

Gateways Congestion-Aware Design of Multi-radio Wireless Networks

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Abstract. In Wireless Mesh Networks (WMNs), traffic is mainly routed by WMN Backbone (WMNB) between the mesh clients and the Internet and goes through mesh gateways. Since almost all traffic has to pass through one of the MGs, the network may be unexpectedly congested at one or more of them, even if every mesh router provides enough throughput capacity. In this paper, we address the problem of congestion of gateways while designing WMNs. We propose a simultaneous optimization of three competing objectives, namely network deployment cost, interference between network channels and congestion of gateways while guaranteeing full coverage for mesh clients. We tailor a nature inspired meta-heuristic algorithm to solve the model whereby, several trade-off solutions are provided to the network planner to choose from. A comparative experimental study with different key parameter settings is conducted to evaluate the performance of the model.

Keywords: Wireless mesh network design problem, Multi-objective model, simultaneous optimization, Congestion of gateways, Meta-heuristic method.

1 Introduction

The success of the Wireless Mesh Network (WMN) technology has caused a paradigm shift in providing high bandwidth network coverage to users. The Wireless Mesh Network Backbone (WMNB) consists of mesh routers (MRs) interconnected with each other through point-to-point wireless links to provide connectivity to mesh clients (MCs). MRs responsible for providing internet access to clients are called access points (APs) while other more expensive MRs, that are equipped with a gateway capability through which they interface with Internet, are called mesh gateways (MGs).

WMNs are highly reliable, scalable, adaptable and cost-effective. They are already pervasive in many diverse environments, such as home networking, enterprises, and universities. Nevertheless, users experience a number of problems, such as intermittent connectivity, poor performance and lack of coverage [1]. In Multi-Radio Multi-Channel (MR-MC) networks, MRs are equipped with multiple network interfaces, thus allowing simultaneous communications over orthogonal channels. However, since the number of available orthogonal channels is limited, interferences happen causing network performance degradation. A proper WMN design is a

fundamental task; if addressed carefully it can considerably improve the network efficiency in terms of coverage, throughput, delay and capacity.

Basically, the design of WMNs involves deciding where to install the network nodes (given a set of candidate locations), which type of nodes to select (AP, MG or simple MR), how many of these nodes to install, and which channel to assign for each node interface, while guaranteeing users coverage, wireless connectivity and traffic flows at minimum cost.

Exploiting the trade-offs among network deployment cost, network throughput, and congestion level of gateways, we propose in this study, a new approach to address the problem of WMNs design. Indeed, minimizing the cost requires stingy resources utilization (deploying fewer routers and/or gateways) which impacts the network performance. With few routers deployed, the traffic is routed on longer paths to get to its destination, thus increasing communications delays. With few gateways deployed, congestion may happen (since all traffic traverses gateways to and from the internet) affecting network throughput. Conversely, deploying more resources (higher deployment cost) helps providing shorter paths and less congested gateways; however, this may cause high interference levels and thus degrade network performance. In fact, optimizing one of these criteria will affect/undermine other(s) criteria(s). Therefore, it is difficult, if not impractical, to have a solution that is optimal in all criteria.

In this paper, we define a multi-objective optimization model that minimizes the network deployment cost, maximizes the network throughput (by minimizing the network interference level), minimizes congestion level of gateways, and guarantees a full coverage to mesh clients.

WMN design problem belongs to the set of Multi-commodity capacitated network design problems (MCNDPs). They are known to be hard combinatorial optimization problems for which several solution strategies have been developed. A number of these strategies involve the relaxation of some problem constraints and the strengthening of the model through the addition of valid inequalities [2]. In this study, we propose a multi-objective approach to search for the near-optimal set of non-dominated planning solutions. This set of trade-off solutions is very much desired by engineers who prefer to have several solutions in hand before taking decisions. An evolutionary population-based multi-objective algorithm based on particle swarm optimization (PSO) is developed to solve the proposed model.

Related research has mainly focused on the problem of performance improvement in order to effectively use WMNs; however, most of existing solutions assume a priori fixed topologies [3], [4], [5], [6]. Indeed, the design of a WMN is still in its infancy and many challenges remain open. Some studies [7],[8] consider topologies where gateways are fixed *a priori*, while others [9], [10], [11], [12], [13], [14], [15], [16], [17], [18] attempt to optimize the number of gateways given a fixed layout of mesh routers. Very recent contributions in, [19], [20] however, propose WMN planning schemes where the locations of routers and gateways are not fixed. Nevertheless, all these studies consider in a way or another minimization of a single objective based on the deployment cost. We also stress the fact that users' coverage is not considered in [19] while QoS requirements, such as delay and throughput are not considered in [20]. None of these approaches tackle the issue of gateways congestion level in their problem formulation.

