A Multi-objective Approach for Wireless Heterogeneous Router Placement in Rural Wireless Mesh Networks

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Abstract. The design of a wireless mesh network is usually posed as a multi-objective optimization problem. In this paper, we consider the planning of a wireless mesh network in a rural region where the network coverage and the cost of the architecture must be optimized. In addition, mesh routers are heterogeneous, meaning that they may have different transmission ranges. In the network model, we assume that the region to serve is divided into a set of small zones of various types, including cost-effective locations and zones of interest for which the coverage is mandatory. The objective is then to minimize the number of routers, their types and locations which maximize the coverage percentage of mandatory zones in terms of coverage while minimizing the overall cost of the architecture. To achieve this, we propose three multi-objective approaches. We test the proposed approaches on several random topologies. The min-max regret metric is used to appreciate the quality of solutions of the Pareto front of different approaches.

Keywords: Centre of mass · Simulated annealing · Multi-objective · Mesh router · min-max regret

1 Introduction

Africa is the second-largest continent in size and population in the world after Asia. However, Africa is still experiencing a low percentage of Internet penetration. According to [1], this percentage is barely over half of the rest of the world. In addition, internet use in Africa is mainly restricted to urban or suburban areas, while rural areas lack coverage because of the lack of guarantee of return on investment. However, with the proliferation of wireless technologies, wireless community networks have emerged as a cost-effective alternative for rural coverage. Those networks are usually in form of wireless mesh networks (WMNs)

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[2]. WMNs are generally composed of nodes connected in a mesh topology to extend the coverage of standard wireless networks. This type of network makes use of off-the-shelf WiFi technology to provide an attractive approach to reduce the digital gap between rural and urban areas. Several initiatives have emerged, such as Zenzeleni Networks in South Africa or Mesh Bukavu in DR Congo. A map of initiatives throughout the continent can be found in [3].

In rural areas, networks known as rural wireless mesh networks (RWMNs) usually encompass a set of mesh routers (MRs), and a sole gateway connected to Internet via a limited solution such as VSAT [4]. Because of the limited budget during the design phase, the overall cost of the architecture should be minimised. This is achieved by minimizing the number and identifying the locations of router nodes that will maximise the percentage of the region to cover. For this reason, the planning of WMNs in rural areas has been considered as coverage-driven instead of capacity-driven [5], meaning that we have an area to cover rather than a set of users to supply. Pötsch et al. proposed a network planning tool for rural wireless ISPs [6]. In their configuration, they consider a set of points to connect (ISPs) rather than an area to cover. Recently, a new approach based on deep reinforcement learning has been investigated to plan topologies for WMNs [7].

In real-life scenarios, the problem of mesh node placement in WMNs is a NP-hard multi-objective and combinatorial optimization problem, and thus the computational complexity grows exponentially [8]. Therefore, it requires approaches based on meta-heuristics for its resolution.

This paper provides a new formulation of this problem and considers the network model found in [9]. The region of interest is divided into small zones. Each zone is either mandatory (i.e. requires network coverage) or optional (does not require coverage).The model also identifies cost-effective locations for node deployment. In real-life scenarios, network operators are also looking for such locations during the planning stage of the network. Moreover, we consider the fact that heterogeneous routers are used. The objective is then to minimize the overall cost (which depends on the locations and types of mesh routers used) while maximizing the coverage percentage of the zone of interest. To achieve this goal, we propose and compare three multi-objective approaches: Multi-objective Centre of Mass (MCM), Multi-objective Simulated Annealing (MSA) and Multi-objective Simulated Annealing based Centre of Mass (MSAC).

This paper is organized as follows: Section 2 briefly presents related work in WMN planning. Section 3 defines the network model and formulates the placement problem. Section 4 presents the different approaches. Section 5 presents the simulation setup and discusses the results of the different approaches. This paper ends with a conclusion and future work.

2 Related Works

Benyamina et al. [10] provide a comprehensive survey of the planning problem in WMNs. Their work categorizes the design problem in WMNs depending on the flexibility of the network topology, which can be predefined or not. In predefined topologies, each node in the network has a fixed location. The design problem consists into defining new MAC protocols [11,12], optimising channel assignment and efficient routing protocols [13–17] or defining cross layer techniques [18]. In non-predefined topologies, the locations of some nodes must be defined: either the location of the gateway(s) or those of mesh routers, or both. In this case, the problem can be cast as a distribution problem involving facilities and locations, where mesh routers represent facilities and the areas to cover represents locations.

