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A multi-objective simulated annealing for the multi-criteria dial a ride problem ☆

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ABSTRACT

The paper describes a multi-objective mathematical model for Dial a Ride Problem (DRP) and an application of Multi-Objective Simulated Annealing (MOSA) to solve it. DRP is to take over the passenger from a place of departure to a place of arrival. In the DRP, customers send transportation requests to an operator. A request consists of a specified pickup location and destination location along with a desired departure or arrival time. The ultimate aim is to offer an alternative to displacement optimized individually and collectively. The DRP is classified as NP-hard problem that's why most research has been concentrated on the use of approximate methods to solve it. Indeed the DRP is a multi-criteria problem, the proposed solution of which aims to reduce both route duration in response to a certain quality of service provided. In this work, we offer our contribution to the study and solving the DRP in the application using the MOSA algorithm. Tests show competitive results on (Cordeau and Laporte, 2003a) benchmark datasets while improving processing times.

1. Introduction

Nowadays, we can note that with the increased travel demand of individuals, the available resources are no longer able to satisfy all users. For example, urban public transport is basically affected by their rigidity (ride scheduling would be the application that adapts to the offer). Individual vehicles help avoid the drawbacks of public transport but they are at the same time non-ecological, and costly. Indeed, individuals seeking ways to a more flexible transport that can meet their needs. The solving of a DRP can meet this expectation. Indeed the DRP is considered as a collective-individualized transport activated on demand. A DRP consists of meeting the travel demands on a set of passengers scattered geographically. Each transport demand is modeled by a request containing the information on this last. This information is the number of passengers, points of departure and destination, and the time windows related to these points. The problem consists of determining the best routing schedule for the vehicles, which minimizes overall transportation costs while maintaining a high level of customer service.

The DRP belongs to the generic class of vehicle routing and scheduling problems which have been extensively studied over the past 40 years (see, e.g., Toth and Vigo, 2002). It is subject to many constraints and must meet several needs. These needs and/or goals may be contradictory, such as reducing travel time, cost reduction generated, maximizing the quality of service. It is classified as NP-hard problem (Gørtz, 2006). The exact methods are not able to solve such a problem in a reasonable time, especially as the problem size is important.

In this case, we often use methods that find approximate solutions in reasonable time by applying heuristics and meta-heuristics, such as those based on genetic algorithms, simulated annealing, tabu search, etc. (Cordeau and Laporte, 2006; Bergvinsdottir, 2004; Baugh et al., 1998). In addition, it is a multi-criteria problem. So we need a multi-objective method to solve the DRP.

The multi-objective methods has a rather different aspect to scalar-objective one. Instead of finding one global optimum, which is a general aim in scalar-objective optimization, multi-objective methods must find a set of solutions, which is called the *Pareto set*, or *Pareto optimal frontier*, as all the Pareto solutions are equivalently important and all of them are the global optimal

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solutions. In our case, we use the Multi-Objective Simulated Annealing (MOSA) to solve the multi-criteria DRP.

In this paper, we present the modelization of the multi-criteria DRP. Subsequently we apply the MOSA algorithm to solve it. The second part of this communication is devoted to the presentation of DRP. In Section 3 we develop the mathematical formulation of the problem concerned. The description of the MOSA algorithm and the proposed approach for the resolution of this problem are given in Section 4. In Section 5, we detail the numerical results obtained that prove the effectiveness of our approach. Finally, we present the conclusion and perspectives of this work.

2. The dial a ride problem (DRP)

The DRP is characterized by a set of transport demands of size "n" and a number of vehicles "m" to serve them. Each transport demand is modeled by a request containing information on demand. To respond to this demand, we must recover a person from a starting point "i" and drop it in "$n+i$". The departure "i" must start in the time window $[a_i, b_i]$. Delivery must be made within the time window $[a_{i+n}, b_{i+n}]$. In fact, the DRP is an extension of the Vehicle Routing Problem (VRP) (Dedong and Qijun, 2008; Boudali et al., 2004). Indeed in the DRP, we have an additional constraint which is the consistency of the order of vehicle passage to serve a request. For example, we obviously cannot pass across a point of arrival of a transport demand before carrying the person making the request. So the aim is to design a set of least cost vehicle routes capable of accommodating all requests, under a set of constraints. The most common constraints relate to vehicle capacity, route duration and maximum ride time, i.e., the time spent by a user in the vehicle. In our case, to execute the service, there is a homogeneous vehicles set with the same load capacity that cannot be exceeded. The passengers are picked and delivered by the same vehicle.

In this work, we will consider the static case where all transportation requests are known in advance. We define an upper limit on the number of vehicles available and assume that customers cannot be rejected. All vehicles have identical capacity Q_v. Some instances might therefore have a feasible solution.

