On the Application of a Novel Grouping Harmony Search Algorithm to the Switch Location Problem

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Abstract. This paper presents the adaptation of a novel heuristic algorithm to the Switch Location Problem (SLP), a NP-hard problem where a set of distributed terminals, with distinct rate demands, is to be assigned to a fixed number of concentrators subject to capacity constraints. Each terminal must be assigned to one and only one concentrator while keeping the overall rate demanded from such concentrator below its maximum capacity. Related literature demonstrates that the inclusion of the so-called *grouping* concept into the allocation algorithm is essential when dealing with this specific kind of optimization scenarios. As such, previous studies introducing Grouped Genetic Algorithms (GGA) combined with local search and/or repair methods show that their proposed allocation procedure alleviates significantly the computational complexity required by an exhaustive search strategy for the SLP problem, while outperforming other hybrid heuristic algorithms. In this manuscript, a novel Grouped Harmony Search (GHS) algorithm designed for the SLP paradigm is hybridized with both a local search method and a technique aimed at repairing the solutions iteratively supplied by the heuristic process. Extensive Monte Carlo simulations assess that our proposal provides faster convergence rate and better statistical performance than the previously proposed GGA, specially when the size of the SLP scenario increases.

Keywords: ANLP/SLP, Heuristic Algorithm, Genetic Algorithm, Harmony Search.

1 Introduction

The last decade has witnessed an abrupt increase of the number of users simultaneously accessing and exploiting communication resources, which has risen the importance of efficiently designing networks' infrastructures and topologies

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to its maximum. This assertion is buttressed by the flurry of densely-deployed communication technologies such as the ever-trendy Wireless Sensor Networks (WSN) or the mobile telecommunication networks.

In this context, among the plethora of problems related to network planning it is worth mentioning the design of fixed network topology [1], optimum base station location [2], Access Node Location Problem (ANLP) [3] and the Terminal Assignment (TA) problem [4], all of which constitute by themselves NP-hard problems. NP-hardness implies that the search for an analytical optimum solution cannot be guaranteed to be found in a polynomial time, the reason being that the solution space increases exponentially with the number of inputs. It was not until the mid 80's when the application of heuristic and/or evolutionary methods were extensively applied to NP-hard problems, mainly due to their near-optimum performance and easy implementation and adaptation to different scenarios (e.g. Tabu Search [5], [6], Simulated Annealing [7] or Genetic Algorithm [8]).

Let us concentrate on the so-called *Switch Location Problem* (SLP), which gravitates on assigning a given set of terminal to a given set of concentrator by minimizing the total average distance (and hence the cost) between terminals and concentrators. Furthermore, only one concentrator can be assigned to one terminal and the capacity of each concentrator must satisfy the overall rate requirements demanded by its assigned terminals. These additionally imposed constraints implies that a global search strategy must be replaced by a restricted search procedure, capable of minimizing the average distance while accounting for the capacity requirements of the scenario at hand. Notice that in the related literature both SLP and ANLP are distinct albeit related version of the Terminal Assignment problem, where a set of M concentrators is drawn from $N > M$ terminals, and the $N - M$ remaining terminals are linked to the M concentrators under a capacity constraint. SLP stands for the case when the value of M is fixed and known beforehand, whereas ANLP generalizes the optimization problem by considering a variable M. As a means to efficiently solve the aforementioned SLP paradigm, hybrid algorithms mixing global search techniques with local techniques were proposed in [4,9]. Within this line of research, the concept of Grouping Genetic Algorithms (GGA) was first introduced by [10,11] and recently applied to the ANLP problem in [3].

This paper advances over the state of the art by proposing the adaptation of the recent Harmony Search (HS) heuristic algorithm to the SLP paradigm. First coined by Zong *et al.* in [12], the HS algorithm mimics the behavior of a music orchestra in the process of music composition. Several optimization problems have benefited from the excellent performance of HS for scenarios of specially high complexity, e.g. water network design [13], multicast routing [14] or multiuser detection [15,16]. To adapt the global search characteristic featured by the HS algorithm to the restricted solution space of the SLP problem tackled herein, it is necessary to include two additional concepts in the nominal HS procedure: 1) a local search method, and 2) a repair criterion of proposed solutions not fulfilling the imposed capacity constraints. In addition, the grouping concept is utilized to encode the iteratively obtained solutions, which gives birth to the Grouping Harmony Search (GHS) allocation strategy here proposed. Monte Carlo simulation results show that the performance of GGA reported in [17] is beaten by that of GHS for a broad range of SLP scenarios, in terms not only of the optimality of the provided solution but also of its computational complexity.

