Hybrid interactive planning under many objectives: An application to the vehicle routing problem

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Abstract

The article presents an adaptive hybrid planning system for the interactive solution of multi-objective vehicle routing problems. A general framework was built, being able to handle various components of general vehicle routing problems, e. g. the simultaneous consideration of six optimization criteria. Solutions are constructed and improved in real time allowing the user to adapt his articulated preference information interactively. Results simulating different types of decision makers are reported, focusing on the adaptability of the system and the quality of the obtained solutions.
In brief, we are able to observe and demonstrate the suitability of the system to different types of decision makers, focussing on cost- or service-oriented criteria, or maintaining a balanced view on the two areas.

1. Introduction

Along with the growing interdependence of the world's economies, the distribution of goods is getting more and more important for the competitiveness of many companies. An efficient way of shipping any type of products entails, among other things, a determination of routes for the available vehicle fleet so that occurring costs are minimized. In addition, a competitive advantage depends on the offered quality of service, especially as customers following a just-in-time (JIT) production strategy expect to be served without any tardiness. Therefore, as a part of the overall delivery planning problem, the related routing problem has to be addressed integrating several criteria.

As the vehicle routing problem (VRP) has attracted the interest of researchers over the last three decades, a rich literature on different abstractions of routing problems can be found. The classical vehicle routing model can be formally defined on 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 $v_1, \ldots, v_n$. A nonnegative matrix $T = t_{ij}$ is defined on A, where t_{ij} represents the time, distance or cost of travel from vertex v_i to vertex v_j. The most basic vehicle routing problem aims to identify a solution that serves each customer exactly once while minimizing the total distances/costs/travel time of the routes.

Different extensions have been proposed to this general problem type to represent real world aspects more closely. While the *capacitated VRP* assumes that each customers v_i demand is a nonnegative quantity q_i of goods and the total demand on a route does not exceed the maximum capacity of the corresponding vehicle Q_k, the *time constrained VRP* specifies bounds T_k for the total duration of the routes. Besides the travel time, nonnegative service times a_i for the customers are considered. Along with this, often time windows are introduced by 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 [13]. In other approaches, the time windows may be violated, leading to a tardy service at some customers. Violations of time windows are either integrated in the overall evaluation of solutions by means of penalty functions [15], or treated as separate objectives in multi-objective approaches [3].

Some problems introduce multiple depots as opposed to only a single depot in the classical case. This problem formulation sometimes results in 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 $\mathcal{NP}$-

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hard. As a result, heuristics and more recently metaheuristics have been developed with increasing success [5,11,12]. In order to improve known results, more and more refined techniques that are able to solve, or at least approximate very closely, a large number of established benchmark instances have been proposed [1]. It has to be mentioned however, that with the increasing specialization of techniques a decrease in generality of the solution approaches follows.

While the optimality criterion of minimizing the total traveled distance is the most common, more recent approaches recognize the vehicle routing problem as a multi-objective optimization problem [6]. Important objectives besides the minimization of the total traveled distance are the minimization of the number of vehicles in use [8], the minimization of the total tardiness of the orders, and the balancing of the routes [7]. Following these objectives, it is desired to obtain solutions that provide a high quality of delivery service while minimizing the resulting costs. As many objectives are however of conflicting nature, not a single solution exists that optimizes all relevant criteria simultaneously. Instead, the overall problem lies in identifying the set of Pareto-optimal solutions P and selecting a most-preferred solution $x^* \in P$. In this context, three different general strategies of solving multi-objective optimization problems can be implemented:

1. *A priori* approaches reduce the multi-objective problem to a single-objective surrogate problem by formulating and maximizing a utility function.

2. *A posteriori* approaches first identify the Pareto set P, and then allow the decision maker to select a most-preferred solution $x^* \in P$.

