On Optimizing the Planning of Multi-hop Wireless Networks using a Multi Objective Evolutionary Approach

D. Benyamina, N. Hallam, A. Hafid

***Abstract*—**The optimization problem of planning Wireless Mesh Networks (WMNs) is a challenging problem that has been regarded as a cost-minimization problem, while other pertinent Quality of Service (QoS) criteria are modeled as constraints to be satisfied. We propose a novel approach that models, to some realistic extent, the problem of planning WMNs as a simultaneous optimization of deployment cost and network throughput under obvious network constraints. We propose two multi-objective models differing mainly in how the throughput objective is optimized. We tailor a nature-inspired meta-heuristic algorithm to solve the two models. The cost and the effectiveness of the planning solutions are two conflicting objectives which undermine each other. In such situations, the network planner would prefer a set of trade-off planning solutions at his disposal to choose from A comparative experimental study with different key-parameter settings on the two instance models is conducted to help network planner decide which planning optimization model to choose given their specific requirements and/or scenarios.

***Keywords*—** Wireless Mesh Network, Planning problem, Multi-objective optimization, Meta-heuristic search algorithm.

I. Introduction

The wireless Mesh Network (WMN) technology is being increasingly deployed and considered as a first step towards providing high bandwidth network coverage to its clients. Its basic building block is the infrastructure which is composed of fixed nodes interconnected via wireless links to form a multi-hop ad-hoc network. Nodes in a WMN are essentially routers and gateways. They act as classical access point to mesh clients. They also interconnect with each other through point-to-point wireless links. Gateways, on the other hand, have extra functionalities which make them more expensive than routers. Simultaneous communication is allowed thanks to the use of multi radios (interfaces) over orthogonal channels. However, since the number of available orthogonal channels is limited, interferences happen thus degrading the network performance.

Nevertheless, end-users experience a number of problems such as intermittent connectivity, poor performance and lack of coverage. Major research efforts have focused on developing planning network solutions for cellular networks and WLANs. However, these solutions strongly differ from those of planning WMN.

Planning a WMN basically involves choosing the installation locations and the type of network nodes and deciding on a judicious channel/node interface assignment, while guaranteeing users coverage, wireless connectivity and traffic flows at a minimum cost.

One may always argue that it is always good to overestimate the number of mesh nodes to avoid lack of coverage and to increase throughput. This choice has a strong impact on the complexity of the channel assignment problem and induces high interference levels, worsening network performance. On the other hand, a well-planned and optimized network can often provide extra capacity with the same infrastructure cost.

The study presented in this paper concerns the design of optimization models that minimize the network deployment cost, maximize the network throughput, and guarantee a full coverage to mesh clients. The problem being NP-hard, a meta-heuristic multi-objective algorithm is then needed to search for the optimal set of non-dominated planning solutions, where each expresses a different trade-off between the planning objectives. The interesting characteristic of these trade-off solutions, also called Pareto solutions, is that they are naturally tailored to a decision making process. Indeed, a network planner is provided with a set of alternative planning solutions from which he/she would have to decide which one to choose based on his/her requirements (budget, customer needs, …etc).

Most of related work focus on the problem of performance improvement, and assume, in a way or another, *a priori* fixed topologies [2], [3], [4], [5], where some of the main drawbacks can be found in [6]. Other studies (e.g., [7-8]) consider topologies where gateways are fixed *a priori*, while the studies in [9], [10] attempt to optimize the number of gateways given a fixed layout of mesh routers.

On the other hand, very recent works in [1], [11], [12] propose WMN planning schemes where the locations of routers and gateways are not fixed. With the exception of the work in [12], exact optimization techniques are used to solve

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the problem models and therefore, are restricted to solve (at best) medium size instance problems. In addition, they all use variants of single-objective optimization model where the total deployment cost is the sole objective to optimize.

Our work differ from the above mentioned contributions in that we plan the WMN from scratch to meet the QoS requirements, taking into consideration interference aware model while meeting the planner's objectives and satisfying his/her constraints.

The quality of the planned network can be constrained by multiple requirements: the signal level received by the mesh clients, the performance quality (in terms of network throughput) or the installation costs.

Up to date, there has been no attempt to model WMN planning problems using multi-objective meta-heuristic optimization approaches where several non-dominated solutions are produced. The concept of non-dominance means that none of the solutions is better than the rest with respect to all objectives. Moreover, this set of trade-off solutions is very much appreciated by engineers who usually prefer multiple non-dominated solutions where each can be used in a different decision making scenario.

We propose a new approach based on multi-objective optimization to model the WMN planning problem and use an evolutionary population based meta-heuristic to solve it.

The rest of the paper is organized as follows. Section II describes the mathematical formulation of two problem solutions. We also propose a new network performance metric which evaluates the balance of channel repartition. Section III presents the meta-heuristic multi-objective optimization technique to solve the mathematical models presented in the preceding section. Numerical results of the experiments conducted on the two mathematical models and a comparative analysis are detailed in Section IV. Finally, we conclude the paper in Section V.

II. Problem Formulation

In this section, we describe our modeling approach in planning WMNs and propose two theoretical bi-objectives optimization models. Let $I=\{1,..,n\}$ be the set of positions of traffic concentrations in the service area (Traffic Spots: TSs) and $L=\{1,..,m\}$ the set of positions where mesh nodes can be installed (Candidate Locations, CLs).