The key contributions of the paper can be summarized as follows: (1) a *novel* multi-objective optimization model; and (2) A meta-heuristic algorithm to resolve the model for real-size networks. To the best of our knowledge, there has been so far no real attempt to model WMN design problems using a pure multi-objective approach. The only work worth mentioning is presented in [11]; it concerns only gateways placement problem where locations of other mesh nodes are known *a priori*. Bing et al. [11] use a multi-objective approach but then aggregate the many objectives into a single one representing a weighted sum of objectives value. This is a classical approach to handle Multi-Objective Problems. However, the biggest problem with this aggregate approach is the inability to find solutions in non-convex fronts [21]. Moreover, the setting of the relative weights for the different objectives is subjective and often leads to favoring some and penalizing others.

The remainder of the paper is organized as follows. Section 2 defines the WMN planning problem and presents the mathematical formulation of the problem solution. The solution approach and the population-based algorithm are described in Section 3. Section 4 evaluates the proposed WMNs planning approach and Section 5 concludes the paper.

2 Network Model and Problem Formulation

Let I be the set of positions of traffic concentrations in the service area (Traffic Spots: TSs) and L 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 all TSs. This will constitute the set of APs.
- Defining the gateways 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 the nodes in G .
- Maintaining the cardinalities of G and S small enough to satisfy the financial and performance requirements of the network planner.

2.1 Network Model

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

Given n TSs and m CLs, let $I=\{1,\dots,n\}$ and $L=\{1,\dots,m\}$. 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 CLs j and 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 CLs j and l can be connected via a wireless link. We define other 0-1 decision variables x_{ij} , g_j , t_j in our formulation

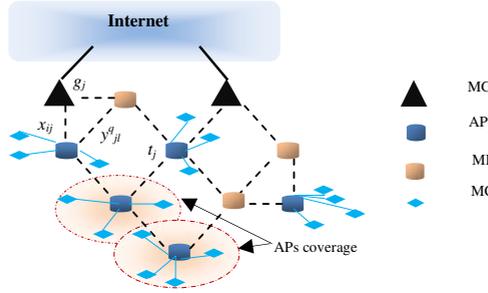


Fig. 1. WMN Planning Problem. A MC covered by many APs is assigned to only one AP.

(see Fig. 1). The variable 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 .

We consider a multi-radio multi-channel WMN and 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 $C = \{1, \dots, c\}$ and c can be at most 12 orthogonal channels if IEEE802.11a 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 , $q \leq k$, $y^q_{jl} = 1$ if a wireless link from CL j to CL l using channel q ($q \leq k$) exists. 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 link between a gateway j and the Internet.

We represent our WMN as an undirected graph $G(V, E)$, called a connectivity graph. Each node v represents a mesh node which can be AP, MR or MG. The neighborhood of v , denoted by $N(v)$, is the set of nodes residing in its transmission range. A bidirectional wireless link exists between v and every neighbor u in $N(v)$ and is represented by an edge (u, v) . The maximum degree of G denoted by Δ is bounded by the number of radio interfaces of each node v . Table 1 summarizes the notation used in the problem formulation.

Table 1. List of Main Parameters/Variables Used in Model Formulation

<i>Par./V</i>	<i>Description</i>
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})
v_j	Capacity limit for AP radio access interface
c_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}

Table 1. (continued)

x_{ij}	Assignment of TS _i to CL _j
z_j^q	Installation of a device at CL _j , assignment of channel q, q<k
y_{jl}^q	Establishing a wireless communication on q Between (CL _j ,CL _l)
f_{jl}^q	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_{jl}^q

2.2 Problem Formulation

The planning approaches in [19], [20] focus on one or two optimization criteria at the expense of other network characteristics. Kodialam et al. [22] report that there exist multiple design criteria for WMNs; their proposal allows optimizing a single objective function at a time but no generic method for dealing with the multiple metrics is provided. The work in [12], propose a model (within a tool) to measure the performance of a designed WMN prior to its deployment. The main idea is to define: (1) a set of metrics that work as evaluation criteria for WMNs; and (2) a weighted combination of the metrics for a simultaneous use of multiple evaluation criteria in WMNs optimization. In the following, we describe the main criteria considered in our problem formulation.

Deployment Cost. Minimum installation cost is a fundamental issue in deploying WMNs. Increasing the number of MGs may increase the network throughput and may lead to a smaller number of gateway bottlenecks. Thus, we need to determine the right places of APs and MGs that result in: (1) a minimum number of APs that provides full coverage; and (2) a minimum number of MGs that provides enough throughput while satisfying QoS constraints. The first objective function to optimize computes the total cost of the network including installation cost c_j and additional MGs installation cost p_j .