3. *Interactive* approaches allow the gradual articulation of preferences by the decision maker and compute a sequence of solutions based on his/her individual statements. Several advantages result from this concept. First, the computational effort is smaller in comparison to the identification of the entire Pareto set. Second, the gradual articulation of preferences allows the decision maker to reflect the chosen settings in the light of the obtained results and therefore adapt and react to the optimization procedure. However, a disadvantage of interactive multi-objective optimization procedures is the need of the presence of a decision maker and the availability of an interactive software to present the results. Also, comparably little time for computations is allowed as the system should be able to react in (almost) real-time to inputs of the decision maker.

While it has been stressed already quite early, that combining computer programs with interactive planning procedures may be a beneficial way of tackling complex routing problems [9,14,16], research in interactively solving multi-objective metaheuristics is a rather newly emerging field of research [10] with so far comparably few applications. However, given the fast improving computing abilities of modern computers, approaches become increasingly interesting as they allow the solution of complex problems under the interactive, individual guidance towards interesting solutions.

2. Solution framework and implementation

In previous research we proposed a general agent-based framework for the interactive solution of different types of multi-objective VRPs [4] which combines clustering (assignments of customers to vehicles) and routing (construction of a route for a given set of customers) in parallel. Main elements of the framework are a *graphical user interface (GUI)*, *vehicle agents* for the representation of each vehicle, a *marketplace* to allow an exchange of information between the agents, and a *decider agent*, controlling the optimization procedure.

While a human decision maker articulates his/her individual preferences via the *GUI*, the *decider agent* stores this information. It is needed for both, clustering and routing. Every time an order has to be assigned to a vehicle, the *vehicle agents* are placing bids for that order on the marketplace. These bids take into consideration the current routes of the vehicles and the potential change when integrating an additional order. Routes are then optimized using Variable Neighborhood Search as described in [4]. Based on the bids on the marketplace and the actual preference information given from the decision maker, the *decider agent* assigns the orders to the vehicles such that the maximum regret when *not* assigning the order to a particular vehicle is minimized (clustering).

The current implementation of the framework allows to handle six optimization criteria within an interactive solution process. These are the total duration of use of all vehicles, including the travel times, service times and waiting times (c_1), the total traveled distances (c_2), the number of vehicles in use (c_3), the total tardiness caused by violating given time windows (c_4), the maximum tardiness (c_5), and the number of tardy orders (c_6). Figure 1 shows a snap-shot of the *GUI* during an interactive search process. The slider bars on the right enable the decision maker to articulate individual preferences.

To aggregate the criteria, a weighted sum approach based on partial utilities is used. Therefore the overall utility of a particular solution vector $y = (c_1, \ldots, c_J)$ is quantified as given in Expression (1).

$$U(y) = \sum_j w_j^a u_j(c_j) \tag{1}$$

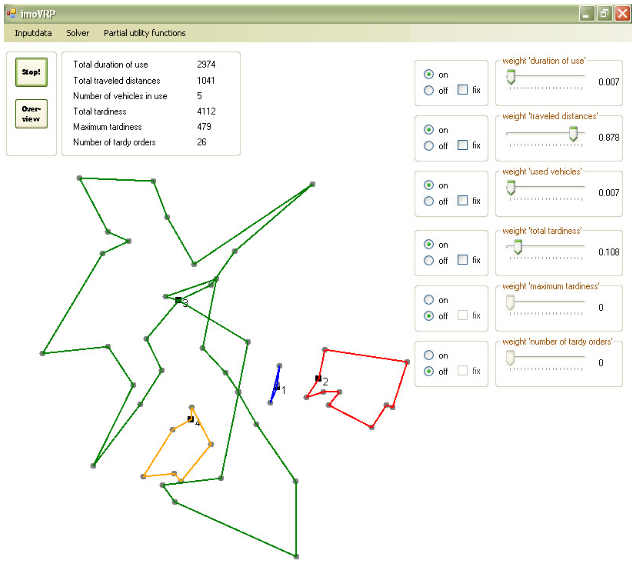

Figure 1. Screenshot of the graphical user interface.

