Market Based Allocation of Transportation Orders to Vehicles in Adaptive Multi-objective Vehicle Routing

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Summary. The article describes a study on vehicle routing problems under multiple objectives. In particular, we investigate the effectiveness of different approaches when assigning orders to vehicles. The resulting clustering problem is studied within a general framework for multi-objective vehicle routing problems where different vehicle agents place bids for orders which are offered on a marketplace. This marketplace gathers information about the current situation and provides the basis for the resolution of the allocation problem. By implementing different specialized but interacting software agents, an adaptation of the concept to various configurations of the studied problem is possible. Experimental investigations of different assignment logics on benchmark instances have been carried out and numerical results are reported. In brief, a tendency towards a particular clustering approach can be observed.

Keywords: Vehicle routing problem, multi-objective, market based allocation, multi-agent approach.

1 Introduction

The distribution of goods plays an increasingly important role in the modern supply-chain of companies. On the one hand, the cost-efficiency of delivery and storage is considered, minimizing occurring costs throughout the supply chain and as a result creating competitive advantages. On the other hand, the quality of service has to be addressed as more and more companies tend to store the smallest possible amount of goods only, following a just-in-time (JIT) delivery strategy. Consequently, meeting delivery dates becomes increasingly important for the avoidance of out-of-stock situations. When combining both aspects, multi-criteria planning problems are derived which take several optimality criteria simultaneously into consideration [9]. From a scientific management perspective, methods, algorithms and systems are needed to support these complex planning problems. In a practical dynamic environment, this implies that the proposed approaches are flexible, allowing an adaptation to changing situations, constraints, optimality criteria, preferences, etc.

The vehicle routing problem (VRP) is one of the main optimization problems in the context of distribution management, which is faced by numerous

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companies and organizations each day. Characteristics of a specific practical problem such as regarded objectives or required constraints are highly variable, and conditions vary from one real world application to the other. However, most of them can be defined on a complete directed network $G = (V(G), A(G))$ with a node set $V(G)$, and a set of arcs $A(G)$ connecting the nodes. In the most classical version with a single depot each node $i \in V(G) \setminus \{0\}$ describes a customer by using various associated parameters, e. g. a corresponding non-negative demand q_i, a non-negative service time d_i or a given time window $[e_i, l_i]$ during which customer i should be or has to be served. Node 0 corresponds to the depot, where a fleet of vehicles with given capacity and/or route length restrictions is stationed to serve the costumers. Analog to the nodes, each arc $(i, j) \in A(G)$ possesses several parameters, foremost a travel-distance a_{ij}, a travel-time t_{ij} or travel-costs c_{ij} occurring by using the connection between i and j.

Several extensions of the classical vehicle routing problem can be found in practice and in literature. Some of them introduce multiple depots, heterogeneous vehicles or the possibility of open routes, where vehicles do not return to the place they depart from. Others take into consideration the dynamics of changing environments [5]. This may result in time-dependent travel times t_{ij} which vary from busy rush hours to quiet times, or in dynamically arriving orders that are either accepted and integrated into the plan or rejected.

Minimizing total travel-distance, total travel-time or overall travel-costs are commonly used objectives in VRPs. More recent approaches aim to identify solutions that provide a high quality of delivery service. In these applications customer satisfaction should be improved, e. g. by integrating specific aspects like the mentioned time windows as hard constraints [29], as soft constraints with some sort of penalty that occurs when a time window is violated [30], or by adding an objective function that minimizes total or maximum tardiness of the served orders [11]. Other service-oriented aspects are balanced workloads of drivers [17, 18] or balanced inequities between the best and the least served costumer [23]. Along with this, VRPs are more and more recognized as multi-objective optimization problems [11, 16, 17, 20, 21, 27]. In this context decision support is not provided by calculating a single optimal solution, but needs to identify a set of Pareto-optimal solutions P and to guide the selection of a most preferred one $x^* \in P$.

Unfortunately, most problems of this domain are $\mathcal{NP}$-hard. Given a fixed fleet size, even finding a feasible solution to the VRP with time windows turns out to be $\mathcal{NP}$-complete itself [28]. As a result, research has concentrated on heuristics and more recently on metaheuristics to obtain good quality solutions in short computing times [14, 25, 26]. Specialized techniques have been used to improve known results for particular VRPs [2] or to provide upper bounds for exact algorithms like column generation algorithms or branch-and-cut algorithms. It has to be mentioned however, that with the increasing specialization of techniques a decrease in generality of the resolution approaches follows. As a result, heuristic optimization frameworks such as HotFrame [10], EasyLocal++ [8], ParadisEO [3, 19] or the MALLBA library [1] try to address this issue by providing generic libraries for the resolution of optimization problems.