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

Network Throughput. Because of the limited number of orthogonal channels, the spatial reuse of channels results in high level of interferences; this degrades the network performance by lowering its overall throughput. We optimize the network throughput by favoring topologies with well balanced channel reuse. The number of occurrences of a channel q' , denoted by $O_{q'}$, is used to compute the gap between the balanced allocation of channel q and the current allocation.

$$\varphi_q = \text{Max} |O_q - O_{q'}| \quad \forall q, q' \in C \quad \text{Where,}$$

$$O_q = \sum_{j,l \in L} y_{jl}^q \quad \forall q \in C$$

Our aim is then to minimize this gap; this is the second objective function of our model.

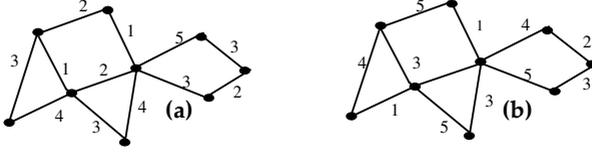


Fig. 2. Same topology with two different channel allocations.

- (a) $O_1=2, O_2=3, O_3=4, O_4=2, O_5=1$ ($\varphi_1=2, \varphi_2=2, \varphi_3=3, \varphi_4=2, \varphi_5=3$),
 (b) $O_1=2, O_2=2, O_3=3, O_4=2, O_5=3$ ($\varphi_1=1, \varphi_2=1, \varphi_3=1, \varphi_4=1, \varphi_5=1$).

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

Illustration in Fig. 2 shows that, spatial channel reuse is better in (b) than in (a). The value of $\sum \varphi_q$ in (a) is equal to 12 while $\sum \varphi_q$ in (b) is equal to 5. This is caused by the unbalanced reuse of some channels (i.e. 2 and 3) in (a).

Congested MGs. When all traffic to or from mesh clients (through APs) traverse a subset of network gateways, it may make these gateways congested; this leads to unfair/unbalanced use of gateways (i.e., some gateways are congested while others are barely used). In this paper, we consider fairness, in using gateways, as another performance metric to be optimized.

One of the conflicting objectives we plan to optimize is to minimize this unfair use of MGs, measured by the standard deviation of flows entering network gateways, as given below.

$$\text{Min} \sqrt{\frac{\sum_{l \in G} F_l^2}{\sum_{l \in G} F_l}} . \quad (3)$$

Full Coverage Criterion. The coverage is defined as the size of the physical area where TS has a route to the core network. The area depends on the locations of APs but more importantly on the amount of APs that have a route to the core network. APs have partially overlapping coverage areas as shown in Fig.1. The APs should be located such that all TSs are covered. Constraint (4) is used to make sure that a given TS i is assigned to only one CL j . Inequality (5) implies that a TS i is assigned to an installed and covering mesh node j .

$$\sum_{j \in L} x_{ij} = 1 . \quad \forall i \in I \quad (4)$$

$$x_{ij} \leq a_{ij} t_j . \quad \forall i \in I, \forall j \in L \quad (5)$$

The optimization model is also subject to other constraints given as follows:

$$\sum_{i \in I} d_i x_{ij} + \sum_{l \in L} \sum_{q \in C} (f_{ij}^q - f_{jl}^q) - F_j = 0. \quad \forall j \in L \quad (6)$$

$$\frac{f_{jl}^q}{u_{jl}} \leq y_{jl}^q. \quad \forall q \in C, \forall j, l \in L \quad (7)$$

$$\sum_{i \in I} d_i x_{ij} \leq v_j. \quad \forall j \in L \quad (8)$$

$$F_j \leq M g_j. \quad \forall j \in L \quad (9)$$

$$2y_{jl}^q \leq b_{jl} (z_j^q + z_l^q). \quad \forall q \in C, \forall j, l \in L \quad (10)$$

$$g_j \leq t_j. \quad \forall j \in L \quad (11)$$

$$\sum_{l \in L} y_{jl}^q \leq 1. \quad \forall q \in C, \forall j \in L \quad (12)$$

$$\sum_{q \in C} z_j^q \leq R t_j. \quad \forall j \in L \quad (13)$$

$$x_{ij}, z_j^q, y_{jl}^q, t_j, g_j \in \{0,1\} \quad \forall i \in I, \forall j, l \in L, \forall q \in C \quad (14)$$

$$f_{jl}^q, F_j \in R \quad \forall j, l \in L, \forall q \in C \quad (15)$$

Constraint (6) defines the flow balance for each mesh node j . Constraint (7) stipulates that a flow on a link cannot exceed the traffic capacity of that link. Constraint (8) denotes that the aggregated demand received by mesh node j does not exceed the capacity of the radio access interface. Constraint (9) implies that the flow routed to the Internet 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. Constraint (10) forces a link between two CL j and CL l using the same channel q 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 (local channel interference). Constraint (13) with objective function (2) prevents local and global imbalances in channel allocation. Constraint (14) 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. We consider the constraint (6) a soft constraint while the remaining constraints are considered hard constraints. The WMN planning system attempts to optimize the three objectives and satisfy all hard and soft constraints as defined above.

