An Adaptive Tabu Search Algorithm for the Multi-Objective Node Placement Problem In Heterogeneous Networks

Ons Abdelkhalek[1], Saoussen Krichen[2] and Adel Guitouni[3]
[1]*LARODEC Laboratory, Institut Supérieur de Gestion, University of Tunis, 2000 Le Bardo, Tunisia*
[2]*Faculty of Law, Economics and Management, University of Jendouba, Jendouba, Tunisia*
[3]*Gustavson School of Business, University of Victoria, Victoria B.C, Canada*

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Abstract: The Multi–objective Node Placement (MONP) problem focuses on extending an existing communication infrastructure with new wireless heterogeneous network components while achieving cost effectiveness and ease of management. This extention aims to broaden the coverage and handle demand fluctuations. In this paper, the MONP problem is modeled as a multi–objective optimization problem with three objectives: maximizing the communication coverage, minimizing active nodes and communication devices costs and maximizing of the total capacity bandwidth in the network. As the MONP problem is $\mathcal{NP}$–Hard, we present a meta–heuristic based on the Tabu Search approach specifically designed for multi–objective problems in wireless networks. An empirical validation of the model is defined based on a selection of a real and large set of instances and supported by a performance comparison between the suggested algorithm and a multi–objective genetic algorithm (MOGA). All tests are performed on a real simulation environment for the maritime surveillance application. We show empirically that the proposed approach is more relevant to solve the MONP problem regarding each objective in term of cardinality-based performance index.

1 INTRODUCTION

A heterogeneous network involves multiple resources (e.g., relays, antennas, etc.) and contains different types of sub-networks with different communication devices (CDs) (e.g., cellular, radio, wifi or Ad Hoc networks) with varying functions and power level. This integration takes advantage of various networking techniques, such as the coverage of the cellular systems, bandwidth of the wired networks and the flexibility of the mobile ad hoc networks. Several studies addressed the integration of various architectures in heterogeneous platforms, as LAN and wireless LAN (WLAN) (Bahri et al., 2005) (Niyato et al., 2009), Wi-Fi and Wi-Max (Ting et al., 2009), and the integration of Ad hoc and cellular networks in (Hongyi et al., 2011). Nevertheless, published research on optimization algorithms for heterogeneous network extension seems much more limited. Most studies reported in the literature focused only on the extension of one existing homogeneous network infrastructure.

In our proposed model, we try to report with fidelity all the aspects of the heterogeneity in merging multiple network technologies by its degree of reliability and how closely it captures the features of the signal quality constraints. In this paper, we address the multi-objective node placement (MONP) (Abdelkhalek et al., 2011, 2013) problem. The MONP problem considers the following settings: a set of candidate sites representing the potential placement of nodes, the traffic distribution estimated by using empirical prediction models and the signal quality propagation model. Other aspects are also taken into account, such as an existing heterogeneous network infrastructure, hardware cost, signal quality and service coverage.

The purpose is to find the convenient way to build and connect the network. In fact the optimal assignment includes the efficient number, position, CDs' nature and connections between active nodes in a special area of coverage while taking into consideration multiple environmental constraints. The problem deals with two aspects of the network management. First we aim to maximize the coverage area within a heterogeneous network. To achieve this goal we attempt

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to maximize the number of users receiving signal. However, this will be constrained by the minimization of the deployed entities' cost. Second, we lead to improve the quality of signal and maximize information flows in the network as we minimize cost of deployed devices in the network.

It's obvious that the problem is highly combinatorial with an enormous number of possible combinations and conflicting objectives. The problem is modeled as a multi-objective optimization problem subject to system constraints. If we reduce the proposed problem to the Antennas Placement Problem (APP) or Transmitter Placement Problem (TPP) (Lee et al., 2000) (Ting et al., 2009), we will clearly conclude that it is an $\mathcal{NP}$–Hard problem. Therefore, heuristic approaches can be considered to solve the problem. We developed a multi-objective tabu search (MOTS) approach (Hansen, 2000) given its ability to tackle the high complexity of similar problems and to generate a promising approximation of the efficient set.