The rest of the manuscript is structured as follows: the problem formulation of the SLP problem is presented in Section 2, whereas Section 3 details the main characteristics of the proposed Grouping Harmony Search (GHS) algorithm. Next, Section 4 discusses a comparison study between the proposed algorithm and the Grouping Genetic procedure for different network configurations. Finally, concluding remarks are drawn in Section 5.

2 Problem Formulation

Let us mathematically define the SLP problem by assuming a set of N terminals $\{l_1, l_2, \ldots, l_N\}$ with associated rate requirements or *weights* $\{w_1, w_2, \ldots, w_N\}$. Each such terminals should be assigned to any of $M \leq N$ concentrators $\{r_1, r_2, \ldots, r_M\}$ drawn out from the N terminals. We assume that such concentrators have maximum capacities $\{p_1, p_2, \ldots, p_M\}$, that $w_i < \min(p_1, p_2, \ldots, p_M)$ $\forall i \in \{1, \ldots, N\}$, and that concentrator nodes should be chosen from the complete set of N nodes because terminal and concentrator share the same network infrastructure. If we further consider that only one concentrator can be assigned to a given terminal, the terminal-concentrator assignment policy should be done by minimizing the total sum of distances between each terminal and its selected concentrator while satisfying, at the same time, the capacity constraint. This optimization problem can be split in 1) connecting the set of terminals to a given set of concentrators, and 2) selecting the nodes which act as concentrators.

All nodes are randomly spread over a $K \times K$ grid. We can then define a $N \times N$ symmetric matrix $\mathbf{D}$ such that each entry $d_{i,j}$ represents the euclidean distance from node i to node j. Let us define matrix $\mathbf{X}$ with binary entries $x_{i,j}$ such that $x_{i,j} = 1$ if terminal i is assigned to concentrator j and $x_{ij} = 0$ otherwise. By using this notation the SLP problem reduces to finding the matrix $\mathbf{X}$ which satisfies, for a given N and M,

$$\min \left(\sum_{j=1}^{M} \sum_{i=1}^{N} d_{ij} \cdot x_{ij} \right), \tag{1}$$

subject to

$$\sum_{i=1}^{N} w_{ij} \cdot x_{ij} \leq p_j \qquad j = 1, \ldots, M, \tag{2}$$

$$\sum_{j=1}^{M} x_{ij} = 1 \qquad i = 1, \ldots, N \tag{3}$$

Observe that expression (1) establishes the metric or fitness function that allows quantifying the cost of each network configuration, while equations (2) and

(3) represent the constraints imposed in the SLP scenario. The first expression ensures that the requirements of the terminals associated to a certain concentrator cannot exceed its maximum capacity, whereas the second constraint accounts for the fact that each terminal can be connected only to one concentrator. Also notice that for this constrained optimization problem a global search technique to optimize the search over the $\binom{M}{N}$ possible solutions is not as adequate as an optimized restricted technique well-suited to meeting the constraints of expressions (2) and (3). The next section details the adaptation of the novel heuristic Harmony Search algorithm towards efficiently solving this optimization problem, which requires a specific encoding of the possible solutions and the inclusion of a local search and repair methods.

3 Grouping Harmony Search for the SLP Problem

The *grouping* encoding strategy finds its roots on partitioning a set of items into several disjoint subsets or, equivalently, on grouping the members of a set into several subsets by following certain criteria (possibly) based on constraints. The first proposed Grouping Genetic Algorithm (GGA) was published by Falkenaurer in [10,11], where it was applied to solve the "Bin Packing and Line Balancing" NP-problem. More than 15 years later, the concept of Grouping has been proven to be essential in the resolution of SLP and/or ANLP problems by Alonso-Garrido *et al.* in [3]. Following the notation and structure proposed therein, in this contribution we transform the Harmony Search heuristic algorithm into a Grouping Harmony Search (GHS) procedure. Each proposed solution vector $\mathbf{s} = (\mathbf{s}_x \mid \mathbf{s}_y)$ will be divided into the assignment part ($\mathbf{s}_x$) and the grouping part ($\mathbf{s}_y$). The assignment part consists of N integer indices from the set $\{1, \ldots, M\}$, which denote to which concentrator (from the $\mathbf{s}_y$ set) is assigned each of the N terminals. On the other hand, the $\mathbf{s}_y$ grouping part is built by concatenating M integer indices from the set $\{1, \ldots, N\}$, denoting which nodes act as concentrators.