$$u_j(c_j) = \frac{UB_j - c_j}{UB_j - LB_j} \quad (2)$$

The individual preference information of the decision maker is integrated by specifying weights for the different criteria (w_j^a). As $\sum_j w_j^a = 1$ holds, the decision maker can change the relative importance of the criteria by either increasing or decreasing the value of one or more weights. For each optimization criterion j, a linear partial utility function normalizes the objective function values with respects to precalculated lower and upper bounds (LB_j and UB_j) in the sense of Expression (2). Consequently, each $u_j(c_j$ computes the partial utility of criterion value c_j.

Each time the articulated weights change, the system adapts the current solution by trying to improve each vehicle's tour (rerouting) and the assignment of orders between the vehicles (reclustering). Adaptation of the routes is done using Variable Neighborhood Search as described in [4]. Also, a new solution is constructed from scratch and compared with the current one in terms of the articulated preferences.

3. Experimental investigation

3.1. Research objectives

The implementation of the presented framework has been investigated in a set of controlled experiments, focusing on two main research objectives, the *adaptability of the system* and the *quality of obtained results*.

The first objective tries to point out whether the implemented framework provides an adaptive hybrid system for the solution of multi-objective VRPs. While the decision maker is interacting with the system, e. g. by changing his articulated preferences in terms of the weights, the so far calculated and presented solution should be adapted to the updated information.

In addition, the obtained results should be of high quality for a certain decision maker. To analyze this, we assume that the decision maker's individual preferences can be expressed and aggregated by a subjective utility function, which is not explicitly known. More precisely, a solution vector y is quantified in terms of the individual utility U^I of Expression (3).

$$U^I(y) = \sum_j w_j^I u_j^I(c_j) \quad (3)$$

$$u_j^I(c_j) = \frac{UB_j^I - c_j}{UB_j^I - LB_j^I} \quad (4)$$

w_j^I represents the decision makers' individual weight of the corresponding criterion j ($\sum_j w_j^I = 1$). The normalization of the individual partial utility functions (4) is done with respect to individual lower and upper bounds (LB_j^I and UB_j^I).

Since the decision maker does not a priori know the appropriate individual weights, the person is changing the articulated weights w_j^a from time to time, reflecting the chosen settings in the light of the presented results. If during this process of interacting with the system the adapted and articulated weights w_j^a are similar to the true individual weights w_j^I, $U^I(y)$ is expected to be high. Vice versa, one could suppose $U^I(y)$ to be low when the articulated and the individual weights are rather different. The distance d between an individual weight vector w^I and an articulated one w^a is measured as described in Expression (5).

$$d = \max_j |w_j^I - w_j^a| \quad (5)$$

To sum up, the subsequent experiments should provide answers to the following questions:

1. Is the optimization framework adaptive in a way, so that an interaction/changing of the articulated weights forces the system to calculate new adapted routes?

2. Are the calculated routes of high quality for the decision maker in terms of his subjective utility, when his articulated preferences are close to his 'real preferences'? Is individual utility U^I decreasing with an increasing d?

3.2. Experimental setup

The optimization framework has been tested on ten benchmark instances taken from [2]. The instances range from 48 to 288 customers that have to be served from 4 to 6 depots, each of which possesses 2 to 7 vehicles. The precise description of the instances is given in [2] and therefore not repeated here. Download of the problem files is e. g. possible from `http://neo.lcc.uma.es/radi-aeb/WebVRP/`.

We simulated three types of decision makers, each regarding a different combination of optimization criteria.

- Decision maker 1 (DM 1) is more cost-oriented. He/ she is interested in minimizing the total duration of use (c_1), the traveled distance (c_2) and the number of used vehicles (c_3). In addition, he/ she pays attention to the service-related minimization of the total tardiness (c_4), but not to the maximum tardiness (c_5) and the number of tardy orders (c_6). Therefore, w_5^a and w_6^a are chosen such that $w_5^a = w_6^a = 0$.