The article is organized as follows. In the following Section 2, a framework for interactive multi-objective vehicle routing is presented that aims to address two critical issues. First, the resolution approach has to be able to solve a range of problems of different characteristics and therefore needs to be of sufficient generality. Second, multiple objectives are integrated and the decision maker is allowed to interact with the system by articulating and adapting individual preferences during the resolution procedure.

An implementation of the framework for multi-objective vehicle routing problems and experimental investigations are presented in Section 3. The system is used to solve instances of multi-depot vehicle routing problems under multiple objectives. In the study presented in this article, we focus in particular on the clustering problem when assigning orders to vehicles. Conclusions are presented in Section 4.

2 A Multi-agent Approach for Interactive Multi-objective Vehicle Routing

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

1. The assignment of customers to vehicles (clustering).
2. The 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. While the clustering of customers to vehicles is an important input for the sequencing, the sequencing itself is of relevance when adding customers to routes as e. g. constraints of maximum travel distances and/or times have to be respected. The two types of decisions can be made either sequential (cluster first-route second vs. route first-cluster second) or in parallel.

The intersection of decisions known from bin-packing (clustering of customers) and the travelling salesman problem (sequencing of customers) results in a problem structure which is considerable more difficult. Even for the most simplistic classical vehicle routing problem known from the scientific literature, obtaining an optimal solution is challenging and quickly becomes infeasible even for medium-sized instances. When considering complex side constraints, this effect is even more present.

As a consequence, we chose to decompose the different types of decisions that have to be made in the VRP, and propose a framework that consists of different agents, each of which addresses a particular aspect of the problem. While each agent is specialized towards optimizing a certain sub-structure, such as minimizing the length of a particular route, an overall solution is obtained by market-based exchange of the gathered information.

Figure 1 gives an overview about the elements of the framework [12].

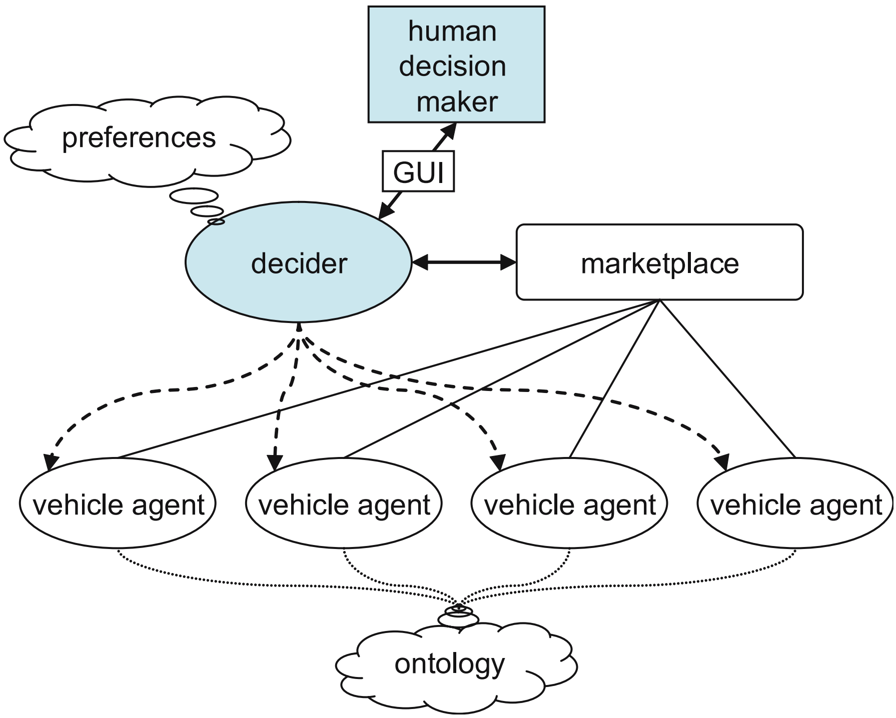

Fig. 1. Illustration of the framework for interactive multi-objective vehicle routing

- The *marketplace* represents the element where orders are offered for transportation and bids for orders, generated and placed by the vehicles, are gathered. In the initial step of the problem solving procedure, all orders are put on the marketplace. The marketplace does not posses any computational intelligence as such, it only consists of a single agent which gathers information from agents and makes the obtained information available to other agents.
- *Vehicle agents* represent the vehicles stationed at the depots. They therefore store information about the current position of the vehicle, its technical details (capacity, speed, maximum distance, etc.), and its currently assigned orders and route. While at the beginning of the optimization procedure the set of assigned orders is empty, routes are subsequently constructed throughout the optimization procedure.

