Chapter 9

NEW HEURISTICS FOR THE VEHICLE ROUTING PROBLEM

Jean-François Cordeau
Michel Gendreau
Alain Hertz
Gilbert Laporte
Jean-Sylvain Sormany

Abstract This chapter reviews some of the best metaheuristics proposed in recent years for the Vehicle Routing Problem. These are based on local search, on population search and on learning mechanisms. Comparative computational results are provided on a set of 34 benchmark instances.

1. Introduction

The classical *Vehicle Routing Problem* (VRP) is defined on an undirected graph $G = (V, E)$ where $V = \{v_0, v_1, \ldots, v_n\}$ is a vertex set and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is an edge set. Vertex v_0 is a depot at which are based m identical vehicles of capacity Q, while the remaining vertices represent customers. A non-negative *cost*, *distance* or *travel time* matrix $C = (c_{ij})$ is defined on E. Each customer has a non-negative demand q_i and a non-negative service time s_i. The VRP consists of designing a set of m vehicle routes (i) of least total cost, (ii) each starting and ending at the depot, and such that (iii) each customer is visited exactly once by a vehicle, (iv) the total demand of any route does not exceed Q, and (v) the total duration of any route does not exceed a preset bound D.

The VRP is a hard combinatorial problem. Exact algorithms (see, e.g., Naddef and Rinaldi, 2002; Baldacci et al., 2004) can only solve relatively small instances and their computational times are highly variable. To this day, heuristics remain the only reliable approach for the solution

of practical instances. In contrast to exact algorithms, heuristics are better suited to the solution of VRP variants involving side constraints such as time windows (Cordeau et al., 2002a), pickups and deliveries (Desaulniers et al., 2002), periodic visits (Cordeau et al., 1997), etc.

In recent years several powerful heuristics have been proposed for the VRP and its variants, based on local search, population search and learning mechanisms principles. Local search includes descent algorithms (Ergun et al., 2003), simulated annealing (Osman, 1993), deterministic annealing (Golden et al., 1998; Li et al., 2005), tabu search (Osman, 1993; Taillard, 1993; Gendreau et al., 1994; Xu and Kelly, 1996; Rego and Roucairol, 1996; Rego, 1998; Barbarosoğlu and Ögür, 1999; Cordeau et al., 2001). The two best known types of population search heuristics are evolutionary algorithms (Prins, 2004; Berger and Barkaoui, 2004; Mester and Bräysy, 2005) and adaptive memory procedures (Rochat and Taillard, 1995; Tarantilis and Kiranoudis, 2002). Examples of learning mechanisms are neural networks (Ghaziri, 1991, 1996; Matsuyama, 1991; Schumann and Retzko, 1995) and ant algorithms Reimann et al. (2004).

The field of VRP heuristics is very active, as witnessed by the large number of recent articles listed in the previous paragraph. This chapter summarizes some of the most important new developments in the area of VRP heuristics and presents comparative computational results.

Several surveys have recently been published on VRP heuristics (Laporte and Semet, 2002; Gendreau et al., 2002; Cordeau et al., 2002a; Cordeau and Laporte, 2004). This chapter focuses on recent material not covered by these surveys. In the following section we provide a general classification scheme for VRP heuristics. We then provide in Section 3 a description of nine recent heuristics, and computational results in Section 4. The conclusion follows.

2. Classification of VRP heuristics

Providing classification schemes in the area of combinatorial optimization can be a daunting task because of the large number of fields and descriptors needed to account for the diversity and intricacy of the concepts involved in the various algorithms — the devil is in the details. By and large broad classification systems that concentrate on the essential ideas can be quite instructive.

At a macro-level, VRP heuristics combine some of the following four components: (1) *construction* of an initial solution; (2) *improvement* procedures; (3) *population* mechanisms; and (4) *learning* mechanisms.