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Review

Improving E-Commerce Distribution through Last-Mile Logistics with Multiple Possibilities of Deliveries Based on Time and Location

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Abstract: The rapid rise of electronic commerce has entailed an increase in logistic complexity, with last-mile logistics being the most critical element in deliveries. Since users prefer goods to be delivered at home, one of the biggest challenges faced by e-commerce is to reduce the number of incidents that occur in the delivery of goods to the homes of customers. In many cases, these deliveries cannot take place because recipients are not at the agreed delivery point, leading to a decrease in the quality of service and an increase in distribution costs. Furthermore, sometimes the delivery policies are not in tune with the customers' expectations. This work presents a new perspective of the last-mile logistics in the context of multichannel retail, asking customers to provide several delivery locations (at home, at work, at a familiar home, in a shop, in a locker, etc.) associated with different time windows. In addition, the customer could state their preferences about these locations. This work formulates the problem and develops different approaches to solve it. A benchmark is proposed to analyze the performance and limitations. The results reveal that a distribution policy with several locations can improve the efficiency of electronic commerce by reducing delivery costs. The findings of this study have several implications for distribution companies.

Keywords: e-commerce; last-mile delivery; quality service; vehicle routing; optimization; priorities

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1. Introduction

Electronic commerce has undergone a significant rise in recent years; the ease of internet access, new businesses focused specifically on this sort of commerce, social network development and, in essence, interconnectivity, are elements that have favored the development of this business model [1]. Ease of shopping from anywhere and any device, and very flexible delivery times that allow the reception of the product at home, are advantages that have enabled the progress of this type of commerce [2].

The importance of electronic commerce has increased over time. According to Eurostat data, the percentage of people who have shopped online among the total population has risen from 6% in 2008 to 22% in 2019 (last available data). This trend continues to increase as a consequence of the COVID-19 pandemic, with 47.2% of online customers not having purchased in the previous year.

Several studies have analyzed the factors that influence customer satisfaction. The authors of [3] analyzed each stage of the online customer experience (pre-purchase, purchase and post-purchase), and identified several factors that are important for customer satisfaction. They found that the delivery order fulfillment has a higher impact than the pre-purchase stage. To deliver the products in time, quantity and quality are critical to the development of e-commerce, because they are closely linked to customer satisfaction. Therefore, the delivery of a product requires speed in the context of e-commerce. This logistical aspect is crucial to the correct development of this business model. The authors of [4] analyzed the principal user motivations that represent a barrier to the development of e-commerce, highlighting the efficiency related to the distribution.

These findings are supported by surveys developed by public agencies. Eurostat reports that delivery time (62.9%) and the possibility of tracking the shipment (60.9%) are the two most important among the factors influencing customer satisfaction, although free shipping continues to be a determining factor in the purchase decision.

These surveys also show the most common problems that customers confront in their online shopping experience. According to INE data [5], in Spain, in 2019, the problems detected in the previous 12 months were delays in deliveries (5.2%), defects in products or services delivered (3.4%), difficult complaints or the lack of a satisfactory response (2.3%), and problems related to fraud (2.1%). At the European level, the problems are delays in deliveries (19%), technical web failures (12%), defects in products or services delivered (11%), and complaint management (6%). A study by the ONTSI [6] highlighted the same problems, with the majority of instances belonging to the delivery process. In this study, 39.9% of the customers did not receive any product, and 36.9% suffered some delay.

Approximately 50.5% of customers consider an appropriate delivery time to be 3 days from the purchase, and 8.2% reduce this time to 1 day. Dealers who offer products that are similar in quality and price are looking for differentiation in the delivery process, be it more flexible, more efficient, or cheaper. In fact, less than two-day delivery is almost standard today, and companies are moving towards one-day or even same-day delivery [7].

Obviously, if these delivery criteria are not achieved, this will generate a negative reaction from the customer [8]. In e-commerce, products could be returned even before they are received. All of this leads to shipping and delivery logistics being considered critical [3].

Since the time between the purchase and the delivery must be short, the delivery performance is one of the key factors affecting e-commerce customer satisfaction [9–11]. Punctuality in deliveries is always mentioned as one of the main aspects of logistical performance influencing e-commerce customer satisfaction [12,13], with delays often resulting in redeliveries [14], decreases in perceived quality, and increased costs [15]. Any inefficiency in the delivery service can be costly—both economically, and in terms of customer perception of the service.