As the MONP is newly modeled multi-objective and heterogeneous, no benchmarks exist. To test our approach, we generated 54 different real problem instances with varying region sizes, locations, density of test points (TPs) and number of active nodes. We compare the MOTS algorithm to the Multi-objective Genetic Algorithm (MOGA) (Abdelkhalek et al., 2011). The empirical application is validated in a maritime surveillance application with a simulation environment called *Inform Lab* (IL) (Abdelkhalek et al., 2013) using real data instances. Antennas are represented by nodes in maritime platforms (i.e. helicopters, ships, boats,..) and CDs represent all the equipment capable to ensure the communication between different technologies (i.e. radio, cellular, WLAN,..).

The remaining of this paper is organized as follows. In Section 2, we provide a brief description of the problem modeling. Section 3 presents the adapted MOTS algorithm to solve the MONP problem. The performance of the proposed algorithm is presented in Section 4 and compared with the MOGA on a bench of realistic problem set.

2 THE MULTI–OBJECTIVE NODE PLACEMENT PROBLEM IN A HETEROGENEOUS NETWORK

The MONP problem (Abdelkhalek et al., 2011, 2013) consists to find the appropriate placements for a set of nodes in an existing heterogeneous network Z^d using a set of pre-defined candidate sites (CSs) as potential locations. For each selected CS, find the appropriate node and CDs, as well as the suitable ad hoc connection strategies between the new deployed node and the existing infrastructure. All these choices must satisfy a set of conflicting objectives and constraints.

2.1 Notation

The following table explains the notation related to the mathematical formulation.

Indexing Set	N	Set of nodes $\{n_1,...,n_N\}$
	D	Set of communication devices $\{d_1,...,d_D\}$
	M	Set of predefined candidate sites of interest $\{l_1,...,l_M\}$
	R	Set of test points (or receivers) $\{r_1,...,r_R\}$
Parameters	$\tau = (p,s,c,t,w,b)$	Each CD has a set of characteristics related to the infrastructure and to the sub node, where: p represents the power, s denotes the capacity between nodes and TPs, c is the cost between CDs (includes the technologies' cost deployed to connect the two devices), t denotes the CD's type (see Table 1), w denotes the transmission range related to a CD, and b denotes the bandwidth between two different nodes when connecting the infrastructure.
	a_{kd}	$= \lvert\{r_f\}\rvert$, if $\forall f$, $\exists i \in N$, $\exists k \in M$ and $\exists d \in D$ where $S^d_{f,i,k} \geq \theta^d_f$ ϕ, otherwise.
	$T_{D\times D}$	Input matrix,$T_{dd'} = 1$ if CD d and d' can communicate
	NL^d	The maximum number of transmitters assigned to a node with CD d
	C_i	Cost of a node n_i
	$S^d_{f,i,k}$	Signal strength between a node n_i with CD d in CS l_k and TP r_f
	p_d	Power of the communication device d.
	G_f, G_i	Antenna gains of TP r_f and node n_i
	λ	The carrier wavelength
	$d_{f,k}$	Euclidean distance from r_f to CS l_k
	(σ^d_f, θ^d_f)	data rate demand (in Erlang) and signal threshold of TP r_f for the CD d
	(α_f, β_f)	Coordinates of the TP r_f
	(α_k, β_k)	Coordinates of the CS l_k
	Z^d	Initial existing networks infrastructure with CD d
	T_{Z^d}	Maximum capacity for Z^d (bandwidth)
Decision Variables	x^d_{ik}	$= 1$ if a node n_i with a CD d is assigned to CS l_k
	y^d_{ij}	$= 1$ if a node n_i is assigned to an other node n_j with a CD d
	w^d_{if}	$= 1$ if TP r_f is assigned to a node n_i with CD d

2.2 Outline of the Problem Formulation

The MONP problem (Abdelkhalek, 2011) is formulated as follows:

$$Max\ \ Z_1(X) = \sum_{d=1}^{D}\sum_{i=1}^{N}\sum_{k=1}^{M} x_{ik}^{d} a_{kd} \tag{1}$$

$$Min\ \ Z_2(X) = \sum_{d=1}^{D}\sum_{i=1}^{N}(C_i + c_d)\sum_{k=1}^{M} x_{ik}^{d} \tag{2}$$

$$Max\ \ Z_3(X) = Min_{\{d,i\neq j\}} y_{ij}^{d} b_d \tag{3}$$

$$s.t.$$

$$y_{ij}^{d} = x_{ik}^{d} x_{jk'}^{d'} \quad \forall i \neq j,\ \forall k \neq k' with\ t_{dd'} = 1 \quad and\ d_{k,k'} \leq Max(w_d, w_{d'}) \tag{4}$$

