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An adaptive hybrid algorithm for vehicle routing problems with time windows

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ABSTRACT

The harmony search algorithm has been proven to be an effective optimization method for solving diverse optimization problems. However, due to its slow convergence, the performance of HSA over constrained optimization problems is not very competitive. Therefore, many researchers have hybridized HSA with local search algorithms. However, it's very difficult to known in advance which local search should be hybridized with HSA as it depends heavily on the problem characteristics. The question is how to design an effective selection mechanism to adaptively select a suitable local search to be combined with HSA during the search process. Therefore, this work proposes an adaptive HSA that embeds an adaptive selection mechanism to adaptively select a suitable local search algorithm to be applied. This work hybridizes HSA with five local search algorithms: hill climbing, simulated annealing, record to record, reactive tabu search and great deluge. We use the Solomon's vehicle routing problem with time windows benchmark to examine the effectiveness of the proposed algorithm. The obtained results are compared with basic HSA, the local search algorithms and existing methods. The results demonstrate that the proposed adaptive HSA achieves very good results compared other methods. This demonstrates that the selection mechanism can effectively assist HSA to adaptively select a suitable local search during the problem solving process.

1. Introduction

The harmony search algorithm (HSA), proposed in 2001 by Geem, Kim, and Loganathan (2001), is a population-based approach inspired by modern nature. HSA mimics the natural steps of musical improvisation taken by musicians to improve their musical tones. It has been shown to be an effective approach for tackling numerous difficult real-world problems, such as binary-coded problems (Wang et al., 2013), nurse rostering (Hadwan, Ayob, Sabar, & Qu, 2013), university course timetabling (Al-Betar, Khader, & Zaman, 2012), structural optimization (Polat, Hasançebi, & Geem, 2016), dynamic optimization (Turky, Abdullah, & Sabar, 2014a, 2014b), portfolio selection problem (Sabar & Kendall, 2014), and other optimization problems (Alia & Mandava, 2011; Shreem, Abdullah, & Nazri, 2014).

HSA is similar to other population-based approaches with regard to the problem of slow convergence (Abdullah, Sabar, Nazri, & Ayob, 2014; Abuhamdah, Ayob, Kendall, & Sabar, 2014; Alia & Mandava, 2011; Blum, Puchinger, Raidl, & Roli, 2011). This problem usually occurs because they operate on a population of solutions that scatter over the landscape of the search space. In addition, most of population-based approaches are not good at exploiting the areas around the explored solutions (Neri & Cotta, 2012; Ong, Lim, Zhu, & Wong, 2006). A local search algorithm has been used within population-based approaches to address this issue (Neri & Cotta, 2012). The local search algorithm (LS) has a good exploitation performance and can thus improve the convergence of HSA. To this end, various LS(s) were introduced in the literature. Hence, the following question will arise (Ong et al., 2006): ***"Which LS algorithm should be used within HSA?"*** Different LS algorithms would perform well over different instances or only during certain stages of the solving process.

Studies such as Gong, Fialho, Cai, and Li (2011), Sabar, Ayob, Kendall, and Qu (2014a, 2014b), Sabar, Ayob, Kendall, and Rong (2013), Sabar, Ayob, Qu, and Kendall (2012), and Thierens (2009) have successfully utilized adaptive parameter setting and internal tuning, to address the problem of selecting suitable parameter values or mutation/crossover strategies for evolutionary algorithms. Their success in attaining good results is because parameter setting is dependent on two issues: problem features and search area (Gong et al., 2011; Sabar,

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Ayob, Qu, & Kendall, 2012).

Inspired by the studies mentioned above, this work proposes an adaptive HSA that uses an adaptive selection mechanism and a set of LS algorithms. The question is "*how to use an effective selection mechanism to adaptively select a suitable local search to be combined with HSA during the search process*?" Among the various selection mechanisms available, such as roulette wheel and tournament mechanisms, we adopt a multi-armed bandit (MAB) selection mechanism (Gong et al., 2011). MAB has been effectively used in solving various optimization problems such as the royal road problem. The MAB is utilized to control the selection of which LS to be used to improve the current instance based on their previous improvement strength in the searching process.

Five common local search algorithms (LSs): Hill climbing, simulated annealing, record to record, great deluge and reactive tabu search are used to enhance the exploitation performance of HSA. That is, at each iteration, the solutions generated by HSA are further improved by LS, and the decision of which LS should be applied is determined by the MAB. Our aims are as follows:

1. To improve the exploitation ability of HSA by hybridizing it with local search algorithms.
2. To propose an adaptive HSA that uses MAB as a selection mechanism that can adaptively and effectively selects a suitable LS from a given set of LS(s) in an on-line manner.
3. To examine the performance of the standard HSA, hybrid HSA and adaptive HSA over a well-known hard optimization problem, the Solomon's benchmark (Solomon, 1987).

The results of the proposed HSA is compared against basic HSA (without the selection mechanism), the five local search algorithms (implemented herein) and the best results reported in the literature.

2. Problem description

Transportation and distribution systems are among the most significant activities in numerous real-world applications. These systems comprise various problems, such as grouping and scheduling. The vehicle routing problem (VRP) (Dantzig & Ramser, 1959) is a well-known challenging problem in transportation field. VRP seeks for a set of vehicle trips to serve a group of customers (Solomon, 1987). The goal is to minimize the total cost (distances or time). A variant of VRP known as vehicle routing problem with time windows (VRPTW) has been widely studied in the literature. This is because of the involvement of the time window constraint which embodies real life conditions (Bräysy & Gendreau, 2005). Consequently, this work focuses on VRPTW in which a particular group of customers are distributed in various areas, and each one of them needs a specific demand to be delivered or picked during its pre-defined time window. The goal is to generate set of vehicle trips to serve all customers at minimal cost while satisfying the following constraints: (i) Each customer should be visited within its time window. (ii) The demands assigned to each route should not be greater than vehicle capacity (iii) Each vehicle must commence at the depot and terminate at the depot (iv) Split deliveries should be avoided.

