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Abstract

This paper proposes a comparison between two fast heuristic algorithms to solve a multi-carrier 2E-VRP in city logistics, under realistic conditions. We propose a cluster-first route second algorithm to compare the performance of two route construction and post-optimization algorithms on real-size test cases. The clustering phase is made by a seep algorithm, which defines the number of used vehicles and assigns a set of customers to it. Then, for each cluster, which represents a vehicle, we build a min-cost route by the two following methods. The first is a semi-greedy algorithm. The second is a genetic algorithm that includes post-optimization at the level of each route. In this work we make the route construction and post-optimization without any possible exchange of the routes to guaranty a pertinent comparison between both algorithms. After presenting both approaches, we apply them, first to classical 2E-CVRP instances to state on the algorithm capabilities, then on real-size instances to compare them. Computational results are presented and discussed. Finally, practical implications are addressed.

Keywords: city logistics, multi-carrier two-echelon vehicle routing, cross-docking, heuristics comparison, route construction.

1. Introduction

The freight transport industry is confronted to a paradox: on one hand, it is a major source of employment and supports the economic development of a country; in another hand, it is at the origin of many adverse effects including congestion and environmental disturbance that affect quality of life, mainly in urban zones. In the last years, several researchers and practitioners have focused on studying and analyzing the urban part of supply chains, although not always in a global logistics perspective (Allen and Browne, 2010). The city logistics is now considered a scientific discipline that aims to understand, identify, analyze and simulate the organizational, locational, regulation, technological, policy-making and environmental aspects of logistics in urban zones as well as their interactions with the urban environment (Taniguchi et al., 2001).

One of the most popular subjects in urban logistics is urban consolidation, i.e., the rationalization of goods into consolidation platforms where better loaded vehicles are composed to deliver city centers. We find several works dealing with that question (some representative examples or compilations of works can be found in Crainic et al., 2004; Gonzalez-Feliu, 2008; Van Duin et al., 2008; Danielis et al., 2010; Vaghi and Percoco, 2011; Allen et al., 2012; Gonzalez-Feliu and Salanova, 2012; Thompson and Hassall, 2012; Verlinde et al., 2012). Those works have motivated the development of vehicle routing problems adapted to multi-echelon transport systems (Crainic, 2008; Gonzalez-Feliu, 2012, 2013; Mancini, 2013). Multi-stage transport systems deal with transport schemes with one or more ruptures of change at intermediary logistics facilities where various operations can be achieved (Gonzalez-Feliu, 2013). In these intermediary facilities, some operations take place, to help the distribution process, reduce costs, give a higher quality service or offer some additional services to vehicle drivers, mainly related to cross-docking (Gonzalez-Feliu, 2012). Concerning vehicle routing, we observe two main types of problems dealing with multi-stage transport (Gonzalez-Feliu, 2013):

- Splitting problems, where it is considered that freight comes to logistics platform using big vehicles that come from the same departure point, after what it is split into a set of smaller vehicles that deliver the final destinations.
- Consolidation problems, where intermediary platforms receive vehicles from two or more departure points, and freight is consolidated at such facilities in order to configure better loaded vehicles of different sizes and characteristics.

In literature, most works deal with splitting problems (according to Gonzalez-Feliu, 2013, only 5 of 38 scientific works deal with consolidation problems for freight distribution, and other 8 with consolidation for freight collection, 25 remaining ones are directly dealing with splitting problems). However, when observing the practical applications, urban consolidation, in its different forms, is directly related to consolidation problems (Thompson and Hassall, 2012; Verlinde et al., 2012; Gonzalez-Feliu, 2013). Public and private decision makers in urban logistics then need to have a robust support that is also easy to understand and reproduce. However, most algorithms applied nowadays to multi-stage transport seem to not have a direct correspondence to real situations. Moreover, in other VRP applications, classical heuristics (with local search) are widely deployed into operational tools, and meta-heuristics, considered as better performing on a computational point of view, have difficulties to enter the market of transport management systems (Partyka and Hall, 2010).

For those reasons a first question emerges: which is the potential of meta-heuristics to solve complex realistic instances of urban goods distribution? To attempt to give an answer, we propose to compare two classical techniques on the basis of two-stage vehicle routing real applications: first is a classical local search algorithm, like those of current TMS, adapted to a two-stage transport schema; second is a genetic algorithm, also adapted to the same problem.