  During the problem resolution process, the vehicle agents place bids for the orders on the *marketplace*. These bids take into consideration the current routes of the vehicles and the potential change when integrating an additional order. Integrating additional orders into existing routes leads to an increase in terms of travelled routes and/or time window violations. This information is reported back to the marketplace where it can be used to compare bids from different vehicles, thus leading to an assignment of orders to vehicles.

In addition to computing bids for orders on the marketplace, the vehicle agents possess computational intelligence techniques to optimize their travelled routes. The actual implementation of these techniques is based on local search, resequencing the orders until a sufficient approximation of the optimal route is identified. With respect to the initially mentioned two types of decision in the VRP, the vehicle agents solve the *sequencing problem*.

- An *ontology* describes the possible properties of the vehicles such as their capacity, availability, current location, technical details, etc. This easily allows the consideration of different types of vehicles (heterogeneous fleet). It also helps to model open routes, where vehicles do not necessarily return to the depot where they depart from.
- A *decider agent* communicates with the human *decision maker* via a graphical user interface (GUI) and builds a preference model of the individual preferences of the human planner. In comparison to generic graphical user interfaces for multi objective optimization such as GUIMOO [4] we chose an approach that also visualizes the actual solution on a map [12], not only the evaluation function value of the currently considered solution. This allows a close investigation of the current solution.

  The decider assigns orders to vehicles, taking into consideration the gathered bids placed for the specific orders. Precisely, this agent represents the *assignment/clustering* logic of orders to vehicles.

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 optimizes the preference model of the decision maker. Reviewing the mentioned variants of solving the clustering/sequencing problems, the presented approach follows the concept of combining both decisions in parallel. The precise method of constructing a solution is given in Algorithm 1.

Algorithm 1. Solution construction procedure

```
place orders on the marketplace
repeat
   for all orders on the marketplace do
      gather bids for orders from the vehicle agents
   end for
   decider agent: select some order from the marketplace
   decider agent: select some bid for the selected order
   decider agent: assign order to vehicle which generated the bid
   vehicle agent: update the route integrating the assigned order
until all orders are assigned
```

It is important to mention that in the proposed framework, the decision maker is allowed to change his/her preferences during the construction of the solution. In this case, the *decider agent* updates the stored preference information and in consequence, the vehicles resequence their orders such that the routes are again optimized for the updated preference information.

3 Implementation and Experiments

3.1 System Configuration

The framework has been implemented in a computer system. In the experiments that have been carried out for this article, two objective functions are considered, the total travelled distances D and the total tardiness T caused by vehicles arriving after the upper bound l_i of the time window. It should be noticed however, that neither the concept presented in Section 2 nor the actual implementation are restricted to the two objective functions only. The general applicability of the framework to other objectives, in particular to the minimization of the maximum tardiness T_{max}, has been shown in [13].

The preferences of the decision maker are represented by introducing a weighted sum of both objective functions. Using the relative importance of the distances $w_D, 0 \leq w_D \leq 1$, the overall utility U of a particular solution can be computed as given in Expression (1).

$$U = w_D \; D + (1 - w_D) \; T \tag{1}$$

In our current implementation, 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, $p_1 \neq p_2$. 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, $p_1 \neq p_2$ 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 vehicles' local search procedure, a neighborhood is randomly picked from the above given set of neighborhoods. We select each neighborhood with equal probability of $\frac{1}{4}$. Then, a random neighboring solution is computed based on the chosen neighborhood structure, e. g. by exchanging two randomly chosen jobs or shifting some job to some other position. The so computed move is accepted if an improvement of the route is obtained, always with respect to the particular utility function as given in Expression 1. In brief, the here presented concept implements a reduced Variable Neighborhood Search approach [15]. This concepts has the advantage of overcoming local optimality with comparably little effort as a set of different operators is repeatedly used. Having a whole set of neighborhood operators is particularly beneficial here as the vehicle agents need to be able to construct routes not only minimizing the length