3 Solution Approach

The rationale behind our planning is:

- 1) The maximization of the network throughput, by minimizing the level of interferences;
- 2) The minimization of gateways congestion level;
- 3) The minimization of the total deployment cost by selecting a minimum number of routers/gateways and choosing their positions so that the network connectivity is ensured while providing full coverage to all mesh clients.

WMN planning is a fairly complex problem; its difficulty lies in the fact that it tries to simultaneously address all the criteria. Joint optimization of the above criteria is defined as a multi-objective search problem. As stated earlier, solving a Multi-Objective Optimization Problem (MOOP) returns a set of Pareto-optimal solutions. Each solution represents a different trade-off between the objectives that is said to be “non-dominated”. We use a multi-objective approach based on Particle Swarm Optimization (PSO) technique [21] to solve our planning problem.

3.1 Solving Multi Objective Optimization Problem (MOOP)

In the last two decades, there have been growing interests in the field of multi-objective optimization to solve real-world problems. Good introduction to this field of research can be found in [21], [23]. Without loss of generality, we assume that the various objectives are to be minimized. Then, the optimization of a MOP can be formulated as:

$$\begin{aligned} \text{Minimize } y = f(x) &= [f_1(x), f_2(x), \dots, f_N(x)] \\ \text{where } x &= [x_1, x_2, \dots, x_D] \in \text{decision space} \\ \text{and } y &= [y_1, y_2, \dots, y_N] \in \text{objective space} \end{aligned}$$

One of the most difficult parts encountered in practical network design optimizations is the handling of constraints. For a constrained problem, the decision variables x are subject to a set of constraints. Every decision variable vector x in the decision space is evaluated through the objective functions. The objective values are then represented as points in the objective value space (Fig.3).

Definition 1 (Pareto Dominance): For two decision vectors a and b , a is said to dominate b or $a \prec b$ if and only if:

$$\begin{aligned} \forall i \in \{1, \dots, N\} \quad f_i(a) \leq f_i(b) \quad \text{and} \\ \exists i \in \{1, \dots, N\} \quad f_i(a) < f_i(b). \end{aligned}$$

Definition 2 (Pareto Optimality): A decision vector a is said to be Pareto Optimal if and only if a is non-dominated.

Definition 3 (Pareto Front): The Pareto Front is a set of all Pareto Optimal solutions (non-dominated solutions) in the objective value space.

Fig.3 shows that points that lie in the three dimensional area are dominated by the origin point (dotted point) of that area.

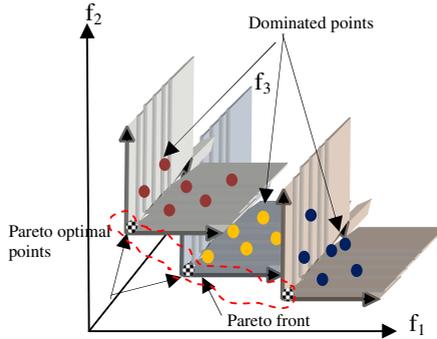


Fig. 3. Pareto Dominance, Optimality and the Front for 3 objective functions

We adapt MOPSO, Multi-Objective Particle Swarm Optimization, as the optimization technique [21], [24] to solve the WMN design problem. We call the variant we use, VMOPSO. Apart from finding the non-dominated solutions, achieving a well-diverse Pareto solution front is the primary goal of the MOOP. 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 [21]. In the following, we provide more details on how the multi-objective generic model is solved using VMOPSO.

3.2 VMOPSO Algorithm

Further the crowding distance incorporated as the deletion method applied on the external repository REP to maintain solutions diversity, we also add a constraint handling mechanism for solving constraints optimization problem, such as WMN design problem.

The crowding distance value, initially defined in [26], is the average distance of two neighboring solutions. The boundary solutions with the lowest or the highest objective function value are given an infinite crowding distance values; thus, 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. Personal best solution ($pBest$) and global best solution ($gBest$) are the most important parameters of a particle that the optimizer determines to guide the swarm, in order to obtain a front of optimal solutions. A formal description of VMOPSO is given below.

