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VL-PLS: A Multi-objective Variable Length Pareto Local Search To Solve The Node Placement Problem For Next Generation Network

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Abstract

In the node placement problem for next generation network, an existing networks coverage is extended by placing new nodes and connecting them via ad hoc technologies so as the global network communication coverage is optimized. Four relevant objective functions are considered : The maximization of the communication coverage, the minimization of the nodes placement and the communication devices costs, the maximization of the total minimum capacity bandwidth to connect the infrastructure, and the minimization of the total overlapping. To tackle this problem, a new multi-objective variable length Pareto local search (VL-PLS) algorithm is proposed. The main incentive of the VL-PLS algorithm is that, in the proposed solution encoding, both substring and solution lengths dynamically vary leading to emphasize the optimization process and look for the optimal number of placed node. Three different neighborhood structures are presented in order to ensure a good exploration of the search space. A comparative study with an existing algorithm from the literature is dressed using different multi-objective performance metrics to support the performance of our algorithm.

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Keywords: Pareto Local Search, Genetic Algorithm, Next Generation Networks, Node Placement Problem, Heterogeneous Network Planning.

1. Introduction

The increasing demand for high data rate wireless communication and the emergence of various wireless technologies creates the need of a new heterogeneous network capable to integrate multiple network technologies and take advance of various networking and techniques. Next Generation Networks (NGN) answer to all new network requirements by creating a new wireless architecture capable to integrate heterogeneous components that can collaborate and exchange data in a cost effective and easy-to-manage process[1]. This new infrastructure aim on creating a network that provides a better levels of quality when matching consumers' expectations that can support heterogeneous services.

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In this paper we address the Node Placement Problem for Next Generation Network (NPP for NGN)[2] described as follows: given a set of communication nodes (CNs), a set of communication devices (CDs) and existing networks infrastructure related to each CD. The purpose is to find where to position CNs and CDs in order to optimize concurrently four objective functions: maximizing networks coverage, minimizing the total costs, maximizing the total minimum capacity bandwidth and minimizing the noise level. Several communication and geographical constraints must be satisfied when optimizing the objective functions. Related works on optimizing the NGN planning in a heterogeneous infrastructure are scarce[3,4,1]. Wong and Leung[4] presented a survey on the location management algorithms for NGN. Douglas et al.[3] discussed the forces that are moving today's networks toward NGN while enumerating the major business challenges facing NGN requirements. Several other studies addressed the integration of heterogeneous networks. Ting et al.[5] solved the transmitters placement with a new multi-objective variable-length genetic algorithm (VLGA). The problem optimize four objectives functions: maximizing coverage, minimizing cost, maximizing capacity satisfaction, and minimizing overlap. A more general model is addressed by Abdelkhalek et al.[6,7,8,9] namely the multi-objective node placement (MONP) problem. It optimizes concurrently three objectives: maximizing the network coverage, minimizing the total network cost and maximizing the minimum bandwidth. Multiple heuristic approaches were proposed to solve the problem applied to real data for maritime surveillance application. Because the NPP for NGN is $\mathcal{NP}$-hard, we propose, in this paper, to design a new variant of the multiobjective Pareto Local Search (PLS) approach namely the Variable-length PLS (VL-PLS) to solve the problem. In fact, PLS has been mainly adopted for solving the multi-objective traveling salesman problem[10] with two and three objectives, various bi-objective permutation flowshop problems[11], and the bi-objective multi-dimensional knapsack problem[12]. To the best of our knowledge, and based on the existing literature, none has yet considered the PLS algorithm for solving the antenna placement problem in network management. The incentive behind choosing such metaheuristic is that it is easily accessible through many free and commercial software packages and this represents a good candidate for solving the NPP for NGN. We propose, to improve the classical PLS algorithm, a new solution encoding where substrings and solution lengths dynamically vary. We also proposed three different neighborhood structures in order to ensure a good exploration of the search space. For the experiments, we compare the proposed VL-PLS to an existing variable-length genetic algorithm (VLGA) that gave very good results applied to the NPP for NGN[2]. The comparison of both algorithms is performed on real data instances for the maritime surveillance application using the *Inform Lab* (IL) simulation environment[13]. The remainder of this paper is organized as follows. Section 2 states brief description of the NPP for NGN problem. Section 3 details the VL- PLS algorithm and section 4 reports the experimental results.

