Solving Router Nodes Placement Problem with Priority Service Constraint in WMNs Using Simulated Annealing*

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Abstract. The QoS performance of wireless mesh networks (WMNs) is measured by the topology connectivity as well as the client coverage, both of which are related to the problem of router nodes placement, in which each mesh client is served as equal. In practice, however, mesh clients with different payments for the network services should be provided by different qualities of network connectivity and QoS. As a result, to respond to the practical requirement, this paper considers the router nodes placement problem in WMNs with service priority constraint in which each mesh client is additionally associated with a service priority value, and we constrain that the mesh clients with the top one-third priority values must be served. Our concerned problem inherited from the original problem is computationally intractable in general, and hence this paper further proposes a novel simulated annealing (SA) approach that adds momentum terms to search resolutions more effectively. Momentum terms can be used to improve speed and accuracy of the original annealing schedulers, and to prevent extreme changes in values of acceptance probability function. Finally, this paper simulates the proposed novel SA approach for different-size instances, and discusses the effect of different parameters and annealing schedulers.

Keywords: Wireless mesh networks, simulated annealing, router nodes placement, annealing schedule.

1 Introduction

Based on Wi-Fi technology, wireless mesh networks (WMNs) [1, 2] are the communication networks made up of radio nodes organized in a mesh topology. This paper considers the problem of router nodes placement (RNP) for the WMNs consisting of mesh routers and mesh clients [3], in which an optimal deployment of mesh routers is determined so that the network connectivity and the client coverage are maximized. In the previous work [4,8,9,10], the RNP problem only considered fixed and simple network environments, in which each mesh client is served as equal.

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In practice, however, each mesh client should be served by different quality of network connectivity as well as QoS [6] according to the user's payment for the service. To respond to the practical requirement, this paper extends the original RNP problem to the router nodes placement problem with service priority constraint in WMNs (WMN-RNPSP), in which each mesh client is associated with a service priority value that represents its service priority in this WMN, and we constrain that the mesh clients with the top one-third priority values must be served. The WMN-RNPSP problem is challenging due to the following three additional characteristics: (a) the locations of mesh routers are not predetermined, (b) mesh routers are assumed to have different radio coverage area sizes, and (c) each mesh client is associated with a different priority value. The last characteristic is designed for our practical requirement for providing users different service qualities. Our objective is to find an optimal placement of mesh routers in the deployment area to maximize both the network connectivity and the client covering.

Like the original RNP problem, the WMN-RNPSP problem cannot be solved by an efficient deterministic polynomial-time algorithm [7]. Hence, we propose a novel simulated annealing (SA) approach by analogy with [5] to solve the WMN-RNPSP problem, which provides an efficient promising solution. Our novel SA approach improves speed and accuracy of annealing schedulers and makes the algorithm become faster by adding momentum terms. In addition, we propose two types of neighbor selection mechanisms, called random scheme and local scheme, for comparing the original neighbor selection mechanism.

The rest of the paper is organized as follows. Section 2 introduces the basic original router nodes placement problem and define the router nodes placement problem with service priority constraint in WMNs. Then, the SA approach phases with momentum terms for constructing a WMN and its detail application phases to WMN-RNPSP problem is presented in Section 3. In Section 4, we present environment setting, simulation results and discussion. Finally, we discuss the future network and make some conclusion in Section 5.

2 Problem Description

This section first gives the basic environmental settings as well as concepts for the RNP problem, and then formulates the RNPSP problem.

2.1 The Router Nodes Placement Problem

An instance for the RNP problem [3, 8] consists of:

(a) m mesh routers each of which has a different-size radio coverage;
(b) a two-dimensional rectangular grid area of size $W \times H$ in which m mesh routers are deployed;
(c) n mesh clients located in arbitrary points of the deployment grid.

Figure 1 gives an instance for the RNP problem, in which according to the locations of mesh routers in the rectangular deployment grid, we can establish a network topology graph. Let the graph denoted by $G = (V, E)$, in which V is the set of all mesh routers and mesh clients, and E is the set of edges, which include two types of connections as follows. First, if the radio coverage of two mesh routers are overlapped, we create an edge between the two mesh routers. Second, if a mesh client is located within the radio coverage of a mesh router, we create an edge between the mesh client and the mesh router. There are two measure for the performance of the WMN. The first measure is the *network connectivity*, which is defined as the size of the greatest graph component of graph G, while the second measure is the *client coverage*, which is defined as the number of covered mesh clients.

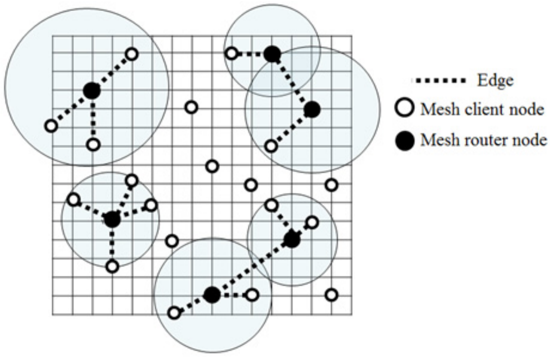

Fig. 1. An instance of WMN

2.2 The Router Nodes Placement Problem with Priority Service Constraint

An instance for the WMN-RNPSP problem consists of:

(a) m mesh router nodes each of which has a different-size radio coverage;
(b) a two-dimensional grid area of size $W \times H$ where m mesh routers are deployed;
(c) n mesh clients located in arbitrary points of the deployment grid each of which is associated with a service priority value.