This paper presents two fast algorithms for real-life collaborative urban logisticsa semi-greedy and a genetic and tests both algorithms on a set of real-life instances, comparing them and highlighting the advantages and limits of each procedure. The paper is organized as follows. First we present the combinatorial optimization problem and the two proposed algorithms. Then, we test them literature instances for a similar problem (the non-collaborative version of the same problem). After that, we propose a set of instances and make a comparative analysis of the algorithms on a solution probleming viewpoint. Finally, to complete this analysis, the capability of the algorithms for scenario assessment and other practical considerations are addressed and discussed.

2. Combinatorial optimization problem and proposed algorithms

We find in literature different vehicle routing models and variants in city logistics Partyka and Hall, 2010 (Cattaruzza et al., 2015). Such approaches deal with different elements of urban freight distribution: multi-stage distribution (Gonzalez-Feliu, 2012), variable travel times (Ando and Taniguchi, 2006), dynamic context (Zeimpekis et al., 2007), multi-trip nature (Cattaruzza et al., 2014), among others. Although some works deal with routing for urban consolidation approaches, those works only take into account the outbound flows (i.e. from the consolidation center to the customers) and not the inbound flows (Qureshi and Hanaoka, 2006; van Duin et al., 2008; Thompson and Hassall, 2012; Battaia et al., 2014). Only few works consider all the flows related to urban consolidation in a systemic view, i.e. inbound and outbound flows (Gonzalez-Feliu, 2013). The particularity of those works is that they consider not only the city logistics flows (from urban consolidation center to city) but also the links to supply chains (from the last intermediary platform or distributor facility to the urban consolidation center), this second set of flows being often considered out of scope in city logistics works. Precedent works aiming to propose a systemic view of urban consolidation use in general a greedy or semi-greedy algorithm to reproduce a realistic route, without an aim of high optimization (Gonzalez-Feliu et al., 2010, 2013; Gonzalez-Feliu and Salanova, 2012). They do not assess the robustness of algorithms but use a well-known method to produce data in order to carry out application-based analyses. However, and as signaled in a first exploratory analysis (Gonzalez-Feliu and Salanova-Grau, 2015), it is important also to explore the suitability of those algorithms, and compare them to most robust approaches. To complete all those works, it is important to analyze if those solutions can be improved keeping computational times at a feasible level for practice purposes. To do this, we aim to propose to generalize previous words by first defining the computational problem and then proposing an alternative to semi-greedy algorithms to compare both heuristics.

First, we define the problem on the form of a graph. In a distribution scheme with urban consolidation centers, the resulting distribution graph presents three types of nodes: the first type is that of depots, corresponding to shippers' locations. The second is that of consolidation centers, which can be seen as intermediary platforms where no warehousing or inventory is allowed, only cross-docking and very short-time storage to wait for loading the concerned goods into the final delivery vehicles; the third is that of customers, the final destinations of goods. Each shipper has its own customers (some of those customers receive goods for more than one shipper, from which the interest of urban consolidation). To reduce the number of times a customer receive a delivery (and then the number of vehicles), shippers bring all their goods to one or more consolidation centers, where all goods transported by the different shippers are consolidated and grouped to form final delivery routes to deliver customers. In this consolidation, all goods delivered by shippers pass through consolidation centers (in other words, we consider for the systemic optimization only goods passing through consolidation centers, those deliveries that are out of the urban consolidation schemes are not considered). Each shipper has its own fleet of vehicles (we consider in a first time that, for each shipper, all vehicles have the same characteristics, but between two shippers vehicles can be different). The same hypothesis is applied to consolidation centers (its consolidation center have its own homogeneous fleet of vehicles, but the composition of each consolidation center's fleet, in number of vehicles and capacity, is different). The objective is then to minimize transport cost by delivering all customers for each shipper using the urban consolidation system. In this case, the optimization problem presents three main issues (Gonzalez-Feliu, and Salanova-Grau 2015):

1. Allocate customers to companies for the last-mile distribution (allocation problem).
2. Locate the most suitable cross-docking points (location-allocation problem).
3. Construct the second-echelon routes (vehicle routing problem)

4. Construct the first-echelon routes (vehicle routing problem) transshipping the freight at the cross-docking facilities in order to load the second-echelon vehicles (matching problem).