2.1. A DRP example

In Fig. 1, we present a simple example of a DRP composed of five transport demands and a fleet of two vehicles. The circles represent the pickups points and the edges represent the deliveries points. Rectangles represent vehicles and arrows represent a vehicle itinerary. The time windows of pickups and deliveries points are represented by the values in brackets. Fig. 1 represents at the same time a solution for DRP.

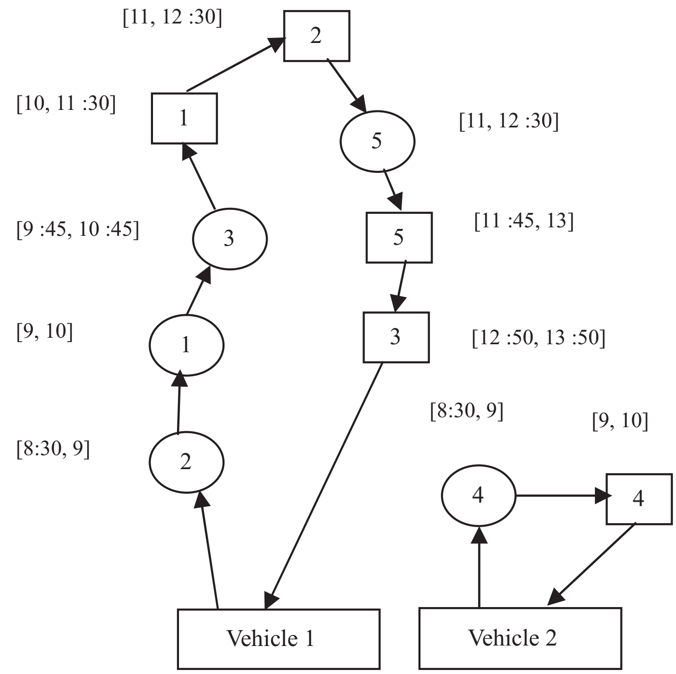

Fig. 1. Schematic representation of a DRP (5 transport requests, 2 vehicles).

2.2. A brief literature review on the DRP

A DRP is an extension of the PDP (Pickup & Delivery Problem) where the transport of goods is replaced by the transport of persons (Krumke et al., 2006). Several versions of the DRP have been studied over the past 30 years. In Cordeau and Laporte (2006), we find a more detailed presentation of the state of the art of this problem. The DRP has been widely studied in literature. In this section, we give a brief literature review on this issue.

There are several variants of the DRP. Indeed, there are DRP with or without time windows and DRP dynamic and static. In the case of dynamic DRP, the problem is usually treated as a succession of static problems (Nabaa and Zeddini, 2004). The majority of research has been focusing on the static DRP but Wilson et al. (1971 have solved the dynamic one. In our case of static DRP, a series of static multiple vehicle pickup and delivery problems with time windows are solved over time, using appropriate information update mechanisms to keep track of the planned routes. Static problems of this kind are typically addressed through heuristic means. Many problem-solving approaches first cluster customers into smaller groups to reduce the main problem into different single vehicle problems, which are then solved exactly or heuristically (Bodin and Sexton, 1986; Dumas et al., 1989; Ioachim et al., 1995). Other approaches are based on pure insertion and exchange methods (Jaw et al., 1986; Madsen et al., 1995).

When the problem size is small, we tend to use exact methods to solve it. In this context we cite the work of Psaraftis who used an exact algorithm of dynamic programming to solve the problem with one vehicle (Psaraftis, 1980). User inconvenience is controlled through a "maximum position shift" constraint limiting the difference between the position of a user in the list of requests and its position in the vehicle route. Only very small instances ($n \leq 10$) can be handled through this algorithm. He studied the case where there are time windows imposed at pickups and delivery points for each request. Desrosiers et al. (1991) further improve upon this methodology by performing the insertions in parallel. Dumas et al. (1991) have extended their single-vehicle exact algorithm to the multiple-vehicle case and applied it to instances with $n \leq 55$.

With the increase in travel demands in a DRP, researchers have decided to solve the problem using heuristics and meta-heuristics. These methods enable to reach an acceptable solution to the problem in a reasonable time. In this context, we mention major works such as those of Cordeau and Laporte (2003a). Recently Claudio et al., have developed a genetic algorithm for the DRP (Claudio et al., 2009). But the genetic algorithm uses lots of memory to store generations, for this reason it is not recommended in this kind of problem characterized by a real-time aspect. So it is preferred in our problem to find an acceptable solution in less time.

The Multi-objective Simulated Annealing algorithm (MOSA) was not used to solve the DRP in the previous works mentioned in the state of the art. For this reason and the advantages of this