Algorithm 2. Least cost bid generation of the vehicle agents

Require: current route $R_j = \{v_{j1}, \ldots, v_{jn}\}$, order v_i to be integrated in R_j

```
Set mincost = ∞, R_j^min = ∅
for all insertion points in the current route do
  insert order, obtaining modified route R'_j
  if R'_j is feasible then
    evaluate new route with respect to the preferences of the decision maker
    (compute U(R'_j))
    if U(R'_j) − U(R_j) < mincost then
      mincost = U(R'_j) − U(R_j)
      R_j^min = R'_j
    end if
  end if
end for
```

but also the total tardiness. Simply, a single operator appears less likely to be able to address both aspects at once.

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 D and total tardiness T gives the prize for the order. This price reflects the individual preferences articulated by the decision maker using the w_D parameter which expresses the tradeoff between distances and time window violations. The following Algorithm 2 illustrates the computational procedure of the vehicles agents for obtaining the least cost insertion point of a given order.

After all bids have been computed by all vehicle agents and gathered on the marketplace, the decider agent assigns orders to vehicles following a particular logic, e. g. myopically minimizing the cost of the next order assignment.

Initial experiments of the framework on benchmark instances investigated the adaptability of the concept to changing inputs on the decision maker [12]. We have been able to observe that the assignment of customers to routes plays an important role for the later adaptation of the solutions. As a corollary, a deeper investigation of the assignment logic, which we are going to present in the following subsection, appears beneficial.

3.2 Experiments

Two different assignment logics have been investigated for the decider agent. First, orders have been assigned giving priority to the bid with the *minimum price*. Second, the assignment has been done giving priority to the bid with the minimum *alternative cost*. This measure is derived by computing the resulting cost difference when *not* assigning an order to a particular vehicle, and therefore having to assign it to some other vehicle, resulting in the payment of another price. The precise computation of this measure consequently is the minimum difference of all other prices to the particular price of a vehicle. The minimum possible numerical value is 0, which is reached when an alternative vehicle exists

Table 1. Problem characteristics of the instances

Instance	vehicles	orders	depots
pr01	2	48	4
pr02	3	96	4
pr03	4	144	4
pr04	5	192	4
pr05	6	240	4
pr06	7	288	4
pr07	2	72	6
pr08	3	144	6
pr09	4	216	6
pr10	5	288	6

with the same price. A maximum value of ∞ has to be assumed when an order can only be assigned to a single vehicle, making this assignment most critical for the construction of a feasible solution.

The two assignment logics of the optimization framework have been tested on ten benchmark instances taken from [6]. 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 vehicles, and may be obtained e. g. from `http://neo.lcc.uma.es/radi-aeb/WebVRP/`. The precise description of the instances is given in [6] and therefore not repeated here. Instead, we give the key characteristics of the instances in the following Table 1.

A full mathematical description of the considered problem has been introduced by [7]. We however modify the precise formulation with respect to the objective functions and consider a multi-objective case of the VRP as given above.

We computed for each assignment logic/problem instance-combination a solution while considering different relative importance values of the distances w_D. The values of w_D varied from 0.1 to 0.9 in steps of 0.1. Extremal values of 0 and 1 have been excluded in the experiments as we did not aim to compute extremal solutions for a single objective function only but focus the investigation to multi-objective vehicle routing. Also, it is important to mention that values of $w_D = 0$ led to difficulties for the minimum price assignment logic where for some instances no feasible solution was found. The algorithm here started to construct routes which initially were optimal with respect to the total tardiness, however traveling routes of such long distances that is later became infeasible for the vehicles to accept additional orders.

3.3 Results

The computational results of the experiments are given in Table 2. As the procedures are deterministic, a single run has been sufficient for each parameter setting. We give for each instance and value of w_D the rounded values of D, T and the overall utility U, depending on the assignment logic. In column 'Diff.', the relative difference of the utility value obtained by the minimum price assignment logic to the utility value obtained by the alternative cost approach is given. Negative values indicate that *minimum price* led to a better overall result, while positive values state the opposite.

For an easier analysis, column 'Indic.' gives an indicator which illustrates the relative differences between the two approaches in a graphical way. Bullets (•) indicate a better performance of *alternative cost*, and the amount of the symbols categorizes the relative difference in steps of ±5%.