The planning problem aims at:

- Selecting a subset $S \subseteq L$ of CLs where a mesh node should be installed so that the signal level is high enough to cover the considered TSs.
- Defining the gateway set by selecting a subset $G \subseteq L$ of CLs where the wireless connectivity is assured so that all traffic generated by TSs can find its way to reach nodes in G.
- Maintaining the cardinalities of G and S small enough to satisfy the financial and performance requirements of the network planner.

In order to describe the problem formally we introduce the following notation.

Given n TSs and m CLs, in the following, unless otherwise stated, i and j belong to I and L respectively. The cost associated to installing a mesh node j is denoted by c_j, while p_j is the additional cost required to install a gateway at location j. d_i is the traffic generated by TS$_i$. u_{jl} is the traffic capacity of the wireless link between CL$_j$ and CL$_l$. v_j is the capacity of the radio access interface of CL$_j$. The coverage and connectivity parameters are given respectively by the binary variables a_{ij} and b_{jl}. a_{ij} takes the value 1 whenever TS$_i$ is covered by a mesh node in CL$_j$. The parameter b_{jl} indicates whether CL$_j$ and CL$_l$ can be connected via a wireless link. We define other decision variables (see Fig.1) in our formulation including: x_{ij} takes the value 1 if TS$_i$ is assigned to CL$_j$ while t_j (g_j) is set to 1 if a router (a gateway) is installed in CL$_j$.

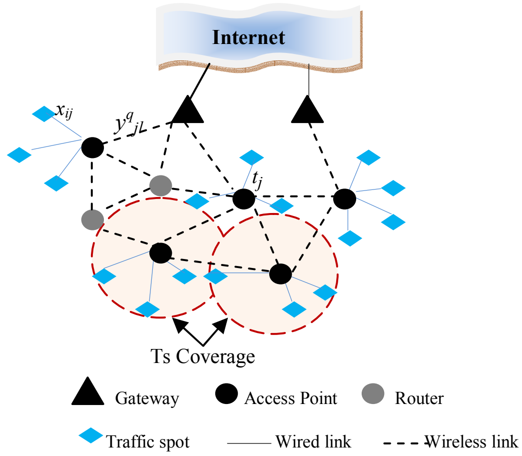


Fig.1. WMN Structure (nodes/Problem variables)

We suppose initially that the mesh nodes operate using the same number of radios R, each with k channels, $(k>R)$ and $k \in C$, where $C=\{1,..,c\}$ and c can be at most 12 orthogonal channels if IEE802.11a is used. Extra installation variables are added: $z^q_j=1$ if a mesh node is installed in CL$_j$ and is assigned channel q, $q \le k$, $y^q_{jl}=1$ if a wireless link from CL$_j$ to CL$_l$ using channel q, $q \le k$ exists. Let N_{jl} be the set of links that cannot be simultaneously active with the link y^q_{jl}. Finally, we define the flow variables f^q_{jl} and F_j. the first variable denotes the traffic flow routed from CL$_j$ to CL$_l$ using channel q, the second is the traffic flow on the wired link between a gateway j and Internet.

For better readability, the following table summarizes the notation used in the problem formulation.

TABLE I: LIST OF SYMBOLS USED IN THE WMN MODELS FORMULATION.

	Description
AP	Access Point
MR	Mesh Router
MG	Mesh Gateway
N	Number of Traffic Spots (TSs)
M	Number of Candidate Locations (CLs)
d_i	Traffic generated by TS$_i$
u_{jl}	Traffic capacity of wireless link (CL$_j$,CL$_l$)
Vj	Capacity limit for AP radio access interface

e_j	A device cost installation
p_j	A gateway additional cost installation
R	Number of radio interfaces
K	Number of channels
a_{ij}	Coverage of TS_i by CL_j
b_{jl}	Wireless connectivity between CL_j and CL_l
t_j	Installation of a device at CL_j
g_j	Installation of a gateway at CL_j
x_{ij}	Assignment of TS_i to CL_j
z^q_j	Installation of a device at CL_j , assignment of channel q, $q<k$
y^q_{jl}	Establishing a wireless communication on channel q between (CL_j,CL_l)
f^q_{jl}	Flow on channel q between (CL_j,CL_l)
F_j	Flow on the wired link from CL_j to Internet
N_{jl}	Set of links interfering with the link y^q_{jl}

In the following, we describe the two optimization models. Both models attempts to simultaneously minimize the deployment cost and maximize the throughput, but they differ in modeling the throughput objective. While the first model maximizes a sort of "flow-capacity rate usage", the second one attempts to minimize radio interferences.

A. Flow-Capacity Maximization Model

Our first interference-aware optimization model is formulated as follows:

$$\mathbf{Min} \sum (c_j t_j + p_j g_j) \tag{1}$$

$$\mathbf{max} \sum_{j\in L} \sum_{l\in L} \frac{f^q_{jl}}{u_{jl}} \tag{2}$$

Subject to:

$$\sum_{j\in L} x_{ij} = 1 \qquad \forall i \in I \tag{3}$$

$$x_{ij} \le a_{ij} t_j \qquad \forall i \in I,\ \forall j \in L \tag{4}$$

$$\sum_{i\in I} d_i x_{ij} + \sum_{l\in L}\sum_{q\in C}\left(f^q_{lj} - f^q_{jl}\right) - F_j = 0 \quad \forall j \in L \tag{5}$$

$$\sum_{k,h\in N_{jl}} y^q_{kh} \le 1 \qquad \forall q \in C,\ \forall j,l \in L \tag{6}$$

$$\frac{f^q_{jl}}{u_{jl}} \le y^q_{jl} \qquad \forall q \in C, \forall j,l \in L \tag{7}$$