Last-mile delivery has emerged as the most critical transport activity [16]. Some authors emphasize that the cost associated with last-mile delivery can represent up to 50% of total logistical costs, making it very sensitive to any changes in delivery factors [17]. Several studies and surveys by private companies stress the high cost of a missed delivery. The firm PCA Predict, by means of a survey of 300 retailers, indicated that 65% identify missed or late delivery as a significant cost (54% of these retailers pay additional costs for redelivery, and 38% offer the customer a discount as compensation).The company Zetes, which specializes in the logistics sector, indicated in its 2020 report that up to 20% of deliveries were failed in a study conducted in Japan, identifying the main cause (42%) as being that customers did not know where the package was to be delivered.

All of these studies and the data shown therein emphasize the importance of successful delivery for both the customer, who requires a product on a specific date and in the right condition, and the retailer, who must optimize deliveries in terms of cost. We must also note that in e-commerce the buyer can alter their decision throughout the delivery process, even cancelling the purchase before it is delivered (if their expectations are not met). Therefore, companies must respond appropriately to customers' needs in order to improve the supply chain [18,19].

The main strategies used today are home delivery and customer pick-up. Shared delivery locations (lockers and shops), which favor omnichannel strategies, have recently started to gain attention [20]. From a logistics operator's point of view, the efficiency of freight vehicle trips can be notably increased by delivering at pick-up points [21,22], but home deliveries remain the most common logistical strategy following online shopping [13], and this is the users' preference [23,24]. The 2019 e-shopper barometer of the DPD group showed that 89% of customers prefer their delivery at home. A study carried out in Brussels [24] reflected that 72.2% of the users using pick-up points had previously had a failed delivery at home. Moreover, among users who chose the collection point as their first choice, only 24.4% actually preferred it over other options. The main advantage that these users point out is the flexibility of collection. The impact of B2C deliveries derived from e-commerce purchases is not clear in terms of efficiency and sustainability, as they result in significant increases in truck fleets and mileage but, in turn, contribute to eliminating many shopping trips from the network [25–27].

The operation of home deliveries incorporates a high degree of complexity into the management of last-mile fleets, and another factor mentioned in the preferences of the customers is related to the flexibility and availability of delivery options [28,29]. Therefore, delivery companies have begun to contemplate the possibility of giving the customer the option to choose a preferred delivery slot, as a way to increase satisfaction [30]. The authors of [31] noted the willingness to pay of certain socioeconomic population segments for this time-based delivery service, stressing the fact that a company that offers this service lowers the amount of consumer effort and, thus, achieves a competitive advantage. From the point of view of fleet optimization, time-based deliveries can be managed with a VRPTW (vehicle routing problem with time windows) approach, where customers are allocated to time windows depending on their preferred slots. However, offering customers this possibility increases the pressure on the carrier's side, possibly resulting in higher peak loads and subsequent costs, as most of the orders would probably have to be delivered in the evening.

In contrast with this approach, and seeking to maintain service standards while keeping costs under control, our proposal is to offer customers the option to suggest different time slots to the carrier associated with different locations, with the compromise that the order will be delivered at one of them, taking into account their preferences. The customer can then, for instance, receive their delivery at home early in the morning, or at work during the day, or at their relatives' house in the evening. This would represent a higher level of flexibility for the carrier to adjust operations, while leaving the perception of delivery service quality undamaged. This new approach—deliveries based both on time and location—requires the formulation of a new methodology, since the VRPTW model no longer encompasses it; customers would be willing to receive their order during different time windows, but each time window would correspond to a different location.

In order to develop the concept of fleet optimization under time and location restrictions with priority suggestions, we studied the related literature, as described in Section 2. The mathematical model for the problem is formulated in the following Section 3. Given its NP-hard nature, Section 4 is then devoted to the description of different heuristics and metaheuristics that can be used to solve large instances, and which are applied to different simulation batteries. Finally, Section 5 analyzes the results obtained, and Section 6 concludes the paper.