Approaches to solve the placement problem in WMNs are based on different formulations proposed in the literature. Those formulations depend on the type of node considered in the design problem: mesh routers [19,20], gateways(s) [21,22], or both [23]. Earlier approaches for tackling this problem were based on linear programming [24]. However, these solutions were limited to small size networks since this problem is known to be NP-hard. For real size deployments, search techniques and meta-heuristics have been used [9,19,20,25].

Several works formulate the node placement as a multi-objective optimization problem with the aim of minimizing the cost and maximizing the coverage of the quality of service of the network. In [9], authors considered a formulation of mesh routers placement in which a set of clients must be covered in a two-dimensional space. Then they provided a simulated annealing approach to maximize the network connectivity and client coverage. The placement problem of mesh routers in a rural region was introduced in [26]. This work was extended later in [10] and [27], which employed approaches based on the Metropolis algorithm and simulated annealing, respectively.

Most of the works in the literature assumes the routers to be homogeneous, meaning that they have the same transmission range. In addition, the cost of the network is typically assumed to depend only on router cost, which does not take into account the dependence of cost on the installation location.

3 Placement Problem Formulation

We model a given region as a two-dimensional irregular form, and consider the smallest rectangle that can contain this form. We divide the region into squares, which are designated as elementary regions (ERs) as in [27,28]. Each ER can be mandatory in terms of network coverage; or its coverage can be considered as optional when the ER is not of essential interest. An ER can also be considered as forbidden location, meaning it cannot host a node (for instance a lake, river, road...). As in real-life scenarios, an ER can also represent an obstacle that could hinder the connectivity. Moreover, we suppose that the region encompasses cost-effective locations which can contribute to the reduction of cost. In the following for simplicity we employ these abbreviations for the different types of ER: Mandatory ER (MER); Non-line-of-sight ER (NER); Cost-effective ER (CER) or Forbidden ER (FER).

We define a set of matrices to characterize the ERs:

$$Coverage(x, y) = \begin{cases} 1 \text{ mandatory,} \\ 0 \text{ optional.} \end{cases} \tag{1}$$

$$Placement(x, y) = \begin{cases} 1 \text{ authorised,} \\ 0 \text{ forbidden.} \end{cases} \tag{2}$$

$$CoverDepth(x, y) = \begin{cases} 0 & \text{MER not covered,} \\ n & \text{MER covered by n routers.} \end{cases} \tag{3}$$

$$LowCost(x, y) = \begin{cases} 0 & \text{no cost reduction,} \\ c & \text{cost reduction (percentage).} \end{cases} \tag{4}$$

The *Coverage*, *Placement*, and *LowCost* matrices indicate whether or not ERs are mandatory, authorized, or cost effective (as node locations) respectively; while *CoverDepth* specifies the number of number of nodes that cover ERs. Thus, all relevant properties of the ER at (x, y) can be specified by the (x, y) entries of matrices (1–4).

In contrast to previous works, we assume routers to be equipped with omnidirectional antennas having different transmission ranges. The transmission range TR_j of a router R_j is expressed as the number of ERs (i.e. $TR_j = 8$ means that the transmission range of R_j stretches over 8 ERs).

Let p be an ER at position(x, y). If R_j is located in p that means the centre of R_j is $Ctr(j) = (x, y)$, then the set of ERs covered by R_j, $C\mathcal{A}_j$, is given by (5).

$$CA_j = \{(a, b), (x - a)^2 + (y - b)^2 < TR_j^2\} \tag{5}$$

The mesh router node placement problem in rural wireless mesh networks can then be expressed as the determination of a minimum set of routers, their types and locations, which maximizes the coverage of MERs, while minimising the overall cost of the architecture. This cost can be minimised by first minimising the number of routers required to cover the region, then by locating as many routers as possible to cost-effective location. The objective functions are given by (6) and (7).

$$f_1 = \max \frac{sign(\text{CoverDepth} \cdot \text{Coverage})}{\sum \text{Coverage}} \tag{6}$$

$$f_2 = \min \frac{1}{|R|} \sum_{i=1}^{|R|} 1 - \text{LowCost}(\text{Ctr}(i)) \tag{7}$$

f_1 maximises the percentage coverage of MERs, while f_2 minimizes the cost of the architecture. To convert f_1 into a minimisation problem, we only consider the MERs that are uncovered, in other terms with CoverDepth $= 0$. The new objective function f_1' is then given by (8).

$$f_1' = \min \frac{\sum sign((\text{CoverDepth} = 0) \cdot \text{Coverage})}{\sum \text{Coverage}} \tag{8}$$

Since we consider Wi-Fi technology standards, the deployment cost of a router in rural regions is higher than the cost of the router itself since deployment requires a mast and an independent power source. However, this cost can be greatly reduced by using cost-effective locations that may provide a power source, and making the mast unnecessary.

