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Solving a dial-a-ride problem with a hybrid evolutionary multi-objective approach: Application to demand responsive transport

Rémy Chevrier[a,*], Arnaud Liefooghe[b,c], Laetitia Jourdan[b,c], Clarisse Dhaenens[b,c]

[a] Université Lille Nord de France, IFSTTAR – ESTAS, 20 rue Élisée Reclus, 59650 Villeneuve d'Ascq, France
[b] Université Lille 1, Laboratoire d'Informatique Fondamentale de Lille, UMR CNRS 8022, Cité Scientifique, Bâtiment M3, 59655 Villeneuve d'Ascq, France
[c] INRIA Lille-Nord Europe, 40 Avenue Halley, 59650 Villeneuve d'Ascq, France

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ABSTRACT

Demand responsive transport allows customers to be carried to their destination as with a taxi service, provided that the customers are grouped in the same vehicles in order to reduce operational costs. This kind of service is related to the dial-a-ride problem. However, in order to improve the quality of service, demand responsive transport needs more flexibility. This paper tries to address this issue by proposing an original evolutionary approach. In order to propose a set of compromise solutions to the decision-maker, this approach optimizes three objectives concurrently. Moreover, in order to intensify the search process, this multi-objective evolutionary approach is hybridized with a local search. Results obtained on random and realistic problems are detailed to compare three state-of-the-art algorithms and discussed from an operational point of view.

1. Introduction

Sparsely inhabited areas usually suffer from a lack of transport service, given that the authorities do not want to accept the cost of a transport service insufficiently used [1]. Demand responsive transport (DRT) tries to address this issue. Indeed, this service of people transportation is activated on demand only and involves the satisfaction of customers' demands. It is necessary for the customers to have booked the service by defining a pick-up point and a destination (delivery) at an arranged time. A DRT service manages a fleet of vehicles and aims at grouping as many customers as possible in the same vehicles in order to reduce the operational costs. Given that each customer has his own destination, the grouping and the routing are optimized according to several criteria and a set of constraints imposed by the capacity of the vehicles (number of seats) and the timetable which is defined by the pre-arranged pick-up and delivery times. One vehicle starts from a depot, then follows an itinerary along which it picks up customers and carries them to the destination while respecting the predefined timetable.

In its usual form, DRT is related to the dial-a-ride problem (DARP) [2,3] or to the vehicle routing problem (VRP) [4]. Indeed, both problems consist in optimizing the vehicle routes by reducing the number of vehicles and the journey times. The VRP is the formulation of routing problems with loads to pick up and deliver [5], whereas the DARP formulates routing problems with passengers (one load equals 1). Another main difference between the DARP and the VRP lies in the precedence constraints imposed by the customer's journeys [6], and in the acceptance of delays (quality of service). Thus, a DRT service is a specific case of the DARP which is the academic formulation of a routing service with passengers.

Globally, the DARP may involve a set of objectives, usually conflicting, and which have to be optimized simultaneously. However, optimizing one objective often happens at the expense of the others. This is the reason why a multi-objective approach may be more than relevant in this context. In this paper, the DARP addressed is a multi-objective combinatorial optimization problem (MCOP) with conflicting criteria. Therefore, the search process aims at concurrently optimizing three objectives. The first one is *economic* and consists in minimizing the number of vehicles used in order to reduce the operational costs. The second one looks to reduce the duration of the vehicles' journeys. This objective could be seen as an *environmental* objective in so far as we try to limit the emission of pollutants (and also to reduce the carbon tax). The last objective minimizes the likely delays which may occur (*quality of service*). Besides, the approach is focused on finding a set of sub-optimal solutions, known as an approximation of the Pareto front when mapped into the objective space. A large number of MCOPs are known to be *NP*-hard and intractable [7], so that large-size problem instances cannot, in general, be solved exactly. Some exceptions can be noticed for small bi-objective [8,9] and multi-objective [10]

* Corresponding author.
E-mail addresses: remy.chevrier@ifsttar.fr (R. Chevrier), arnaud.liefooghe@univ-lille1.fr (A. Liefooghe), laetitia.jourdan@lifl.fr (L. Jourdan), clarisse.dhaenens@lifl.fr (C. Dhaenens).

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problems. Since the DARP is known to be *NP*-hard in its single-objective formulation [2], so is its multi-objective variant.

Although there are a lot of approaches solving the DARP [2], very few use evolutionary algorithms with a multi-objective approach. Indeed, they usually aggregate multiple objective functions for optimizing a single-objective problem [11–14]. Although methods based on multi-objective evolutionary algorithms exist to solve the VRP [5,15], these are not necessarily adapted to solve a DARP. However, a recent study deals with a multi-objective DARP, but not necessarily with evolutionary algorithms. In [16], a two-phase heuristic is proposed, but for two-objective cases only.

In this paper, the approach proposed to solve the DRT problem (DRTP) is the result of a preliminary work based on evolutionary algorithms [17]. An encoding mechanism based on a two-dimensional representation is provided, as well as a specific initialization strategy and adapted variation and improvement operators. Furthermore, a body of additional values are proposed to significantly improve the DRTP solving. To this end, a set of performance analysis is proposed, detailed and discussed, in particular: a calibration of crossover and mutation rates is carried out through two performance indicators; an iterative local search (ILS) is added in the mutation operator; an experimental analysis of performance along time is performed on several sets of instances (random, realistic and large-size). Finally, a comparison with and without the ILS is provided and analyzed.