2. A Multi-objective Node Placement Problem for Next Generation Network

The NPP for NGN deals with two different sub-problems simultaneously: node placement and network connection problem, both applied on multi–objective framework. The mains goal is to extend an existing networks coverage by placing new nodes and connecting them via ad hoc technologies in order to optimize the global network communication coverage. The main setting of the NPP for NGN are: N communication nodes (CNs), D communication devices (CDs) and Z^d existing network infrastructure related to each CD d. To ensure the connectivity between different ad hoc technologies, boundary nodes (BN) are deployed and can include more than one CDs. To simulate the traffic demand, we introduce a set of service test points (STPs), were a STP can represent one or multiple mobile users. The main purpose is to find a "good" placement of nodes (CNs and BNs) and CDs in order to optimize the network infrastructure. The NPP for NGN mathematical formulation is as follows:

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

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

$$Max\ \ Z_3(X) = \sum_{d=1}^{D}(Min_{\{d,i\neq j\}} y_{ij}^d z_i b_d z_j) + \sum_{d=1}^{D}(Min_{\{d,i\neq j\}} x_{ik}^{dd'} z_i b_d) \tag{3}$$

$$Min\ \ Z_4(X) = \sum_{t=1}^{T} overlapped(t_f) \tag{4}$$

$$s.t.$$

$$y_{ij}^d = z_i x_{ik}^d . z_j x_{jk'}^{d'} \quad \forall i \neq j,\ \forall k \neq k' with\ T_{dd'} = 1 and \quad d_{k,k'} \leq Max(w_d, w_{d'}); i \neq j \quad and \quad k \neq k' \tag{5}$$

$$\sum_{f=1}^{R}\sum_{k=1}^{M} \sigma_f^d w_{if}^d x_{ik}^d \leq s_d \quad \forall i \in \{1,...,N\}, d \in \{1,...,D\} \tag{6}$$

$$x_{ik}^d = v_{ik}^d \forall v_{ik}^d = 1 \quad or \quad 0, If \quad v_{ik}^d = 1 \quad then \quad z_i x_{ik}^d = Z_d \tag{7}$$

$$\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\sum_{d=1}^{D} b_d y_{ij}^d \leq b_{Z_d} z_i \quad \forall Z_d \tag{8}$$

$$\sum_{\forall i \in N-\{j\}} y_{ij}^d \leq NL^d \quad \forall j \in \{1,\ldots,N\} \tag{9}$$

$$x_{ik}^d \leq z_i \forall i \in \{1,\ldots,|Z^d| + N\} \tag{10}$$

$$x_{ik}^{d,d'} t_{dd'} \leq 1 \forall d, d' \in \{1,...,D\}, d \neq d', \forall i \in \{1,...,N\}, k \in \{1,...,M\} \tag{11}$$

$$\sum_{k=1}^{M} x_{ik}^d = 1 \forall i \in \{1,...,N\}, \exists d \in \{1,...,D\} \tag{12}$$

$$\sum_{i=1}^{N} x_{ik}^d \leq 1 \forall k \in \{1,...,M\}, \exists d \in \{1,...,D\} \tag{13}$$

$$\sum_{i=1}^{N} y_{ij}^d \geq 1 \forall d \in \{1,...,D\} \quad and \quad j \neq i, j \in \{1,...,N\} \tag{14}$$

$$\sum_{i=1}^{N} y_{iZ^d}^d \geq 1 \forall d \in \{1,...,D\} \tag{15}$$

$$x_{ik}^d, y_{ij}^d, z_i \in \{0,1\} \quad \forall i,k,j,d \tag{16}$$

Four objectives are considered: maximizing the communication coverage (Eq 1), minimizing nodes placement and CDs costs (Eq 2), maximizing the total minimum capacity bandwidth to connect the infrastructure(Eq 3), and minimizing the total overlapping (Eq 4). Our problem includes various types of constraints differing in difficulty and complexity which make the problem extremely hard to solve. More details regarding the mathematical formulation of the NPP for NGN can be found in[2].