This problem can be seen as an extension to multidepot of the well-known 2E-LRP (two-echelon location routing problem). A first formuation can be obtained by reduction of the NE-LRP formulation of Gonzalez-Feliu (2012) to two echelons. This problem being NP-hard, the formulation is quickly limited even for very small instances, and for practical reasons, it is important to provide robust quick heuristics. As said before, we aim to compare the semi-greedy frameworks to a genetic algorithm. To make this comparison homogeneous, we propose a cluster-first route second algorithm where the composition of routes is chosen during the clustering phase, and the post-optimization phase takes place independently inside each cluster. In this way, the effectiveness of genetic algorithm is comparable to that of semi-greedy and the results are similar to those that commercial tools used in practice can offer for more simple problems.

In the clustering phase, customers are assigned to each 2nd-echelon vehicle, and then to a satellite using the well-known Sweep Algorithm (Toth and Vigo, 2002). The algorithm, well known in literature, allows partitioning the entire set of customers in a number of clusters up to the maximum number of vehicles of the fleet. This algorithm has been adapted to the fact that each satellite has its own fleet of vehicles, so each cluster is a priori assigned to a consolidation center and the vehicle characteristics are included in the clustering phase. In other words, each cluster will verify the following condition: the total commodity quantity (in weight) corresponding to the customers assigned to the cluster must be lower than or equal to the capacity of a single vehicle of the fleet of the corresponding consolidation platform.

After clusters are constituted, routes can be constructed. We propose two heuristic approaches for route estimation, the already introduced semi-Greedy algorithm and a Genetic algorithm. Those algorithms are described below.

2.1. The semi-greedy algorithm with local search post-optimization

The Semi-Greedy algorithm works as follows. Given the satellite clusters defined in the first phase, we build routes using a semi-greedy algorithm (Hart and Shogan, 1987). This procedure constructs routes following an iterative procedure that adds each customer to a route. Given iteration i and an uncompleted route, a list of candidates is defined by taking the n closest customers to the last point of the route. This is made by defining a distance threshold δ. Customers whom distance to the last point of the route is less than δ are included into this list, which will be called Restricted Candidate List (RCL). Then, the customer inserted on the route is chosen at random from the RCL customers. Finally, the first stage routes are built following the same principle, knowing the load that will transit on each satellite from the second-stage routes. The proposed algorithm solves instances of more than 1000 customers and 5 satellites in less than 1 second.

2.2. The multi-start heuristic with genetic post-optimization

The genetic algorithm is applied to build a near-optimal route from the clustering results. In this context, the problem to solve is the classic Travelling Salesman Problem (TSP). This choice is motivated by the fact that a genetic algorithm is time consuming, and the complexity of the chosen problem applied to real applications needs fast and robust algorithms. For this reason, the proposed genetic algorithm is a mutation algorithm that starts from a set of possible solutions then each generation is generated by mutating the anterior one for finding the best route in each cluster. Details regarding the genetic post-optimization process can be found in Gonzalez-Feliu and Salanova-Grau (2015).

3. Computational results

To assess the capacity of the proposed algorithms to deal with the targets of potential users (and then address their applicability) we will propose a solution probleming analysis (Ackhoff, 1977). This vision of operational research contrasts to classical problem solving in the fact that it aims to address the real operability and applicability of the proposed methods. Problem solving approaches define a problem, develop a method to solve the problem and address the capability of methods and algorithms to improve the solution, find the theoretical optimum or compute quickly but without stating on the real applicability of the methods (which have consequences on the final usage of the methods proposed). In opmposition to that, solution probleming is focused, not on finding “the best solution ever” for a problem, but in finding a solution then assessing its satisfaction degree with respect to given targets and the related optimization problem, then modifying (when applicable) this problem or the used methods if the obtained solution is not considered satisfactory. In other words, problem solving goes from problem to solution whereas solution probleming does the opposite path, i.e. from solution to problem (Ackhoff, 1977).