- Decision maker 2 (DM 2) is more service-oriented. He/ she focuses on minimizing the total tardiness (c_4), the maximum tardiness (c_5) and the number of tardy orders (c_6). As a cost-related aspect, he/ she tries to minimize the total traveled distance (c_2). Other than that, $w_1^a = w_3^a = 0$.

- Decision maker 3 (DM 3) is cost-service-balanced. Hence he/ she uses two cost-oriented (c_1 and c_2) and two service-oriented (c_4 and c_5) criteria while interacting with the system. The other two criteria, c_3 and c_6 are not considered, hence $w_3^a = w_6^a = 0$.

In brief, interacting with the system means for e. g. DM 1 changing the values of w_1^a, w_2^a, w_3^a and w_4^a, while w_5^a and w_6^a remain unmodified ($w_5^a = w_6^a = 0$).

To simulate the process of interaction of a specific DM-type with the system, sequences of weight vectors were constructed. The order of the weight values imitates the way of searching/changing the weights of the corresponding decision maker. Due to the results of previous experiments on bi-criteria problems [4], each sequence of weights starts with initial values of 0.25 for the DM-type-relevant criteria. Afterwards, the weight of one of the four investigated criteria (w_k^a) is increased while simultaneously decreasing the others until an extrem weight vector ($w_k^a = 1$ and $w_j^a = 0 \; \forall \; j \neq k$) is reached. Here c_k is chosen randomly.

Next, the direction of search is shifted towards a randomly chosen weight vector and, starting from the extrem vector, weights are adapted until the random vector is reached. The simulation continues by again changing towards another extrem vector, followed by a randomized one, etc. Each time a modification on the basis of a new search direction is needed, the weights are adapted iteratively, reaching their particular direction value after ten steps. Table 1 shows a subset of a specific sequence of weights to simulate the search process of DM 3.

Table 1. Subset of a sequence of weight-values simulating DM 3. Start ($\star$), extrem ($\bullet$) and random ($\circ$) weight vectors are labeled.

	w_1^a	w_2^a	w_3^a	w_4^a	w_5^a	w_6^a
$\star$	0.250	0.250	0	0.250	0.250	0
	0.225	0.325	0	0.225	0.225	0
	0.200	0.400	0	0.200	0.200	0
	0.175	0.475	0	0.175	0.175	0
	0.150	0.550	0	0.150	0.150	0
	0.125	0.625	0	0.125	0.125	0
	0.100	0.700	0	0.100	0.100	0
	0.075	0.775	0	0.075	0.075	0
	0.050	0.850	0	0.050	0.050	0
	0.025	0.925	0	0.025	0.025	0
$\bullet$	0.000	1.000	0	0.000	0.000	0
	0.039	0.905	0	0.017	0.039	0
	0.078	0.810	0	0.034	0.078	0
	0.117	0.715	0	0.051	0.117	0
	0.156	0.620	0	0.068	0.156	0
	0.195	0.525	0	0.085	0.195	0
	0.234	0.430	0	0.102	0.234	0
	0.273	0.335	0	0.119	0.273	0
	0.312	0.240	0	0.136	0.312	0
	0.351	0.145	0	0.153	0.351	0
$\circ$	0.390	0.050	0	0.170	0.390	0
	0.351	0.045	0	0.253	0.351	0
	0.312	0.040	0	0.336	0.312	0
	0.273	0.035	0	0.419	0.273	0
	0.234	0.030	0	0.502	0.234	0
	0.195	0.025	0	0.585	0.195	0
	0.156	0.020	0	0.668	0.156	0
	0.117	0.015	0	0.751	0.117	0
	0.078	0.010	0	0.834	0.078	0
	0.039	0.005	0	0.917	0.039	0
$\bullet$	0.000	0.000	0	1.000	0.000	0

For each type of decision maker ten sequences of weight-values were generated, each of which consists of ten changes of directions towards an extrem vector and therefore of other nine turnarounds back to randomized weight-values. In total the ten benchmark instances were tested by applying ten simulation runs for each DM-type.