3. VL-PLS: A Variable Length Pareto Local Search Method

The Pareto Local search (PLS)[14] is a generalization of the local search algorithms to handle more than one objective. The basic version of the algorithm maintains a random set of potentially efficient solutions, called archive A_{ND} and tries to iteratively improves this set by exhaustively exploring its entire neighborhood. As an acceptance criterion, PLS adopts the Pareto optimality concept: a solution is accepted only if it is non-dominated by all solutions in the archive.

3.1. Solution representation

In the NPP for NGN, we consider a variable length solution representation depicted in Fig. 1. Each CN $n \in N$ is represented as a substring that illustrates: the location index of the CS, the assigned CDs and the network links between existing nodes in the network. For the location of CSs, each index represents a specific and unique placement for our CN and varies from 0 to $(M-1)$. The length of the second part of our substring will be equal to the number of available CD in the network D. The third part represents the existing infrastructure with which the node n_i is connected added to the total number of active CN deployed in the network. Its length gradually increase depending on the number of placed CNs in each solution and varies from $\{|Z^d|, .., |Z^d| + N\}$.

Both substring and chromosome lengths dynamically vary since the number of active CN is variable. Consequently, the proposed algorithm can search automatically for the appropriate number of CN while optimizing all objectives detailed above.

	$Node_1$	$Node_2$	...	$Node_{n-1}$
Solution	(2) (01001) (110010)	(15) (11000) (1110001)	...	(35) (11100) (00100..111)

Fig. 1. Example of a solution representation

3.2. Neighborhood structures

Three different neighborhood types are defined for the VL-PLS: (i) *Swap*: switch between two node placements. If the obtained solution is not feasible, an adjustment process is triggered in order to fulfill all constraints. (ii) *Exchange*: move an already placed node from a selected CS to a vacant location. Then, make a variation on one of its CDs by either assigning a new device or removing an existing one. (iii) *Insert*: assign a new CD to a random node having the maximum amount of uncovered TPs' demand.

3.3. The VL-PLS

The solution approach proposed for solving the NPP for NGN is mainly based on PLS. The lengths of both of the substring and the solution change dynamically since the number of active CN is variable. Hence, the algorithm can search automatically for the appropriate number of CN and optimize the position and connection type for a maximum coverage, minimum cost, maximum of bandwidth and minimum overlap. Furthermore, we design three different neighborhood structures, namely *Swap*, *Exchange* and *Insert* so as to guarantee a good exploration the search space. The pseudo-code of the VL-PLS is outlined in Algorithm 1.

The VL-PLS starts from a random generated population which is evaluated according to the Pareto optimality concept in order to form the archive A_{ND}. At each iteration, an unvisited solution $s \in A_{ND}$ is randomly chosen, and its neighborhood is fully explored by a randomly selected neighborhood structure $N_k(s)$. Every non-dominant neighbor becomes a candidate to be added to the archive if it is non-dominated by all solutions in the archive. After examining the neighborhood of the current solution, it is marked as *visited*. VL-PLS stops when all the solutions in the archive are visited.

4. Experiments

In this section, we present the experimental study of the proposed VL-PLS.