The suitability of the methods has been discussed and justified in Gonzalez-Feliu and Salanova-Grau (2015), comparing them to the best-known lower bounds obtained by exact methods (Baldacci et al., 2013), for single-depot 2E-VRP instances (Gonzalez-Feliu, 2008). However, in a solution probleming approach, it is important to question about the suitability of the reference. An exact method is often limited by its high computational times, and in real distribution the main goal of optimization is not to find a theoretical optimum but a fast and suitable solution. For those reasons, we re-propose the comparison with respect to the best solutions found (Hemmelmayr et al., 2012). We are aware that those algorithms are not the best for this problem, since they have been adapted to a more complex case and aim to find a suitable solution quickly. Moreover, routes obtained with this algorithm follow behavioral patterns that are close to the reality, as it is observed when comparing results of single routes with the route database, in terms of travelled distances.

We observe that results obtained by the semi-greedy algorithm (that has not post-optimization procedures) are far from theoretical optima (from the 21 instances solved, only one result presents a gap to the theoretical optimum lower than 5%, and five under 10%). Those results allow us to state on the interest of improving intra-route post optimization (for 5 of the 21 instances, the solution obtained by the genetic algorithm presents a gap to the theoretical optimum of less than 5%, and for 11 instances this gap is under 10%). Although those results show that the algorithms are not the best for solving single-depot 2E-CVRP, they are on the line of what commercial tools can give (see Partika and Hall, 2010 for a survey of tools used in practice) and as shown by Gonzalez-Feliu et al. (2014a) such type of algorithms reproduce routes that are close to average distance and route characteristics in real urban goods transport. For those reasons, instead of focusing on finding theoretical optima, we propose a comparison of both algorithms in terms of applicability and operability.

Table 1. Details of computational results on Gonzalez-Feliu's (2008) instances

Instance	Best solution			Comp. time		Literature optimum	Gap to best solution	
	Semi-greedy	Genetic	Gap	Semi-greedy	Genetic		Semi-greedy	Genetic
E-n22-k4-s6-17	490,24	431,69	11,94%	0,03	257,52	417,07	17,54%	3,51%
E-n22-k4-s8-14	429,31	414,83	3,37%			384,96	11,52%	7,76%
E-n22-k4-s9-19	528,67	497,03	5,99%			470,60	12,34%	5,62%
E-n22-k4-s10-14	435,46	422,61	2,95%			371,50	17,22%	13,76%
E-n22-k4-s11-12	468,95	458,16	2,30%			427,22	9,77%	7,24%
E-n22-k4-s12-16	461,38	453,02	1,81%			392,78	17,47%	15,34%
E-n33-k4-s1-9	805,32	765,44	4,95%	0,03	261,30	730,16	10,29%	4,83%
E-n33-k4-s2-13	768,65	747,71	2,72%			714,63	7,56%	4,63%
E-n33-k4-s3-17	770,66	750,48	2,62%			707,48	8,93%	6,08%
E-n33-k4-s4-5	999,58	938,27	6,13%			778,74	28,36%	20,49%
E-n33-k4-s7-25	787,62	770,29	2,20%			756,85	4,07%	1,78%
E-n33-k4-s14-22	841,20	796,12	5,36%			779,05	7,98%	2,19%
E-n51-k5-s2-17	710,73	650,20	8,52%	0,02	177,56	597,49	18,95%	8,82%
E-n51-k5-s4-46	845,12	723,61	14,38%			530,76	59,23%	36,33%
E-n51-k5-s6-12	635,26	604,02	4,92%			554,81	14,50%	8,87%
E-n51-k5-s11-19	705,33	654,54	7,20%			581,64	21,27%	12,53%
E-n51-k5-s27-47	659,41	655,65	0,57%			538,22	22,52%	21,82%
E-n51-k5-s32-37	842,66	759,25	9,90%			552,28	52,58%	37,48%
E-n51-k5-s2-4-17-46	811,44	727,09	10,40%	0,02	116,99	530,76	52,88%	36,99%
E-n51-k5-s6-12-32-37	859,46	800,73	6,83%			531,92	61,58%	50,54%
E-n51-k5-s11-19-2 7-47	762,71	691,43	9,35%			527,63	44,55%	31,04%

Once the suitability and limits of the proposed algorithms have been presented, we apply them on specific instances in urban context. Those instances are based on scenarios proposed in Gonzalez-Feliu and Salanova (2012) and Gonzalez-Feliu et al. (2013). The first scenario considers no collaboration, so a single VRP (one stage) is defined. Scenarios 2 and 3 propose a first level of collaboration, but based on infrastructures (no freight transport pooling is allowed but all transport carriers use 2E-VRP approaches). Then, scenarios 4 and 5 propose a real transport pooling approach. More detail on scenarios can be found in Gonzalez-Feliu and Salanova (2012) and Gonzalez-Feliu et al. (2013).

