Metaheuristics for the Vehicle Routing Problem and Its Extensions: A Categorized Bibliography

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Summary. We provide a categorized bibliography of metaheuristics for solving the vehicle routing problem and its extensions. The categories are based on various types of metaheuristics and vehicle routing problems.

Key words: Metaheuristics; vehicle routing; categorized bibliography.

1 Introduction

This chapter is a categorized bibliography of applications of metaheuristics for the Vehicle Routing Problem (VRP) and its extensions. It is basically a

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structured list of references based on the various metaheuristics and problem types.

In the early years, specialized heuristics were typically developed for solving complex combinatorial optimization problems, like the VRP. Then, more generic solution schemes, called metaheuristics by Fred Glover in 1986, were designed [5, 11, 13]. The challenge is then one of adapting those generic solution schemes to the problems at hand. This exercise typically requires much less work than developing a specialized heuristic from scratch. Furthermore, a good metaheuristic implementation can provide near-optimal solutions in reasonable computation times. Vehicle routing problems, in particular, exhibit an impressive record of successful metaheuristic implementations.

In this chapter, we focus on the most popular types of metaheuristics. They are introduced in the sections that follow.

1.1 Ant Colony Optimization

This metaheuristic is inspired from a natural metaphor, namely the communication and cooperation mechanisms among real ants that allow them to find short paths from their nest to food sources. The communication medium is a chemical compound, known as pheromone, which is laid down on the ground. While an isolated ant would more or less wander randomly, an ant detecting a pheromone path will follow it, with some probability, and will strengthen it with its own pheromone. Thus, the probability that other ants will follow a given path in the future increases with the number of ants that previously followed it. This leads to the emergence of shortest paths, since pheromone tends to accumulate faster on those paths. In the artificial metaphor known as Ant Colony Optimization (ACO) [4], a number of artificial ants construct solutions in a randomized and greedy way at each cycle. Each ant chooses the next element to be incorporated into its current partial solution based on some heuristic evaluation of that element and the amount of pheromone, represented by a weight, associated with it. The pheromone represents the memory of the system and is related to the presence of that element in good solutions previously constructed by the ants. ACO has quite naturally been applied to the Traveling Salesman Problem (TSP), where a shortest Hamiltonian cycle must be found over a complete graph. However, the ACO metaheuristic has also been adapted to the VRP and some of its extensions.

1.2 Genetic Algorithms

Evolutionary algorithms are a wide class of metaheuristics, also inspired from a natural metaphor, with Genetic Algorithms (GAs) [14] being one of the best known. Basically, they mimic the way species evolve and adapt to their environment, according to the Darwinian principle of natural selection. Under this paradigm, a population of solutions (often encoded as bit or integer strings, known as chromosomes) evolves from one generation to the next through the application of operators that are similar to those found in nature, like selection of the fittest, genetic crossover and mutation. Through the selection process, only the best solutions are allowed to become parents and to generate offspring. The mating process, known as crossover, then takes two selected parent solutions and combines their most desirable features to create one or two offspring solutions. This is repeated until a new population of offspring is obtained. Finally each offspring is randomly perturbed by a mutation operator. Starting from a randomly or heuristically generated initial population, this cycle is repeated for a number of generations, and the best solution found is returned at the end. When applied to vehicle routing problems, the classical GA solution scheme is often modified. In particular, the encoding of solutions into chromosomes is either completely ignored (by applying the various operators directly on the solutions) or designed in a very particular way to take advantage of specialized crossover and mutation operators.

1.3 Greedy Randomized Adaptive Search Procedure

The basic idea of the Greedy Randomized Adaptive Search Procedure (GRASP) [18] is to use a randomized greedy construction heuristic within a multi-start procedure to generate a variety of solutions. At each step of the greedy construction heuristic, the elements not yet incorporated into the current partial solution are evaluated with a heuristic function, and the best elements are kept in a restricted candidate list. One element is then randomly chosen from that list and incorporated into the partial solution. When the construction process is completed, the solution is further improved with a local search. The best solution obtained after a certain number of restarts is then returned at the end.

1.4 Simulated Annealing

This metaheuristic is a randomized local search method, where a modification to the current solution that leads to an increase in solution cost can be accepted with some probability. This mechanism allows the method to escape from bad local optima. Simulated Annealing (SA) [16] comes from an analogy with the physical annealing process aimed at generating solids with low-energy states. In condensed matter physics, annealing is a process in which a solid is first melted by increasing its temperature. This is followed by a gradual temperature reduction to recover a solid state of low energy. A careful annealing through a series of temperature levels, where the temperature is held long enough at each level to allow the system to reach equilibrium, leads to the more regular structures associated with solids with low-energy states. In a vehicle routing context, a solution or set of routes corresponds to a state and the solution cost to its energy. At each iteration, the current solution is modified by randomly selecting a modification based on a particular class of modifications that defines the neighborhood structure. If the new solution is better than the current one, it becomes the current solution. Otherwise, the new solution is accepted according to a probabilistic criterion, where a modification is more likely to be accepted if a parameter called the temperature (by analogy with the physical process) is high and the cost increase is low. During the procedure, the temperature parameter is progressively lowered according to some predefined cooling schedule, and a number of iterations is performed at each temperature level. When the temperature is sufficiently low, only improving modifications can be accepted and the method stops in a local optimum. As opposed to most metaheuristics, it has been shown that SA asymptotically converges to a global optimum. The success of SA has sparked the development of deterministic analogs whose performance has been quite similar to that of SA: Threshold Accepting [7], Record-to-record Travel [6], and the Great Deluge Algorithm [6]. In these methods, as in SA, the acceptance of deteriorating solutions becomes progressively less frequent as the algorithm unfolds.