4.1. Experimental protocol

For each search method, a set of 20 runs *per* instance were performed with different initial populations. In order to assess the quality of the approximated Pareto front generated for every test instance, we first compute a reference set Z^r of non-dominated solutions extracted from the union of all approximated fronts. Then, we consider the upper bound

Algorithm 1 The VL-PLS template

Initialization

Set an initial set of non-dominated solutions A_{ND}
Define the set of neighborhood structure N_k (k=1..3)

Iterative process

for all $s \in A_{ND}$ **do**
  $visited(s) \leftarrow False$
end for
while $\exists s \in A_{ND}$ and $visited(s) = False$ **do**
  Choose randomly $s \in A_{ND}$
  Select randomly one of the neighborhoods N_k
  for all $s' \in N_k(s)$ **do**
    if $s' \geq s$ **then**
      Add (s', A_{ND})
      $visited(s') \leftarrow False$
    end if
  end for
  $visited(s) \leftarrow True$
end while

vector $Z^u$of the objective functions for all fronts approximations. To evaluate the quality of a generated non-dominated set A_{ND} versus Z^r, we use two different multi-objective performance indicators that inform about the convergence and the diversity of the generated fronts approximations. The unary hyper-volume metric [15,16] (I_H^-) computes the portion of the objective space that is weakly dominated by Z^r and not by A_{ND}. We also consider the unary additive ϵ-indicator ($I^1_{\epsilon+}$) proposed in [16] that gives the minimum value by which an approximation A_{ND} has to be translated in the objective space to weakly dominate the reference set Z^r. Note that Z^u is considered as the reference point for both indicators.

4.2. Computational results

In this section, we present the experimental results of the comparison of the proposed VL-PLS to an existing multi-objective variable length genetic algorithm (VLGA)[2]. Three different and uniform STPs distribution are applied in addition to five different CDs settings to ensure the network connection. The features of the CDs and STPs' distribution are detailed in [2]. As shown in Tables 1, 2 and 3, the instances are classified into small, medium and large problems having respectively 76, 171 and 676 STPs. A total of 54 different problem instances were generated for the tests. Different number of CSs, CNs and CDs settings are considered. All benchmarks' description is available in [2]. Common strategies for stopping multi-objective metaheuristics are generally related to an arbitrary user-given number of iterations or evaluations. However, there is no relation between an evolutionary algorithm iteration and a local search iteration. Therefore the stopping criterion is related to the computational time. We arbitrarily set the amount of runtime according to the size of the instance under consideration. For each value of STPs distribution $\in \{76, 171, 676\}$, the runtime is equal to $\{60, 90, 120\}$ seconds respectively for a single simulation run per instance and per algorithm. Tables 1, 2 and 3 compare VL-PLS and VLGA algorithms with respect to several quality indicators. For each test instance and each algorithm, we report the average value of the number of potentially efficient solutions $|P_{ND}|$, the maximum number of active nodes $\#PN$ (according to the set of non-dominated solutions), I_H^- and $I^1_{\epsilon+}$ metrics. It is worthy to note that a lower average of the two latter indicators (i.e. I_H^- and $I^1_{\epsilon+}$) signifies a "better" approximation set.

Based on the experimental results among the 54 different problem instances, we clearly conclude that the proposed VL-PLS is significantly better than the VLGA. A first remark is that the proposed algorithm explored the Pareto front better than the VLGA. In fact, we can note from Fig. 2 that it has greater number of potentially efficient solutions $|P_{ND}|$ for about 70% of the problem instances. This gives the decision maker the flexibility to choose the best placement strategy among a wider range of efficient possibilities.