$$\sum_{f=1}^{R}\sum_{k=1}^{M} \sigma_f^d w_{if}^{d} x_{ik}^{d} \leq s_d \quad \forall i,d \tag{5}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{d=1}^{D} b_d y_{ij}^{d} \leq T_{Z_d} \quad \forall i \neq j, \forall Z_d \tag{6}$$

$$\sum_{i\in N/\{j\}} y_{ij}^{d} \leq NL^d \quad \forall j \in \{1,\ldots,N\} \tag{7}$$

$$\sum_{d=1}^{D} x_{ik}^{d} T_{it} \geq 1 \quad \forall i \in N \tag{8}$$

$$\sum_{k=1}^{M} x_{ik}^{d} = 1 \quad \forall i \in \{1,\ldots,N\}, \exists d \in D \tag{9}$$

$$\sum_{i=1}^{N} x_{ik}^{d} \leq 1 \quad \forall k \in \{1,\ldots,M\}, \exists d \in D \tag{10}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{M} x_{ik}^{d} w_{if}^{d} \leq 1 \quad \forall d \in D \tag{11}$$

$$\sum_{i=1}^{N} y_{ij}^{d} \geq 1 \quad \forall j,t \quad and \quad j \neq i \tag{12}$$

$$\sum_{i=1}^{N} y_{iZ^d}^{d} \geq 1 \quad \forall d \tag{13}$$

$$x_{ik}^{d}, w_{if}^{d}, y_{ij}^{d} \in \{0,1\} \quad \forall i,k,f,j,d \tag{14}$$

The MONP problem addresses three main objectives for the problem:

- *Maximizing the communication coverage* by maximizing the number of covered TPs in the area of interest (see equation (1)). Thus, it ensures that the received signal power from a given location has met the received sensitivity of the TP.
- *Minimizing active nodes and communication devices costs* through equation (2), by reducing the number of deployed nodes and CDs.
- *Maximizing of the total capacity bandwidth in the network* by maximizing the amount of traffic held by the network in equation (3). This leads to maximize the total minimum capacity bandwidth deployed in all the network in order to ensure the QoS.

These objectives are subject to two main sets of constraints:

- *Communication Node Constraints:* It represents all constraints related to the traffic carried in the network, receivers sensitivity threshold of the mobile and the mobility of users in the area of interest. Equation (4) ensures that two nodes n_i and n_j can be connected only if their CDs d and d' can communicate and their Euclidean distance $d_{k,k'}$ from CS l_k to CS l'_k is less or equal to the maximum power range between w_d and $w_{d'}$ related to CDs d and d'. In equation (5), the sum of the total data rate demand of the covered TPs by a node n_i with CD d cannot exceed the capacity s_d of the CD. We assume in equation (6) that the total traffic capacity of all nodes connected to an existing network Z_d, should not exceed the maximum capacity of this network T_{Z_d}. Links capacity constraints are presented in equation (7) where we assume that all nodes connected to node n_j should not exceed the maximum capacity of links NL^d allowed for n_j and related to his CD.
- *Connection Node Constraints:* It ensures the connection between different entities in the network based on their CD's range, CS' distance, link constraints,..,etc. Equations (8), (9) and (10) ensures simultaneously that we can assign more than one CD to a node n_i, each nodes n_i is assigned to one CS l_k and, finally, that each CS l_k is assigned to at most one node n_i. We assume in equation (11), (12) and (13) that each TP r_f can be assigned to at most one node n_i with CD d, that each node n_i should be connected at least to another node n_j and ,finally, that at least one node n_i should be connected to the existing networks Z^d in order to ensure that all sub-networks are inter-connected. X represents the efficient solution with a combination of our decision variables.

Due to the $\mathcal{NP}$-hardness of the MONP problem, no exact solution can be find to generate the Pareto optimal front. We propose to apply an adapted MOTS algorithm in order generate a promising sample of potentially efficient solutions.