2. Related Literature

To the best of our knowledge, the first publication of the VRPTW with alternative delivery locations for each customer was proposed by Moccia et al. [32], who implemented an incremental tabu search. The most recent and complete surveys of VRP (vehicle routing problem) applications and variants [33–35] do not mention the possibility of contemplating different locations for the same customer. The authors of [36,37] covered the taxonomy of VRP variants extensively, and their only reference to the location of customers was related to the possibility of their placement either in nodes or in arcs. Other contributions have devoted attention to shared delivery locations [38–42]. This is therefore a novel and current problem that may also be generalizable to other VRPs [43].

The vehicle routing problem with roaming delivery locations is a specific variant of the problem proposed in this work [44–48]. However, real applications of roaming deliveries seem to be limited, because of both the necessity of revealing sensitive information and the requirement of trust in the carrier [49]. Other proposals are far from being able to see real implementation, such as the use of mobile parcel lockers [50].

Nevertheless, these works do not take into account customer preferences. Customer preferences and location selection are considered only in some works. The authors of [51] present a generalized pickup and delivery problem with multiple time–location combinations for service and declared preferences that are solved by means of an adaptive large neighborhood search metaheuristic. The authors of [52] analyzed three possible preferences of the customer: attended home delivery, shared delivery locations, or both. Moreover, the customers receive monetary compensation if assigned to a shared delivery location. The authors of [53] also considered different sizes of parcels and slots of the parcel lockers. The authors of [43] developed a branch-price-and-cut algorithm to solve a vehicle routing problem, in which some deliveries can be shipped to alternative locations and customers may prefer certain delivery options. A minimum service level regarding customer preferences is required.

3. Problem Formulation

The problem is formulated on a graph G(N,A), where the set of nodes N contains all of the different customer locations plus the depot, and A is the set of undirected arcs joining all of the nodes in N pairwise. We denote by I the set of all customers, and by N′ the set of customer locations, without including the depot. The customers have to be serviced by a fleet K of identical vehicles, without taking into account capacity restrictions, as is often the case in B2C e-commerce deliveries [54]. Each customer $i \in I$ is associated with a set of time windows V_i, with each time window $v_i \in V_i$ defined by an earliest and latest arrival time (e_{vj} and l_{vj}), and by a specific location on the graph corresponding to one of the nodes in N'. The data used to formulate the problem also include $d_{v_i v_j}$, which is the distance from the location of customer i during time window v_i to the location of customer j during time window v_j, and A as a sufficiently large constant. The first set of variables used in the formulation are $x^k_{v_i v_j}$, which take a value of 1 if vehicle $k \in K$ travels from customer i (departing during time window v_i for that customer) to customer j (arriving during time window v_j for that customer), and 0 otherwise. The other variable used is t_j, which corresponds to the arrival time at customer j. The mathematical formulation of the problem is thus as follows:

$$\text{Minimize} \sum_{k \in K} \sum_{v_i \in V_i} \sum_{v_j \in V_j} d_{v_i v_j} x^k_{v_i v_j} \tag{1}$$

$$\text{Subject to} \sum_{k \in K} \sum_{i \in I} \sum_{v_i \in V_i} \sum_{v_j \in V_j} x^k_{v_i v_j} = 1 \quad \forall j \in I \tag{2}$$

$$\sum_{k \in K} \sum_{i \in I} \sum_{v_i \in V_i} \sum_{v_j \in V_j} x^k_{v_i v_j} = 1 \quad \forall \mathrm{i} \in I \tag{3}$$

$$\sum_{i \in I} \sum_{v_i \in V_i} x^k_{v_i v_j} = \sum_{\mathrm{r} \in I} \sum_{v_r \in V_r} x^k_{v_j v_r} \forall \mathrm{j} \in \mathrm{I}, \forall \mathrm{v_j} \in \mathrm{V_j}, \forall \mathrm{k} \in \mathrm{K} \tag{4}$$

$$t_i + d_{v_i v_j} \sum_{k \in K} x^k_{v_i v_j} \le t_j + A\left(1 - \sum_{k \in K} x^k_{v_i v_j}\right) \forall i \in I, \forall v_i \in V_i, \forall \mathrm{j} \in I, \forall v_j \in V_j \tag{5}$$