Table 1. Computational performance of VL-PLS to the NPP for NGN for 76 STPs

Pbs.	VLGA				VL-PLS			
	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H
C_1	19	10	0,437	0,871	34	8	0,00	2,22E-16
C_2	15	11	0,175	0,075	20	14	0,137	0,096
C_3	12	16	0,18	0,251	20	15	0,00	0,00
C_4	15	7	0,312	0,555	24	9	0,00	0,00
C_5	13	13	0,448	0,111	20	15	0,097	0,026
C_6	17	14	0,076	0,203	25	15	0,00	0,00
C_7	5	9	0,7	0,089	9	4	1,00	0,393
C_8	7	8	0,666	1,154	11	15	0,00	4,44E-16
C_9	6	9	0,45	0,121	16	28	0,038	0,035
C_{10}	10	7	0,285	0,445	9	7	0,045	0,041
C_{11}	14	8	1,00	1,414	4	9	0,00	0,00
C_{12}	16	11	1,00	1,325	6	5	0,058	0,003
C_{13}	5	8	0,238	0,567	5	5	0,00	0,00
C_{14}	13	10	0,56	0,958	12	18	0,00	0,00
C_{15}	9	12	0,24	0,245	12	13	0,181	0,245
C_{16}	10	6	0,375	0,119	7	5	0,727	0,429
C_{17}	13	13	1,00	0,979	5	6	0,307	0,029
C_{18}	11	18	1,00	1,027	8	23	0,285	0,019
Avg.	-	-	**0,508**	**0,584**	-	-	**0,159**	**0,073**

Table 2. Computational performance of VL-PLS to the NPP for NGN for 171 STPs

Pbs.	VLGA				VL-PLS			
	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H
C_{19}	8	10	0,141	0,345	37	9	0,00	0,00
C_{20}	9	17	0,058	0,045	16	16	0,039	0,046
C_{21}	12	22	0,163	0,280	27	14	0,147	0,252
C_{22}	10	9	0,116	0,215	26	9	0,00	0,00
C_{23}	12	10	0,009	0,756	31	15	0,002	0,0011
C_{24}	14	10	0,419	0,943	24	14	0,00	2,22E-16
C_{25}	13	6	1,00	0,907	6	6	0,383	0,025
C_{26}	14	11	0,361	0,621	6	17	0,294	0,0612
C_{27}	15	15	0,29	0,287	38	26	0,138	0,087
C_{28}	12	10	1,00	1,3	4	9	0,076	0,004
C_{29}	16	13	0,14	0,661	12	17	1,00	1,24
C_{30}	18	17	0,727	0,084	12	27	0,00	0,00
C_{31}	10	8	0,143	0,016	5	8	1,00	0,2
C_{32}	16	9	1,00	1,37	8	16	0,00	0,00
C_{33}	15	12	0,813	1,024	6	6	0,00	0,00
C_{34}	8	9	0,361	0,469	11	9	0,111	0,038
C_{35}	12	13	0,594	0,091	9	19	1,00	0,414
C_{36}	15	12	0,441	0,052	9	28	1,00	0,783
Avg.	-	-	**0,432**	**0,535**	-	-	**0,288**	**0,175**

The VL-PLS has significantly a better performance in terms of $I^1_{\epsilon+}$ metric for the three problem classes. In fact, as we can see from Tables 1, 2 and 3, that the proposed method has a lower average value for both metrics. This gap become smaller for big problem instances when we consider 676 STPS. In fact, the VLGA got a better performance only for instances C_7,C_{16}, C_{29}, C_{31}, C_{35} , C_{36}, C_{43}, C_{44} , C_{46}, C_{47} , C_{48} where the VL-PLS dominates in all other

Table 3. Computational performance of VL-PLS to the NPP for NGN for 676 STPs

Pbs.	**VLGA**				**VL-PLS**			
	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H	$\|P_{ND}\|$	$\#PN$	$I^1_{\epsilon+}$	I^-_H
C_{37}	9	8	0,238	0,363	26	8	0,00	2,22E-16
C_{38}	10	12	0,227	0,184	32	14	0,0957	0,014
C_{39}	16	12	0,356	0,298	33	13	0,00	2,22E-16
C_{40}	24	7	0,381	0,504	22	8	0,055	0,0153
C_{41}	18	13	0,09	0,075	32	15	0,055	0,011
C_{42}	15	16	0,187	0,261	25	15	0,00	0,00
C_{43}	10	6	0,148	0,197	13	8	0,429	0,116
C_{44}	12	16	0,216	0,206	18	17	0,531	0,358
C_{45}	14	22	0,705	0,027	15	21	0,26	0,916
C_{46}	11	8	0,528	0,975	10	7	0,751	0,034
C_{47}	15	11	0,168	0,532	10	12	0,32	0,719
C_{48}	20	19	0,13	0,409	7	26	0,564	0,837
C_{49}	12	5	0,37	0,758	12	8	0,00	0,00
C_{50}	11	10	1,00	1,30	24	14	0,054	0,004
C_{51}	14	12	1,00	1,17	4	7	0,181	0,01
C_{52}	13	6	1,00	1,22	11	6	0,101	0,01
C_{53}	14	12	0,632	0,805	14	10	0,00	1,11E-16
C_{54}	15	21	0,581	0,738	11	28	0,069	0,761
Avg.	-	-	**0,442**	**0,557**	-	-	**0,193**	**0,168**