As introduced in Section 1, the Harmony Search (HS) algorithm is based on mimicking the behavior of a music orchestra in their attempt to achieve the best harmony. In this seeking process, Harmony Search works with a set of φ possible solutions or harmonies commonly denoted as Harmony Memory (HM), which are evaluated at each iteration under an aesthetic point of view. The Harmony Memory is updated whenever any of the φ improvised harmonies at a given iteration sounds *better* (under a certain fitness criterion) than any of the φ harmonies kept from the previous iteration. This procedure is iteratively repeated until the best harmony is reached or alternatively, until a fixed number of attempts or iterations are completed. For the sake of conformity with the notation in [12], we will hereafter refer to a possible candidate vector (i. e. s_x) as *harmony*, and *note* will stand for any of its compounding entries.

The harmony improvisation process of the seminal HS algorithm is controlled by just two parameters: 1) *Harmony Memory Considering Rate*, HMCR; and 2) *Pitch Adjusting Rate*, PAR. Similar to [16], in this contribution the proposed improvisation procedure differs from the original HS implementation by introducing a third parameter (Random Selection Rate, RSR), which allows for an improved control of the tradeoff between the explorative and the exploitative behavior of the algorithm.

The flow diagram of the algorithm here proposed is schematically shown in Figure 1, and consists of four steps:

A. The **Initialization** process is only executed at the first iteration. At this point, since no a priori knowledge of the solution is assumed the harmony notes (i.e. the entries of $\mathbf{s}_x$) are filled with values picked randomly from the corresponding alphabet $\{1, \ldots, M\}$.

B. The **Improvisation** process is sequentially applied to each note of the complete set of harmonies. As opposed to the nominal HS scheme three arbitrary parameters are used to control the proposed method:
   - The Harmony Memory Considering Rate, HMCR $\in [0, 1]$, which establishes the probability that the new value for a note is drawn from the values of the same note taken in all the other $\varphi - 1$ harmonies included in the Harmony Memory.
   - The Random Selection Rate, RSR $\in [0, 1]$, which stands for the probability that the proposed new value for a note is selected randomly from the corresponding alphabet (in general it will be set different from the complementary probability 1-HMCR used by the nominal HS algorithm).
   - The Pitch Adjusting Rate, PAR $\in [0, 1]$, which sets the probability that the new note value is picked from its neighbor value in the alphabet.

C. The existence of capacity limits at the concentrators requires the transformation of the global search behavior of the algorithm into a constrained search process. Heretofore the search is not limited to a certain set of valid candidates; in other words, the procedure does not consider any of the conditions imposed by expressions (2) and (3). Therefore, the iterative global search process is not as efficient as an hybridized approach. To overcome this issue, it is necessary to include two additional processes:
   - The so-called *GreedyExp* algorithm is the **local search method** adopted in this work, which was first proposed by Salcedo-Sanz *et al.* in [18,3] as an optimized version of the original *Greedy* algorithm [19].
   - The **repair criterion** in [18,3] is applied to the harmonies when capacity constraints are not satisfied.

D. At each iteration the quality **evaluation** of the improvised harmony memory is made based on the fitness function in expression (1). Once the local search and repair criteria are applied, if any of the proposed melodies does not satisfy the capacity constraints its metric are penalized to avoid its future inclusion in the Harmony Memory. Then, based on these metric evaluations and their comparison with the fitness of harmonies from previous iterations, the φ best harmonies are kept and the Harmony Memory is hence **updated**.

D. A simple **stop criterion** is selected for the scenario at hand: the algorithm finishes when a fixed number of iterations $\mathcal{I}$ is reached.