In light of the above, the WMN-RNPSP problem can be stated as follows:

The WMN-RNPSP Problem: We are given a graph underlying a WMN distributed in a two-dimensional $W \times H$ grid area where the locations of mesh clients located in arbitrary collations of the grid area and each of mesh clients has a priority value, while the locations of mesh routers need be assigned. The objective of the problem is to find a placement X of the mesh routers so that the network connectivity and the client coverage are maximized while the mesh clients with the top one-third service priority values must be served.

3 Our Novel SA Approach to the WMN-RNPSP Problem

This section focuses on the annealing schedule and the acceptance probability module of our proposed novel SA, by analogy with [5]. Finally, we present in detail the key steps of our proposed novel SA.

3.1 Simulated Annealing Algorithm

Simulated annealing (SA) is a metaheuristic algorithm used for solving combinatorial optimization problems. The basic idea of SA is to simulate the cooling process of metals by heating and cooling of a material to increase the size of crystals and reduce defects. Initially, a feasible solution for the problem is represented a state of the metals. Heating causes the metals to change and rearrange their current state, while cooling finds a state with lower energy than the previous one. Note that the cooling process follows an annealing schedule. In each iteration of the annealing schedule, the SA considers a neighboring state of the current state, and bases the Metropolis rule to probabilistically decide whether the system moves to the neighboring state or stays at the current state. Those steps are repeated until the system reaches a state that is good enough, or the maximal number of iterations is achieved. The final state would be associated with a locally optimal solution of the concerned optimization problem.

The SA algorithm contains two main phases: annealing schedule and Metropolis rule. The annealing specifies "when and what temperature must be decreased", and the Metropolis rule considers a probability function and specifies "whether to replace the current state by a neighboring state". The probability is used to overcome the local optimal problem and lead the system to move the optimal solution of lower energy gradually. This paper considers three types of annealing modules: Geometric, Logarithmic, and Boltzmann. Unless stated otherwise, we use the most popular Boltzmann acceptance probability function.

3.2 A Novel Simulated Annealing Algorithm Using Momentum Terms

The novel SA approach is similar to the SA, and it speeds up the system time and enhances the accuracy of solution greatly on SA by adding momentum terms. Momentum terms are used to improve cooling speed and prevent extreme changes in values on acceptance probability function. This section summarizes three newly annealing modules: Hybrid, Extended logarithmic and Extended Boltzmann and one acceptance probability function: Extended Boltzmann function as follows. Note that T_i is the temperature of the i-th iteration, and ΔT is the difference between current temperature and previous temperature. Readers are referred to [5] for more details of those designs.

- **Hybrid:** $T_{k+1} = T_k - \alpha T_k - k \cdot \Delta T / e^k$ where α is similar to that used in the Geometric annealing module, and k is the number of iterations.
- **Extended logarithmic:** $T_k = C / \log(T_0 + k) - k / e^k - (\log(k))^{1/2}$ where C is constant.
- **Extended Boltzmann:** $T_k = T_0 / \log(1 + k) - \log(1 + k)$.

- **Extended Boltzmann function:** $P(\Delta E) = e^{-\Delta E / bt}$ where ΔE is calculated as follows: $\Delta E = (E_i - E_j) - \alpha b T_i (E_i - E_j)^{1/2}$ where α is a running time parameter, and b is the Boltzmann constant.

3.3 Our Novel SA Approach to the WMN-RNPSP Problem

This section gives in detail my novel SA approach to the WMN-RNPSP problem: solution representation of each candidate solution, fitness function, scheme of neighboring solution selection and acceptance criteria.

3.3.1 Solution Representation

The (x, y)-coordinates of the routers should be determined as a candidate solution, which is expressed by two vectors (current and current best solutions) and two fitness values (current and current best fitness).

3.3.2 Fitness Function

The objective $f(X)$ for a placement X of our concerned problem is to maximize the network connectivity $\phi(G)$ and the client coverage $\psi(G)$ at the same time. Note that G is the topology graph underlying the placement X. The fitness function is calculated as follows:

$$f(X) = \lambda \cdot \frac{\phi(G)}{n+m} + (1-\lambda)\frac{\psi(G)}{m}$$

where λ is the weighting scale in the range [0, 1]. Note that the denominator of each term of the equation is used for normalization.

3.3.3 Neighbor Selection

The implementation of SA considers three types of moving schemes as follows:

- **Standard:** Choose a router randomly and place it in a new position randomly.
- **Random:** All of the mesh routers are reconfigured randomly.
- **Local:** Choose a router randomly and place it in a new position within the specified range randomly.