Table 2. Computational results of both algorithms on proposed realistic instances

Test	Number of vehicles	Total travel distance			Computational times (s)	
		Semi-greedy	Genetic	Gap	Semi-greedy	Genetic
1.1	1	88 720	80 477	9,29%	0,06	95,18
1.2	2	119 013	101 903	14,38%		
1.3	2	189 732	177 316	6,54%		
1.4	2	124 321	116 321	6,43%		
1.5	2	210 067	203 896	2,94%		
2.1	10	175 181	168 016	4,09%	0,08	330,26
2.2	14	258 751	250 090	3,35%		
2.3	7	208 460	193 354	7,25%		
2.4	9	211 255	203 615	3,62%		
2.5	8	236 175	228 780	3,13%		
3.1	9	227 833	215 045	5,61%	0,15	454,09
3.2	13	325 064	304 525	6,32%		
3.3	8	350 684	338 468	3,48%		
3.4	9	249 141	234 965	5,69%		
3.5	10	346 400	333 958	3,59%		
4.1	14	258 751	250 090	3,35%	0,09	355,91
4.2	9	211 255	203 615	3,62%		
4.3	8	236 175	228 780	3,13%		
4.4	15	329 158	315 968	4,01%		
5.0	48	1 976 812	1 168 780	40,88%	0,01	437,93

We report in Table 2 the detail of the solutions obtained for each instance, in terms of total traveled distance (for each algorithm), their gap and the corresponding computational time. Instances being grouped to simulate different scenarios, and each scenario computed in one time, computational times are presented as the overall for each scenario, and not detailed for each instance. We observe that the route lengths obtained by the semi-greedy algorithm are in average 5.5% higher than the routes obtained by the GA. Moreover, we observe than those gaps are not uniform. We observe relatively small gap for instances with no or few collaboration. This gap is very high (almost 41%) for the last instance, which presents a strong level of collaboration. In terms of computation time, the semi-greedy algorithm has an average time of 0,078 seconds to solve each scenario (i.e. group of instances), while the genetic algorithm needs from 1,5 to 7,5 minutes. Although the genetic algorithm presents higher times they remain feasible under real conditions: a user can wait few minutes for a solution if the solution produced is significantly better than that obtained by a very fast algorithm. For that reason, we can see the interest of using the genetic algorithm in collaborative instances, but taken into account time gaps, we can say that the usage of both algorithms will be suitable for non-collaborative instances.

To go in-depth on the differences in computational time, we propose to analyze Figure 1, which reports the computational times of computing each route (we remember that each route (corresponding to each cluster obtained using the sweep algorithm) is computed separately, without exchanges with other routes, even in the post-optimization phase. In terms of computation time, the semi-greedy algorithm has an average time of 0.001 seconds, while the genetic algorithm needs 5.25 seconds. The computation time grows exponentially with the number of nodes for both algorithms, but we have to take into account that the GA has a fixed time of 5 seconds for data preparation and population generation that cannot be reduced (see Figure 1). The semi-greedy algorithm remains (even for routes with more than 30 customers) very fast. The genetic algorithm is very stable in computational time for routes up to 20 customers, and times increase exponentially after 25 customers approximately. This is explained by the fact that the genetic algorithm needs to generate a sample of route configurations before starting to post-optimize, which needs few seconds to be done, and the post-optimization phase itself is very quickly for routes having less than 20 customers.