As the available space of this conference publication is limited, we have to restrict the presentation of the results on a subset of the data. However, as the derived conclusions hold for all investigated instances and types of decision makers, this presents a feasible step in the current experimental setting.

3.3. Results

Table 2 lists the results for the optimization criteria c_1 to c_6, obtained during an adaption of the weights as given in Table 1. It can be seen that the system satisfies the expectation of being adaptive rather well. Starting with an initial total distance (c_2) of 2916, the value of c_2 is constantly decreasing while the corresponding weight w_2^a is increasing. Simultaneously, the total duration of use (c_1) and the tardiness-related criteria (c_4 to c_6) are degrading with their decreasing weights. Finally a distance of 1557 is reached when w_2^a assumes 1, reducing the initial value by almost 50 %.

With the upcoming new search direction, especially w_1^a and w_5^a are increasing up to a value of 0.39 each, while w_2^a declines. This results in improving values for c_1, c_4 and c_5 (and consequently for c_6 as well), while the travel distance increases. Towards the next extreme weight vector ($w_4^a = 1$) the system calculates routes without any time window violation ($c_4 = c_5 = c_6 = 0$), while the total duration of use and the total traveled distance are rising again.

Concerning our second research objective, Figure 2 exemplary plots the results of the test runs for each of the three decision makers on instance 2, assuming that the unknown individual weights (w_j^I) are 0.25 for each of the relevant criteria. The values of U^I were normalized to the interval $[0; 1]$ in order to increase the clarity of the plots. It should be noticed that aggregated results and interpretations for the other problem instances are quite similar to those shown in Figure 2.

It can be seen, that for all types of decision makers the obtained individual utility tends to be high when d is small. As long as d is not greater than 0.2, the variance of the solutions in terms of U^I remains small with high average utility values. It therefore can be stated that the system is able to provide solutions of high quality for the investigated types of decision makers, if their articulated preferences are nearby their 'real' ones, independent of the particular criteria of interest.

Moreover, average values of U^I are decreasing while d is rising, but along with this the corresponding variance is increasing as well. On one hand, this means that calculated and presented solutions tend to change for the worse when the interacting decision maker moves away from his particular 'real' preferences. On the other hand, even settings with high distances d may result in solutions with high individual utility U^I, particularly for the service-oriented DM 2.

Table 2. Calculated results for the subset of weight-values simulating DM 3, instance `pr02` from [2]. Results of start ($\star$), extrem ($\bullet$) and random ($\circ$) weight vectors are labeled.

	c_1	c_2	c_3	c_4	c_5	c_6
$\star$	5008.6	2916.0	9	387.2	115.9	7
	4949.5	2815.0	9	106.1	44.7	7
	4794.7	2220.5	9	869.0	152.3	18
	4794.7	2220.5	9	869.0	152.3	18
	4758.7	2184.5	9	902.1	150.4	19
	4646.7	2043.4	9	1233.4	177.3	19
	4646.7	2043.4	9	1233.4	177.3	19
	4902.8	1800.7	9	2028.3	361.5	21
	5062.8	1725.1	9	3160.7	361.5	30
	5170.5	1660.6	9	4122.0	361.5	41
$\bullet$	5829.6	1557.4	9	13995.8	586.6	62
	5829.6	1557.4	9	13995.8	586.6	62
	5003.3	1702.2	9	3261.5	361.5	33
	5003.3	1702.2	9	3261.5	361.5	33
	5003.3	1702.2	9	3261.5	361.5	33
	4853.7	1824.1	9	1756.2	310.1	21
	4823.5	1856.8	9	1405.7	252.0	19
	4823.5	1856.8	9	1405.7	252.0	19
	4823.5	1856.8	9	1405.7	252.0	19
	4698.3	2175.8	9	843.7	252.0	15
$\circ$	4575.2	2425.2	8	521.2	252.0	6
	4784.7	2577.0	9	94.2	52.3	4
	4754.6	2548.2	9	15.3	12.6	2
	4754.6	2548.2	9	15.3	12.6	2
	4754.6	2548.2	9	15.3	12.6	2
	4691.4	2488.9	9	2.7	2.7	1
	4691.4	2488.9	9	2.7	2.7	1
	4691.4	2488.9	9	2.7	2.7	1
	4691.4	2488.9	9	2.7	2.7	1
	4713.9	2511.4	9	0.0	0.0	0
$\bullet$	4713.9	2511.4	9	0.0	0.0	0

