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An adaptive guidance approach for the heuristic solution of a minimum multiple trip vehicle routing problem

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ABSTRACT

One of the most important problems in combinatorial optimization is the well-known vehicle routing problem (VRP), which calls for the determination of the optimal routes to be performed by a fleet of vehicles to serve a given set of customers. Recently, there has been an increasing interest towards extensions of VRP arising from real-world applications. In this paper we consider a variant in which time windows for service at the customers are given, and vehicles may perform more than one route within a working shift. We call the resulting problem the minimum multiple trip VRP (MMTVRP), where a "multiple trip" is a sequence of routes corresponding to a working shift for a vehicle. The problem objective is to minimize the overall number of the multiple trips (hence the size of the required fleet), breaking ties in favor of the minimum routing cost.

We propose an iterative solution approach based on the decomposition of the problem into simpler ones, each solved by specific heuristics that are suitably combined to produce feasible MMTVRP solutions. An adaptive guidance mechanism is used to guide the heuristics to possibly improve the current solution. Computational experiments have been performed on a set of real-world instances arising from a multi-regional scale distribution problem. The obtained results show that the proposed adaptive guidance mechanism is considerably effective, being able to reduce the overall number of required vehicles within a limited computing time.

1. Introduction

The vehicle routing problem (VRP) calls for the determination of the optimal routes to be performed by a fleet of vehicles to serve a given set of customers, and is one of the most important, and studied, combinatorial optimization problems. The interest on VRP is indeed motivated both by its practical relevance and by its considerable difficulty. During the last 40 years hundreds of papers have considered all the main variants of this problem for which both exact and heuristic approaches were proposed: the capacitated VRP, the VRP with time windows (VRPTW), the VRP with Backhauls and the pickup and delivery problem, just to mention the most important ones. A complete overview of the state-of-the-art on VRP is given in the book by Toth and Vigo [25], where exact and heuristic approaches for the main variants of VRP are examined, together with some relevant case studies from real-world applications. This survey was recently updated in [12,15].

In recent years, there has been an increasing interest towards so-called "rich" VRP models. These are extensions of VRP incorporating important issues arising in real-world applications and generating new and interesting families of optimization problems. A first survey summarizing several of these extensions is given by Bräysy et al. [8,9].

In several routing applications vehicles may perform more than one route during a given working shift. This may happen when either customer demands are relatively large with respect to vehicle capacity, hence few customers may be served in a single route, or when tight time windows or spread time constraints are imposed. In all these cases the same vehicle may be assigned to more than one route, hence reducing the overall number of required vehicles. In the route aggregation into *multiple trips* some additional operational constraints must be taken into account. Namely, (i) the routes must not overlap in time and be compatible in terms of vehicle requirements (e.g., capacity, loading equipment, etc.), (ii) there exists a sufficient time interval between consecutive routes so as to allow loading/unloading operations to be performed at the depot, and (iii) the overall *spread time* of the working shift (i.e., the time interval between the departure of the first scheduled route and the arrival at

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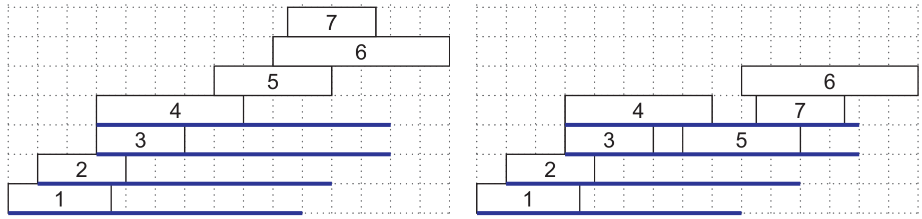

Fig. 1. Example of route aggregation into multiple trips.

the depot of the last one) does not exceed a given maximum length. This family of problems is generally known as that of multiple trip VRP (MTVRP). An illustrative example of route aggregation into multiple trips is given in Fig. 1 that shows in the left part the set of seven initial routes. The thick line below some of the routes indicates the associated working shift spread time. In the right part of the figure, two multiple trips are obtained by aggregating two routes into each of them.

The most widely studied variant of MTVRP considers a fixed fleet made up of identical vehicles available at a central depot. A set of customers is given, each having a specific demand and service time. Each vehicle may perform more than one route during a working shift. The working shift has a standard duration, but in general *overtime* is permitted. The MTVRP goal is to define a set of multiple trips, (i.e., working shifts) servicing all the customers once, without violating the capacity constraint on each single route, and minimizing a suitable function of the routing cost and overtime. Note that this is a single day problem and not a periodic one, since all the shifts will be operated in the same calendar day.