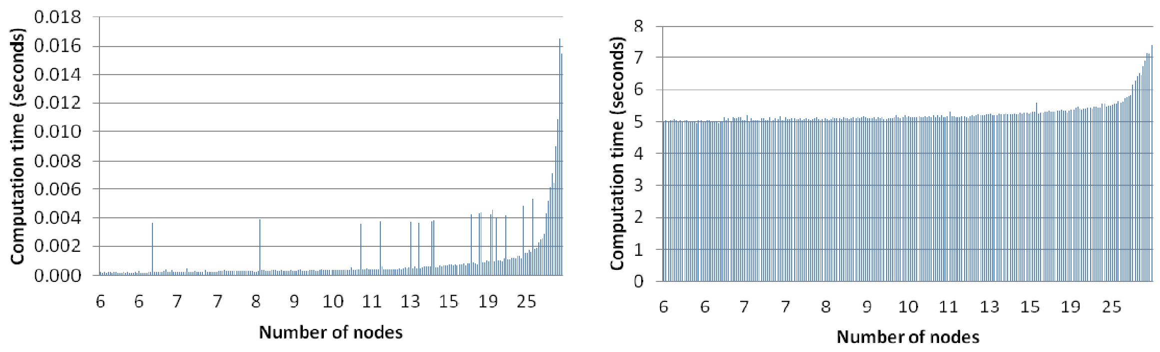

Figure 1. Computation time comparison between semi-greedy (left) and genetic (right) algorithms

The computation time of the Greedy is in average 99.98% smaller than the computation time needed by the GA, which can be compensated by the fact that in most complicated instances the performance of GA overcomes that of the semi-Greedy in all instances. In order to further explore those gap differences, we present in Figure 2 a diagram reporting the average gap between the two algorithms related to route length, by category. We present 5 categories: less than 10 delivery points, from 11 to 20, from 21 to 30, from 31 to 60 and more than 60 (extending the categorization of routes presented in Gonzalez-Feliu et al., 2014a and Gonzalez-Feliu and Morana, 2014). We observe that the gap between thee solutions proposed by each algorithm are very small for small routes. Indeed, the average gap for the first category (less than 10 customers in a route) is about only 2%. Moreover, such routes are quite homogeneous in number of customers since they have between 6 and 10 customers (no routes with less than 3 customers have been obtained). Due to the low capacity of the smaller trucks (sometimes 3 times lower than that of the biggest trucks), most of these routes (55%) have less than 10 nodes, so we can state here on the suitability of both algorithms for questions regarding strategic decisions (more related to location, capacity respect and demand carchment than to strong optimization). For longer routes, the average gap is about 10%, with smaller gaps (8%) for routes of second category (from 11 to 20 customers), confirming that the big differences are obtained for long routes with more customers.

However, we observe that the category presenting the higher gap is the third (21 to 30 customers), which is in general the main category for goods transport with big vehicles (Gonzalez-Feliu and Morana, 2014). Then, the gap decreases (12% and 10% respectively for the two categories with the highest number of customers per route). However, the two last categories are less representative, since there are only few routes with more than 30 customers in our assessments.

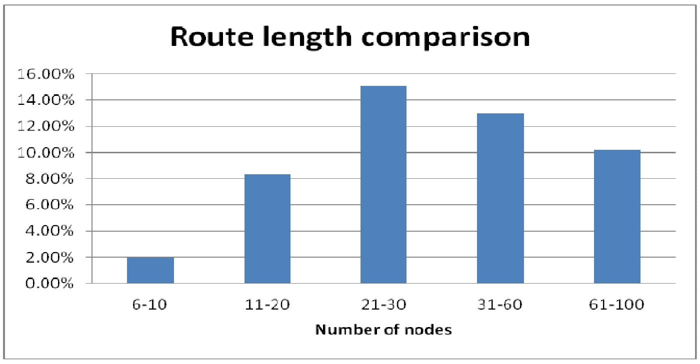

Figure 2. Route length comparison between Greedy and GA

After having compared both algorithms on single instances it is important to state the robustness of those algorithms in assessing scenarios (the goal of developing them). For this, we group instances reported in Table 2 to assess the 5 scenarios proposed in Gonzalez-Feliu and Salanova (2012), and this using both algorithms. The scenarios are the following:

1. Non-collaborative situation where only the big trucks are used. Those trucks visit a large number of clients due to the bigger capacity of the vehicles. Here we solved five different and independent CVRPs.
2. Non-collaborative situation that represents an access restriction to city center, in terms of vehicle size. In this scenario, big trucks are used for distributing the cargo to the satellites, and from there to the final clients using the smaller trucks. Here we solved five different and independent 2E-VRPs, where the capacity of the big trucks is limiting the capacity of the satellites.
3. Infrastructure sharing scenario. In this, all the consolidation platforms can be used by each operator for transferring cargo from the big trucks to the small ones, and to the final clients. Here we solved five different and independent 2E-VRPs, where the capacity of the small trucks is limiting the capacity of the satellites.
4. Partial collaborative transportation sharing network. Two operators are collaborating, while the other operators are acting as in the second scenario. The collaborating clients share their satellites, and consolidate cargo destined to the same clients, sharing also their fleets of small trucks. Here we solved four 2E-VRPs, one of them with heterogeneous fleet.
5. Total collaborative transportation sharing network. All the operators are collaborating, using all the satellites for consolidating the cargo destined to the same clients and sharing their fleet of small trucks. Here we solved one 2E-VRP with heterogeneous fleet.

