alpha \times \text{SGC}(\mathbf{x}_{ij}, \mathbf{y}_{ij}) + \beta \times \text{NCMC}(\mathbf{x}_{ij}, \mathbf{y}_{ij}).$$

Where α and β are weight-coefficient of SGC and NCMC, respectively.

Routers replacement method: A mesh router has x , y positions and velocity. Mesh routers are moved based on velocities. There are many moving methods in PSO field, such as:

Constriction Method (CM)

CM is a method which PSO parameters are set to a week stable region ($\omega = 0.729$, $C_1 = C_2 = 1.4955$) based on analysis of PSO by M. Clerc et. al. [30], [31].

Random Inertia Weight Method (RIWM)

In RIWM, the ω parameter is changing randomly from 0.5 to 1.0. The C_1 and C_2 are kept 2.0. The ω can be estimated by the week stable region. The average of ω is 0.75 [31].

Linearly Decreasing Inertia Weight Method (LDIWM)

In LDIWM, C_1 and C_2 are set to 2.0, constantly. On the other hand, the ω parameter is changed linearly from unstable region ($\omega = 0.9$) to stable region ($\omega = 0.4$) with increasing of iterations of computations [31], [32].

Rational Decrement of Vmax Method (RDVM)

In RDVM, PSO parameters are set to unstable region ($\omega = 0.9$, $C_1 = C_2 = 2.0$). The V_{max} is kept decreasing with the increasing of iterations as

$$V_{max}(x) = \sqrt{W^2 + H^2} \times \frac{T - x}{x}.$$

Where, W and H are the width and the height of the considered area, respectively. Also, T and x are the total number of iterations and a current number of iteration, respectively.

Linearly Decreasing Vmax Method (LDVM)

In LDVM, PSO parameters are set to unstable region ($\omega = 0.9$, $C_1 = C_2 = 2.0$). A value of V_{max} which is maximum velocity of particles is considered. With increasing of iteration of computations, the V_{max} is kept decreasing linearly [33]. In this work, we apply this method to optimize the weight-coefficients of SGC and NCMC.

IV. SIMULATION RESULTS

In this section, we show simulation results using WMN-PSO system. In this work, the area size is considered 32×32 . We use Normal distribution of mesh clients. The number of mesh routers is considered 16 and the number of mesh clients 48. We evaluate weight-coefficients α and β for SGC and NCMC, respectively. The total number of iterations is considered 6400 and the iterations per phase is considered 32. We consider the number of particle-patterns 32. The

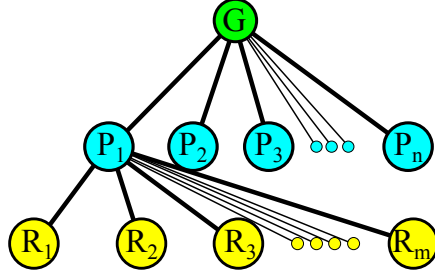


Figure 1. Relationship among global solution, particle-patterns and mesh routers.

Table I
SIMULATION PARAMETERS.

Parameters	Values
Clients distribution	Normal distribution
Grid size	32×32
Number of mesh routers	16
Number of mesh clients	48
Total iterations	6400
Iteration per phase	32
Number of particle-patterns	32
Radius of a mesh router	From 1.5×1.5 to 2.5×2.5
Weight-coefficients α and β	from 0.1 to 0.9
Movement method	LDVM

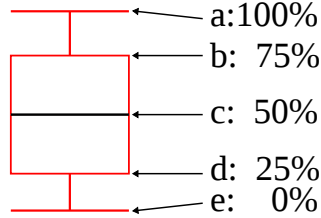


Figure 2. A model of boxplot that we use to analyze the simulation results.

simulation parameters and their values are shown in Table I. We conducted simulations 30 times, in order to avoid the effect randomness and create a general view of results. We used box-plots to analyze the range of data values. In Fig. 2, we show an example of box-plot in order to explain how to analyze the data. The bottom and top of the box (b and d) are the 75th and 25th percentile (the upper and lower quartiles, respectively), and the line of the box (c) is the 50th percentile (the median). The ends of the whiskers (a and e) represent the maximum and minimum of all solution data.

