Optimization of a Demand Responsive Transport Service Using Multi-objective Evolutionary Algorithms

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ABSTRACT

This paper addresses the problem of optimizing a Demand Responsive Transport (DRT) service. A DRT is a flexible transportation service that provides on-demand transport for users who formulate requests specifying desired locations and times of pick-up and delivery. The vehicle routing and scheduling procedures are performed based on a set of requests. This problem is modeled as a multi-objective Dial-a-Ride problem (DARP), in which a set of objectives related to costs and user inconvenience is optimized while respecting a set of constraints imposed by the passengers and vehicles, as time windows and capacity. The resulting model is solved by means of three Multi-objective Evolutionary Algorithms (MOEA) associated with feasibility-preserving operators. Computational experiments were performed on benchmark instances and the results were analyzed by means of performance quality indicators widely used for multi-objective algorithms comparison. The proposed approaches demonstrate efficient and higher performance when optimizing this DRT service compared to another algorithm from the literature.

KEYWORDS

Demand Responsive Transport, Dial-a-Ride Problem, Multi-objective Evolutionary Algorithm

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1 INTRODUCTION

Demand Responsive Transport is a term used to name flexible transport services that operate on-demand through a fleet of vehicles (buses, vans, cars, etc.) which is scheduled to carry passengers in accordance with their needs [9]. To solicit a DRT service, users formulate requests in which they determine desired pick-up and delivery locations and time. Usually, a DRT service is shared, that is users coming from different requests, but with characteristics in common, whether the location and/or moment of operation of the service can be served simultaneously by the same vehicle [5]. This type of service is considered an intermediate form of transport located somewhere between the conventional bus services (shared and general transport) and the taxis (individual and personalized transport) [9].

This paper addresses the problem of optimizing both routing and scheduling plan of a DRT service. In general, this problem is modeled as a multi-objective Dial-a-Ride problem (DARP). The DARP consists of planning vehicles routes and defining time schedules in an on-demand collective people transportation service [3]. In the standard problem, multiple users make their requests for transportation from specific origins to destinations and the transportation service provider seeks to meet all these requests minimizing operating costs while a set of constraints ensures service level requirements.

The first researches in the context of transport of passengers appeared in the decade of 70 [13]. Mainly since [3, 4], studies about DARP have received considerable attention within the scientific community. Most of the researches published about DARP are real-world applications. Extensive reviews of both the DARP literature and some of its main variants were made by [7, 10].

Most of the DARP solution approaches optimize service cost-related objectives. As stated by [10], a DARP that optimizes a single operational objective does not provide any incentive to improve service quality, although many authors consider user inconvenience in terms of hard constraints, such as time windows, maximum user ride times, maximum waiting times, among others. In many publications, quality-related objectives have been considered, usually used instead of an operational objective or even in combination with it. In the second situation, we have a multi-objective DARP. The simplest way to deal with this type of problem is through a weighted sum of objectives. It scalarizes a set of objectives into a single objective in which each objective has a user-supplied weight (e.g. [8]). A second way is considering a lexicographic objective function. The objectives are optimized by following a hierarchical structure based on their importance. (e.g.[12]). The third type is the Pareto multi-objective approaches which have been the subject of recent researches (e.g. [1, 2, 11]).

In [1], a DRT service is addressed as a multi-objective DARP. To solve the problem, an evolutionary approach was proposed as well as a new solution representation and variation operators. Such mechanisms were integrated into three Multi-objective Evolutionary Algorithms (MOEA) state of the art: Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA-2) and Indicator-Based Evolutionary Algorithm (IBEA). In order to intensify the search process in the solution space, [2] introduce a hybrid multi-objective evolutionary approach based on the algorithms used in [1]. The routes are improved by a local search strategy based on the metaheuristic Iterated Local Search (ILS) together with the local search 2-opt algorithm within the mutation operator. In both publications, the infeasibility of the solution is allowed, that is, the algorithms explore the entire search space. Infeasible solutions (constraints about time conditions and vehicle capacities are not guaranteed) are penalized during the evaluation step by receiving high objective values. This procedure eliminates these solutions in future generations.

