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A Multi-Start Split based Path Relinking (MSSPR) approach for the vehicle routing problem with route balancing

P. Lacomme [a,*], C. Prins [b], C. Prodhon [b], L. Ren [a]

[a] Université Blaise Pascal, Laboratoire d'Informatique (LIMOS) UMR CNRS 6158, Campus des Cézeaux, 63177 Aubière Cedex, France
[b] Université de Technologie de Troyes, ICD-LOSI UMR CNRS 6281, 12 rue Marie Curie, CS 42060 10004 Troyes Cedex, France

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ABSTRACT

This paper addresses the vehicle routing problem with route balancing (VRPRB), which aims at minimizing two criteria simultaneously: the total routing cost and the difference between the largest and smallest route cost. We propose a multi-start approach based on two search spaces each of them using a different solution presentation: a TSP tour that denotes an indirect solution based on a sequence of customers as in the Traveling Salesman Problem, and a VRPRB solution that denotes a complete solution containing a set of vehicle trips. Switching from an indirect to a complete solution is possible through an adaptation of a splitting algorithm considering both optimization criteria. More precisely, such an adaptation requires an acceptance criterion allowing the generation a set of non-dominated VRPRB solutions from a single TSP tour. A path relinking algorithm improves the set of obtained VRPRB solutions. The proposed method is evaluated on VRPRB instances derived from classical VRP instances and the results reveal the method as effective in comparison with the best published algorithms for the problem optimizing the total routing cost. Regarding both criteria, the method competes with a previous published method handling the VRPRB. In fact, it is able to provide similar results in shorter computational time and since no details are available on state-of-the-art fronts, no further conclusion can be made. A web page presents all the solutions on our fronts to favor future comparative studies. Furthermore, the proposed method allows tackling a variant of the problem ignored by the previous works on VRPRB, which integrates limitation on vehicle service time.

1. Introduction

1.1. Vehicle routing problems

The generic problem under consideration in this paper is related to the class of vehicle routing problems (VRP), in which the aim is to serve the demand of a set of customers with trips performed by vehicles that travel through routes at least cost. The basic version, the Capacitated VRP (CVRP), is often defined on a complete undirected graph $G=(X, E)$. The node-set X contains $n+1$ nodes, one depot (node 0) and n customers indexed from 1 to n. An unlimited fleet of identical vehicles with capacity Q is based at the depot to serve the demand d_j of each customer j. In general the fleet size is not imposed: the number of vehicles used is a decision variable. The cost to travel from node i to node j is c_{ij}, representing the cost of a shortest path from node i to node j in the real road network. The objective of the CVRP consists in finding a set of minimal cost trips to serve all the customers taking into account the following constraints:

- deliveries cannot be split (each customer must be served by a single vehicle);
- each route starts and ends at the depot;
- the total demand of the customers served by one vehicle must fit its capacity.

The CVRP is NP-hard and exact methods experience particularly large computational time to handle instances with up to 100 customers (Baldacci and Mingozzi, 2009). Among some of the best heuristic approaches for the CVRP, hybrid genetic algorithms seem a good approach (Prins, 2004; Nagata and Braysy, 2009; Vidal et al., 2014). Furthermore, Mester and Braysy (2007) propose a very efficient metaheuristic that hybrids guided local search and evolutionary strategies. Extensive research has been proposed to solve this NP-hard problem (Golden et al., 2008). However, usual methods do not take into account the route balancing objective and may result in a high disparity in the route lengths. That might

* Corresponding author.
E-mail addresses: placomme@sp.isima.fr (P. Lacomme), christian.prins@utt.fr (C. Prins), caroline.prodhon@utt.fr (C. Prodhon), ren@isima.fr (L. Ren).

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be problematic in real context when routes are performed by employees that should have some kind of equivalent schedules in terms of workload. Hence minimizing the disparity through a balance function is relevant.

Specific variants of the VRP address balanced driver workload or other balancing objectives (for example the number of customers visited, the quantity of goods delivered or the time required or the tour length). Let us note the special objective denoted balanced cargo (BCVRP) explicitly considered by Lee and Ueng (1999) and Lee and Tseng (1998) for the distribution of agricultural products, in which the balance criterion stands on the load. A similar problem including time windows (TW) and denoted BCVRPTW has been introduced in (Kritikos and Ioannou, 2010).

In this paper, we focus on the balance on the cost criterion. In fact, in our study, the cost is relative to the distance, which is also equivalent to the duration. Thus, the aim is to provide a fair scheduling to the drivers by minimizing the difference between their workload. In fact, when the length of the longest and the shortest routes are close, this induce that all the routes have similar durations.

1.2. Vehicle routing problem with route balancing

VRP with route balancing is an extension of the CVRP, denoted VRPRB, in which two criteria are optimized in a bi-objective fashion:

- The minimization of total cost related to the distance traveled by the vehicles;
- The minimization of the difference between the largest route cost and the smallest route cost that is also the difference between the longest and shortest routes if the cost is proportional to the distance, with the same factor for any vehicle. This condition holds in most of the VRP benchmarks, and the cost will be the only feature used in the description of our method.