4. Conclusions

An adaptive hybrid optimization system for interactive multi-objective vehicle routing has been presented, combining computational intelligence techniques with a human planner. Its implementation has been tested and analyzed on several benchmark instances. The investigation focused on two research objectives, the *adaptability of the system* and the *quality of obtained results*. We simulated three types of decision makers differing in their considered optimization criteria.

As a result of the experiments it becomes clear that the system is able to adapt identified solutions during the interaction of the decision maker with the system. While the articulated weights were changed for the benefit of a particular criterion, the new adapted routes actually turn out to be improved in terms of the corresponding criterion.

It also can be stated that the system provides auspicious solutions for the investigated types of decision makers. As long as the interactively articulated weights are close to the 'real' ones, almost all obtained solutions are of high quality with respect to the DM-type-individual utility U^I. Hence the identification of the 'real' preferences of a particular decision maker is not necessary, since due to the possibility of reflecting on current presented solutions and interactively adapting them, satisfying results will be found during the search procedure.

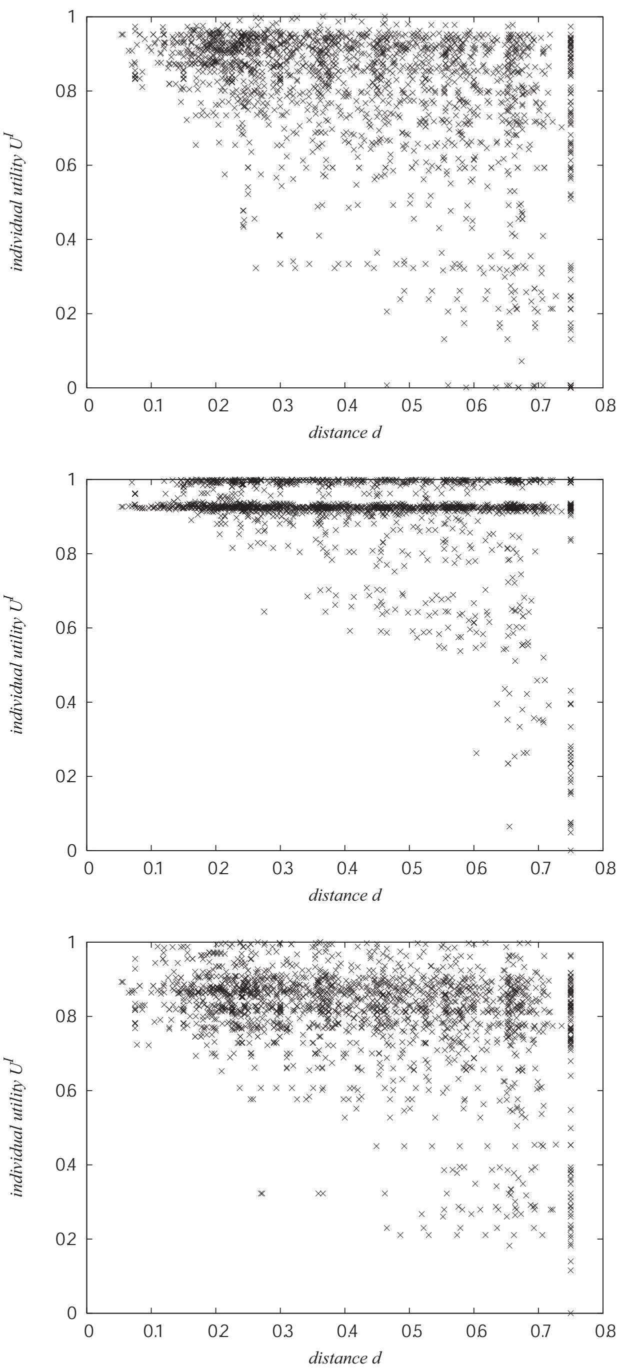

Figure 2. Results of test runs on instance `pr02` for DM 1, DM 2 and DM 3.

References

[1] J. E. Beasley. OR-library: Distributing test problems by electronic mail. *Journal of the Operational Research Society*, 41(11):1069–1072, 1990.

[2] J.-F. Cordeau, G. Laporte, and A. Mercier. A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational Research Society*, (52):928–936, 2001.

[3] M. J. Geiger. Genetic algorithms for multiple objective vehicle routing. In J. Pinho de Sousa, editor, *MIC'2001: Proceedings of the Forth Metaheuristics International Conference*, pages 349–353, Porto, Portugal, 2001.