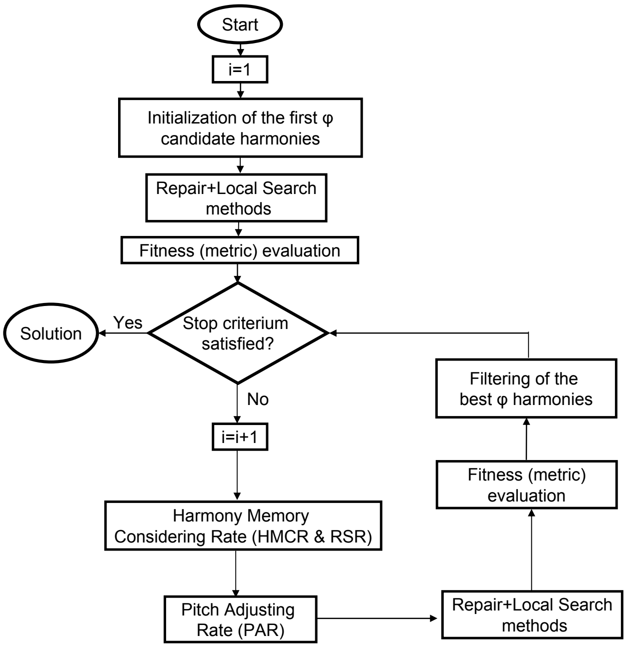


Fig. 1. Flow diagram of the proposed GHS algorithm (i denotes iteration)

Before proceeding to the simulation results, it should be emphasized that the proposed method not only adapts the Harmony Search algorithm from [12] to the SLP problem, but works rather differently than other previous GGA-related works (e.g. [3]) where the selection, crossover and mutation processes are jointly applied to the $\mathbf{s}_x$ and $\mathbf{s}_y$ vectors. In the present scheme, the algorithm improvises the melodies included in the Harmony Memory by applying the improvisation process only to the $\mathbf{s}_x$ part of the solution (i.e. without considering the $\mathbf{s}_y$ vector). After the $\mathbf{s}_x$ vector is modified, $\mathbf{s}_y$ is built by selecting as concentrator such node that minimizes the sum of distances from itself to all terminals grouped in the corresponding $\mathbf{s}_x$ assignment part.

4 Simulation Results

In order to assess the performance of the proposed hybrid GHS scheme when applied to the SLP problem, a comparison study between GHS and GGA has been done based on extensive Monte Carlo simulations. In [18,17] it is shown that the performance rendered by the application of GGA to the SLP paradigm considered herein is significantly better than that of previous related works where alternate evolutionary algorithms are considered. Therefore, the present comparison study is based on the results and scenarios published in [17].

Fairness in this study is ensured by utilizing the same physical locations (x- and y coordinates), rate demands and maximum capacities of the nodes for both

Table 1. Parameters of the simulated scenarios

Instance	N	M	Grid
1	20	3	500×500
2	40	4	500×500
3	50	4	500×500
4	60	5	500×500
5	80	8	500×500
6	90	9	500×500
7	100	10	500×500
8	110	10	500×500
9	150	15	500×500

GGA and GHS algorithms. Furthermore, the scalability of the proposed heuristic allocation procedure is verified by considering 9 different network instances: from the simplest $N = 20$ and $M = 3$ to the most complex $N = 150$ and $M = 15$. Table 1 details the parameters for all problem dimensions handled in this paper. In all these scenarios the nodes coordinates are randomly generated in a 500×500 grid, whereas terminal rate requirements are drawn from a normal distribution with mean 10 and standard deviation 5. Besides, as a means to guarantee the existence of a solution in the setup, i.e.

$$\sum_{i=1}^{N} w_i < \sum_{j=1}^{M} p_j, \tag{4}$$

the capacities of the concentrators $\{p_j\}_{j=1}^{M}$ are generated as a function of terminal requirements by setting

$$p_j = \frac{1,1 \cdot \left(\sum_{i=1}^{N} w_i \right)}{M} \tag{5}$$

where w_i is the rate requirement of the i-th terminal, and N and M are the overall number of terminals and concentrators, respectively. On the other hand, the selection of the parameters (HMCR, RSR, PAR) and the maximum number of iterations $\mathcal{I}$ for the simulated GHS approach are based on a previous optimization study made for the most complex scenario ($N = 150$, $M = 15$). A range from 0.01 to 0.99 for the three aforementioned parameters was simulated in more than 40 different sets of network realizations. The best performance was obtained for (HMCR, RSR, PAR)=(0.1, 0.07, 0.03), values that will be hereafter utilized for the comparison study.