$$\sum_{i\in I} d_i x_{ij} \le v_j \qquad \forall j \in L \tag{8}$$

$$F_j \le M g_j \qquad \forall j \in L \tag{9}$$

$$2 y^q_{jl} \le b_{jl}\left(z^q_j + z^q_l\right) \qquad \forall q \in C, \forall j,l \in L \tag{10}$$

$$g_j \le t_j \qquad \forall j \in L \tag{11}$$

$$\sum_{l\in L} y^q_{jl} \le 1 \qquad \forall q \in C,\ \forall j \in L \tag{12}$$

$$\sum_{q\in C} z^q_j \le R\ t_j \qquad \forall j \in L \tag{13}$$

$$x_{ij}, z^q_j, y^q_{jl}, t_j, g_j \in \{0,1\} \qquad \forall i \in I, \forall j,l \in L, \forall q \in C \tag{14}$$

$$f^q_{jl}, F_j \in R \qquad \forall j,l \in L, \forall q \in C \tag{15}$$

In this model, the objective function (1) minimizes the total cost of the network including installation cost c_j and additional gateway installation cost p_j. The aim of the objective function (2) is to maximize the total throughput by computing the overall flow-capacity ratio of the network. Constraint (3) is used to make sure that a given TS_i is assigned to only one CL_j. Inequality (4) implies that a TS_i is assigned to an installed and covering mesh node j. Constraint (5) defines the flow balance for each mesh node j**.** Constraint (6) limits link interferences. Inequalities (7) and (8) are respectively flow-link capacity and demand-radio access capacity constraints. Constraint (9) implies that the flow routed to the wired backbone is different from zero only when the mesh node installed is a gateway. M is a very large number to limit the capacity of the installed gateway. Using the same channel q, constraint (10) forces a link between CL_j and CL_l to exist only when the two devices are installed, wirelessly connected and tuned to the same channel q. Constraint (11) ensures that a device can be a gateway only if it is installed. Constraint (12) prevents a mesh node from selecting the same channel more than once to assign it to its interfaces. Constraint (13) states that the number of links emanating from a node is limited by the number of its radio interfaces. It also states that if a channel is assigned only once to a mesh node, it is a sufficient condition for its existence. Constraint (5) is called a soft constraint while others are defined as hard constraints.

B. Interference Minimization Model

In the second model, the overall network interference is sufficiently important for the network performance, and thus is elevated to the status of an objective that needs to be minimized. Indeed, instead of just limiting interferences, as defined in constraint (6), it would be more effective to have it as an objective to be optimized altogether with the deployment cost. For this purpose, we propose a novel performance metric defined below.

Interference Level Metric: *We define the Balanced Channel Repartition (BCR) metric as follows:*

φ_{q1}=max|O_{q1}-O_{q2}| $\forall q_1,q_2 \in C$. where, $O_q = \sum_{j,l\in L} y^q_{jl}$, $q\in C$

In other words, the number of occurrences of channel q, denoted by O_q, is used to compute the gap between the balanced allocation of channel q and the current allocation. Our aim is to minimize this gap. The second objective function is then defined as follows:

$$Min \sum_{q\in C} \varphi_q$$

The second model is therefore defined as minimizing both the following two objectives:

$$\textbf{Min} \sum (c_j t_j + p_j g_j) \quad (1)$$

$$Min \sum_{q\in C} \varphi_q \quad (2)$$

subject to the same set of constraints as that defined in section II.A but without constraint 6. In Section IV, a comparative experimental study is conducted on these two instance models.

III. Planning Problem Solution

Our WMN planning optimization is essentially the maximization of the network throughput (depending on which perspective is used) while at the same time ensuring the minimization of the total deployment cost. This is achieved by selecting a minimum number of routers/gateways and adequately choosing their positions so that the network connectivity is ensured while providing full coverage to all mesh clients. It is proven that a WMN planning optimization problem is NP hard [12]. Its difficulty lies on the fact that it tries to optimize the conflicting objectives (cost and throughput) simultaneously while addressing all the constraints.

As stated earlier, solving a Multi-Objective Problem (MOP) returns a set of Pareto-optimal solutions. Each Pareto solution represents a different trade-off between the objectives that is said to be “non-dominated”, since it is not possible to improve one criterion without worsening another.

The two most popular classes of MOP solvers are based on genetic algorithms (NSGA-II, SPEA2, PAES, PPREA, etc…) and on swarm intelligence (Particle Swarm Optimization and Ant Colony Optimization based algorithms). We opted for an optimizer based on PSO technique [13] to solve our WMN planning problem.

A. Solving a Multi Objective Problem Using PSO

1) Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization technique based on an evolutionary approach introduced by Kennedy and Eberhart [13]. It models the dynamic movement or behavior of the particles in a search space. By sharing information across the environment over generations, the search process is accelerated and is more likely to visit potential optimal or near-optimal solutions. Moreover, it is easy to implement with simple concepts and requires few parameters to adjust.

PSO has been extended to cope with an MOP which mainly consists of determining a local best and global best Potential Solutions (PSs) of a particle in order to obtain a front of optimal solutions. There are some efficient and well-known multi-objective techniques based on PSO algorithms, of which MOPSO [14] seems to be the most effective. We use a variant of MOPSO (which we call VMOPSO) to design our WMN optimization algorithm.