3 THE TABU SEARCH ENCODING ALGORITHM FOR THE MONP PROBLEM

We propose an adaptation of the basic TS (Hansen, 2000) algorithm especially designed to the MONP problem in order to generate the non-dominated solution set. TS starts from an initial feasible solution and moves repeatedly from a solution to a neighbor one. Let $s \in S$ be a current solution and $N(s)$ the neighborhood of s.

A solution s is encoded as a discrete vector of size N. Each vector's position represents a combination between the index $k = 1,...,M$ of the CSs and the index $d = 1,...,D$ of the CD to which a node is assigned. Figure 1 illustrates an example of a solution encoding with 19 deployed nodes and 2 different CDs. Through this Figure, we can see that every node has been assigned to one CS and has at least one CD. Every CS has a unique index that indicates its position in the map. Every node is assigned to a different CS.

3.1 Initial Solution

The initial solution is built based in a greedy based algorithm. Nodes' placement are randomly picked from the set of CSs $\{1,2,\ldots,M\}$, then we assign a CS's index. CD's types are piked from the set of available CDs D based on the demand distribution. After assigning a CS, we search for the maximum number of neighbors TP for each communication type and assign a CD accordingly. The number of other nodes to which they are connected is then constructed based on constraints (4). If the initial solution is not feasible, the set of constraints described above are used through an adjustment process in order to drive the search toward feasible solutions. In this process, a modification of the node assignment is made in order to fulfill each constraint sequentially.

3.2 Neighborhood Exploration and Evaluation

Each move consists in modifying one variable of the vector X in an iteration it. The following moves are considered for our model:

- remove a node n_i from a selected CS l_k
- move a node n_i which is already installed at a given location l_k to a vacant location l'_k
- assign a node n_i the nearest CS l'_k
- assign a new CD d to a node n_i for a certain CS l_k
- assign a node n_i to an existing initial network Z^d

We only consider moves that preserve the connection and communication constraints. Each time a move is applied, the neighbor is evaluated based on the three objective functions detailed above. A randomly non-dominated solution from the neighborhood replace the current solution even if it is not improving in order to escape from the local optima. The whole process is stopped if a given number of iterations it_{max} have been accomplished or when no improvement is performed on the set of efficient solutions obtained after a certain number of iterations.

3.3 Tabu List

In order to escape the local optima and prevent revisiting previously explored solutions, a tabu list L is used. This list keeps track of the last $|L|$ modifications during the search process. Over multiple runs, TS is able to find non–dominated solutions that represent good placement of a set of nodes from the list of CS. At each step of the algorithm, a list that contains non–dominated solutions P_{ND} is generated when the MONP optimization problem is solved. The tabu list L may prohibit attractive neighbors that have not yet been generated. Hence, it is necessary to use a perturbation criterion to accept forbidden neighbors. Our perturbation criterion consists in choosing randomly a tabu neighbor from the P_{ND} list.

The MOTS is compared to the MOGA, previously applied to the MONP problem for the maritime surveillance application and detailed in (Abdelkhalek et al., 2011). The main steps of the algorithm are summarized as follows:

Begin
$L := \{\}$, $P_{ND} := \emptyset$, $it := 0$,
Generate randomly a feasible starting solution S,
  Repeat
    Determining the best move s to its neighbor $s' \in N(s)$
    Determine the number of iterations for which the node is tabu
    If Fitness(X') *Dominates* Fitness(X) **Then**
    $P_{ND} \leftarrow P_{ND} \cup \{s'\}$
    update Tabu List L
    End If
  it++
  Until Stopping criterion
  End

4 EXPERIMENTATIONS AND NUMERICAL RESULTS

Results are run using a testbed simulator for real data instances called *Inform Lab* (IL) (Abdelkhalek et al., 2013). Each instance is solved with 30 independent runs. A maximum number of iterations it_{max} is set to 500 iterations for each run. The algorithm stops when no improvement is performed on the objective functions after 100 iterations or when the maximum number of iteration is reached. The number of iterations that a node can be tabu is set between $[5,10]$.