In this paper, we present a comparative study in which we evaluate a different search strategy from the one used in [1, 2] that drives a search in the entire search space. Our strategy performs a search only in the feasible search space. The main goal is to produce a large set of well spread non-dominated solutions close to the Pareto-optimal set, that proves the effectiveness of performing the search only in the feasible search space. A constructive heuristic, that creates the initial population and new variation operators, that produce new solutions and diversity, are presented. These modules are integrated into the same three MOEAs used in [1]. The proposed approaches are compared to an algorithm of the literature by means of two different performance quality indicators.

The remainder of this paper is organized as follows: Section 2 presents a formal definition of the DRT service addressed. Section 3 introduces the heuristic approaches. Finally, the computational experiments and conclusion are presented in sections 4 and 5, respectively.

2 PROBLEM DEFINITION

Presented in [1] and [2], the DRT service under study can be formulated as a multi-objective DARP, which optimizes three objective functions $f = (f_1, f_2, f_3)$ while satisfies a set of constraints. It minimizes the number of vehicles routes (f_1), the total duration of the routes (f_2) and the total delay in the delivery of passengers (f_3). Given that the problem addressed is a generalization of DARP, it is also classified as NP-hard.

To introduce flexibility to the service, the authors use a relaxation strategy and time windows. In addition, slight delays during the journeys, motivated by detours, are allowed. Making detours allows the service provider to group the customers into the same vehicle more easily while producing some delays.

In this DRT service, all n users have to be served by some vehicle route. Each user formulates a request r, in which defines the pick-up point r^+, the delivery point r^-, the number of people to be carried q_r and the desired pick-up time h_{r^+}. A time window duration w_{r^+} at the pick-up point r^+ is proportional to the journey duration t_{r^+,r^-} from r^+ to r^-. It is defined as: $w_{r^+} = k_w \cdot t_{r^+,r^-}$, being k_w a coefficient that indicates the percentage of the duration allocated to the time window. The theoretical arrival time h_{r^-} at the delivery point is the sum of the desired pick-up time and the journey duration from r^+ to r^-, resulting in $h_{r^-} = h_{r^+} + t_{r^+,r^-}$. The maximal delivery time h'_{r^-} is defined as: $h'_{r^-} = h_{r^+} + (k_r \cdot t_{r^+,r^-})$, being k_r a coefficient of relaxation.

A feasible route must respect a set of constraints. It is feasible if:

- It starts and ends at the depot;
- For every request r, the points r^+ and r^- belong to the same route and the point r^- is visited later than the point r^+;
- The load of the vehicle does not exceed at any time the max capacity;
- The service at a pick-up point r^+ begins in the interval $[h_{r^+}, (h_{r^+} + w_{r^+})]$ and the service at a delivery point r^- begins in the interval $[h_{r^-}, h'_{r^-}]$;

3 HEURISTIC APPROACHES

In this section, we present the components integrated into the three MOEAs used (for more details, see NSGA-II [6], IBEA [14], SPEA2 [15]).

3.1 Chromosome and Evaluation

In this work, a candidate solution is represented through a vector of vehicle routes. Computationally, the chromosome (individual) adopted is encoded as a two-dimensional representation. Each route is represented as a vector of transportation request identifiers. Given that each user request is associated with a pair of points, each one appears twice in the associated vehicle route. The first occurrence of the request identifier in the route represents the user pick-up point r^+ and the second one the delivery point r^-. Note that the request identifiers together with the appropriate signals are stored in the order in which they should be visited by the vehicle. Omitted in the route encoding, the first and last points of each route are the depot, location in which all vehicles start and finish their journey. Figure 1 presents an example of a solution for a fictitious test instance composed of eight requests and four vehicle routes.

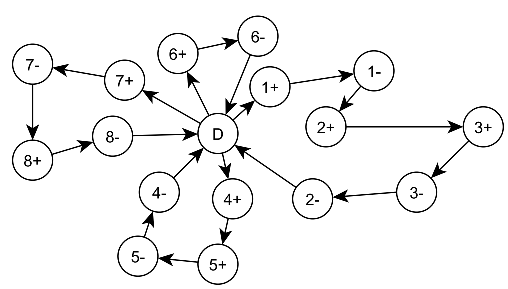

Figure 1: Solution Example

A chromosome is evaluated through the evaluation function $F = (f_1, f_2, f_3)$. This function computes and returns an objective vector with three values, which represents the solution in the objective space. Given that unfeasible individuals are not generated during the optimization process, penalty strategies are not used.