4 Placement Approaches Based on Pareto Front

Two approaches are generally used in multi-objective optimisation: combining objective functions into one by defining weights; or using Pareto front which is composed of non-dominated solutions. Since the determination of weights is usually subjective, the Pareto front approach is preferred.

Usually, objective functions in multi-objective optimization are conflicting. For instance, reducing the number of uncovered MER (f_1) is done at the expense of the cost of the architecture (f_2). Rather than combining objective functions, Pareto optimisation consists of trading-off conflicting objective functions to determine a set of optimal solutions. In a Pareto optimisation, the Optimally is based on the concept of dominance [29].

Definition 1 (Pareto Dominance): Let two solutions (with $x_1 \neq x_2$), x_1 dominates x_2 if x_1 is better than x_2 in at least one objective function and not worse with respect to all other objectives.

Definition 2 (Pareto Optimality): $x^* \in$ X is a Pareto optimum if and only if it is non-dominated by any other element of X. The set of Pareto optima is called Pareto set.

Definition 3 (Pareto Front): The Pareto Front is the set of all Pareto optimal solutions (non-dominated solutions).

An example of Pareto optimization with two functions is given in Fig. 1. Three approaches based on Pareto fronts are proposed: Multi-objective Centre of Mass (MCM), Multi-objective Simulated Annealing (MSA), and Multi-objective Simulated Annealing based Centre of Mass (MSAC).

4.1 Initialisation and Global Parameters of Algorithms

The initial number of routers is unknown at the beginning. A set R of routers with a total coverage RCover $= \gamma \cdot$ TCover (the number of MER which represents the total area to cover) is randomly generated. The multiplicative factor γ is initially set to 1.5, and is gradually decreased to 1. When γ changes, a new R is generated. The initial solution is obtained by placing routers from R randomly in the area to cover. For each router we randomly select an ER until Coverage (ER) $=1$ and Placement (ER) $=1$ be satisfied. We therefore place the current router in this ER. All the three algorithms are run nRun times. When $\gamma = 1$, the nRun decreases and γ is reset. All the algorithms stop when nRun $= 0$.