$$\mathrm{e_{v_j}} - \mathrm{A}\left(1 - \sum_{k \in K} \sum_{i \in I} \sum_{v_i \in V_i} x^k_{v_i v_j}\right) \le t_j \le l_{v_j} - A\left(1 - \sum_{k \in K} \sum_{i \in I} \sum_{v_i \in V_i} x^k_{v_i v_j}\right), \forall j \in I, \forall v_j \in V_j \tag{6}$$

$$\sum_{\mathrm{j} \in I} \sum_{v_j \in V_j} x^k_{0 v_j} = 1 \quad \forall k \in K \tag{7}$$

$$\sum_{\mathrm{i} \in I} \sum_{v_i \in V_i} x^k_{v_j 0} = 1 \quad \forall k \in K \tag{8}$$

$$x^k_{v_iv_j} \in 0,1; t_j \geq 0$$

The constraints in Equations (2) and (3) guarantee that vehicles arrive at and depart each of the customers, independently of their locations, during the established time windows. The constraints in Equation (4) imply that vehicles must arrive at and leave each node during the same time window. The constraints in Equation (5) ensure that the arrival at customer *j*, visited later than customer *i*, cannot happen later than the arrival at customer *i*. The constraints in Equation (6) set the limits of the arrival time at each customer depending on the specified time windows. The constraints in Equations (7) and (8) force all of the vehicles in the fleet to start and end their journeys at the depot, even though the possibility exists to follow a direct loop arc that starts and ends at the depot with zero cost for unused vehicles. Finally, the objective function minimizes the total length of the routes. The routing problem thus defined is NP-hard, with its size (number of variables and restrictions) being $\mathrm{O}(\#\mathrm{N})^2$.

This formulation can be extended to problems of priorities, where customers state their preferences among the possibilities of delivery, changing the objective function (1) by (9). $w_{v_iv_j} = \alpha \mathrm{A} c_{v_iv_j} + \beta \mathrm{B} \mathrm{p}_{v_iv_j}$ is a consideration of cost $c_{v_iv_j}$ and priorities $p_{v_iv_j}$, where α and β, $\alpha + \beta = 1$, represents the relative preference of the decision maker, and A and B are scale constants.

$$\text{Minimize} \sum_{k \in K} \sum_{v_i \in V_i} \sum_{v_j \in V_j} w_{v_iv_j} x^k_{v_iv_j} \tag{9}$$

4. Solution Procedures

After decades of research on vehicle routing, there is still no general consensus with respect to the ideal procedure to employ with the different variants of this NP-hard problem. According to [55], the metaheuristic procedures showing the best performances for the VRPTW are based on local search, neighborhood search, and evolutionary algorithms. However, [56] claimed that the most successful metaheuristics are often overengineered, powerful tools to address very specific problem characteristics. The author of [57] observed a tradeoff between solution time and complexity between techniques based on simulated annealing, genetic algorithms, and ant colony optimization. From a different perspective, [58] presents a survey on metaheuristics for routing problems.

In the case of the vehicle routing problem with deliveries based on time and location, we decided to test a number of techniques in order to compare their performance when confronted with the main characteristics of the problem. Combinatorial methods working on vehicle routing rely on the fact that if the distance between customers *i* and *j* is short, then sending a vehicle through the arc (*i,j*) should be attractive in general for the overall solution, and the question is where to insert those two customers in one of the routes. In our case, however, the distance between customers *i* and *j* can switch from being very short to very long, depending on the time of the day, and depending on the locations stated by those two customers for their different time windows.

We implemented and compared six numerical techniques, including three ad hoc heuristics, one ad hoc metaheuristic (evolutionary procedure), and two standard metaheuristics. Their main characteristics are described briefly in the following sections.

4.1. Ad Hoc Heuristics

Savings heuristic (SH): Initially, a route is formed to service every customer location independently; that is, there exist as many routes as customer locations. Then, the best merging operation is completed, as long as it is feasible, and according to a weighted sum of distance reduction, waiting time between the two routes, and distance between the last customer in the merged route and the depot. After two routes have been thus merged, all of the other locations corresponding to the customers in the merged routes are eliminated. The procedure is repeated until there are no more saving possibilities. Then, if there remain customers with more than one location active, all are eliminated except for the best one.