3.2 Initial Population

In order to create the initial population, which will be improved over the generations by the used MOEAs, a guided aleatory approach based on the population initialization strategy introduced by [2] was proposed. The main difference between the two approaches is the criterion adopted to prioritize the most urgent user requests. Given a set of available requests R, taking into account that the entire fleet of vehicles is initially located in the depot, the proposed procedure considers the desired pick-up time (h_{r^+}) and journey duration between the depot and the requested pick-up point (t_{D,r^+}) to define the most urgent requests. Initially, all available requests are sorted according to $h_{r^+} - t_{D,r^+}$. After that, the m first requests of the ordered list are assigned to m distinct vehicles, where m is an input parameter. In this way, the requests that demand greater urgency in the departure of the vehicles will be prioritized. The remaining user requests are sorted according to their pick-up time (h_{r^+}). Then, in order, they are added randomly and feasibly to an existing route. If the request cannot be added, a new vehicle route is allocated for serving the request. Note that, in each solution, the number of vehicle routes belongs to a range between m and the number of available requests $|R|$ (worst case, considering the objective function f_1).

3.3 Crossover Operator

The crossover operator used in this work is based on the classical operator with one cutting point. Let P_1 and P_2 be two parent individuals randomly selected from the current population and C_1 and C_2 two individuals built from $P1$ and $P2$. Initially, C_1 and C_2 are copies of P_1 and P_2, respectively. To modify C_1, the recombination operator selects one cutting point l between 1 and $min(|P_1|, |P_2|)$. After that, all routes in the route vector of C_1 after l are removed. Then, a copy of each route in the route vector of P_2 after l is concatenated in the route vector of C_1. Before that, in order to avoid duplicate data, all requests coming from P_2, that are also in some route of C_1, are removed of C_1. Finally, all available requests that have not yet been assigned to any route of $C1$ are inserted into the route and position with the lowest possible insertion cost (less increase in the total duration). The individual $C2$ is produced in the same way by exchanging $P1$ and $P2$ roles. A crossover rate P_c is defined to control the probability of performing.

3.4 Mutation Operator

To produce diversity in the current population, we use a mutation operator that exchanges a single user request between two different routes. First, a random request r is removed from a random vehicle route. After that, a different route is chosen to insert r. To that insertion does not cause significant delays and therefore, bring on less impact on the service quality, for both pick-up and delivery points, the insertion procedure starts the attempts in the last position of the route and performs the insertion on the first feasible position found. If all insertion possibilities, in the current route, results in an unfeasible route, a subsequent route is tried until the insertion is feasible. In the case of r cannot be accommodated by any route, a new one is created. A mutation rate P_m is defined to control the probability of performing.

3.5 Stopping Condition

As for the most optimization algorithms, for a MOEA there are no unanimous stopping criteria among researchers. In this study, all algorithms are stopped when they reach t seconds of elapsed CPU time, where t is an input parameter.

4 COMPUTATIONAL EXPERIMENTS

In this section, we discuss the results obtained on several computational experiments. In order to compare the performance of the two search strategies, the hybrid algorithm based on IBEA ($IBEA_H$) introduced by [2] (better performance among all evaluated), was coded following the authors’ descriptions. The proposed and the literature algorithms were coded in C++. The computational tests were run on a 2.50 GHz Intel Core i5 computer, with 6 GB RAM running Ubuntu 18.04.1 LTS.

All computational experiments were realized using two sets of test instances introduced by [2]. The first set called “`Rnd100`” has 10 instances with an almost homogeneous distribution of customers (conflicting time windows), which contain 100 user requests randomly generated. The second set denoted “`Gravit100`” contains 10 instances with a non-homogeneous distribution of customers, each one with 100 user requests generated using a geographical model of people or freight flows.

4.1 Quality Indicators

To measure the quality of the approximation sets obtained by all algorithms during the computational experiments, we have used two different quality indicators frequently employed in the literature on MOEAs. First, for each instance, we create the set Z^{all} that is the union of all the approximation sets obtained by the evaluated algorithms. In order to give a roughly equal range to all objective functions, each objective vector $z \in Z^{all}$ is normalized. Finally, we compute the reference set Z^* containing all the non-dominated points of Z^{all}.