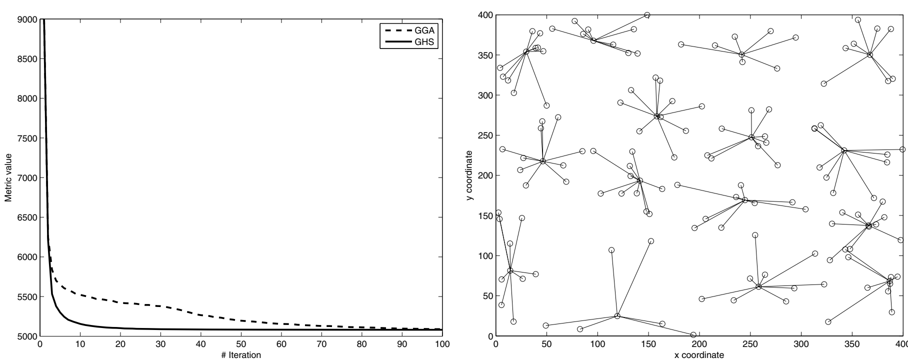
Furthermore, the computational cost is set the same for the GGA and GHS allocation techniques. In this study, both algorithms work without any previous knowledge about the scenario and with the same memory size (i.e. the population size of the GGA – 50 chromosomes – equals that of the Harmony Memory in the GHS technique). However, the maximum number of iterations for GHS is

Table 2. Statistical metric results (best/average/standard deviation) for GGA and GHS in the different SLP instances detailed in Table 1

SLP instance	GGA	GHS	Theoretical lower bound
1	1419/1419/0	1419/1419/0	1395
2	2455/2455/0	2455/2455/0	2403
3	3712/3712/0	3712/3712/0	3684
4	3800/3813/17	3800/3800/0	3706
5	3806/3819/18	3806/3807/1	3713
6	3792/3807/16	3792/3795/10	3684
7	4455/4498/26	4455/4464/13	4359
8	4724/4745/28	4724/4728/4	4563
9	5059/5127/47	5059/5080/19	4823

set to $\mathcal{I} = 100$, as opposed to the GGA proposed in [3] which iterates until a maximum number of 200 generations is reached. Consequently, the GHS results later detailed are obtained with half the computational complexity of the GGA approach for the same SLP scenario.

Table 2 summarizes the metric results obtained by both algorithms for the SLP instances detailed in Table 1. Notice that the last column indicates the theoretical lower bound when no capacity limits are assumed for the concentrator nodes. Note that in most cases this theoretical lower bound is unattainable if capacity requirements are imposed. For each case, the results are obtained by averaging the metric – as defined in expression (1) – over 20 and 50 different realizations of the network. Observe that the three simplest scenarios (1 to 3) render the same statistical results for GGA and GHS. However, notice that at



(a) (b)

Fig. 2. (a) GGA and GHS average metric (over 50 network realizations) versus iteration index for the most complex scenario (N, M)=(150, 15); (b) Example of obtained optimum distribution for the same SLP scenario

instance 4, the standard deviation of the GHS approach is still equal to zero (i.e. the algorithm provides the same minimum metric for all all Monte Carlo simulated network realizations), whereas that of the GGA technique is bounded away from 0. As for instances 5 to 7, the same minimum metric is reached, but GHS provides better average results and a lower standard deviation, difference that gets even higher for the last two network instances. These results for GHS are obtained at half the computational complexity of GGA, which enlightens the benefits entailed by our proposal.

Let us elaborate further on the convergence behavior of GGA and GHS by considering Figure 2, where the average metric of both algorithms is plotted versus the iteration index for the most complex scenario ($N = 150$, $M = 15$). Observe that GHS has a faster convergence rate than GGA, which motivates reducing the maximum number of iterations $\mathcal{I}$ for GHS (in fact, in light of these simulation results one could further decrease $\mathcal{I}$ below the selected value of 100, since the average metric is kept constant beyond 50 iterations of the GHS algorithm). Finally, Figure 2.b depicts an example of the optimum network configuration (N, M)=(150, 15).

5 Conclusions

In this paper we have proposed a novel hybrid grouping heuristic algorithm for solving the so-called Switch Location Problem. Our approach is based on the Harmony Search global search algorithm in conjunction with a *GreedyExp* Local Search criterion and a repair solution method. Based on the parameters governing the behavior of the algorithm (selected as a result of an intensive optimization study), simulation results show that GHS outperforms previous GGA approaches in terms of convergence rate, computational complexity and distance to the theoretical metric lower bound assuming no capacity constraints. Consequently, the overall cost of the network design is reduced with respect to other avantgarde techniques.

Further work on this topic will focus on extending the applicability of GHS to the more general Access Node Location Problem (ANLP), where the number of concentrators is not fixed. Research effort will also be conducted towards the inclusion of perturbing criteria or the dynamic adjustment of the GHS parameters during the iterative process, as means to narrow the gap between the obtained average metric results and the capacity-unconstrained theoretical lower bound.

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