

Active-guided evolution strategies for large-scale capacitated vehicle routing problems

David Mester^{a,*}, Olli Bräysy^b

^aMathematical and Population Genetics Laboratory, Institute of Evolution, University of Haifa, 31905 Haifa, Israel

^bAgora Innoroad Laboratory, Agora Center, University of Jyväskylä, P.O. Box 35, FI-40014, Finland

Available online 13 December 2005

Abstract

We present an adaptation of the active-guided evolution strategies metaheuristic for the capacitated vehicle routing problem. The capacitated vehicle routing problem is a classical problem in operations research in which a set of minimum total cost routes must be determined for a fleet of identical capacitated vehicles in order to service a number of demand or supply points. The applied metaheuristic combines the strengths of the well-known guided local search and evolution strategies metaheuristics into an iterative two-stage procedure. The computational experiments were carried out on a set of 76 benchmark problems. The results demonstrate that the suggested method is highly competitive, providing the best-known solutions to 70 test instances.

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Keywords: Vehicle routing; Heuristics; Evolution strategies; Guided local search

1. Introduction

Logistics, and especially the distribution of goods, lies at the heart of business activity. Formally, most problems in the domain of goods distribution can be viewed as vehicle routing problems (VRP). The capacitated VRP (CVRP) constitutes the classical version of the VRP and assuming the symmetry of the cost matrix, we define the problem formally on an undirected graph $G = (V, E)$ where $V = \{v_0, \dots, v_n\}$ is the vertex set and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is an edge set. Vertex v_0 represents a depot, while the remaining vertices correspond to customers. With each vertex $v_i \in V$ is associated a non-negative demand q_i and a service time s_i . With each edge (v_i, v_j) is associated a non-negative cost, c_{ij} , interpreted here as a travel time. All vehicles have identical capacity, Q , and the number of vehicles is not determined a priori. The CVRP consists in determining a set of vehicle routes (a) starting and ending at the depot, and such that (b) each customer is visited exactly once, (c) the total demand of any vehicle route does not exceed Q , (d) the duration of any route (including service times) does not exceed a (possibly) preset upper limit, and (e) the total cost of all routes is minimized.

Here, one must note that in the literature the above described VRP with route duration limit is often separated from CVRP and called distance-constrained VRP. The algorithms presented in this paper are designed for and used to solve problems both without and with route duration limit. As the VRP is a very complex NP-hard problem, solving the VRP to optimality is not always possible within the limited computing time one often has in practical situations. In

* Corresponding author.

E-mail address: dmester@research.haifa.ac.il (D. Mester).

these cases one must focus on heuristic and metaheuristic solution methods that will produce high-quality solutions in limited time. For more details, we refer to extensive surveys of Laporte et al. [1], Laporte and Semet [2], Gendreau et al. [3] and Cordeau et al. [4,5]. For exact solution methods, we refer to surveys by Toth and Vigo [6], Naddef and Rinaldi [7] and Bramel and Simchi-Levi [8].

Given the practical importance of VRPs, it is crucial that new solution algorithms are developed to solve VRPs as efficiently as possible. The main contribution of this paper is the adaptation of the active-guided evolution strategies (AGES) metaheuristic of Mester and Bräysy [9] for the CVRP. Our experiments on 76 CVRP benchmarks from the literature demonstrate that the proposed algorithm is fast, cost-effective and highly competitive. It finds the best-known solutions to 70 out of the 76 tested CVRP instances.

The remainder of this paper is outlined as follows. The main features of the AGES metaheuristic are described in Section 2. Section 3 details the parameter values of the tested algorithm configurations and presents the results of a comprehensive computational study. Finally, in Section 4 conclusions are drawn.

2. The problem solving methodology

The AGES metaheuristic consists of two phases. The goal of the first phase is to create a starting solution for the second phase. The starting solution is generated by creating first a set of s solutions with the hybrid cheapest insertion heuristic of Mester et al. [10] and then selecting the best solution found as the starting solution. The exact value of s depends on the chosen algorithm configuration. After the starting solution has been created, the filling procedure of Bent and Van Hentenryck [11] is optionally applied to reduce the number of routes in the starting solution before proceeding to the second phase. The usage of the filling procedure depends on the chosen algorithm configuration as detailed in Section 3.1.

In the second phase an attempt is made to improve the starting solution with a two-stage procedure. The first stage makes use of the well-known guided local search (GLS) metaheuristic [12,13]. GLS operates by augmenting the objective function with a penalty term based on particular solution features (e.g. long edges) not considered to be part of a near-optimal solution. The GLS is used to guide a composite local search procedure, consisting of 3–5 different improvement heuristics, described in more detail in the next subsection. When no more improvements have been found for a given number of iterations, the second stage is started. The second stage operates by performing a series of removal and reinsertion operations as in the large neighborhood search of Shaw [14]. As the removal and reinsertion operations follow the principles of the 1 + 1 evolution strategies (ES) metaheuristic [15,16], the second stage is called ES-stage. The second stage is continued until no more improvements can be found and then the search goes back to the first stage. The two stages are repeated iteratively, and the search is stopped if no more improvements can be found by neither stages. We call the configuration presented in Mester and Bräysy [9] for the CVRP with time window constraints the *AGES VRPTW best* configuration. In this paper we propose two alternative configurations for CVRP, noted as *AGES VRP best* and *AGES VRP fast*.

2.1. The improvement heuristics

Before proceeding to a description of the global heuristic, we first recall the main features of the improvement heuristics that it will control and guide. Four of the available six heuristic procedures (forward Or-exchange, backward Or-exchange [17], 1-interchange [18] and 2-opt* [19]) are used for inter-route improvements only, i.e., they modify two routes simultaneously. 2-opt [20] works on a single route at a time and relocate [21] is used for both inter- and intra-route reinsertions.

The basic idea of the relocate and forward and backward Or-exchange procedures is to reinsert a single customer at a time in an alternate position in the solution vector. Here, the solution vector consists of an ordered list of all customer indexes (integers). The solution vector is divided in r subsequent sets (routes) that are in a determined order based on the previously created solution. Relocate examines all possible insertion positions between two consecutive customers both in the current route of the customer considered for relocation and in alternate routes. Forward Or-exchange considers reinsertions only to positions in alternate routes located after the present route of the customer in the current solution vector. Correspondingly, backward Or-exchange attempts reinsertions only to routes located before the origin route in the solution vector. The 1-interchange swaps simultaneously the position of two customers in two different routes and

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