The first quality indicator is the unary hypervolume indicator I_H proposed by [16], which measures the hypervolume of the portion of the objective space that is weakly dominated by an approximation set A. The higher the value of the indicator, the better is the quality of the solutions of A. We also use the unary additive epsilon indicator I_{ϵ^+} proposed by [17]. Given an approximation set A, $I_{\epsilon^+}(A, Z^*)$ represents the minimum factor ϵ that any objective vector in Z^* has to be added to obtain a set that is weakly dominated by A. A small $I_{\epsilon^+}(A, Z^*)$ value is preferable. Note that Z^* is used instead of the true Pareto front.

4.2 Parameter Settings Tuning

To obtain the best performance of our proposed algorithms, we carried out a parameter settings tuning. All computational experiments at this stage were performed using a sample composed of 8 test instances. For each algorithm, the crossover rate P_c and the

Table 1: Indicator values of all algorithms (average on all instances groups and runs)

Instance	IBEA_LIT [2]		IBEA		NSGAII		SPEA2	
	Hypervolume	Epsilon	Hypervolume	Epsilon	Hypervolume	Epsilon	Hypervolume	Epsilon
Gravit100 Set Avg.	0.2709	0.4768	**0.7787**	**0.0742**	0.7706	0.0802	0.7777	0.0767
Rnd100 Set Avg.	0.4329	0.1795	**0.5693**	**0.0307**	0.5540	0.0370	0.5604	0.0364
Global Avg.	0.3519	0.3282	**0.6740**	**0.0525**	0.6623	0.0586	0.6690	0.0566

mutation rate P_m were tested using four levels $\{0.2, 0.5, 0.8, 1.0\}$. All combinations of these values were tested. For a reliable analysis, in each instance, we apply all algorithms 10 times with 10 different seeds. Each run performed with a computation time of 1 minute and the population and the archive with 100 individuals. According to results, the best parameter setting for the NSGA-II, IBEA and SPEA2 are $P_c = 0.8$ and $P_m = 0.8$, $P_c = 0.8$ and $P_m = 0.2$ and $P_c = 0.8$ and $P_m = 0.5$, respectively.

4.3 Final Results

In order to show the efficiency of feasibility-preserving operators presented here, for each algorithm, we performed 30 independent runs on each test instance. Each run was performed with a computation time of 1 minute. We performed the $IBEA_H$ [2] in the same way, using the parameter setting defined by the authors. Table 1 presents the hypervolume and epsilon means of each instance set and the global mean of each algorithm. We observe that our algorithms are better in all instance sets, whatever the indicator used. The IBEA_H is always outperformed by its challengers and NSGAII and SPEA2 appears less efficient than IBEA.

We applied the nonparametric Kruskal-Wallis test to the two indicator values in order to determine whether our algorithms performed better than the IBEA_H at the significance level of 5%. Both the hypervolume and epsilon values presented P-value < 0.05, that is the null hypothesis (medians of all the experiments are equal) should be rejected. Therefore, there is a statistically significant difference between the obtained results at a 95% confidence level, whatever the indicator. To check which algorithms differ from each other, the Nemenyi test was used. When considered the hypervolume indicator, by evaluating the p-values of the pairwise comparisons, we can see that the test revealed a significant difference between the IBEA_H and the others (P-values < 0.05). Also between IBEA and NSGA-II (P-value = 0.02) there is a significant difference. The test did not present evidence of a significant difference between IBEA and SPEA2 (P-value = 0.50) and between NSGA-II and SPEA2 (P-value = 0.43). Regarding the epsilon indicator, the test presented evidence of a significant difference between IBEA_H and the others (P-values < 0.05). Also between IBEA and NSGA-II (P-value = 0.00) and between IBEA and SPEA2 (P-value = 0.01) there are significant differences. However, there is no significant difference between NSGA-II and SPEA2 (P-value = 0.79).

5 CONCLUSIONS

In this study, we propose new operators that keep the feasibility of the solutions. According to the two quality indicators widely used in the literature, the proposed approach performed better than the literature approach that works with infeasible solutions. The obtained numerical results have been statistically validated. Therefore, the focus on the feasible search space has brought improvements in the quality of the solutions. Future works include the use of other meta-heuristics, mainly those with selection based on quality indicators in order to find a better reference set for larger instances. Another direction is the use of multi-agent systems to conduct the optimization process in a distributed way.

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