Algorithm 1: VMOPSO Main Algorithm

Input $fmut$: Mutation factor, $MaxGeneration$

Output REP : Repository

- 1: Initialize the swarm (Build feasible solutions that satisfy all the constraints defining the optimization problem)
 - For** each particle i in the swarm
 - a. Initialize feasible position,
 - b. Set the personal best guide $pBest$ to that position

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c. Initialize velocity /* see definition below*/
d. Specify lowerBoundi and upperBoundi /*0-1 for integer
   variables*/
e. Set the global best guide gBest to pBest
End For
2: Initialize the iteration counter t=0
3: Evaluate all particles in the swarm /*evaluation of objective functions*/
4: Store non dominated solutions found in step 1 into REP.
5: Repeat
a. Compute the crowding distance values for each j∈REP
b. Sort REP in descending crowding distance values
c. For each particle i in the swarm
   i. Set gBest[i] to the randomly selected particle from the
      top 10% of the sorted REP.
   ii. Compute the new velocity, position of particle i
   iii. Check particle boundaries, if violated change particle
        search direction (i.e., velocity(i) * -1)
   iv. If (t < MaxGeneration*fmut) then mutate
   v. Evaluate particle i
      End for
d. Check for constraints satisfaction
e. Check for non dominance of all particles in the swarm,
   insert non-dominated and feasible solutions into REP and
   delete dominated solution from REP
f. If REP is full then
   i. Compute the crowding distance values for each j∈REP
   ii. Randomly selected particle from the bottom 10% of the
        sorted REP (most crowded portion).
   iii. Replace it with the new solution.
      End if
g. Update pBest
h. Increment t
Until (t= MaxGeneration)

```

During the exploration of the search space, each particle has access to two pieces of information: the best Potential Solution (PS) that it has encountered (*pBest*) and the best PS encountered by its neighbors (*gBest*). This information is used to direct the search by computing velocities: $velocity[i] = iw * velocity[i] + r_1 * (pBest[i] - position[i]) + r_2 * (REP[gBest] - position[i])$, where r_1, r_2 are random numbers in the range of [0,1]. *iw* is the inertia weight. A large inertia value will cause the particles to explore more of the search space, while small one directs the particles to a more refined region. The importance of inertia weight was pointed out by Shi and Eberhart [25] who reported that 0.4 is the best value.

3.3 Solving the WMN Planning Problem Using VMOPSO

Physical Representation Layout. In [16] and [17], authors have shown the benefits of grid topologies over random topologies where coverage, connectivity, average fair capacity, and network throughput are better in grid topologies, especially square grid topologies, than random topologies. In this study, we adopt a *square-grid-like* layout as the physical representation of our WMN planning. Each grid cell corner is a Candidate Location 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 with respect to Constraint (13).

Particles Encoding. In Particle Swarm Optimization, 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_j^q), device connectivity (y_{ji}^q), gateway existence (g_j), link flows (f_{ji}^q), and gateway/backbone link flows (F_j). All decision variables are 0-1 value variables except flow variables (f_{ji}^q, F_j) that are assigned real (float) values. A feasible solution must satisfy all hard and soft constraints. During the search, non-feasible solutions that violate only the soft constraint (6) can be included in the population. This increases the likelihood of a non-feasible solution to mutate and provide a feasible one in later generations. The followings are the phases involved in the resolution of the proposed model.

Building Initial Feasible Solutions. WMN planning problem is a constrained optimization problem; therefore, 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 (4) to (15) represents the most challenging part in our optimization process.

First, we start by selecting randomly a CL_j from the set of CLs that cover that TS_i (Fig 4.a). An AP (Access Point) is then installed at this location CL_j only if it has not yet been selected. By applying the same procedure to all TSs, we obtain the set S_1 of APs locations that provide 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 (4) and (5) are satisfied and the initial set contains vertices of a disconnected graph as shown in Fig.4.a.