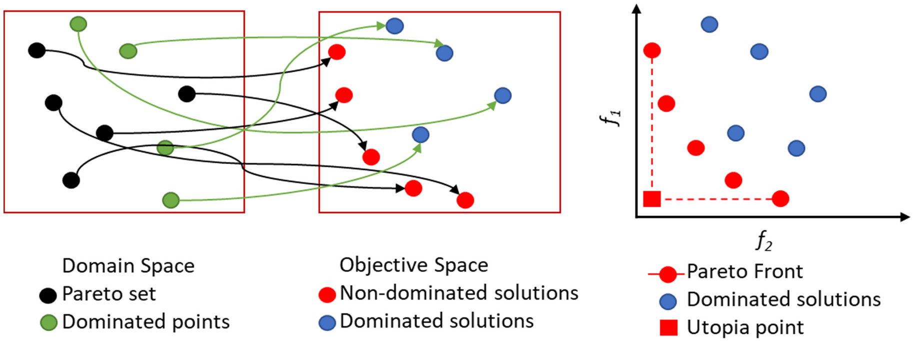

Fig. 1. Example of Pareto optimization

4.2 Multi-objective Centre of Mass (MCM)

Algorithm 1: Multi-Objective Centre of Mass algorithm for single coverage

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Input  : f'_1: First Obj. Funct. (Coverage) f_2: Second Obj. Funct. (Cost)
Output: arch: Pareto Front of non-dominated Solutions
begin
    s:= InitialSolution();
    (cost,cov):= (f_2(s),f'_1(s));
    arch:= createList(1,(cost,cov));
    while stopping condition not met do
        i := selectARouter();
        if multiple coverage of i is too large a fraction then
            Search for an ER with CoverDepth = 0, Coverage = 1, and
             Placement = 1 ;
        else
            Move i to the centre of mass of his single coverage
        end
        s:= NewSolution(i); (cost,cov):= (f_2(s),f'_1(s));
        if (cost,cov) is non-dominated by any (cost',cov') in arch then
            arch:=updateAndPrune(arch, (cost,cov));
            reset stopping condition;
        end
    end
    return arch
end
```

The MCM algorithm is an enhancement of the Centre of Mass of single coverage (CM) algorithm [30]. It is an attempt to provide CM with features to support multi-objective optimisation problems. The idea behind the MCM approach is to reduce the area covered by multiple nodes by moving each node to the centre of mass of area it is covering alone. The idea is guided by the fact that new uncovered MER can be easily reached in a small number of moves. The MCM basic algorithm is given in Algorithm 1. The following expression is used to check whether multiple coverage is too large a fraction at line 7, as in [30]:

$$(\mathrm{sCov(i)} + \mathrm{mCov(i)})^2 \cdot rand(x) \leq (mCov(i)))^2 \tag{9}$$

where sCov(i) and mCov(i) represent respectively single and multiple coverage of router i. rand(x) is used to provide some stochastic properties. More details can be found in [15].

A new solution (line 11) is generated by accepting the new location of router i while maintaining other routers in their current locations. If a non-dominated solution is not found after a certain number of iteration (Stop_MCM), we suppose therefore having reached the optimal and the algorithm stops. updateAndPrune inserts (cost,cov) in arch and removes all dominated solutions from arch.

4.3 Multi-objective Simulated Annealing (MSA)

The MSA algorithm is an enhancement of SA algorithm proposed in [27]. The flowchart of MSA is presented in Fig. 2.

A router is selected and randomly moved, and the coverage change of MER is evaluated. If the change is accepted, we check if the new solution is not dominated by any solution in arch. In this case, the new solution is inserted, updating arch.