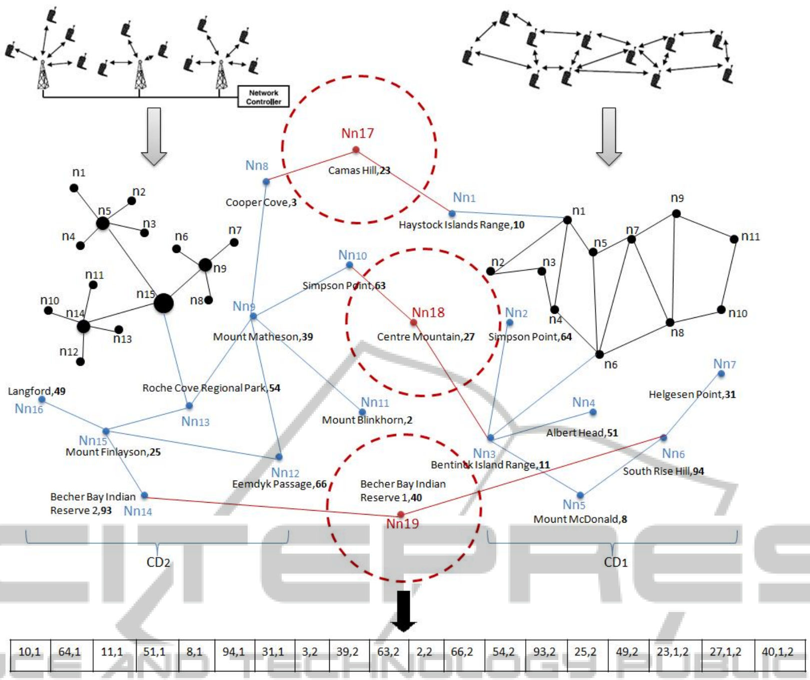

Figure 1: An example of the TS encoding scheme for a heterogeneous network extension.

These parameters were selected after multiple experimentations. The existing heterogeneous network infrastructure includes 8 nodes and 3 CDs in Vancouver Island area.

The free space signal propagation model proposed in (Ting et al., 2009) is used in the experimental design. Moreover, different region sizes, locations and densities of TPs are considered. For each size of the area, three instances of the problem were generated with different region size. We deploy simultaneously 10, 20 and 30 nodes. For each instance nine different TPs distribution are applied as presented in Tables 3, 2 and 4. Furthermore, ten different CD's settings are used in order to ensure a heterogeneity in the network connections (see Table 1). The frequency and ranges are used to compute the signal strength and the bandwidth to optimize Z_3. The number of CSs is always greater than the number of nodes to place. Three different settings are used: for 10 active nodes we plan 17 CSs, 100 CSs for 20 active nodes and 183 CSs for 30 active nodes. A total of 54 different problem instances were generated for the tests.

For each instance, we report the following measures: The average CPU time, number of non dominated solutions ($|P_{ND}|$) and values of the three objective functions for both MOTS and MOGA where Z_1 is the number of covered TPs, Z_2 the total cost of deployed CD and nodes, and finally Z_3 represents the total minimum capacity bandwidth deployed in all the network.

Table 1: Communication Devices' Settings.

Link #	Bandwidth (kbit/s)	Frequency (Hz)	Range (km)
1	400	1E09	300
2	4000	8.23E09	3600
3	1000	6E09	2000
4	600	1.75E09	500
5	800	2E09	600
6	3000	3E09	500
7	500	1.5E09	2000
8	4000	2E09	3000
9	1000	8E09	800
10	2000	7E09	1000

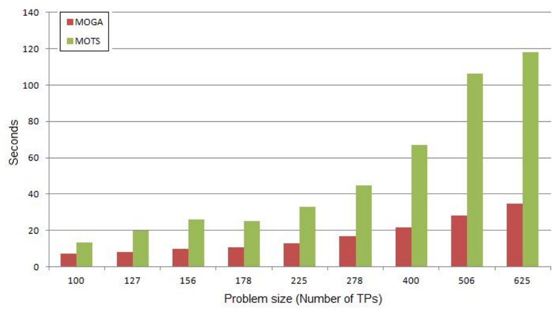

Figure 2: CPU in term of the number of TPs.

Because of the $\mathcal{NP}$-hardness of the MONP problem, potentially Pareto-optimal solutions are generated. In order to compare the performance of our two

Table 2: Computational performance of MONP for 10 nodes and 17 CSs.