1.5 Tabu Search

Like SA, Tabu Search (TS) [12] is a local search-based metaheuristic where, at each iteration, the best solution in the neighborhood of the current solution is selected as the new current solution, even if it leads to an increase in solution cost. Through this mechanism, the method can thus escape from bad local optima. A short-term memory, known as the tabu list, stores recently visited solutions (or attributes of recently visited solutions) to avoid short-term cycling. The search stops after a fixed number of iterations or after a number of consecutive iterations have been performed without any improvement to the best known solution.

1.6 Variable Neighborhood Search

Variable Neighborhood Search (VNS) [15] is another local search-based metaheuristic which exploits many different transformation classes, or neighborhoods, to escape from bad local optima. When a local optimum is reached with regard to a given neighborhood, another neighborhood is selected and used in the following iterations. More precisely, given a set of (often nested) neighborhoods, a solution is randomly generated in the first neighborhood of the current solution, from which a local descent is performed (possibly based on a completely different neighborhood structure). If the local optimum obtained is not better than the current solution, then the procedure is repeated with the next neighborhood in the nested structure. The search restarts from the first neighborhood when either a solution which is better than the current solution is found or all neighborhoods have been tried. A well-known variant is the Variable Neighborhood Descent (VND) where the best neighbor of the current solution is considered instead of a random one. Also, no local descent is performed on this neighbor. Rather, the latter becomes the new current solution if it provides an improvement. The search is then restarted from the first neighborhood. Otherwise, the next neighborhood is considered.

1.7 Other Methods

The category *Others* groups together the remaining metaheuristics, including hybrids.

1.8 Problems

The problems considered are the VRP, the VRP with time windows (VRPTW), the VRP with backhauls (VRPB), the VRP with pick-ups and deliveries (VRPPD), the VRP with multiple use of vehicles, the VRP with multiple depots (MDVRP), the vehicle fleet size and mix VRP (FSMVRP) (including the VRP with trailers – VRPT) and the dynamic VRP. Note that within each subsection, entries are given in chronological order.

1.9 Selection of Papers

We have chosen to restrict this to papers published in journals and conference proceedings. We exclude working papers, dissertations, and theses, because these are often difficult to obtain. Considering the large number of papers that have been devoted to the application of metaheuristics to vehicle routing problems, we could not include in this bibliography all published papers. We emphasize more recent papers, and have tried to include all papers that have had a major impact on the development of the field. We apologize to the authors whose papers have been left out.

2 Vehicle Routing Problem

The VRP [19] can be formally defined as follows. Let $G = (V, A)$ be a graph with A the arc set and $V = \{1, ..., n\}$ the vertex set, where vertex 1 is the depot and the other vertices are cities or customers to be served. With every arc (i, j), $i \neq j$, is associated a non-negative distance matrix $D = (d_{ij})$, where d_{ij} can be interpreted either as a true distance, a travel time or a travel cost. Note that the undirected version of the VRP is obtained when D is symmetric. A fleet of vehicles, based at the depot, is available for serving the vertices. Usually, the number of vehicles is variable, and a fixed cost f is incurred each time a new vehicle is used. It can also happen that the number of vehicles is fixed or upper bounded. A non-negative weight or demand q_i is associated with each vertex $i > 1$ and the sum of demands on any vehicle route should not exceed the vehicle capacity. The capacity and fixed cost can be the same for all vehicles (homogeneous fleet) or not (heterogeneous fleet).

In some variants, the total travel distance or total travel time of each vehicle is also constrained. The problem is to find a set of least-cost vehicle routes such that:

- each vertex in $V - \{1\}$ is served exactly once by exactly one vehicle;
- each vehicle route starts and ends at the depot;
- all side constraints are satisfied (capacity, maximum travel distance or maximum travel time).

Note that this section also covers methods developed to solve Open VRP (OVRP), in which each route is a Hamiltonian path instead of Hamiltonian cycle; this difference comes from the fact that vehicles do not return to the starting depot or, if they do so, they must follow the same path backwards. Problems with multiple objectives are also considered.

The reader is referred to [9] for a general survey about metaheuristics for the classical VRP with capacity constraints. References on specific metaheuristics are found in the following subsections.