[4] M. J. Geiger and W. Wenger. On the interactive resolution of multi-objective vehicle routing problems. In S. Obayashi at al., editors, *Evolutionary Multi-Criterion Optimization, Fourth International Conference, EMO 2007*, volume 4403 of *Lecture Notes in Computer Science*, pages 687–699, Berlin, Heidelberg, New York, 2007. Springer Verlag.

[5] M. Gendreau and O. Bräysy. Metaheuristic approaches for the vehicle routing problem with time windows: A survey. In *MIC'2003: Proceedings of the Fifth Metaheuristics International Conference*, pages 1–10, Kyoto, Japan, August 2003.

[6] N. Jozefowiez, F. Semet, and E.-G. Talbi. Multi-objective vehicle routing problems. *European Journal of Operational Research*, 189(2):293–309, September 2008.

[7] T.-R. Lee and J.-H. Ueng. A study of vehicle routing problems with load-balancing. *International Journal of Physical Distribution & Logistics Management*, 29(10):646–658, 1999.

[8] J. Pacheco and R. Marti. Tabu search for a multi-objective routing problem. *Journal of the Operational Research Society*, (57):29–37, 2006.

[9] Y. B. Park and C. P. Koelling. An interactive computerized algorithm for multicriteria vehicle routing problems. *Computers & Industrial Engineering*, 16(4):477–490, 1989.

[10] S. P. Phelps and M. Köksalan. An interactive evolutionary metaheuristic for multiobjective combinatorial optimization. *Management Science*, 49:1726–1738, 2003.

[11] J.-Y. Potvin and S. Bengio. The vehicle routing problem with time windows. Part II: Genetic search. *INFORMS Journal on Computing*, 8(2):165–172, Spring 1996.

[12] J.-Y. Potvin, T. Kervahut, B.-L. Garcia, and J.-M. Rousseau. The vehicle routing problem with time windows. Part I: Tabu search. *INFORMS Journal on Computing*, 8(2):158–164, Spring 1996.

[13] M. M. Solomon and J. Desrosiers. Time window constrained routing and scheduling problems. *Transportation Science*, 22(1):1–13, February 1988.

[14] P. J. Stacey. Practical vehicle routeing using computer programs. *Journal of the Operational Research Society*, 34(10):975–981, 1983.

[15] E. Taillard, P. Badeau, M. Gendreau, F. Guertin, and J.-Y. Potvin. A tabu search heuristic for the vehicle routing problem with soft time windows. *Transportation Science*, 31(2):170–186, May 1997.

[16] C. D. J. Waters. Interactice vehicle routeing. *Journal of the Operational Research Society*, 35(9):821–826, 1984.