Insertion heuristic (IH): The procedure starts by opening a single empty route, and then feasible customer locations are inserted into it according to a weighted sum of the distance to the customer location, the distance between that customer location and the depot, and the extra waiting time required. When a customer location is inserted into the route, all of the other locations corresponding to that customer are eliminated from the list. Then, when the route is full and there are no more feasible insertion possibilities, a new route is initialized, and the process continues until all of the customers have been allocated to a route.

Parallel insertion (PI): Similar to the previous heuristic, there is always an empty route available other than the active one. Then, customer locations can be inserted into either of them, depending on the evaluation of the insertion process.

4.2. Ad Hoc Metaheuristics

Evolutionary procedure (EP): Solutions in the population are coded using a data structure containing the routes and the customer locations inserted in each of them. Each generation conducts a tournament process where four individuals are selected, and the best two are chosen as parents. Then, the best route in each parent (smallest distance/number of customers ratio) replaces the worst route in the other one, and then the missing customers are inserted in the best possible positions on all of the routes, taking into account their different locations and time windows. With respect to mutation, it is applied to descendants according to a fixed probability, and it randomly eliminates one-third of the customers in the routes, and then assigns them one of their locations and the associated time window randomly, and inserts them in the best possible position on all of the routes. The descendant replaces another individual in the population, selected randomly from among the worst 10%. When the population's average fitness is only 8% greater than the best individual's, the population is restarted except for the five best solutions. The algorithm stops after four restarts, or when a maximum number of iterations is reached.

4.3. Standard Metaheuristics

Tabu search (TS): The neighborhood is formed by all of the possible insertions of each customer into each route, under any of its possible time windows. The best solution in the entire neighborhood is selected as the new solution in each iteration, unless it is included in the tabu list. Only if the desired insertion is better than the absolute best is it selected, even if it appears in the tabu list.

Simulated annealing (SA): The neighborhood criteria are the same that were used for the TS procedure, only here a single neighbor is chosen. This neighbor is selected as the new solution if $rand[0,1] \leq e^{\frac{fitness_{old} - fitness_{new}}{t}}$.

After a certain number of neighbors have been tested, the cooling procedure reduces the temperature t by 1%. The algorithm ends when the final temperature is reached, or after a given number of iterations do not result in any improvements.

5. Results and Discussion

The proposed problem was tested by means of different batteries developed using the Solomon VRPTW instance. These batteries help to test and compare the performance of the above algorithms. We developed instances with random customer distribution, and assuming that each customer has three time windows (and, thus, three different locations) during the day. In each case, we kept the same depot, and then the first three customers in Solomon's instance corresponded to the three locations and time windows for the first customer in our problem, the next three customers to the second, and so on, until reaching a given number of customers. The fact that, when thus generating simulation batteries, some scenarios may occur where the different time windows for a given customer may overlap is irrelevant from a methodological point of view.

We then calibrated the heuristics and metaheuristics with the first scenario in each battery, obtaining the following parameter values:

1. SH: the weights of the distance to the depot, distance to the next customer location, and waiting time were taken as 0.34, 0.14, and 0.52, respectively.
2. IH: in this case, the above weights were taken as 0.21, 0.49, and 0.30, respectively.
3. PI: the weights were chosen as 0.26, 0.49, and 0.25, respectively.
4. EP: maximum number of iterations equal to 50 times the total number of customer locations; population size equal to 150 for 10 and 25 customers, and to 200 for 50 and 100 customers; probability of mutation equal to 15%.
5. TS: maximum number of iterations equal to 20 times the total number of customer locations; residence time in the tabu list approximated by the total number of customer locations divided by 7.
6. SA: initial temperature equal to 1000; final temperature equal to 1; number of neighbor tests before cooling approximated by the total number of customer locations divided by 7.

The experiment was run on an Intel® Core™ i5-4460 CPU @ 3.20 GHz processor.

5.1. Delivery Options vs. Only One Option

Table 1 shows a comparison between the best results of batteries with 25 customers using the proposed approach of deliveries—VRPTWDO—where three location–times are possible, and the classical approaches of deliveries in parcel companies. Regarding classical approaches, two possibilities are considered: (a) only one localization–time possibility—VRPTW—and (b) there do not exist time window constraints, and delivery must be performed in a strict location—VRP. The results reveal that this new method improves the quality of the service (offering more possibilities of deliveries to the customers) and can result in cost savings. The best results are marked in bold type.