We report in Table 3 the results of those scenarios' assessment. We take scenario 1 as the reference situation. We observe that for non-collaborative scenarios (for both single-echelon and two-echelon configurations), the differential between the total travelled distance is similar (about 50% for scenario 2, about 105% for scenario 3 and about 45% for scenario 4). For those scenarios, the use of one or the other algorithm has no different impact on identifying the trend and the differential between a scenario and a reference situation. In other words, even if the solution (in absolute value) is different, when estimating the trend to a reference we obtain very similar results. This is confirmed when examining the gap between the solutions of both algorithms, which remain similar (between 3 and 7%). However, it is at the collaboration stage that we observe a big gap between the use of both algorithms (the genetic obtains a better solution with a gap to that of the semi-greedy of almost 70%. This has an impact on the differential to the reference solution, since the generic algorithm gives a closer solution to the reference that the semi-greedy. In this case, both algorithms do not estimate the trends of collaboration in the same manner, so it is important for a user to well set its hypothesis and detail which algorithm is used and for which reasons (see below).

To add a few comments on the scenario simulation (see Gonzalez-Feliu and Salanova, 2012 for more details), we observe that the distance is not necessarily the best criterion to examine when assessing urban goods transport, and other indicators, like road occupancy, monetary costs or travel (and stop) times will be more pertinent (Gonzalez-Feliu, 2011), since in urban areas, routes at city center present small travelled distances but very low speeds (about 8-9% according to Pluvinet et al., 2012) so very high travel times. Moreover, big vehicles need more time to be loaded and unloaded, which increase significantly the stop times. However, this analysis is focused on the capacity of the algorithms to meet the users' targets and not on application. Applications of the semi-greedy algorithm can be seen in Gonzalez-Feliu and Salanova (2012) and Gonzalez-Feliu et al. (2013).

Table 3. Scenario assessment results using both algorithms

	Semi-greedy algorithm		**Genetic algorithm**		**Gap between algorithms**
Scenario	**Total distance (km)**	**Gap to reference situation**	**Total distance (km)**	**Gap to reference situation**	
1	732	-	680	-	7,64%
2	1090	48,91%	1044	53,53%	4,40%
3	1499	104,84%	1427	109,87%	5,06%
4	1035	41,47%	998	46,85%	3,69%
5	1977	170,11%	1169	71,90%	69,13%

To complete a solution probleming analysis, we need to address practical implications. We recall that those algorithms are developed for simulation and assessment aims, and not for classical optimization. A comparison with classical algorithms (which follow a problem solving approach without regarding applicability and practical implications) seems not appropriate, since our proposed algorithms are (in terms of computational performance of the solution) less performant from those proposed in the literature. However, they seem more adapted for practice for two reasons. The first is related to the complexity that the real conditions of the problem bring. Indeed, the problem of collaboration (ant the multiple stakeholder nature of the problem) addresses issues and constraints that add a high increase of complexity to the combinatorial optimization problem of optimizing urban goods transport. This is translated into an exponential increase of computational time. Moreover, the size of the problem (5 depots, 12 satellites and potentially about 400 customers to deliver) is not usually addressed in classical problem solving approaches (except a few papers in literature that dealt with real distribution problems, literature algorithms are used on theoretical instances, see Gonzalez-Feliu, 2013 for more details). The problem of collaboration is only addressed in literature by the precedent works to this one (that used greedy or semi-greedy algorithms) and classical approaches (exact methods and metaheuristics) are only applied to the case with one carrier (i.e., two-echelon but non-collaborative) with instances up to 250 customers (although only 3 papers present results for instances with more than 50 customers). Asking to some authors about the limits of their algorithms, we observe that exact methods are limited in size because computational time to prove that a solution is the exact optimum explodes when the size of the instance increases (they solve well instances up to 50 customers but have strong difficulties for instances with more customers) and meta-heuristics performance is related to the size of routes, in a similar way that our proposed algorithms. For that reason, the proposed analysis presents an interest for researchers aiming to go in-depth on the subject of collaborative urban goods transport optimization, and the proposed algorithms remain nowadays the only ones that have developed to deal with this type of problems.