Once the coverage is done, 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 consists, mainly, of choosing the closest neighbor in one component graph to any node of a different component. Then, the path between the two nodes is augmented

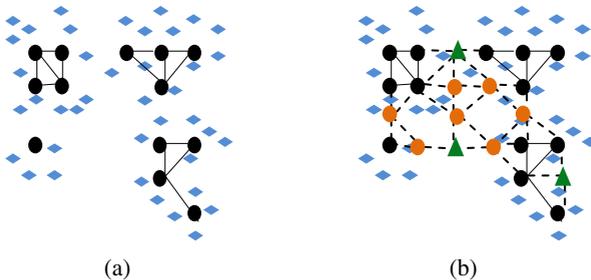


Fig. 4. A Feasible Particle position example. (a): TSs assigned to CLs and a subset S_1 is formed (b): S_1 is augmented and MGs are selected.

(place a router j at the appropriate CL_j $j \in L-S_1$). The algorithm stops when the final graph is connected (see Fig.4.b) and finally, gateways are selected from the set of eligible positions to place gateways. 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. [27] and we implement Edmonds-Karp's max flow algorithm [28] to assign a value on each link y_{jl} using channel q to route a flow. All remaining constraints (i.e., 6-15) are then satisfied.

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, S_1 is augmented to ensure the connectivity.

After this solution-construction process, the velocities, the position and the fitness (values of the three 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.

Algorithm 2: Planning Solution

Input $fmut$: Mutation factor, $MaxGeneration$

Output REP : External repository

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t=0;
Construct_Initial_Soft&Hard_feasible_solutions();
While (t<MaxGeneration)
  For each particle in the swarm
     $S_1 \leftarrow$  Mutate( $S_1, fmut$ ) ;
     $S \leftarrow$  Augment( $S_1$ );
     $Y_1 \leftarrow$  Construct_connectivity_matrix();
   $Y \leftarrow$  Assign_channels( $Y_1$ );
   $G \leftarrow$  PlaceGateways();
  Compute_flows();
  Construct_New_Particle() Endfor
Compute_Velocities();
Update_Positions();
Evaluate_Particles();
 $REP \leftarrow$  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 move (to the new position) 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 is 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). Consequently, all retained positions are then 0-1 integers.

3.4 Complexity Study

Let the number of functions to be optimized be M , and the size of the swarm and the repository be n and N , respectively. In Algorithm 2, the complexity is mainly influenced by checking for feasible non-dominated solutions and the diversity computation operation. However, the cardinality of the set of feasible solutions generated iteratively is much lower than the size of the repository allowed, due to the number of constraints a solution has to satisfy. Consequently, the diversity computation function, based on a crowding factor calculation, is very rarely performed. For checking a particle for its non dominance within $N+n$ particles, $M(N+n)$ comparisons are needed. Therefore, the worst case complexity of this function will be $O(M(n+N)^2)$. Considering the worst case complexity by assuming that the repository truncation is possible, sorting on the basis of each objective will have a complexity of $O(MN\log(N))$. Then, the worst case complexity (with $n+N$ elements in the repository) is $O(M(N+n)\log(N+n))$. Thus, the overall worst case complexity is $O(M(N+n)^2)$.

4 Experimentations and Results Analysis

In this section, we evaluate the performance of our approach. We consider the following key parameters of WMNs: the number of TSSs n , the number of CLs m , the client demands d_i , and the number of radio interfaces R . The purpose of our experimental approach is to study the performance of our model by varying one WMN key-parameter at a time while maintaining others fixed. For this purpose, we define the Standard Setting (SS) of the WMN as the following: SS=[(n :150), (m :49), (d_i :2Mb/s), (u_{ji} :54Mb/s), (v_j :54Mb/s), (M :128Mb/s), (c_j :200), (p_j : $8*c_j$), (R :3), (k :7)]. The algorithm is coded in the Java programming language and all the experiments were carried out on a Pentium M 1.5 GHz.