We use a crowding distance mechanism in order to maintain diversity of Pareto front solutions and we incorporate a mutation factor (*fmut*) to boost the exploration capability of the standard MOPSO. The crowding distance value of a solution, as thoroughly studied in [15], is the average distance of its two neighboring solutions. The boundary solutions with the lowest or the highest objective function value are given an infinite crowding distance values so that they are always selected. This process is done for each objective. The final crowding distance value of a solution is computed by adding the entire individual crowding distance values in each objective value.

Despite the crowding distance incorporated as the deletion method applied on the *Archive* and to maintain solutions diversity, we add a constraint handling mechanism for solving constraints optimization problem, such as WMN design problem. In the following, we provide more details on how the multi-objective generic model is solved using VMOPSO.

```
Algorithm 1: VMOPSO Main Algorithm
Input fmut: Mutation factor, MaxGeneration
Output   Archive: External repository

Step 1: Initialize the swarm (Build feasible
     solutions that satisfy all the
     constraints defining the optimization
     problem)
      For each particle i in the swarm
       1. Initialize feasible position,
       2. Specify lowerBound_i and upperBound_i
          /*boundary

          limits
       3. Initialize velocity
       4. Set the global best guide gBest to
          pBest
       5. Set the personal best guide pBest
          to that position
      End For
Step 2: Initialize the iteration counter t=0
Step 3: Evaluate all particles in the swarm
   /*compute
                         objective functions
                       f1 and f2
Step 4: Store non dominated solutions found
      in step 1 into Archive.
Step 5: Repeat
     1. Sort Archive in descending crowding
        distance values
     2. Compute the crowding distance values
        for each j∈Archive
     3. For each particle i in the swarm
             a. Set gBest[i] to the randomly
                selected particle from the top
                10% of the sorted Archive.
             b. Compute new velocity, position
```

```
        of particle i
     c. Check particle boundaries, if
        violated change particle
        search direction
        (i.e.,velocity(i)*-1)
     d. If (t< MaxGeneration*fmut)
        then mutate
     e. Evalute particle i
   End For
4. Check for constraints satisfaction
5. Check for non dominance of all
   particles in the swarm, insert non-
   dominated and feasible solutions
   into Archive and delete dominated
   solution from Archive
6. If Archive is full then
     a. Compute the crowding distance
        values for each j∈Archive
     b. Randomly selected particle
        from the bottom 10% of the
        sorted Archive (most crowded
        portion).
     c. Replace it with the new
        solution.
   End If
7. Update pBest
8. Increment t
Until (t= MaxGeneration)
```

The very first step is to initialize the positions, the boundary limits, the velocities of each solution *i* (particle) in *S*. At this step, only feasible solutions are considered.

Each of these particles would then go through an evaluation process, i.e., an assessment of the quality of the solution, which is nothing but the evaluation of the two objective functions.

During the exploration of the search space, each particle has access to two pieces of information: the best Potential Solution (PS) that it had encountered (*pBest*) and the best PS encountered by its neighbors *(gBest)*. This information is used to direct the search by computing velocities: velocity[i] = *iw* * velocity[i] +r_1 * (*pBest*[i] – position[i]) +r_2* (*Archive*[*gBest*] – position[i]), where r_1, r_2 *are* random numbers in the range of [0,1] and *iw i*s the inertia weight . A large inertia value will cause the particles to explore more of the search space, while a small one directs the particles to a more refined region.

The *Archive* is then updated by inserting into it all the currently non-dominated (fittest) solutions. This insertion process ends up in removing dominated solutions. In the case where the archive is full and there are still non-dominated solutions to be inserted, priority is then given to those particles that would ultimately enhance the diversity of the archive set, which is achieved by using the crowding distance technique. When the decision variable exceeds its boundaries, it takes the value of its corresponding boundary and the velocity is changed to the opposite direction.

B. Solving the WMN Planning Problem: Logical and Physical Modeling.

This section describes how our *initial* WMN planning solutions are constructed and fed to the VMOPSO optimizer. Given a set of TSs scattered in a geographical region, the idea is to construct a network of mesh nodes (APs, MRs, MGs) that will best service the users TSs with minimum cost and under many constraints.

1) A Grid Topology for a Network Deployment Scheme

The first issue to address is what topology to adopt when constructing a network of mesh node to properly handle users TSs demands.

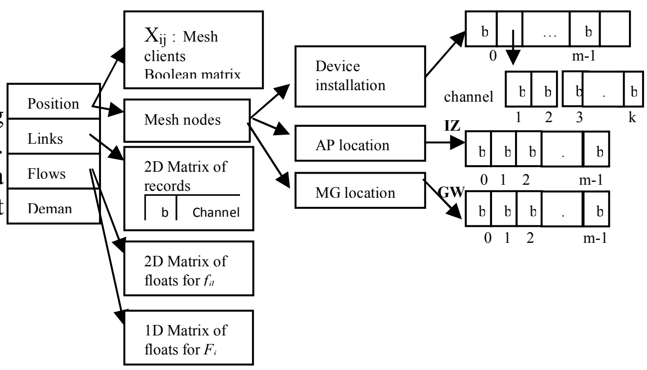
Robinson and Knightly [16] conducted a performance study of deployments factors and concluded the benefits of adopting grid topologies over other topologies. In the same context Li et al. [17] studied the gateway placement for throughput optimization in WMNs using a grid-based deployment scheme. Their method of placing exactly *k* gateways has achieved better throughput in the grid scheme than in random schemes.

Based on these findings, we adopt a *square grid* layout as the physical representation of our WMN planning. Each grid cell corner is a CL where a mesh node can be installed. If a mesh node is installed at a given CL, it establishes a wireless communication with its eight direct-neighbors. This assumption will increase the chances of selecting a candidate neighbor among the eight with which a wireless link will be set up in the channel assignment procedure.