The second reason is related to the application of the algorithms. Those algorithms are developed to be used by researchers and practitioners in strategic planning decision support in terms of suitability of deploying collaborative logistics solutions. They do not have an aim of estimating the costs for optimization purposes but for before-after scenario analyses. For this reason, it is important to have algorithms that are robust and relevant taken into account the aims and objectives of their users. We observe from the computational results that the semi-greedy algorithm is very quick, but has difficulties on reducing travel distances in instances with collaboration. Indeed, the gap between both algorithms for instances without collaboration is between 3 and 10% and increases to around 65% for the instance that represents the collaborative scenario. Taking into account that scenario assessment takes place at strategic or tactical levels, instances and scenarios can be computed in few minutes, and the genetic algorithm seems more robust that the semi-greedy one. Indeed, as shown in table 1, when comparing both algorithms to literature in instances without collaboration where the exact optimum is known, the gaps of the solutions obtained with the genetic algorithm to literature are less variable than those obtained with the semi-greedy algorithm.

Those algorithms can then be used in practice, mainly to state if collaborative solutions can be deployed. Some examples of using the semi-greedy algorithm can be seen in Gonzalez-Feliu et al., (2013), mainly for private purposes (analyzing the suitability of collaboration among different partners in terms of urban freight transport). The semi-greedy algorithm has been appointed here as less robust and consistent that the genetic algorithm, and has difficulties on estimating routes for big instances. However, it reproduces routes with characteristics are close to reality than the genetic algorithm (as shown in Gonzalez-Feliu et al., 2014a and Gonzalez-Feliu and Morana, 2014). Those characteristics, in terms of vehicles, are ensured by the instances' hypotheses, and in terms of number of customers per route, are the result of the sweep algorithm, which is common to the two route construction approaches. In terms of distances, both algorithms remain in the ranges of realistic routes (see Gonzalez-Feliu et al., 2014a for details on the variability of those routes) so we can state that both algorithms give realistic sets of routes.

4. Conclusion

This paper extends the exploratory analysis proposed in Gonzalez-Feliu and Salanova-Grau (2015) by proposing a solution probleming analysis to the comparison of two fast algorithms in evaluating their suitability to be used for strategic planning decisions concerning collaborative urban freight transport planning and management. The analysis show that both algorithms give solutions that are far from theoretical optima (for non-collaborative instances, since there are no proven optima for collaborative transport test cases) but that remain good estimations of routes in “realistic” configuration. Concerning the assessment of scenarios of collaboration, we first compared the algorithms on the basis of the different routes estimated. The routes obtained by the genetic algorithms are shorter than the routes obtained by the Greedy Algorithm (from 2% to 14%). Regarding computational times, although the semi-greedy algorithm is much faster, the genetic algorithm mobilizes computational times that remain suitable for strategic and tactical assessment (less than ten minutes). Even in big instances, with a high level of collaboration among different stakeholders, the total computational time remains suitable (about seven minutes). The gaps between both algorithms in terms of distance optimization remain similar for non-collaborative instances (in the proposed scenario simulation, scenarios 2 to 4), more precisely between 3 and 10% for all instances of scenarios 2 to 4, but in collaborative scenarios (scenario 5), the genetic algorithm overcomes the semi-greedy (more than 65% of difference between both algorithms). Knowing this, it appears important to well set the hypotheses and tools of the simulation since the behavior of both algorithms is different: the semi-greedy being much faster, it allows to simulate big quantities of data, so it can be used for strategic decisions comparing a big number of alternatives, or needing fast estimations of routes to calculate different sets of indicators (as for example accessibility like in Gonzalez-Feliu et al., 2014b).

Further developments include a further development of the algorithms to take a systemic post-optimization, a second development to better consider the difference between theoretical routes and current practices and the development of an integrated scenario assessment for collaborative decision support.

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