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3 VRP with Time Windows

In the VRP with Time Windows (VRPTW) [2], a time interval $[a_i, b_i]$ is associated with vertex $i \in V$. In the hard time window variant, the vertex must be served within that interval (although the vehicle can wait, if it arrives before the lower bound a_i). In the soft time window variant, the vertex can be served outside of its time interval, but a penalty is incurred in the objective. A general survey about metaheuristics for the VRPTW is found in [1].

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4 VRP with Backhauls

In the VRP with Backhauls (VRPB) [20], the demand at each vertex i corresponds either to a delivery or a pick-up (backhaul) which is then brought back to the depot. While goods are picked up or delivered, the quantity on board should never exceed the capacity of the vehicle. This problem is a special case of the VRPPD (see Section 5).

4.2 Genetic Algorithms

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5 VRP with Pick-ups and Deliveries

In the VRP with Pick-ups and Deliveries (VRPPD) [3], a transportation request i is associated with two vertices o_i and d_i, and the demand q_i should be picked up at o_i and delivered at d_i. For a solution to be feasible, both o_i and d_i should be in the same route. Furthermore, o_i should appear before d_i in the route. In this problem, capacity constraints can be present or not, depending on the application, and a time window is typically associated with each vertex. For example, in transportation-on-demand applications where people with special needs are transported (a problem referred to as the Dial-A-Ride Problem), there are both capacity and time window constraints. Furthermore, there is a constraint on the maximum ride time of each passenger.

5.1 Ant Colony Optimization

K. Doerner, R.F. Hartl and M. Reimann. Ants solve time constrained pickup and delivery problems with full truckloads, in *Operations Research Proceedings 2000*, B. Fleischmann, R. Lasch, U. Derigs, W. Domschke and U. Rieder, eds., Springer, Berlin, 395–400, 2001.

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5.4 Simulated Annealing

S.M. Hart. The modeling and solution of a class of dial-a-ride problems using simulated annealing. *Control and Cybernetics*, 25:131–157, 1996.

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N. Bianchessi and G. Righini. Heuristic algorithms for the vehicle routing problem with simultaneous pick-up and delivery. *Computers & Operations Research*, 34:578-594, 2007.

6 VRP with Multiple Use of Vehicles

In standard vehicle routing problems, it is implicitly assumed that each vehicle serves a single route. In some cases, however, it might be possible or even necessary to assign the vehicle to several routes. This situation happens, for example, when the capacity of the vehicle is relatively small. In this case, frequent returns to the depot are required to load or unload the vehicle.

6.2 Genetic Algorithms

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7 Fleet Size and Mix VRP

When the number of vehicles is free and the fleet is heterogeneous, one is faced with the Fleet Size and Mix VRP (FSMVRP) [8], which exhibits special features that need to be addressed through specific algorithmic procedures.

In particular, the benefits of replacing one type of vehicle by another for serving a particular route must be taken into account. We also include in this section methods devised for solving the VRP with trailers (VRPT), where one has to determine the optimal deployment of a vehicle fleet of truck-trailer combinations.

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V. Yepes and J. Medina. Economic heuristic optimization for heterogeneous fleet VRPHESTW. *Journal of Transportation Engineering*, 132:303–311, 2006.

8 VRP with Multiple Depots and Periodic VRP

In the VRP with Multiple Depots (MDVRP), there is not a single depot, but rather a number of depots with different locations and an associated fleet of vehicles. Depending on the variant considered, each vehicle may be required to terminate its route at its starting depot.

The Periodic VRP (PVRP) is an extension of the VRP in which customers must be visited one or more times during a planning horizon of several periods with routes performed by vehicles in each period. By substituting days for depots, one can show the equivalence of some variants of the MDVRP and the PVRP.

8.1 Ant Colony Optimization

A.C. Matos and R.C. Oliveira. An experimental study of the ant colony system for the period vehicle routing problem. *Lecture Notes in Computer Science*, 3172:286–293, 2004.

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S.R. Thangiah and S. Salhi. Genetic clustering: An adaptive heuristic for the multidepot vehicle routing problem. *Applied Artificial Intelligence*, 15:361–383, 2001.

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A. Lim and W. Zhu. A fast and effective insertion algorithm for multi-depot vehicle routing problem with fixed distribution of vehicles and a new simulated annealing approach. In *IEA/AIE 2006, Lecture Notes in Artificial Intelligence 4031*, M. Ali and R. Dapoigny, eds., Springer, 282–291, 2006. Springer-Verlag.

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9 Dynamic VRP

In dynamic vehicle routing problems [10, 17], some data about the problem are not known beforehand. That is, new information are revealed on-line, as the routes are executed by the vehicles. In most cases, a quick or real-time response time is also required. The new information often correspond to the occurrence of a new vertex (customer) that must be included into the current routes. It can also be some new information about the travel time of a vehicle, the current customer status (e.g., cancelation of a transportation request), etc. This section includes (repeats) papers on the dynamic variant of the VRPPD.

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9.2 Genetic Algorithms

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C. Rego and C. Roucairol. Using tabu search for solving a dynamic multi-terminal truck dispatching problem. *European Journal of Operational Research*, 83:411–429, 1995.

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