The equilibrium state of MSA is controlled by *Stop*, and it is reached when $Stop = 0$. Therefore, the temperature T decreases. MSA stops when $T \leq T_{min}$, the minimal temperature.

4.4 Multi-objective Simulated Annealing Based CM (MSAC)

The MSAC algorithm is a sequential combination of MCM and MSA. At the first stage, the MCM algorithm is used. Then the output serves as the input for MSA. The MCM will provide a rapid initial convergence, and MSA will refine the solution. This can be considered as a multi-objective extension of the Simulated Annealing based Centre of mass introduced in [28]. The flowchart of MSAC is provided in Fig. 3.

5 Simulation Results

To compare the proposed approaches, we randomly generate 12 instances with mandatory areas in terms of network coverage and cost-effective locations. We consider two grids of 50×50 and 100×100, with Stop_MCM = 500, StopEq = 250, nRun = 20. Router transmission range $TR \in [6, 10]$. The unit represents the length of an ER. If size (ER) = 20 m, the radius will be TR $\in [120\,\mathrm{m}, 200\,\mathrm{m}]$, and the grids $1\,\mathrm{km} \cdot 1\,\mathrm{km} = 1\,\mathrm{km}^2$ and $2\,\mathrm{km} \cdot 2\,\mathrm{km} = 4\,\mathrm{km}^2$. This is realistic since 802.11a/b/g/n routers have a theoretical outdoor transmission range ranging 120 m to 250 m. The simulations were conducted using Scilab 5.4.

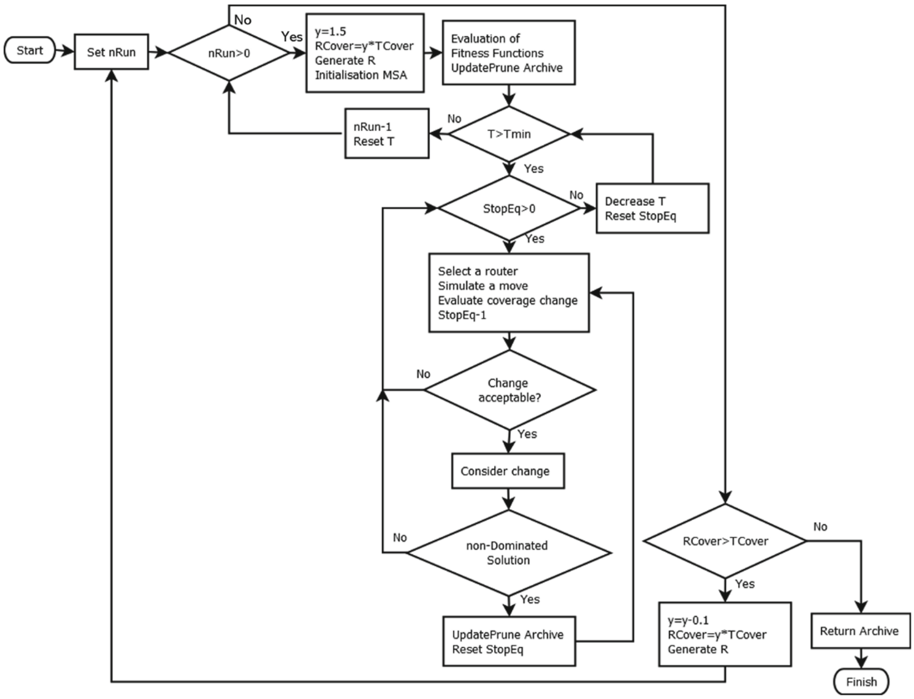

Fig. 2. Flowchart of MSA approach

Although this work is an extension of [9], it cannot be compared directly with the original work because of the multi-objective nature of the new formulation. The work in [9] did not consider the cost and was only focused on the coverage. To evaluate the quality of solutions of the Pareto front of the three approaches the min-max-regret criterion has been used. This metric is suited for non-repetitive decisions, that means the replacement of a solution after its implementation will not be acceptable. Given a solution s ∈ S, its regret value under the scenario x ∈ X is defined by (10).

$$Rg(s,x) = (val(s(1),x) - val_x^*(1))^2 + (val(s(2),x) - val_x^*(2))^2 \qquad (10)$$

where $x \in \{1,2,3\}$ represents the different placement approaches, and val_x^* the optimal solution. Since we are in a minimisation problem using non-analytical objective functions, we consider the utopia $val_x^* = (0,0)$, that means the number of MER that are uncovered is zero as well as the cost of the system. The maximum regret value $Rg_{max}(x)$ of solution s is defined as $Rg_{max}(s) = max_{x \in X} Rg(s,x)$. The min-max-regret value is therefore the solution with the minimum maximum regret value. It can be defined by (11).

$$\min_{s \in S} Rg_{max}(s) = \min_{s \in S} \max_{x \in X} (val(s,x) - val_x^*) \qquad (11)$$