We show the simulation results in Fig. 3. We evaluate the simulation results by using 2 metrics (SGC and NCMC). In Fig. 3(a), with increasing of α , the SGC is increased. However, in Fig. 3(b), with increasing of α , the NCMC is decreased. The reason is that α has higher priority for SGC and β can be decided by $\alpha + \beta = 1.0$. In other words, α and β are in trade-off relation. The fitness function follows a hierarchical approach in which the main objective is to maximize the SGC in WMN. The median of SGC get to

G: Global Solution
P: Particle-pattern
R: Mesh Router
n: Number of Particle-patterns
m: Number of Mesh Routers

100% when $\alpha = 0.7$. Therefore, the best weight-coefficients of SGC and NCMC are 0.7 and 0.3, respectively.

V. CONCLUSIONS

In this work, we implemented a simulation system using PSO in order to solve the mesh router placement problem in WMNs. We investigated fitness function weight-coefficients for optimization in WMN-PSO simulation system.

From the simulation results, we found that with increasing of α , the SGC is increased, but the NCMC is decreased. In other words, α and β are in trade-off relation. The fitness function follows a hierarchical approach in which the main objective is to maximize the SGC in WMN. The median of SGC got to 100% when the $\alpha = 0.7$. Therefore, the best weight-coefficients of SGC and NCMC were 0.7 and 0.3, respectively.

In our future work, we would like to evaluate the performance of the proposed system for different parameters and patterns. Moreover, we would like to compare its performance with other algorithms.

ACKNOWLEDGEMENT

This work is supported by a Grant-in-Aid for Scientific Research from Japanese Society for the Promotion of Science (JSPS KAKENHI Grant Number 15J12086). The authors would like to thank JSPS for the financial support.

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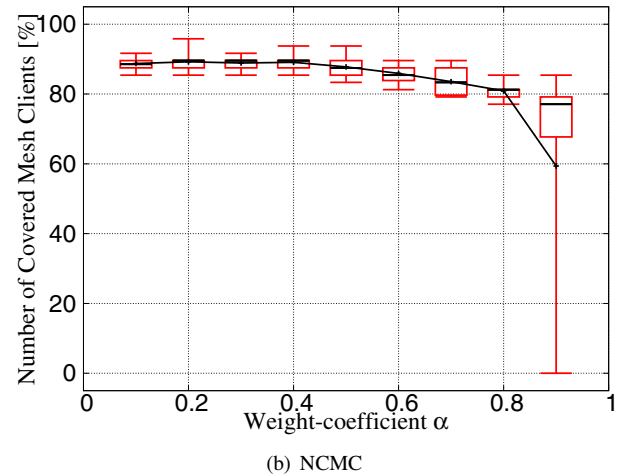
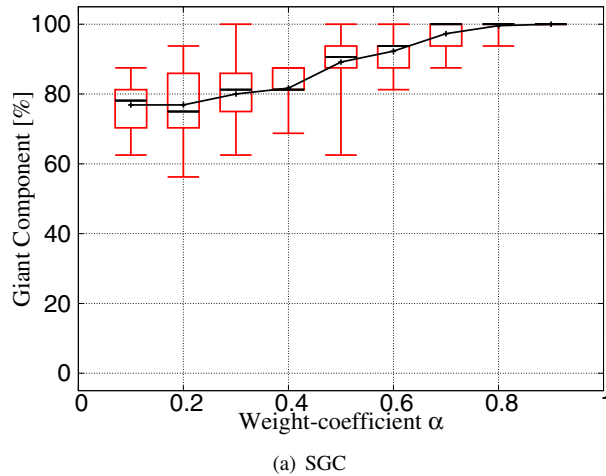


Figure 3. Simulation results.

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