A framework for the interactive resolution of multi-objective vehicle routing problems

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Abstract

The article presents a framework for the resolution of rich vehicle routing problems which are difficult to address with standard optimization techniques. We use local search on the basis on variable neighborhood search for the construction of the solutions, but embed the techniques in a flexible framework that allows the consideration of complex side constraints of the problem such as time windows, multiple depots, heterogeneous fleets, and, in particular, multiple optimization criteria. In order to identify a compromise alternative that meets the requirements of the decision maker, an interactive procedure is integrated in the resolution of the problem, allowing the modification of the preference information articulated by the decision maker. The framework is prototypically implemented in a computer system. First results of test runs on multiple depot vehicle routing problems with time windows are reported.

Keywords: User-guided search, interactive optimization, multi-objective optimization, multi depot vehicle routing problem with time windows, variable neighborhood search.

1 Introduction

The vehicle routing problem (VRP) is one of the classical optimization problems known from operations research with numerous applications in real world logistics. In brief, a given set of customers has to be served with vehicles from a depot such that a particular criterion is optimized. The most comprehensive model therefore consists of a complete graph \( G = (V,A) \), where \( V = \{v_0,v_1,\ldots,v_n\} \) denotes a set of vertices and \( A = \{(v_i,v_j) \mid v_i,v_j \in V, i \neq j\} \) denotes the connecting arcs. The depot is represented by \( v_0 \), and \( m \) vehicles are stationed at this location to service the customers \( v_1,\ldots,v_n \). Each customer \( v_i \) demands a nonnegative quantity \( q_i \) of goods and service results in a nonnegative service time \( d_i \). Traveling on a connecting arc \( (v_i,v_j) \) results in a cost \( c_{ij} \) or travel time \( t_{ij} \). The most basic vehicle routing problem aims to identify a solutions that serves all customers, not exceeding the maximum capacity of the vehicles \( Q_k \) and their maximum travel time \( T_k \) while minimizing the total distances/costs of the routes.

Various extensions have been proposed to this general problem type. Most of them introduce additional constraints to the problem domain such as time windows, defining for each customer \( v_i \) an interval \( [e_i,l_i] \) of service. While arrival before \( e_i \) results in a waiting time, arrival after \( l_i \) is
usually considered to be infeasible [9]. In other approaches, the times windows may be violated, leading to a tardy service at some customers [3].

Some problems introduce multiple depots as opposed to only a single depot in the classical case. Along with this sometimes comes the additional decision of open routes, where vehicles do not return to the place they depart from but to some other depot. Also, different types of vehicles may be considered, leading to a heterogeneous fleet in terms of the abilities of the vehicles.

Unfortunately, most problems of this domain are \(NP\)-hard. As a result, heuristics and more recently metaheuristics have been developed with increasing success [5]. In order to improve known results, more and more refined techniques have been proposed that are able to solve, or at least approximate very closely, a large number of established benchmark instances. With the increasing specialization of techniques goes however a decrease in generality of the resolution approaches.

While the optimality criterion of minimizing the total traveled distances is the most common, more recent approaches recognize the vehicle routing problem as a multi-objective optimization problem [4, 6–8]. Here, the overall problem lies in identifying a Pareto-optimal solution \(x^*\) that is most preferred by a decision maker. As the relevant objective functions are often of conflicting nature, a whole set of potential Pareto-optimal solutions exists among which this choice has to be made.

In the current article, a framework for interactive multi-objective vehicle routing is presented that aims to address two critical issues: (i) the necessary generality of resolution approaches when trying to solve a range of problems of different characteristics, and (ii) the integration of multiple objectives in the resolution process.

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Independent from the precise characteristics of the particular VRP, two types of decisions have to be made when solving the problem.

1. Assignment of customers to vehicles (clustering).
2. Construction of a route for a given set of customers (sequencing).

It is well-known that both types of decisions influence each other to a considerable extent. The here presented framework therefore proposes the use of a set of elements to handle this issue with upmost generality. Figure 1 gives an overview about the elements used.

- The marketplace represents the element where orders are offered for transportation.
- Vehicle agents place bids for orders on the marketplace. These bids take into consideration the current routes of the vehicles and the potential change when integrating an additional order.
- An ontology describes the precise properties of the vehicles such as their capacity, availability, current location, etc. This easily allows the consideration of different types of vehicles.
A decider communicates with the human decision maker via a graphical user interface (GUI) and stores his/her individual preferences. The decider also assigns orders to vehicles, taking into consideration the bids placed for the specific orders.

A solution is constructed by placing the orders on the marketplace, collecting bids from the vehicle agents, and assigning orders to vehicles while constantly updating the bids. Route construction by the vehicle agents is done in parallel using local search heuristics so that a route can be identified that maximizes the preferences of the decision maker.

### 3 Implementation and preliminary experiments

The framework has been prototypically implemented in a computer system. In the first experiments, two objective functions are considered, the total traveled distances \(DIST\) and the total tardiness \(TARDY\) caused by vehicles arriving after the upper bound \(l_i\) of the time window.