4 Implementation and Experimental Results

Based on the proposed SA approach described in the previous section, we implemented our proposed novel SA approach to the WMN-RNPSP problem. This section is divided into three subsections mainly. We first give the parameter setting, and then present the type of optimal neighbor selection on SA and novel SA in the individual various cases. Second, we use the result of the first one, compare all annealing schedules mentioned in Section 3 with Boltzmann and extended Boltzmann probability. Finally, we summarize all the previous results to give the experimental results in a variety of cases.

4.1 Data and Simulation Environment

Similar to [8], we consider the following three cases:

Case 1: There are 16 mesh routers and 48mesh clients on a 32 × 32 area.
Case 2: There are 32 mesh routers and 96mesh clients on a 64 × 64 area.
Case 3: There are 64 mesh routers and 192 mesh clients on a 128 × 128 area.

Table 1. Performance of neighbor selection on the original and our novel SA approaches for 32 × 32, 64 × 64 and 128 × 128 grid area

CASES	SA/NSA	Standard	Random	Local
32 × 32 grid size	Original SA	0.955385	0.744469	0.743010
	Novel SA	0.982656	0.783781	0.788635
64 × 64 grid size	Original SA	0.923776	0.876479	0.873375
	Novel SA	0.999229	0.871833	0.879516
128 × 128 grid size	Original SA	0.884500	0.860487	0.859797
	Novel SA	0.981529	0.868177	0.866550

One important aspect of the SA process is to study the performance under different neighboring selection methods. Table 1 shows the statistics results of the fitness values under different selection schemes for original SA and novel SA. We can see that the Standard scheme of neighbor selection on original or novel SAs can generate better solutions for all cases.

4.2 Annealing Schedule Method and Acceptance Probability Function

We give in Table 2 the computational results of six types of annealing schedule methods with Boltzmann and extended Boltzmann probability acceptance functions. Due to page limitation, we only put the results of case 1, 32 × 32 grid size. In Table 2 it is illustrated that the proposed acceptance function of novel SA has better results than original SA and almost all annealing schedule methods showed high quality performance under novel extended acceptance probability function.

Table 2. Comparison of annealing schedules with Boltzmann and extended Boltzmann probability for 32 × 32 grid size

Annealing schedule	Boltzmann	Extended Boltzmann
Geometric	0.950729	0.982292
Logarithmic	0.767517	0.981375
Boltzmann	0.759705	0.985792
Hybrid	0.769045	0.978687
Extended logarithmic	0.765486	0.983083
Extended Boltzmann	0.755781	0.982406

4.3 Experimental Results

After the fine tuning of above parameters was done, we measured the performance of the novel SA algorithm for all the problem instances. The statistics of all the problem instances are given in Table 1, in which four columns stores best fitness, average fitness, worst fitness, and the standard deviation of fitness values; ten rows indicates each 5 instances of clients distributions. We observe that our novel SA approach performs high efficiency and almost achieves to maximum both network connectivity and client coverage.

Table 3. The statistics of all cases

Instance	Case 1				Case 2				Case 3			
	Best	Mean	Worst	SD	Best	Mean	Worst	SD	Best	Mean	Worst	SD
uniform_1	1.0000	0.9823	0.9474	0.0155	1.0000	1.0000	1.0000	0.0000	0.9952	0.9860	0.9711	0.0089
uniform_2	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.9904	0.9846	0.9711	0.0047
uniform_3	1.0000	0.9953	0.9615	0.0090	1.0000	1.0000	1.0000	0.0000	0.9952	0.9888	0.9855	0.0025
uniform_4	1.0000	0.9978	0.9672	0.0068	1.0000	1.0000	1.0000	0.0000	0.9952	0.9852	0.7978	0.0276
uniform_5	1.0000	0.9691	0.9423	0.0152	1.0000	0.9992	0.9615	0.0055	1.0000	0.9955	0.9904	0.0015
nniform_1	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.9952	0.9935	0.9855	0.0025
normal_2	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.9952	0.9907	0.9904	0.0012
normal_3	1.0000	0.9963	0.8172	0.0259	1.0000	1.0000	1.0000	0.0000	0.9952	0.9929	0.9855	0.0026
normal_4	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.9952	0.9941	0.9855	0.0026
normal_5	1.0000	0.9965	0.8271	0.0243	1.0000	1.0000	1.0000	0.0000	0.9952	0.9928	0.9892	0.0025
average	1.0000	0.9937	0.9463	0.0097	1.0000	0.9999	0.9961	0.0005	0.9952	0.9904	0.9652	0.0057

5 Conclusion and Future Work

A novel simulated annealing approach for optimizing the placement of mesh router nodes for mesh clients with service priority constraint in wireless mesh networks has been proposed and implemented. The experimental results showed the efficient implementation of our proposed novel SAs for the WMN-RNPSP problem. The results also confirmed that our proposed novel SA is an effective method for the problem as it achieved the network connectivity of almost all mesh router nodes and covered almost all mesh client nodes in variety of grid sizes. In addition, the performance of our proposed novel SA is always better than original SA.

In the future, we intend to solve the dynamic version of the WMN-RNPSP problem or consider the optimization of other objectives at the same time, so that the problem is more realistic and can be used in the community.

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