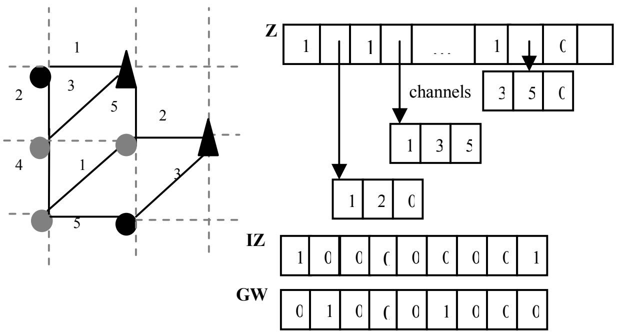
2) A Particle in the Swarm: Modeling a WMN planning Solution.

In PSO, a particle (a position in the search space) represents a set of assignments that is a solution to the problem. In our case, a particle is a complex data structure that provides information about user connectivity (x_{ij}), device installation (t_j) and (z^q_j), devices connectivity (y^q_{jl}), gateway existence (g_j), link flows (f^q_{jl}), and gateway/backbone link flows (F_j). Fig 5.a depicts different components of a particle data structure. The building blocks of a particle structure are *Positions, Links, Flows* and *Demands*. The block *Positions* is the most important one, as it provides information about user connectivity and the type of devices, as well as their locations and installation. The *mesh nodes* component contains the locations of APs (represented by IZ vector), the locations of MGs (represented by GW vector) and the list of channels assigned to radio interfaces of every mesh node installed (MR included). Fig.5.b illustrates an example of the *mesh nodes* component of a particle.

A feasible solution must satisfy all hard and soft constraints. However, those solutions that violate only the soft constraint (5) can be included in the population if space allows. This increases the likelihood of a non-feasible solution to mutate and provide a feasible one in later generations.



(a)



(b)

Fig. 5: Particle encoding (b: stands for Boolean value)
(a) Particle data structure, (b) A Particle position example with *m*=3, *R*=3, *K*=5(right side figure), Mesh nodes component of the particle position (left side figure).

3) *Building the initial set of feasible solutions*

In continuous optimization problems, getting the initial position and velocity is more straightforward because a simple random initialization is used. However, since the problem of planning a WMN is a constrained optimization problem, the initial positions must represent feasible solutions, and thus, need to be designed carefully.

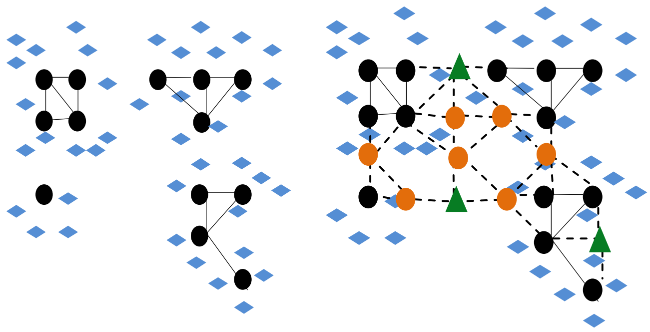
Constructing an initial set of feasible solutions that satisfy the constraints (3) to (15) represents the most challenging part in our optimization process. Building such an initial set requires three main design stages, namely coverage insurance, connectivity augmentation and gateway assignment.

Coverage insurance: Recall that a TS_i can be covered by one or many CLs. This stage handles the assignment of each TS_i to one and only one CL_j . We start by selecting randomly a CL_j from the set of CLs that cover that TS_i (Fig 6.a). An AP (Access Point) is then installed at this location CL_j only if it has not yet been selected (see Fig 6.b). By applying the same procedure to all TSs, we obtain a set S_1 of APs location that provides full coverage to all TSs. More formally, $S_1=\{ j\in L, CL_j \text{ covers } TS_i, i\in I \}$. At this stage, constraints (3) and (4) are satisfied and the initial set contains vertices of a disconnected graph as shown in Fig.6.b.

Connectivity augmentation: Once the coverage is done, there is no guarantee that the graph is connected. Therefore there is a need to augment the set S_1 by adding new MRs (Mesh Routers) to connect the APs together. We apply a neighborhood based selection algorithm to find the next node to be inserted. The augmentation algorithm (which is not detailed in this paper) is recursive and stops when the final graph is connected (see Fig.6.c).

Gateway assignment: is based on a random selection from the set of nodes that are eligible to be gateways. However, this last design stage (gateway assignment) could be a subject of further investigation to improve network performance without changing the generic model.

For computational purposes, we use a symmetric adjacency matrix to represent the connectivity graph. We apply the fixed channel assignment algorithm described by Das et al. [18] and we implement Edmonds-Karp's max flow algorithm [19] to assign a value on each link y_{jl} using channel *q* to route a flow. All remaining constraints (i.e., 5-15) are then satisfied.



(a) *(b)*

Fig. 6: A feasible Particle position example:
(a)TSs locations, TSs assigned to CLs. (b) S1 augmented, MGs selected.

4) *Breeding Potential Planning Solutions: The WMN Planning Algorithm*

For each particle in the swarm, the iterative algorithm (Algorithm 2) consists of constructing a subset S_1, mutating it, placing gateways and then assigning flows and channels. The most important phase is the repetitive task of constructing the set S_1 of APs locations to cover all TSs and then mutating it over and over until it satisfies at least all hard constraints. Then S1 is augmented to ensure the connectivity constraints.