Pbs.	TPs	CDs	MOGA					MOTS				
			$\|P_{ND}\|$	CPU(s)	Z_1	Z_2	Z_3	$\|P_{ND}\|$	CPU(s)	Z_1	Z_2	Z_3
1	100	5	4	3	100	271907	400	4	5	100	271900	400
2		10	4	4	100	271230	1000	3	7	100	271222	1000
3	127	5	4	4	127	270271	400	5	7	127	270260	500
4		10	4	5	127	282275	2000	5	10	127	282265	2000
5	156	5	3	4	156	269173	400	4	7.5	156	269125	500
6		10	5	5	156	284970	500	6	11	156	285190	500
7	178	5	4	3	178	271026	800	5	7	178	271136	1000
8		10	7	6	178	278942	600	6	9	178	278930	600
9	225	5	4	5	223	275473	400	3	12	225	275402	500
10		10	5	7	225	280714	600	6	23	225	280504	800
11	278	5	3	5	272	275594	400	4	13	276	275590	400
12		10	2	9	277	283442	500	4	29	278	283412	600
13	400	5	5	7	400	270507	400	4	19	392	270517	500
14		10	5	12	400	281589	800	6	30	400	281459	1000
15	506	5	6	8	490	270778	500	4	20	498	270768	600
16		10	5	20	500	282749	4000	5	55	506	282650	3000
17	625	5	7	15	580	271530	400	9	35	622	271538	400
18		10	7	17	591	283484	2000	9	48	625	283564	1000

Table 3: Computational performance of MONP for 20 nodes and 100 CS.

Pbs.	TPs	CDs	MOGA					MOTS				
			$\|P_{ND}\|$	CPU(s)	Z_1	Z_2	Z_3	$\|P_{ND}\|$	CPU(s)	Z_1	Z_2	Z_3
1	100	5	3	6	100	471677	400	3	10	100	471665	400
2		10	3	8	100	484913	3000	2	15	100	484895	1000
3	127	5	3	7	127	468713	400	4	15	127	468688	400
4		10	5	9	127	482211	600	5	20	127	482013	800
5	156	5	4	9	156	470028	400	5	22	156	470128	400
6		10	4	12	156	487340	1000	5	30	156	487250	1000
7	178	5	4	9	178	477123	400	3	19	178	477083	400
8		10	5	13	178	492783	800	4	33	178	492780	500
9	225	5	3	11	218	468145	400	4	30	222	468045	400
10		10	2	17	220	482626	400	3	37	225	482603	1000
11	278	5	4	14	270	470694	400	3	38	277	470630	400
12		10	4	17	275	476757	400	3	40	278	476650	500
13	400	5	6	17	398	467905	600	7	42	400	467899	500
14		10	4	24	400	490869	500	6	78	400	490779	600
15	506	5	5	21	480	473621	400	5	69	500	473660	400
16		10	5	42	495	479550	500	7	188	503	479525	400
17	625	5	7	30	605	463591	800	8	72	608	463513	800
18		10	10	38	608	488099	500	10	96	612	486005	400

approaches, we use a simple cardinality-based index namely *Coverage of two sets index (C)* (Zitzler and Thiele, 1999). It's used to compare the relative dominance (i.e. coverage) between the two non dominated solution sets, defined as:

$$C(S_1,S_2) = |\{s_2 \in S_2; \exists s_1 \in S_1; s_1 \succeq s_2\}|/|S_2|$$

where S_1 and S_2 represent the set of non-dominated solutions generated simultaneously by the MOTS and MOGA. Table 5 reports the performance of the MOTS and MOGA according to the C index. In fact, two main results are pointed out: the dominance regarding each objective function Z_i (coverage / Objective) and the relative dominance that reflects the performance of each method regarding to all objectives simultaneously. To this end, we count the set of non-dominated solutions generated by both algorithms. Then we compute, for each instance, the average dominance between the two sets ($C(S_1,S_2)$ and

Table 4: Computational performance of MONP for 30 nodes and 183 CS.