Table 1. Comparison with classical approaches of deliveries (25-customer problem).

Instance	VRPTWDO	VRPTW	VRP
r25_3_1	349.26	567.58	**317.26**
r25_3_2	**294.40**	523.99	342.69
r25_3_3	**267.77**	436.43	340.07
r25_3_4	**232.36**	393.20	304.87
r25_3_5	**310.91**	493.10	347.42
r25_3_6	**271.09**	460.06	326.25
r25_3_7	**260.37**	404.27	348.73
r25_3_8	**231.49**	374.97	367.14
r25_3_9	**272.37**	428.79	358.40
r25_3_10	**243.74**	412.46	336.69
r25_3_11	**241.77**	397.84	318.76
r25_3_12	**230.82**	392.83	324.04
mean	***267.19***	*440.46*	*336.03*

5.2. Comparison of Solution Procedures

Table 2 shows the results obtained by the heuristic and metaheuristic procedures for four simulation batteries (10, 25, 50, and 100 customers). The table shows only the fitness values obtained. The best results obtained are marked in bold for each instance. Finally, the instances of the battery of 10 customers were also solved using mathematical formulations by means of the Gurobi solver for the sake of validation. Gurobi could not obtain solutions for the scenarios with 25 or more customers. These results prove that the EP can achieve a high performance in the resolution of the proposed problem. Table 2 shows that the EP always provides the best results, replicating the optimal results in almost all of the smaller problems, and outperforming the other algorithms in the larger ones.

More information is provided in the case of the evolutionary procedure and the standard metaheuristics (Table 3). The EP, TS, and SA were run 50 times for each scenario, and the table shows the average and best fitness values obtained, the standard deviation of the results, and the average computation time in seconds.

Table 2. Comparison of solution procedures.

Customers	Instance	Gurobi	SH	IH	PI	TS	SA	EP
10	r10_3_1	**156.77**	218.55	182.54	182.54	158.20	**156.77**	**156.77**
	r10_3_2	**129.01**	170.72	193.66	241.75	**129.01**	**129.01**	**129.01**
	r10_3_3	**122.46**	206.31	197.14	208.26	**129.01**	**129.01**	**122.46**
	r10_3_4	**113.72**	151.51	181.42	175.79	133.47	**113.72**	**113.72**
	r10_3_5	**154.15**	184.45	191.13	191.13	154.76	**154.15**	**154.15**
	r10_3_6	**129.01**	155.48	230.56	201.63	**129.01**	**129.01**	**129.01**
	r10_3_7	**99.90**	187.06	169.36	179.07	129.01	122.46	122.46
	r10_3_8	**113.72**	151.51	148.29	175.79	128.34	**113.72**	**113.72**
	r10_3_9	**141.67**	172.37	178.49	178.49	**141.67**	**141.67**	**141.67**
	r10_3_10	**121.87**	206.18	199.99	199.99	129.56	123.32	**121.87**
	r10_3_11	**129.01**	163.29	152.73	221.45	**129.01**	**129.01**	**129.01**
	r10_3_12	**114.28**	151.51	188.42	170.23	**114.28**	**114.28**	**114.28**
25	r25_3_1		466.34	627.87	576.40	401.59	395.89	**349.26**
	r25_3_2		494.06	550.33	453.79	336.32	342.97	**294.40**
	r25_3_3		451.88	372.21	431.85	296.95	308.38	**267.77**
	r25_3_4		409.21	349.75	357.18	253.32	255.09	**232.36**
	r25_3_5		438.77	522.69	494.48	317.50	326.46	**310.91**
	r25_3_6		390.57	380.89	366.43	306.73	319.54	**271.09**
	r25_3_7		400.16	373.07	343.99	290.91	305.26	**260.37**
	r25_3_8		382.33	382.65	351.15	233.86	251.57	**231.49**
	r25_3_9		409.52	461.67	441.79	303.11	310.18	**272.37**
	r25_3_10		399.46	421.96	448.25	268.57	276.74	**243.74**
	r25_3_11		374.57	454.23	401.71	285.02	280.77	**241.77**
	r25_3_12		400.73	420.28	375.77	**227.98**	229.34	230.82
50	r50_3_1		1297.38	1548.89	1707.91	1118.22	1141.15	**987.70**
	r50_3_2		1216.53	1586.59	1405.93	1093.75	965.66	**890.44**
	r50_3_3		1084.07	1088.47	1136.47	936.67	861.56	**803.45**
	r50_3_4		955.23	981.75	958.16	870.22	**722.52**	749.97
	r50_3_5		1290.79	1537.16	1544.38	1137.34	1039.29	**944.77**
	r50_3_6		1063.07	1547.61	1311.73	1022.85	922.67	**868.44**
	r50_3_7		1057.04	1238.69	1054.89	878.92	**832.91**	833.60
	r50_3_8		901.20	987.49	1043.09	814.85	**711.16**	781.93
	r50_3_9		1068.03	1538.13	1478.49	1036.22	974.39	**838.68**
	r50_3_10		1174.49	1264.31	1272.67	949.90	905.58	**837.46**
100	r100_3_1		2849.88	4163.91	4116.51	2915.56	2705.07	**2464.56**
	r100_3_2		3033.32	3850.26	3441.89	2611.55	2322.26	**2288.27**
	r100_3_3		2488.50	2804.90	2381.78	2266.40	**2026.82**	2096.77
	r100_3_4		2222.10	2051.82	2128.04	2010.68	**1798.69**	2048.31
	r100_3_5		3018.96	4146.17	4014.05	2989.49	2611.47	**2513.44**
	r100_3_6		2894.37	3449.80	3166.35	2536.25	**2152.14**	2208.82
	r100_3_7		2376.72	2467.02	2445.43	2326.58	**1987.55**	2050.95
	r100_3_8		2096.30	2051.91	1863.85	1967.73	**1769.55**	2017.25
	r100_3_9		2931.43	3816.00	3572.80	2766.03	2483.00	**2437.38**
	r100_3_10		2672.54	3323.05	3400.73	2541.36	2230.80	**2210.17**