After this solution-construction process, the velocities, the positions and the fitness (values of the two objective functions) of the particles are computed. Then some of these particles are inserted into the archive provided that they dominate or at least are non-dominated by the previously "archived" non-dominated solutions.

Algorithm2: Planning Solution
Input MaxGeneration, *pMut,*
Output ***Archive:*** `External repository`

t=0 ;
S_1 :=Construct_Initial_Solutions () // *see III.B.3*
while (t<MaxGeneration)
  for each particle in the swarm
    S_1 := Mutate(S_1,pMut) ;
    S := Augment(S1); /**Connectivity augmentation*
    Y_1:=Construct_connectivity_matrix(S) ;
    Y:= Assign_channels(Y1) ;
    G := PlaceGateways(Y); /**Gateway assignment*
    Compute_flows(G) ;
    Construct_New_Particle();
  endfor
  Compute_Velocities(); /* *As described in section III.A.1*
  Update_Positions();
  /* *New position= current position + computed velocity*
  Evaluate_Particles(); /*`compute functions f1 and f2`

```
    Archive ← Insert_feasibleNonDominated_Solutions();
    Update_ParticuleBest();
    t++
endwhile
```

A position in the search space is a solution to our planning problem; however, the values, returned by Update_Positions() procedure, are not guaranteed to be integers (0 or 1). For this purpose, we add a final process that we call *particle filtering* to allow only particles with a considerable progress to change to 0 (respectively 1). If the difference between the two positions (initial and updated one), that a particle gets in the search space, goes beyond a given threshold α (based on experiments, we set α to 0.3), then, the final position will be the reverse of the initial one (i.e., 0 if it was 1 and vice-versa); otherwise, the new position is discarded (the particle remains in its original position for further improvement). Thus, all retained positions are 0-1 integers.

IV. Numerical Experiments and Analysis

In this section, we present and discuss the preliminary results obtained by experimenting both models. We consider WMN key parameters the following: n, m, R, the gateway factor cost p_j, and d_i the client demands.

We also define the Standard Setting (SS) of the WMN key parameters as the following: SS= [(n:150),(m:49), (d_i:2Mb/s), (u_{jl}:54Mb/s), (v_j:54Mb/s), (M:128Mb/s), (c_j:200),(p_j:8*c_j,),(R:3),(k:11)]. Our numerical experiments given below are based on this SS setting.

We study the performance of our algorithm over grid graphs and under many deployment scenarios. For practical reasons, the throughput objective of the flow-capacity model is rewritten as a minimization of the inverse of the overall network flow-capacity aggregate.

A. Parameter Settings

The positions of the n TSs are randomly generated. A run of our algorithm involves 100 generations each with a population size and an archive size of 50 and 20 particles respectively. It must be noted that in our very recent experiments [20],[21], we came to a conclusion that mutating at a rate of 50% (*pMut*=0.5) of the population leads to the best Pareto front of optimal solutions. Our results are extracted from 10 runs for variation (scenario) of each of the key parameter.

B. Plotting and graphs interpretation

For each model and each key parameter variation, the planning objectives (deployment cost against performance) that constitute a (Pareto) front of non-dominated solutions are plotted in a (objective space) graph. Important characteristics of the fronts such as the number of the solutions, the width of the spectrum of the solutions, the uniform-distribution of the solutions, can all prove very important in decision making. In addition, for each scenario we plot the device utilization graphs.

C. Results and Analysis of Key parameters variation

1) Effect of number of candidate locations m

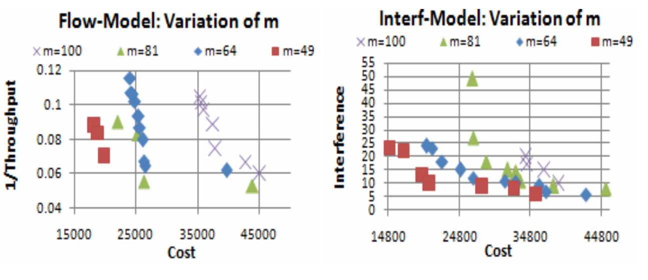
Results from Fig. 7 and Fig.8 show that there is consent in both models that a 7x7-grid is the best in satisfying the Standard Setting *SS*. From a decision making perspective, the cardinality, the width of the spectrum and the spacing between the planning solutions are better in Interference Model. These observations, drawn from Fig.7, suggest that a network planner with 'flexible' requirements would necessarily opt for Interference Model as it offers better diverse planning solutions.

It is clear that Interference Model is rather more careful in using the gateways (NG). It tends to add more routers (NR) if necessary. Notice that in both models, a higher number of candidate locations leads to an increase in the number of routers and gateways even for the same number of users (see Fig. 8). The reason is the fact that increasing the number of CLs increases the probability of a MC not being connected to an AP through a multi hop wireless path, which leads to installing more nodes.

2) Effect of changing the number of radio interfaces R.

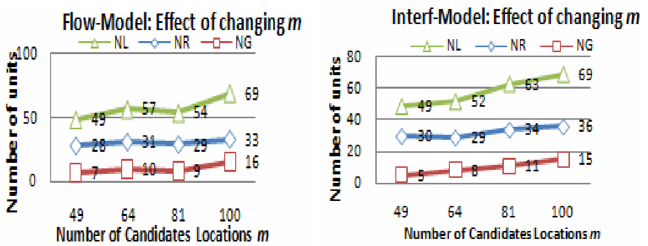
We conducted four experiments by varying R (with 11 channels) from 2 to 5. Interference Model seems to be more careful than Flow Model when increasing the number of radio interfaces. Indeed when shifting to higher number of radio interfaces, the planning solutions are at least as good as those with less number of radio interfaces. Regarding the Pareto front, notice that increasing the number of radios increases the number of non-dominated solutions offered to the network planner and provide the best Pareto front (when R=5) as shown in Fig. 9. On the other hand, Flow Model shows a disruption when the number of radios goes from 4 to 5 (see Fig. 10.a). The non-dominated planning solutions are not well stretched nor evenly spaced as those in Interference Model.