Pbs.	TPs	CDs	MOGA					MOTS				
			$\lvert P_{ND}\rvert$	CPU(s)	Z_1	Z_2	Z_3	$\lvert P_{ND}\rvert$	CPU(s)	Z_1	Z_2	Z_3
1	100	5	3	9	100	807153	400	3	19	100	807140	400
2		10	2	13	100	811918	2000	3	25	100	811820	1000
3	127	5	3	10	127	806046	400	3	28	127	806015	500
4		10	4	14.5	127	842980	1000	4	40	127	842953	800
5	156	5	3	11	156	788932	400	4	39	156	788920	400
6		10	3	17	156	806433	3000	4	47	156	806360	2000
7	178	5	3	13.5	178	798788	400	4	36	178	798741	400
8		10	3	18	178	821985	2000	4	48	178	821935	2000
9	225	5	3	13	218	784453	400	3	30	223	784257	500
10		10	4	24	222	834403	600	5	65	225	834323	600
11	278	5	4	25	275	795268	400	5	62	276	795250	400
12		10	6	31	278	833327	800	5	86	278	833225	500
13	400	5	6	26	385	801875	400	5	96	395	801690	400
14		10	6	45	400	831033	1000	5	137	400	831009	1000
15	506	5	6	30	491	778785	800	7	75	500	778750	600
16		10	5	47	500	840161	500	6	230	502	840053	800
17	625	5	12	44	612	803887	600	11	200	620	803967	600
18		10	10	64	615	822732	400	11	258	625	822546	400

$C(S_2,S_1)$) for all objectives. The results obtained by the two approaches are compared. Thus, we can state the following remarks:

- Starting from 225 TPs, we can notice that in 96% MOTS generates better solutions (i.e. 24 instances out of 25). Moreover, in more than 50% of the problem instances (i.e. 29 instances out of 54), both MOTS and MOGA reach the total network coverage in terms of TPs covered.
- The cost is proportional to the size of the problem instance. We can notice that the more TPs we deploy in the area, the more expensive the cost of our placement. This is due to the heterogeneity of the network and the CDs' cost. As can be gathered from Table 5, the proposed MOTS is able to find solutions that are mostly better than MOGA. In fact, Z_2 for MOTS are on average 33% better than those proposed by MOGA.
- Regarding the maximization of the minimum bandwidth, in 46.29% (i.e. 25 instances out of 54) we get the perfect equality with the two methods. However on the 29 remaining instances, MOGA got better solutions on 18 instances (i.e. 62%).
- As we can see in Figure 3, MOGA requires less CPU time. This gap becomes more important as the problem size increase since MOTS still has to go through several iterations due to its tracking process using tabu lists. This behavior is due to the numerous iteration that MOTS has to go through.
- For large instances, MOTS has better results then the MOGA algorithm in terms of network coverage. Also, we can notice that 100% of TPs coverage were achieved in 53% of the problem instances.
- If we rate the total dominance of the two algorithms for the set of non dominated solutions P_{ND} (Table 5), we clearly see that MOTS dominates MOGA in 37.96% comparing to 34.25% for the MOGA among the whole set of 54 problem instances.
- We can clearly see from Tables 3, 2 and 4, that the number of non dominated solutions P_{ND} is related to the number of active nodes deployed in the network. The more nodes we activate, the bigger is the number of non dominated solution.

Table 5: Comparison of the coverage based index obtained using MOTS and MOGA.

Solution approaches	Coverage / Objective Z_1	Z_2	Z_3	Average Coverage
MOTS	96%	66%	38%	37.96%
MOGA	4%	33%	62%	34.25%

Based in the numerical results reported in tables 3, 2, 4 and 5, we can note that the MOGA failed to meet 100% of TPs coverage for large scaled problems. This is due to the repairing process used in MOGA to handle a large set of constraints in our problem formulation. However, we can clearly see that MOTS outperforms MOGA to minimize the network's cost and maximize the total network coverage. This can be explained by the capacity of MOTS to explore a large set of solutions where MOGA, due to its crossover and mutation process, can reduce considerably the feasible region.

5 CONCLUSIONS

Throughout this paper, we studied the MONP problem. This problem consists of deciding to the location, the number and the interconnection of nodes in order to extend an existing network. It also aims to decide of the optimal type and number of deployed CDs to ensure the heterogeneity of the infrastructure. As the problem is multi–objective and heterogeneous, no benchmarks exist. We thus generate three groups of problem instances to test our approach based on the number of active nodes deployed in the network and the number of associated candidate sites. We presented two resolution approaches that iteratively solve the MONP problem. Our computational experiments show that the tabu–based heuristic produced solutions that were in 37.96% better than those produced with the genetic algorithm. These are considered as promising results if we take into consideration the difficulty and complexity of the problem that we have studied. However, the MOGA still get better results on the execution time. Other research lines should be carried out in future work to assess the performance of our method.

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