Unless stated otherwise, we use the standard setting SS. The positions of the n TSSs are randomly generated. A run of our algorithm involves 200 generations each with a population size and archive size of 30 and 20 particles respectively. It must be noted that in our very recent experiments [29], mutating at a rate of 50% of the population leads to the best Pareto front of optimal solutions when compared to optimal solutions. Therefore, we take $fmut=0.5$ as our standard setting for the remaining experiments.

4.1 Performance Evaluation

For each of the following key parameter variation studies (called scenarios), results are reported after 10 runs. Additional filtering process is required to maintain the non-dominance aspect of the collected Pareto fronts. We use OriginPro [30] to plot the 3D objective space graph of planning solutions. For a scaling purpose, the second and third objective values are multiplied by 10^3 . In addition, for each scenario we plot also the devices utilization graphs (only cheapest solutions are considered) in terms of total number of mesh nodes (MN), access points (AP), gateways (MG), and links (Links).

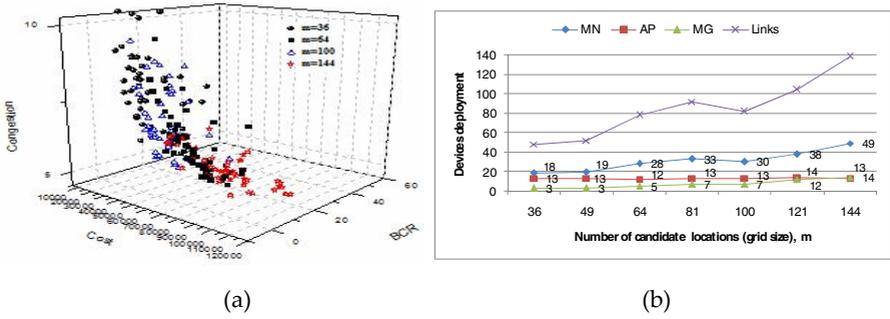


Fig. 5. Effect of changing the number of candidate locations m

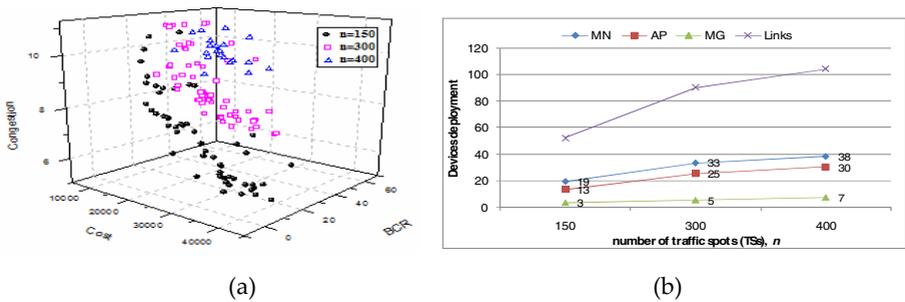


Fig. 6. Effect of changing the number of traffic spots n

Effect of Changing the Number of Candidate Locations m . Notice, from Fig.5.a, that a larger size of grid can improve the network performance (congestion of gateways decreases), but also increases the total deployment cost, which is highly affected by the number of gateways deployed. Therefore, in practice, the network planner has to decide on the appropriate grid size that satisfies both cost and performance requirements. Notice also, that a 10×10 -grid topology is shown to be the best in satisfying the Standard Setting (SS). As shown in Fig.5.b, the number of APs remains relatively stable. A higher number of CLs leads to an increase in the number of routers even for the same number of users. The fact of increasing the number of CLs increases the number of mesh nodes (AP, MR and MG) that are not connected to each other, which leads to install more MRs to construct multi-hop wireless paths between them. On the other hand, the increase of links to ensure connectivity constraints increases the network interference level, as shown in Fig. 5.a (BCR axis).

Effect of Changing the Number of Traffic Spots n . We also study how our algorithm (Algorithm 2) would behave when n varies. Naturally, when n increases (i.e., more mesh clients need to be covered and connected) then more routers need to be connected to the backbone. As shown in Fig. 6.b, the number of APs is increased to cover more mesh clients, in the same time the number of MGs is increased to connect them to the Internet while a smaller increase of MRs is observed to satisfy connectivity constraints. Fig. 6.a shows that the more mesh clients are connected, the

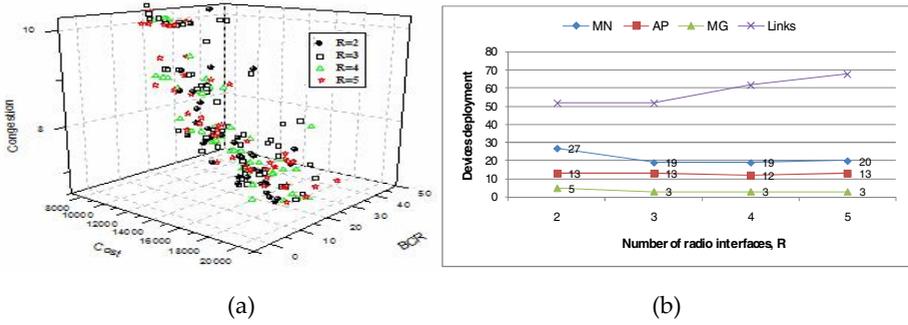


Fig. 7. Impact of the number of radio interfaces on network planning

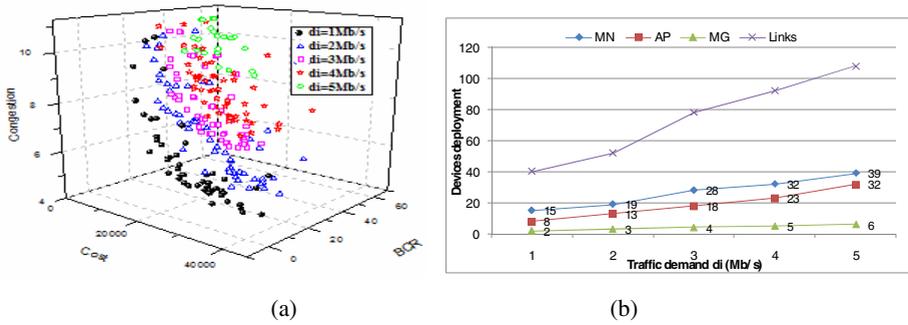


Fig. 8. Effect of varying traffic demand d_i on network planning

more gateways are congested, if the deployment cost is not adjusted accordingly. Given a set of alternative solutions, the network planner makes his/her final decision by selecting the best solution that fits best his/her financial/performance requirements.

Effect of Changing the Number of Radio Interfaces R . We gradually vary the number of radio interfaces from 2 to 5, each with 7 channels. The more radio interfaces we deploy the more links are established, and the less MGs we need. Notice, from Fig. 7.a, that $R=4$ provides the best Pareto front as it has a better solutions spectrum width and cardinality. Also, based on visual observation, the solutions of the same Pareto front ($R=4$) have less MGs congestion level compared to the other Pareto fronts. With respect to devices deployment, Fig.7.b, shows that the cheapest solution returned when $R=4$ is also the cheapest solution amongst all others ($R=2, 3$ and 5) as it requires a smaller number of APs, MGs, and MRs. Regarding the Pareto front, notice that increasing the number of radios increases the width of the spectrum of non-dominated solutions offered to the network planner.