As can be seen in Fig. 10, the number of gateways decreases the more we add radio interfaces. However, for Flow Model, this number increases when we pass from 4 radio interfaces to 5. This can be caused by the high level of interferences which leads to look for alternative paths to route the traffic forcing more gateways to be installed.



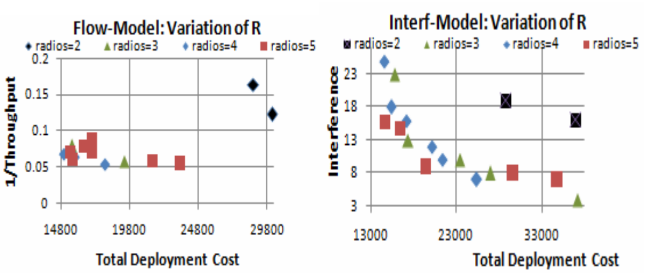
(a) (b)

Fig.7.Pareto Fronts of Planning Solutions For different Grids. (a) Flow-Model, (b) Interference Model.



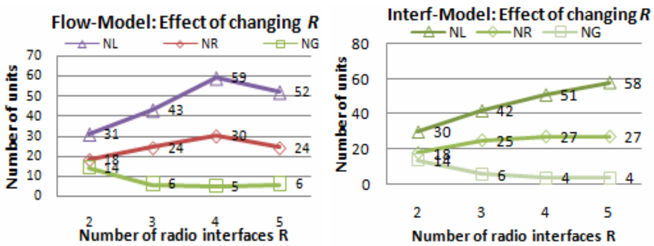
(a) *(b)*

Fig.8. Network Devices Utilization For Different Grids. (a) Flow-Model, (b) Interference Model.



(a) *(b)*

Fig.9. Pareto Fronts of Planning Solutions For different radio interfaces. (a) Flow-Model, (b) Interference Model.

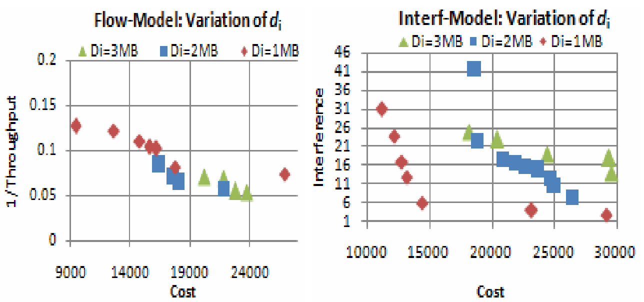


(a) *(b)*

Fig.10. Network Devices Utilization For Different Radio Interfaces. (a) Flow-Model, (b) Interference Model.

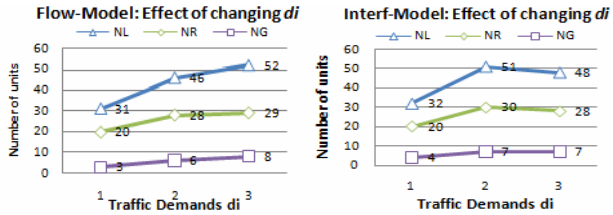
3) *Effect of changing the demand d_i*

Both models return no solution when d_i is more than 3Mb/s. That is simply because a 7x7 grid (along with how the SS is set) is too small to handle all the 150xd_i overall network demands. On another side, Interference Model returns more planning solutions; however Flow Model seems to better handle the increase of demands. This can be seen from Fig.11.*a* where the fronts for d_i=1,2 and 3 do not dominate each other. As can be seen From Fig. 12.), when demand increases the number of gateways increases accordingly to satisfy connectivity constraints by creating new routing paths. More relays than APs are added in order to connect these APs to newly added gateways.



(a) *(b)*

Fig.11. Pareto Fronts of Planning Solutions For different demands. (a) Flow-Model, (b) Interference Model.



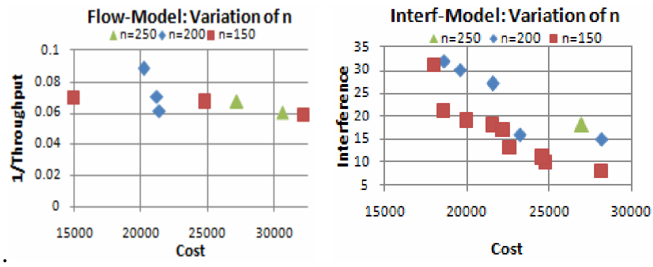
(b) *(b)*

Fig.12. Network Devices Utilization For Different Demands. (a) Flow-Model, (b) Interference Model.

4) *Effect of changing the number of Traffic Spots n*

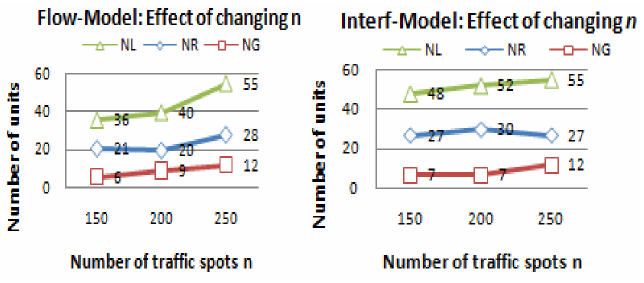
As in the previous experiments, Fig. 13 shows that more and diverse planning solutions are produced by Interference Model.