Table 2. Results

		Alternative cost			Minimum price				
Inst.	w_D	D	T	U	D	T	U	Diff.	Indic.
pr01	0.1	1362	0	136	1390	1	140	2.67%	•
	0.2	1305	8	267	1390	1	279	4.11%	•
	0.3	1270	13	390	1390	1	418	6.67%	••
	0.4	1334	21	546	1311	24	539	-1.35%	○
	0.5	1342	41	692	1311	24	667	-3.65%	○
	0.6	1306	115	830	1191	75	744	-11.48%	○○○
	0.7	1169	103	849	1164	75	837	-1.37%	○
	0.8	1169	103	955	1102	154	912	-4.74%	○
	0.9	1118	214	1027	1021	256	944	-8.78%	○○
pr02	0.1	2391	6	244	2385	1	240	-1.87%	○
	0.2	2331	6	471	2385	1	478	1.57%	•
	0.3	2206	28	682	2395	1	719	5.22%	••
	0.4	2169	52	899	2333	46	961	6.49%	••
	0.5	2176	58	1117	2227	116	1172	4.66%	•
	0.6	2100	63	1285	2226	62	1360	5.54%	••
	0.7	2073	78	1475	2160	156	1559	5.42%	••
	0.8	2002	408	1683	1979	162	1616	-4.15%	○
	0.9	1743	506	1619	1801	303	1651	1.93%	•
pr03	0.1	3455	3	349	3689	3	371	6.14%	••
	0.2	3346	27	691	3689	3	740	6.68%	••
	0.3	3336	27	1019	3725	35	1142	10.74%	•••
	0.4	3213	53	1317	3399	52	1391	5.27%	••
	0.5	3152	70	1611	3584	53	1819	11.40%	•••
	0.6	3206	98	1963	3183	164	1975	0.63%	•
	0.7	3034	167	2174	3466	174	2479	12.28%	•••
	0.8	3032	277	2481	2983	167	2420	-2.53%	○
	0.9	2804	372	2561	2793	277	2541	-0.77%	○
pr04	0.1	3970	2	398	4481	0	449	11.19%	•••
	0.2	3975	4	798	4109	19	837	4.58%	•
	0.3	3891	20	1182	4176	34	1277	7.45%	••
	0.4	3644	40	1481	4119	138	1730	14.39%	•••

Table 2. (*continued*)

		Alternative cost			Minimum price				
Inst.	w_D	D	T	U	D	T	U	Diff.	Indic.
	0.5	3533	138	1836	4206	85	2145	14.43%	●●●
	0.6	3379	199	2107	3610	181	2239	5.88%	●●
	0.7	3233	213	2327	3795	184	2711	14.17%	●●●
	0.8	3059	242	2496	3491	376	2868	12.98%	●●●
	0.9	2920	349	2663	3123	356	2846	6.44%	●●
pr05	0.1	4501	6	455	4624	5	467	2.55%	●
	0.2	4500	14	911	4204	8	848	-7.49%	○○
	0.3	4283	21	1300	4116	37	1261	-3.12%	○
	0.4	4451	40	1805	4161	52	1696	-6.42%	○
	0.5	4500	66	2283	4170	86	2128	-7.27%	○○
	0.6	4408	159	2709	3994	107	2439	-11.05%	○○○
	0.7	4267	112	3020	3835	201	2745	-10.05%	○○○
	0.8	3898	401	3198	4012	153	3240	1.29%	●
	0.9	3899	482	3557	3494	303	3175	-12.03%	○○○
pr06	0.1	5540	4	557	5302	1	532	-4.89%	○
	0.2	5297	35	1088	5130	15	1038	-4.79%	○
	0.3	5222	35	1591	5399	26	1638	2.86%	●
	0.4	5184	40	2098	5376	39	2174	3.49%	●
	0.5	4989	68	2529	5298	73	2686	5.83%	●●
	0.6	4866	154	2981	5268	153	3222	7.48%	●●
	0.7	4715	176	3353	4707	212	3358	0.15%	●
	0.8	4330	273	3519	4608	231	3732	5.72%	●●
	0.9	4106	399	3735	4379	434	3985	6.26%	●●
pr07	0.1	1864	0	186	1818	0	182	-2.55%	○
	0.2	1864	0	373	1818	0	364	-2.55%	○
	0.3	1828	8	554	1780	7	539	-2.69%	○
	0.4	1834	32	753	1846	15	747	-0.79%	○
	0.5	1801	32	917	1846	15	930	1.43%	●
	0.6	1737	53	1063	1691	156	1077	1.24%	●
	0.7	1658	143	1204	1576	156	1150	-4.68%	○
	0.8	1619	220	1339	1596	156	1308	-2.37%	○
	0.9	1408	347	1302	1465	194	1338	2.66%	●
pr08	0.1	3375	3	340	3108	0	311	-9.39%	○○
	0.2	3136	17	641	3065	16	626	-2.40%	○
	0.3	3233	30	991	2892	71	917	-7.99%	○○
	0.4	3048	30	1237	2847	83	1189	-4.06%	○
	0.5	2959	119	1539	2950	83	1517	-1.47%	○
	0.6	2808	130	1737	2888	215	1819	4.53%	●
	0.7	2815	233	2041	2494	301	1836	-11.12%	○○○
	0.8	2619	257	2147	2424	180	1976	-8.66%	○○
	0.9	2239	379	2053	2534	361	2317	11.41%	●●●