The topic of the paper is to study the relevance of this kind of approach in an operational context. That is why several aims have to be achieved. One of them is to be capable of producing solutions in a short period of time. Indeed, a lot of DRT services usually impose booking several hours in advance and need methods allowing the reduction of this time. Besides, the use of a multi-objective approach would help decision-makers by providing them with a set of compromise solutions. This method will benefit from the features of evolutionary multi-objective optimization algorithms, which have received a particular interest over the last decades. Such methodologies have shown their efficiency to solve real-life problems [18]. In this perspective, the ILS will be used in the mutation operator in the same way as in a memetic algorithm [19]. The relevance of using an iterated local search in the mutation operator will be analyzed and discussed. As the instances used in the benchmarks are very often not relevant to real life, realistic instances will be used to assess the performance of the proposed approach. That is why the second aim of the approach is to be able to cope with both realistic and random instances. The third aim of this work consists of the comparison of three state-of-the-art evolutionary algorithms: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [20], the Strength Pareto Evolutionary Algorithm 2 (SPEA-2) [21] and the Indicator Based Evolutionary Algorithm (IBEA) [22]. The candidate algorithms are compared according to a set of different parameters: mutation and crossover rates, instances sizes and structures, computation time. These experiments tend to highlight the best candidate algorithm in an operational context.

The paper is organized as follows. The formulation of the problem under consideration is provided in Section 2. The main principles of multi-objective optimization and the three candidate algorithms used in this work are presented in Section 3. The encoding of the problem, as well as the initialization and the variation operators, are detailed in Section 4. Results are provided and discussed in Section 5. Finally Section 6 concludes the paper.

2. Problem definition

In order to help the reader, the symbols used in the paper are summarized in Table 1.

Table 1
Definition of symbols used for the DRTP.

Input data	
f_i	Objective function i
Λ	Set of the used vehicles
D	Depot of the vehicles
V	Set of the pick-up (V^+) and delivery (V^-) points such that $V = V^+ \cup V^-$
x, y	Arbitrary points such that $\{x, y\} \in V$
$t_{x\to y}$	Journey duration from x to y
d_x	Delay at a point x
R	Set of the requests
r	A request such that $r \in R$
r^+ (resp. r^-)	Pick-up (resp. delivery) point of the request r such that $r^+ \in V^+$, $r^- \in V^-$
q_r	Number of people of request r to be carried
v	A vehicle such that $v \in \Lambda$ When crossing point x, it is denoted: v_x
Q_v	Capacity of vehicle v, $v \in \Lambda$
h_{r^+}	Desired pick-up time
h_{r^-}	Theoretical arrival time
k_r	Relaxation coefficient
k_w	Coefficient for the time windows
Variables	
R_{min}	Set of minimal requests such that $R_{min} \subset R$
t_v	Amount of all journey durations between each point visited by vehicle v
d_v	Sum of each delay of vehicle v at delivery points
p_v	Number of passengers in vehicle v
H_x	Effective arrival time at point x
w_x	Time window at point x

2.1. Objectives formulation

The multi-objective problem under study can be formulated as a set of three objective functions to optimize ($f = (f_1, f_2, f_3)$) and a set of constraints to be taken into account. Problem solving is based on specific parameters, such as a relaxation and time windows which introduce more tolerance and flexibility to the slight delays which may occur during the journey. Since the DRTP is analogous to a DARP, the reader can refer to [2] to have mathematical models. Here we only detail the specificities of the DRTP and its multi-objective formulation. Therefore, in the DRTP under study, we aim to optimize three objectives: (1) minimize the number of vehicles used: function f_1 (Eq. (2)); (2) minimize the journey durations: function f_2 (Eq. (3)); (3) minimize the delays: function f_3 Eq. (4).

$$f = (f_1, f_2, f_3) \tag{1}$$

$$f_1 = \min |\Lambda| \tag{2}$$

$$f_2 = \min \sum_{v\in\Lambda} t_v \tag{3}$$

$$f_3 = \min \sum_{v\in\Lambda} d_v \tag{4}$$

2.2. Introduction of delay tolerance and time windows

A usual DRT service uses the tolerance of the customers to accept delays. Making detours allows a vehicle to group the customers even if that produces delays. To deal with these delays, a coefficient of relaxation k_r is introduced and applied to the journey duration for defining a maximal delivery time. Let $t\prime_{r^+\to r^-}$ be the slackened journey duration when $k_r > 1$: $t\prime_{r^+\to r^-} = k_r.t_{r^+\to r^-}$. Consequently, the maximal delivery time $h\prime_{r^-}$ is defined as follows: $h\prime_{r^-} = h_{r^+} + t\prime_{r^+\to r^-}$

In routing problems, the time windows define the time slots during which the picking up and the deliveries can be done. A time window at point r^+ is denoted w_{r^+} and its size is proportional to the theoretical journey duration to the point r^-: $w_{r^+} = k_w.t_{r^+\to r^-}$,