For decision makers, route balancing has several meanings. The most common interpretation is to minimize the cost of the most expensive route (min–max objective), which corresponds to minimizing the makespan in scheduling theory if the costs represent durations. The underlying goal can be to avoid long routes for the sake of equity among drivers, for instance, but also to complete the distribution process as soon as possible when the routes are performed in parallel. In practice, the balance criterion is optimized subject to a notion of time/cost limitation on the routing. For instance, Lacomme et al. (2004) propose a memetic algorithm to minimize makespan in the Capacitated Arc Routing Problem (CARP) with a fixed fleet. Then, Lacomme et al. (2006) describe a bi-objective genetic algorithm, inspired by a non-domination based genetic algorithm (NSGA-2) but reinforced by a local search procedure for the CARP with the classical objective (total cost of traversed arcs) and the minimization of the makespan.

The drawback of this kind of min–max objective is that it acts on the longest route but not on the others, which can still have dispersed durations. A possible remedy is then to minimize lexicographically the sorted route lengths, an approach used by (Saliba, 2006) for the CVRP. The VRP with Route Balancing (VRPB) considers two objectives, the usual one (total routing cost) and another interpretation of the balancing criterion, that is the spread of the route costs. For a solution composed of r routes with costs 1_k, $k=1,2,\ldots,r$, this spread is defined as $\max\{l_k|\ k=1\ldots r\} - \min\{l_k|\ k=1\ldots r\}$. Very few papers deal with this problem.

A first study from Jozefowiez et al. (2006) considers the VRPRB and proposes an NSGA-2, an optimization scheme used in numerous bi-objective problems. This first study, published in a conference paper, do not provide many details on the generated front. Yet, to evaluate solutions in a multi-objective context, numerous quality measures criteria have been introduced (Hansen and Jaszkiewicz, 1998; Knowles and Corne, 2002). Zitzler et al. (2003) propose an overview highlighting their advantages and limitations. Three families of measures can be identified: (i) quality measure for a front (dedicated to one front only), (ii) quality measure using a second set of solutions which is commonly the optimal Pareto set, and (iii) quality measure allowing a comparison between two fronts without any assumption on the optimal Pareto front. The C-measure introduced by Knowles and Corne (2002) and denoted $C(F_1, F_2)$ represent the percentage of solutions in F_2 which are weakly dominated by solutions of F_1. When $C(F_1, F_2)=1$ all solutions of F_2 are dominated by solutions of F_1. Jozefowiez et al. (2009) present three variants of a multi-objective evolutionary algorithm to solve the VRPRB. In their paper, they still provide no detailed information on the front of obtained solutions, but the evaluation encompasses the C-measure between each three versions of the algorithm. The conclusion is that most efficient version is the one using a new mechanism, called the elitist diversification, implemented with parallelization techniques.

1.3. Proposal

In this paper, our aim is to develop a new efficient approach to tackle multi-objective routing problems, and particularly the VRPRB. An adaptation of the split procedure (Prins, 2004) is developed to compute a set of non-dominated solutions from any TSP tour (also denoted indirect representation). To further search the solution space, a method based on a path relinking algorithm allows to evaluate solutions encountered on paths between TSP tours. The rest of the paper is organized as follows. Section 2 gives an overview of the solution method before focusing on its key points. Section 3 is dedicated to the adaptation of a splitting procedure to tackle bi-criteria VRP. Section 4 is devoted to the path relinking algorithm developed to explore the solution space. Section 5 describes the overall pseudo code for solving the VRPRB. Results are exposed in Section 6. Conclusions and perspectives are given in Section 7.

2. Overview of proposed solution method and originality

The proposed algorithm for the VRPRB is a bi-objective evolutionary metaheuristic based on Pareto optimality, called Multi-Start Split-based Path Relinking (MSSPR). It can be summarized as follows, knowing that some details are skipped for the sake of clarity:

- The method works with two populations of non-dominated VRPRB solutions, POP and GPOP.
- GPOP stores the approximate Pareto front, returned at the end of the algorithm.
- Each iteration builds a set POP of new solutions and adds it to GPOP.
- MSSPR alternates between two search spaces: the space of TSP tours, also called giant tours, and the space of VRPRB solutions.
- The initialization of POP begins in the space of giant tours: two randomized heuristics are called to generate giant tours. An evaluation procedure, described below, is applied to each tour to deduce several non-dominated VRPRB solutions which are stored in POP.
- POP is then evolved using a path relinking (PR) procedure as recombination operator.
- The PR is applied to a given pair (A, B) of VRPRB solutions but traces a path in the space of giant tours. A and B are first converted into two giant tours T and U by concatenating their routes and removing depot nodes. Guided by a permutation-