Table 2. (*continued*)

		Alternative cost			Minimum price				
Inst.	w_D	D	T	U	D	T	U	Diff.	Indic.
pr09	0.1	4148	1	416	4283	1	429	3.03%	•
	0.2	4025	45	841	4108	6	826	-1.76%	○
	0.3	3888	45	1198	4062	41	1247	3.99%	•
	0.4	3817	52	1558	4106	54	1675	6.99%	••
	0.5	3760	56	1908	4116	73	2095	8.92%	••
	0.6	3581	175	2219	3995	79	2429	8.67%	••
	0.7	3620	161	2582	3779	70	2667	3.17%	•
	0.8	3597	280	2934	3672	146	2967	1.12%	•
	0.9	3188	370	2907	3495	226	3168	8.26%	••
pr10	0.1	5508	2	552	5669	1	568	2.72%	•
	0.2	5340	31	1093	5731	2	1148	4.75%	•
	0.3	5360	40	1636	5484	16	1657	1.24%	•
	0.4	5465	80	2234	5523	30	2227	-0.29%	○
	0.5	5146	133	2639	5261	73	2667	1.03%	•
	0.6	4828	271	3005	5318	73	3220	6.67%	••
	0.7	4842	269	3470	4983	276	3571	2.82%	•
	0.8	4516	255	3664	4602	138	3709	1.23%	•
	0.9	4310	353	3914	4593	324	4166	6.04%	••

When analyzing the investigated assignment logics, it becomes clear that differences in the quality of the obtained solutions exist. The *alternative cost* assignment logic led in more cases to superior results compared to the *minimum price* approach. This behavior is especially obvious for instances pr03, pr04, pr09 and pr10. Other instances such as pr02 and pr06 show the same tendency, however with a considerable smaller significance. It is however interesting to see that there are several counterexamples, namely instances pr01, pr05 and pr08 where the opposite conclusion is reached.

There does not appear to be an significant influence of the parameter w_D on the relative performance of the two assignment logics. For all values of w_D, one or the other clustering approach led to superior results, always depending on the particular instance. The recommendation for one or the other assignment logic appears to be based and depending on the instance as such, and not on the relative importance of the criteria.

It has to be pointed out, that several observed differences are rather small. While there are instances in which a particular logic reliably leads to better results, the are some cases in which the differences do not permit a certain recommendation of either one of the approaches.

4 Conclusions and Synthesis

A framework for the resolution of multi-objective vehicle routing problems has been presented. After having previously analyzed the behavior of the approach in interactive scenarios where the decision maker changes his/her preferences [12], we have been able to see that the clustering of customers to vehicles plays an important role in the resolution process, particularly when having to adapt to changing inputs.

The current investigation therefore compared different clustering approaches in multi-objective vehicle routing. The experimental investigation have been based on benchmark instances taken from the literature.

In conclusion, it is possible to state that the *alternative cost* assignment logic is preferable to the *minimum price* approach in most cases. However, as counterexamples can be found, we cannot entirely rule out the applicability of the otherwise weaker assignment logic. As a synthesis, both approaches could be, given appropriate time for computations, used in parallel while clearly giving priority to the alternative cost approach first.

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