Compared to Flow Model, Interference Model requires fewer gateways, routers, and links to be added when more users are added in (see Fig. 14). This implies that Interference Model may be better in handling the scalability issue.



(a) *(b)*

Fig.13. Pareto Fronts of Planning Solutions For different Traffic Spots. (a) Flow-Model, (b) Interference Model.



(a) *(b)*

Fig.11. Network Devices Utilization For Different Traffic Spots. (a) Flow-Model, (b) Interference Model.

V. Conclusion

The bulk of the contributions in planning WMNs assume a fixed topology and use exact methods to perform the optimization process. Therefore, they are all bound to medium size instance problems and optimize a single objective, namely the network deployment cost. In this context, we proposed a generic WMN planning model where the two objectives of deployment cost and network throughput are optimized simultaneously. While the deployment cost is trivial, maximizing the throughput can be achieved in two ways, namely flow maximization or interference minimization. Based on this, we instantiated two specific WMN planning models:a flow-capacity based model (Flow Model) and an interference-based model (Interference Model). We proposed a new metric to measure the network interference level and used it as the cornerstone for the throughput objective function of the second model. We conducted some numerical experiments on both models to study the impacts of some key parameter variations on network performance. In the light of the results shown in Section IV, the Interference Model gives a broader set of non-dominated solutions, favors cost-effective solutions, and guarantees a diverse and well dispersed set of solutions. As future work, we plan to investigate the issue of selecting gateways to guarantee a minimum APs-MGs communication delays.

REFERENCES

[1] E. Amaldi, A. Capone, M. Cesana, F. Malucelli. Optimization Models for the Radio Planning of WMNs., *Computer Networks, 2007*

[2] K. Jain, J. Padhye, V. N. Padmanabhan, and L. Qiu. Impact of interference on multi-hop wireless network performance. *ACM MOBICOM, 2003*

[3] A. Raniwala, T. Chiuch, Architecture and Algorithms for an IEEE 802.11-based Multi-channel WMN, *IEEE INFOCOM 2005,* 2005

[4] R. Draves, J. Padhye, and B. Zill, Routing in multi-radio, multi-hop wireless mesh networks. *ACM MOBICOM*, 2004

[5] M. Alicherry et al. , Joint Channel Assignment and Routing for Throughput Optimization in Multi-radio WMNs, *ACM MOBICOM*, 2005

[6] D. Benyamina, A. Hafid, M. Gendreau, N. Hallam : Managing WMN: Analysis and proposals, *IEEE WIMOB*, 2007

[7] S. Sen and B. Raman, Long distance wireless mesh network planning: problem formulation and solution. *Conference on World Wide Web*, 2007

[8] C. Chen and C. Chekuri. Urban wireless mesh network planning: The case of directional antennas. *Technical Report* UIUCDCS-R-2007-2874, Dept. of Computer Science, UIUC, 2007

[9] R. Chandra, L. Qiu, K. Jain, and M. Mahdian. Optimizing the placement of internet taps in wireless neighborhood networks. *IEEE ICNP*, 2004

[10] B. Aoun, R. Boutaba, Y. Iraqi, and G. Kenward, Gateway Placement Optimization in Wireless Mesh Networks with QoS Constraints, *IEEE Journal on Selected Areas in Communications*, vol. 24, 2006

[11] A. Beljadid, A. Hafid, M. Gendreau, Optimal Design of Broadband Wireless Mesh Networks, *IEEE CLOBECOM*, 2007

[12] A. Capone, M. Cesana, I. Filippini and F. Malucelli, Optimization models and methods for planning wireless mesh networks, *Computer Networks*, 2008 (to appear).

[13] J. Kennedy and R. C. Eberhart, Particle Swarm Optimization, *In Proc.of the IEEE International Conference on Neural Networks*.1995.

[14] C. A. Coello, and M. S. Lechuga, Mopso: A proposal for multiple-objective particle swarm optimization, *Proceedings of IEEE, World Congress on Computational Intelligence*, 2002.

[15] C. R. Raquel, C. Naval, An effective use of crowding distance in multi-objective optimization, ACM Conf. on Genetic and Evolutionary computation, 2005.

[16] J. Robinson and E. W. Knightly, A performance Study of Deployment Factors in WMNs, *IEEE INFOCOM,* 2008

[17] F. Li, Y. Wang, and X. Y. Li, Gateway Placement For Throughput Optimization in WMNs, *IEEE ICC*, 2007

[18] A. K. Das, H. Alazemi, R. Vijaykumar, S. Roy. Optimization models for fixed channel assignment in Wireless Mesh Networks with Multiple Radios, *IEEE SECON*, Sept. 2005.

[19] J. Edmonds and R. M. Karp . Theoretical improvements in algorithmic efficiency for network flow problems. *Journal of the ACM , 1972.*

[20] D. Benyamina, A. Hafid, M. Gendreau, Wireless Mesh Network Planning, A Multi-objective Optimization Approach, *IEEE BROADNET*, 2008.

[21] D. Benyamina, N. Hallam, Multi-criteria optimization approach for the deployment planning problem of multi-hop wireless networks, WSEAS CIS, 2009.