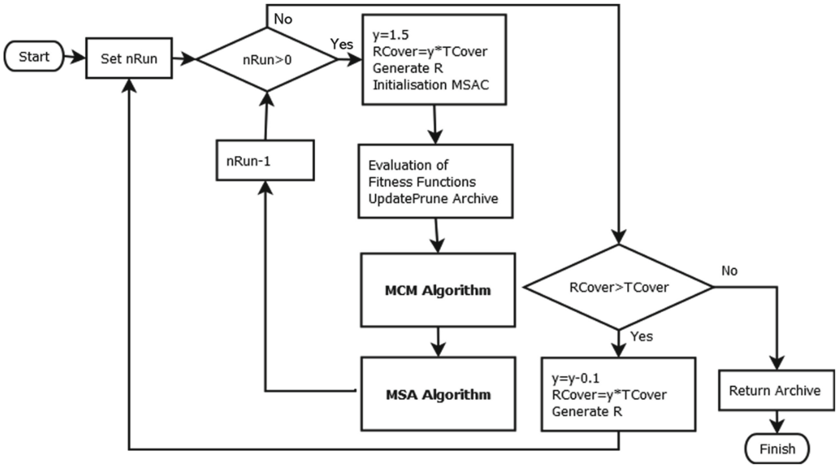

Fig. 3. Flowchart of MSAC Approach

Table 1. max and min-max-regret values.

Instances	1_50	2_50	3_50	4_50	5_50	6_50
MCM	0,925	0,887	0,93	1,001	1,001	0,859
MSA	0,862	0,795	0,703	0,974	0,834	0,716
MSAC	0,78	0,722	0,583	0,922	0,777	0,786
Instances	1_100	2_100	3_100	4_100	5_100	6_100
MCM	0,94	0,94	0,844	0,968	0,928	0,84
MSA	0,867	0,863	0,858	0,932	0,892	0,883
MSAC	0,961	0,884	0,892	0,926	0,916	0,842

Table 1 provides the max-regret value from different approaches for each instance. The min max-regret value is in bold. From Table 1, MSAC provides the min-max-regret value in x_50 instances. However, in larger instances (x_100), MSA dominates the others, apart from instance 5_100 where the MAS value is less than the one of MSAC.

Although the min-max-regret minimizes "the regret" of choosing a solution s, it can sometime skew the result. For instance, Figs. 4 and 5 present the Pareto fronts produced by the different approaches respectively for instances 4_50 and 5_100. In both Figures, MSAC provides the best Pareto front, that means, the Pareto front of MSAC dominated almost all the solutions of the Pareto fronts of other approaches. In other terms, MSAC provides the best trade-offs with the smallest cost percentage and the smallest percentage of uncovered MER. In fact, MSAC is able to relocate as much as possible mesh routers to cost-effective location to reduce the cost of the architecture, according to objective f_2, while maximizing the mandatory region covered by the set of selected routers.

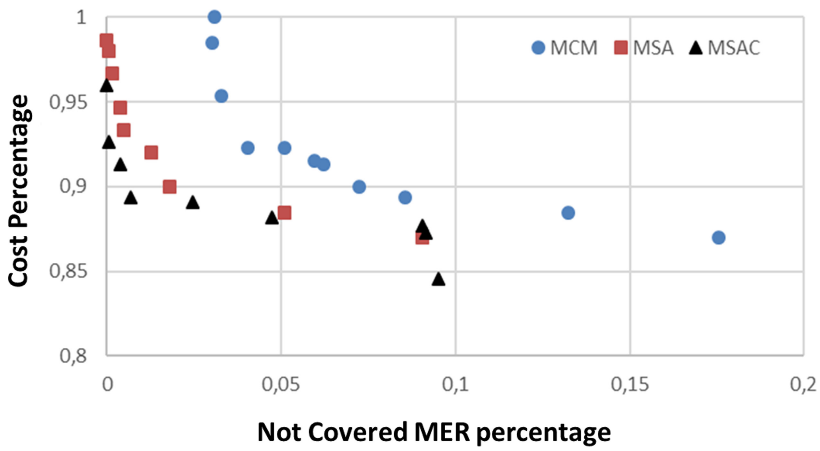

Fig. 4. Pareto fronts in Instance 4_50

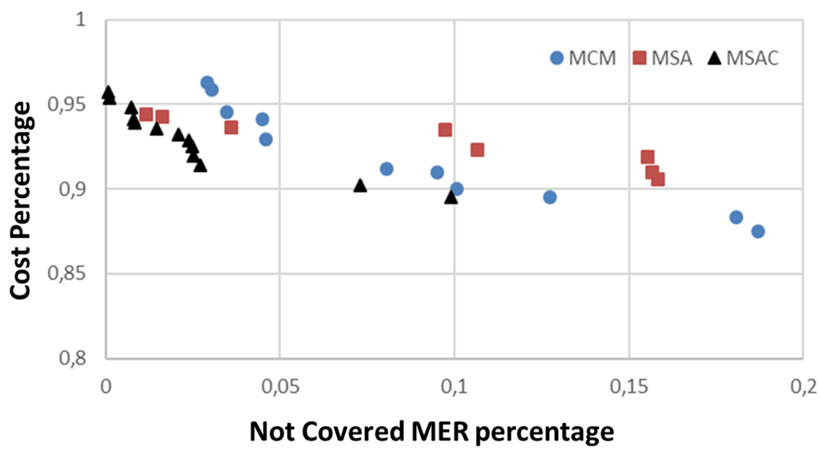

Fig. 5. Pareto fronts in Instance 5_100

6 Conclusion and Future Work

In this paper we introduce a new formulation of the mesh router placement problem in rural areas. Heterogeneous routers have been considered, as well as cost-effective locations that can reduce the cost of the architecture. Three multi-objective approaches have been defined to solve the problem: Multi-objective Centre of Mass (MCM), Multi-Objective Simulated Annealing (MSA), and Multi-Objective Simulated Annealing based Centre of Mass (MSAC). Simulation results have shown a better min-max regret of Pareto front in small instances and large instances respectively for MSAC and MSA. Although MSAC does not provide the min-max regret value in most of large instances, in most of the cases it provides a better Pareto front, meaning a better trade-off between the coverage and the cost of the architecture. Apart from improving MSAC in terms of quality of solution and robustness, future works will integrate suitable empirical path loss models such those defined in [31].

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