The MTVRP was introduced by Fleischmann [14], who used a savings based algorithm to construct the routes and a bin packing heuristic to combine them into working shifts. Taillard [24] generated a large set of routes through a tabu search algorithm for the VRP, followed by a bin packing heuristic for the working shift aggregation. Brandao and Mercer [7] defined a tabu search algorithm that starts from a solution built with a *nearest neighbor* insertion heuristic and uses insertion and swap moves. The tabu search considers variable-sized tabu lists, aspiration criteria and allows infeasible solutions with respect to the maximum permitted overtime. The same authors applied a similar approach to solve a real-world application with several additional constraints, see [6], whereas further real-world variants are considered by Avella et al. [2], Jeon et al. [16], and Cornillier et al. [13]. Petch and Salhi [22] considered an iterative approach, with initial solutions built through a savings algorithm followed by a packing heuristic. New routes are iteratively constructed through a route-first-cluster-second method and then again packed into working shifts. Recently the same authors also proposed a genetic algorithm, see [23]. An adaptive memory approach has been considered by [21] where the adaptive memory contains a large pool of routes. At each iteration a subset of these routes is chosen and improved through a tabu search procedure that also aggregates them. The resulting routes are returned into the adaptive memory and the process is iterated. We finally mention Alonso et al. [1] who used tabu search to solve a more general class of periodic problems that has MTVRP as a special case, and Azi et al. [3] who developed an exact column generation approach for the solution of small sized instances of the variant including time windows and a single vehicle.

In this paper we consider a variant of MTVRP arising from a real-world problem concerning the strategic fleet sizing in the distribution of goods to supermarkets on a multi-regional scale territory. As other MTVRPs from the literature this is a single day problem and not a periodic one, since the reassignment of deliveries to different days is not admitted. The main differences between our problem and previously studied variants of MTVRP are (i) the presence of time window constraints, (ii) the impossibility of overtime, (iii) the goods belong to multiple commodities that cannot be transported together on the same vehicle, and (iv) the strategic requirement of minimizing the overall number of used vehicles. This latter issue has indeed a huge practical relevance, being related to the minimization of fixed and investment costs, but it has received relatively little attention in the literature in which the emphasis is mainly devoted to the operational context, i.e., to the minimization of variable routing costs, including overtime. We call the resulting problem minimum multiple trip VRP (MMTVRP) and to the best of our knowledge, no specific solution approach for it has been presented so far.

We propose a general iterative algorithm that makes use of existing heuristics developed for related problems and guides them towards the construction of good overall solutions. This approach is strongly related with hyperheuristics (see [10]), where different heuristics are combined into an overall algorithm through a coordinating metaheuristic as well as with self-adaptive guidance strategies developed within evolutionary algorithms (see [18]) and reactive search (see [5]).

The main component of our algorithm is a two-phase heuristic that defines a feasible MMTVRP solution by decomposing the problem into two subproblems. In the first one, a set of routes is determined by means of a VRPTW heuristic, while in the second step the resulting routes are aggregated into multiple trips through a greedy approach. This heuristic is the building block of an overall iterative process. At each iteration, critical time intervals are detected through the computation of a lower bound on the number of multiple trips required to aggregate the current set of routes. Then, a penalty mechanism is used to discourage the VRPTW heuristic in creating routes that cross the critical time intervals. A further feedback mechanism forces the VRPTW heuristic to generate some routes having a delayed starting time or a shortened spread time. The resulting routes are more likely to be combined into a smaller number of multiple trips. This iterative approach was used to solve the real-world MMTVRP involving three commodities with different service requirements and several hundreds of customers at a multi-regional scale. In a few iterations the algorithm proved able to produce substantial improvement with respect to the initial solution, reducing on average by about 5% the total number of required vehicles. This overall guidance scheme is fairly general and of some use for practitioners. It may be easily adapted to other contexts in which one has simple heuristics at hand and wants to use them for the solution of a more general problem that has a different objective function.

The rest of the paper is organized as follows. The next section discusses in detail the MMTVRP and introduces the necessary notation. Section 3 describes the basic heuristic and the adaptive guidance framework. The result of the testing on real-world MMTVRP instances is given in Section 4, and Section 5 draws some conclusions.

2. Problem description and notation

The specific problem we address in this paper originates from a real-world application concerning the distribution of goods to