The preferences of the decision maker are represented introducing a weighted sum of both objective functions. Using the relative importance of the distances \(w_{DIST}\), the overall utility \(UTILITY\) of a particular solution can be computed as given in Expression 1.

\[
UTILITY = w_{DIST} \times DIST + (1 - w_{DIST}) \times TARDY
\]

The vehicle agents are able to modify the sequence of their orders using four different local search...
neighborhoods.

- Inverting the sequence of the orders between positions $p_1$ and $p_2$. While this may be beneficial with respect to the distances, it may pose a problem for the time windows as usually orders are served in the sequence of their time windows.

- Exchanging the positions $p_1$ and $p_2$ of two orders.

- Moving an order from position $p_1$ and reinserting it at position $p_2$, $p_1 < p_2$ (forward shift).

- Moving an order from position $p_1$ and reinserting it at position $p_2$, $p_1 > p_2$ (backward shift).

In each step of the local search procedure, a neighborhood is randomly picked from the set of neighborhoods and a move is computed and accepted given an improvement.

Bids for orders on the marketplace are generated by the vehicle agents, taking into consideration all possible insertion points in the current route. The sum of the weighted increase in distance DIST and tardiness TARDY gives the prize for the order.

The decider assigns orders to vehicles such that the maximum regret when not assigning the order to a particular vehicle, and therefore having to assign it to some other vehicle, is minimized. It also analyzes the progress of the improvement procedures. Given no improvement for a certain number of iterations, the decider forces the vehicle agents to place back orders on the market such that they may be reallocated.

The optimization framework has been tested on a benchmark instance taken from [1]. The instance comprises 48 customers that have to be served from 4 depots, each of which possesses two vehicles.

We simulated a decision maker changing the relative importance $w_{DIST}$ during the optimization procedure. First, a decision maker starting with a $w_{DIST} = 1$ and successively decreasing it to 0, second a decision maker starting with a $w_{DIST} = 0$ and increasing it to 1, and third a decision maker starting with a $w_{DIST} = 0.5$, increasing it to 1 and decreasing it again to 0. Between adjusting the values of $w_{DIST}$ in steps of 0.1, enough time for computations has been given to the system to allow a convergence to (at least) a local optimum. Figure 2 plots the results obtained during the test runs.

The first decision maker starts with $DIST = 975$, $TARDY = 6246$ and moves to $DIST = 1412$, $TARDY = 0$ while the second starts with $DIST = 2953$, $TARDY = 0$ and moves to $DIST = 1326$, $TARDY = 3654$. Clearly, the first strategy outperforms the second. While an initial value of $w_{DIST} = 0$ allows the identification of a solution with zero tardiness, it tends to construct routes that, when decreasing the relative importance of the tardiness, turn out to be hard to adapt. In comparison to the strategy starting with a $w_{DIST} = 1$, the clustering of orders turns out the be prohibitive for a later improvement.

When comparing the third strategy of starting with a $w_{DIST} = 0.5$, it becomes obvious that this outperforms both other ways of interacting with the system. Here, the solutions start with $DIST = 1245$, $TARDY = 63$, go to $DIST = 946$, $TARDY = 4342$, and finally to $DIST = 1335$, $TARDY = 0$. Apparently, starting with a compromise solution is beneficial even for both extreme values of $DIST$ and $TARDY$. 

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4 Summary and further development

A framework for the interactive resolution of multi-objective vehicle routing problems has been presented. The concept has been prototypically implemented in a computer system. Preliminary results on a benchmark instance have been reported.

First investigations indicate that the concept may successfully solve vehicle routing problems under multiple objectives and complex side constraints. In this context, an interaction with the system is provided by a graphical user interface. The relative importance of the objective functions can be modified by means of a slider bar, resulting in different solutions which are computed in real time by the system, therefore providing an immediate feedback to the user. Figure 2 shows two extreme solutions that have been interactively obtained by the system.

Future developments are manifold. First, other ways of representing preferences than a weighted sum approach may be beneficial to investigate. While the comparable easy interaction with the GUI by means of a slider bar enables the user to directly change the relative importance of the objective functions, it prohibits the definition of more complex preference information, e.g. involving aspiration levels.

Second, different and improved ways of implementing the market mechanism have to be investigated. First results indicate that the quality of the solutions is biased with respect to the initial setting of the relative importance of the optimality criteria. It appears as if more complex reallocations of orders between vehicles are needed to address this issue.

Finally, more investigations on benchmark instances will be carried out. Apart from test cases known from literature we aim to address particularly problems with unusual, complex side constraints and
multiple objectives. An additional use of the system will be the resolution of dynamic VRPs. The market mechanism provides a platform for the matching of offers to vehicles without the immediate need of accepting them, yet still obtaining feasible solutions and gathering a prize for acceptance of offers which may be reported back to the customer.

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