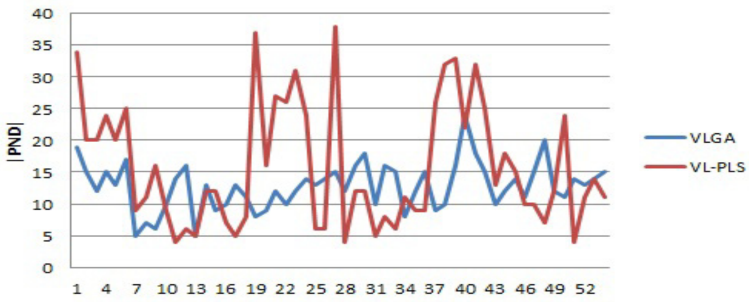

Fig. 2. Number of non dominated solutions per problem instance

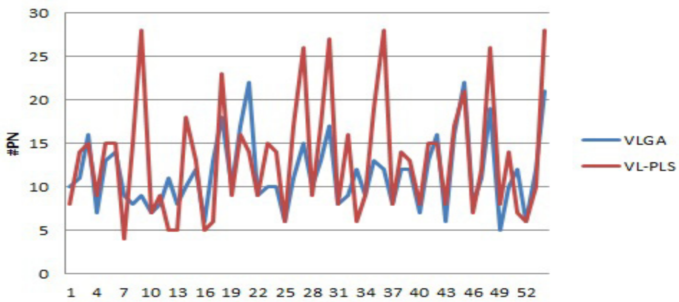

Fig. 3. Number of placed nodes per problem instance

instances. Same for the I^-_H metric, where we can see that VL-PLS dominates VLGA in $\simeq$ 80% of test problems whereas VLGA leads to better results for about 20% of the problem instances.

Both VLGA and VL-PLS did not exceed the threshold of the maximum allowed number of CNs (see Fig. 3). This can be explained by the fact that as we are minimizing the total network infrastructure cost, this leads us to automatically minimize the number of placed nodes. Moreover, the variable length aspect of the solution encoding strengthens the threshold constraint. However, comparing to the VLGA, the VL-PLS generates a greater #*PN* which could lead to increase the networks cost. So despite good metrics performances values, the VL-PLS generated, in some instances, results of lower quality in term of network cost compared to the VLGA.

5. Conclusion

In this paper, a new VL-PLS is introduced in order to solve the NPP for NGN problem.The NPP for NGN aims at extending an existing heterogeneous network while simultaneously maximizing networks coverage, minimizing the total costs, maximizing the total minimum capacity bandwidth and minimizing the noise level. The main idea of the VL-PLS is to handle a new solution encoding that dynamically vary both substring and solution lengths. Three different neighborhood structures are integrated within the algorithm in order to ensure a good exploration the search space. VL-PLS exhaustively explore all of its neighborhood before it stops running. The proposed VL-PLS is compared to an existing algorithm from the literature, namely VLGA. To assess the performance of these two methods, 54 instances are generated by varying the problem input parameters. The comparison is based on several multi-objective performance metrics. Computational experiments show that VL-PLS was significantly more efficient than VLGA with respect to the considered performance metrics. However, the VL-PLS generates a greater #*PN* which could lead to results of lower quality in term of network cost. As a future work, a cooperative schema between both local search and evolutionary algorithms could be an interesting approach to get better solutions' quality.

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