Effect of Varying Traffic Demand. We further study demand variation. The results (Fig.8.a) show that when increasing demand d_i from 1 to 5Mb/s, the number of APs increases. This is expected; new APs are added to guarantee coverage to all mesh clients under capacity constraints. Notice also that the number of MGs increases accordingly to satisfy connectivity constraints by creating new paths to the newly

added APs. However, there hardly exist feasible solutions when d_i is more than 4Mb/s. This is because a 7×7 grid is insufficient to support the $d_i \times n$ demand. Fig. 8.b shows that when d_i increases, the interference level (BCR axis) and gateways congestion level increase for almost all Pareto solutions.

4.2 A Comparison with Related Work

Validating our results against other known models for WMN planning problems turns out to be “impossible” since it is unpractical to compare a set of Pareto (three-dimension) optimal solutions with a one-dimension optimal solution. Moreover, there is no close related work that considers congestion of gateways when designing WMN from scratch. Nevertheless, we can at least check the one common objective function (deployment cost) to see whether the results fall in the same range. We compare our results to the (only) closest related work reported in [20] that considers WMN design from scratch. We refer to the model in [20] as AML and to ours as MOBD. The authors in [20] used the following parameters setup ($d_i=3\text{Mb/s}$, $n=100$, $m=50$, $R=3$ and $k=11$.) and obtained a “single” planning solution which is the mean value over 10 runs. Using the same parameters setup, we obtained 71 non-dominated planning solutions (some of them are shown in Table 2). We report our cheapest and most expensive planning solutions together with the single solution of AML in Table 3.

The solutions of MOBD are numerous and diverse, ranging from very cheap solution (MOBD1 line in Table 3) to very expensive solution (MOBD2 line in Table 3) differing mainly by the measured performance indicators: (1) BCR: interferences over network channels; and (2) S.D: Gateways congestion level.

Results in Table 2 show that our approach tends to provide some solutions which may be more expensive than that of AML in some instances. The network performance is increased by increasing overall network throughput (by minimizing network interferences) and by minimizing network bottlenecks (MG nodes). None of such performance considerations is considered in AML model formulation, which is essentially a single-objective model. This fact led us to compare only the common objective (cost objective function) on a single objective basis. Table 3 shows that MOBD generates from 10% less expensive solution to almost double-price solutions when compared to AML generated solution for the same parameters settings.

Table 2. 9 solutions of MOBD,
 $d_i=3\text{Mb/s}$, $n=100$, $m=50$, $R=3$ and $k=11$

MR	AP	MG	Links	Cost	BCR	S.D.
21	12	3	74	9800	14	10.72
25	15	4	78	12200	13	10.75
27	15	4	80	12600	6	10.90
28	18	4	86	12800	8	10.66
29	16	4	90	13000	15	10.64
21	13	5	70	13200	16	9.88
21	14	5	70	13200	19	9.76
21	14	6	70	15000	6	8.82
34	17	9	124	23000	10	7.25

Only the first 8 solutions and the last (71th) solution are shown in TABLEII.

Table 3. Solutions of MOBD versus the solution of AML

	MR	MG	Links	Cost
AML	23.65	3.3	21.35	10660.0\$
MOBD1	21	3	74	9800.0\$
MOBD2	34	9	57	23000.0\$

MOBD1: Cheapest solution, MOBD2: most expensive solution ($c_f=200$, $p_f=8* c_f$).$

5 Conclusion

In this paper, we have addressed and formulated the WMN topology design problem. We have considered a simultaneous optimization of deployment cost, network interference level and congestion of gateways while satisfying other criteria. We proposed an efficient nature inspired search algorithm to solve the model formulated whereby different trade-off solutions are provided to the network planner to choose among. We carried out a detailed experimental study, to show and assess the effectiveness of our approach. In the light of the results shown in Section 4, and under many deployment scenarios, we observed the impact of the grid size and the number of radio interfaces on network performance. The variation of the number of mesh clients and the traffic demand has shown how network scalability is handled under our approach. Following the same strand, next we will investigate optimal gateways placement and its impact on network performance.

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