Many solution techniques have been suggested to solve VRPTW. These techniques are divided into two groups (Bräysy & Gendreau, 2005): exact methods and meta-heuristic methods. Exact methods are capable of achieving optimal results (Kolen, Kan, & Trienekens, 1987). Nonetheless, they are only recommended to deal with small-sized problems (Bräysy & Gendreau, 2005). Thus, for large VRPTW, researchers have employed meta-heuristic methods, as they can provide good quality solutions in a practical amount of time, yet they do not guarantee the optimality of these solutions (Talbi, 2009). Such techniques include, for example, particle swarm optimization (Gong et al., 2012), simulated annealing (Czech & Czarnas, 2002), genetic algorithm (Cheng & Wang, 2009), GRASP (Kontoravdis & Bard, 1995), and tabu search (Garcia, Potvin, & Rousseau, 1994).

The VRPTW is described using a graph (N, A). N refers to the group of nodes $N = \{0, 1, 2, \ldots, n, n+1\}$ where nodes 0 and $n+1$ refer to the depot, and the rest nodes $1, 2, \ldots, n$ refer to the group customers 'symbolized by C'. Connections between the nodes are referred to by the arc set A, $A = \{(i, j): i \neq j \text{ and } i, j \in N\}$ in which all routes in this graph should originate at node 0 and terminate at note $n+1$. Each arc $(i, j) \in A$ has two elements: cost (c_{ij}) and travel time (t_{ij}) where the latter encompasses the customer i service time. The symbol V refers to the set of vehicles whose capacities 'q' are identical. Each customer i, $i \in C$, has a demand d_i and should be visited with the time window $[a_i, b_i]$. All vehicles must depart at the depot (node 0) and return to the depot (node $n+1$). Any vehicle arrives before a_i it should wait until the beginning of the time window. On the other hand, if the vehicle arrives after b_i it vehicle cannot serve the customer. All vehicles depart the depot (node 0) at time 0. There are two kinds of variables, X_{ij}^k and S_i^k. The decision variable X_{ij}^k is defined as follow (Bräysy & Gendreau, 2002):

$$X_{ij}^k = \begin{cases} 1 & \text{if vehicle } k \text{ travelled directly from customer } i \text{ to } j \\ 0 & \text{Otherwise} \end{cases}$$

The decision variable S_i^k refers to the time at which the vehicle k starts to serve the customer i. Consequently, if the customer i is not served by vehicle k, the S_i^k has no meaning. It can be assumed that $S_0^k = 0$, while S_{n+1}^k refers to k vehicle arrival time at the depot (node $n+1$). The goal of solving VRPTW is to generate feasible routes that serve all customers with minimal cost (see Eq. (1)) and satisfying the four conditions mentioned above. The mathematical formulations are as follows (Bräysy & Gendreau, 2002):

$$f(S) = \min \sum_{k \in V} \sum_{(i,j) \in A} c_{ij} X_{ij}^k \tag{1}$$

$$\text{s.t.} \quad \sum_{k \in V} \sum_{j \in N} x_{ij}^k = 1 \quad \forall\ i \in C \tag{2}$$

$$\sum_{i \in C} d_i \sum_{j \in N} X_{ij}^k \leqslant q, \quad \forall\ k \in V \tag{3}$$

$$\sum_{j \in N} X_{0j}^k = 1, \quad \forall\ k \in V \tag{4}$$

$$\sum_{i \in N} X_{ih}^k - \sum_{j \in N} X_{hj}^k = 0, \quad \forall\ h \in C, \quad \forall\ k \in V \tag{5}$$

$$\sum_{i \in N} X_{i,n+1}^k = 1, \quad \forall\ k \in V \tag{6}$$

$$X_{ij}^k (S_i^k + t_{ij} - S_j^k) \leqslant 0, \quad \forall\ (i,j) \in A, \quad \forall\ k \in V \tag{7}$$

$$a_i \leqslant S_i^k \leqslant b_i, \quad \forall\ i \in N, \quad \forall\ k \in V \tag{8}$$

$$X_{ij}^k \in \{0,1\}, \quad \forall\ (i,j) \in A, \quad \forall\ k \in V \tag{9}$$

Based on the mathematical model above, the constraint set (2) ensures that each customer is served one time only. Constraint set (3) ensures that the capacity of the vehicle is not surpassed. The flow constraint sets (4)–(6) ensure that each vehicle k departs node 0 only once, departs node h, $h \in C$, only if it enters that particular node, and comes back to node $n+1$. It is worth noting that set (6) in the model is redundant, yet it is kept to underline the structure of the network. To allow empty tours in the network, the arc $(0, n+1)$ is involved. Constraint set (7) ensures that vehicle k service node j after $S_i^k + t_{ij}$ when it moves from node i to node j. All time windows are taken care of through constraint (8), and finally (9) constitutes the set of constraints integration.

3. Basic harmony search algorithm

HSA has been introduced as a new nature inspired population-based approach (Geem et al., 2001). HSA works with a population of solutions