With respect to the other ad hoc heuristics, they are much faster, with SH providing slightly better results—particularly for larger problem instances—although their comparison with the Gurobi results for the smaller instances and with the EP results for the larger ones show how far they remain from the best solutions found. In the case of the standard metaheuristics, on the other hand, the TS seems to result in a worse performance pattern; the SA shows a peculiar behavior, also reaching the optimum in most of the smaller instances, losing pace in the scenarios with 25 and 50 customers, and then almost outperforming the EP in the larger scenarios with 100 customers. In any case, the computational times required by the EP (around 6.5 min for the larger scenarios with 100 customers and 300 customer locations) are notably more reduced than those needed by the two standard metaheuristics, and are acceptable for industrial applications. The results provided by the EP are also more robust by comparison, with much smaller values of the standard deviations of solution fitness obtained in the 50 runs completed for each scenario.

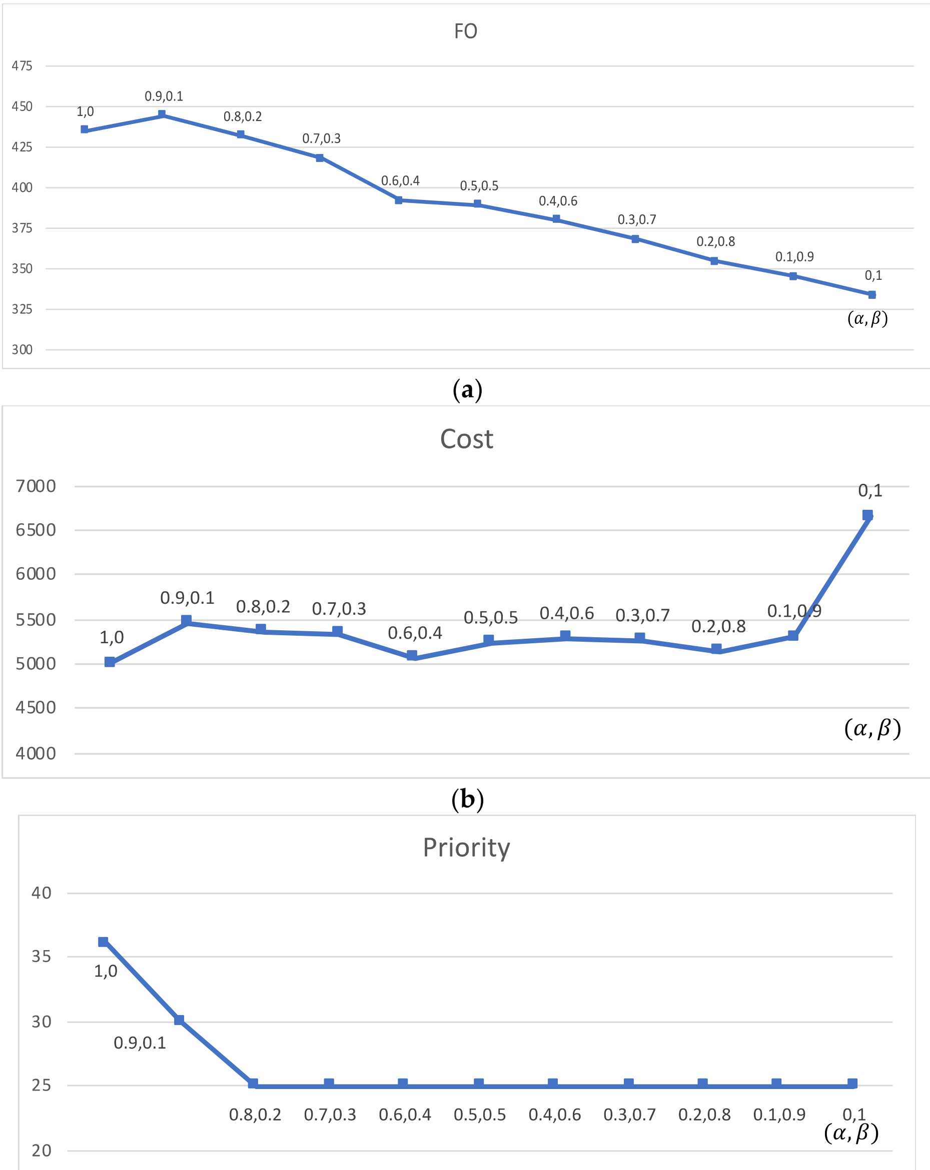
Table 3. Performance measures of metaheuristic procedures.

Customers	Instance	TS			SA			EP		
		Avg.	Std. Dev	Time	Avg.	Std. Dev	Time	Avg.	Std. Dev	Time
10	r10_3_1	177.33	13.10	11.14	162.85	5.33	6.00	157.31	1.57	5.28
	r10_3_2	153.43	21.17	14.92	137.06	4.94	6.00	129.15	1.02	5.28
	r10_3_3	147.76	11.47	18.76	133.26	4.15	8.00	123.55	4.05	5.99
	r10_3_4	144.85	6.05	19.54	128.08	4.10	10.24	115.79	3.68	6.22
	r10_3_5	161.52	6.64	12.98	156.35	1.82	6.00	154.95	0.93	5.18
	r10_3_6	140.76	12.79	14.72	134.22	4.91	7.00	132.97	9.24	5.27
	r10_3_7	144.76	17.91	21.66	130.18	3.50	8.26	125.52	6.03	6.01
	r10_3_8	141.08	12.27	18.56	123.22	5.68	10.90	114.22	1.82	6.29
	r10_3_9	154.72	13.20	14.74	146.36	3.39	7.00	147.62	7.54	5.29
	r10_3_10	140.73	20.06	20.10	129.46	0.89	8.52	127.00	8.44	5.24
	r10_3_11	145.33	18.81	19.56	131.51	3.40	8.02	132.53	4.20	5.50
	r10_3_12	135.75	21.04	19.40	122.71	5.68	11.98	114.68	1.78	5.93
25	r25_3_1	452.10	27.14	47.98	430.42	12.09	66.48	365.24	11.21	27.49
	r25_3_2	396.71	28.75	60.58	370.88	9.71	83.08	301.42	4.69	29.95
	r25_3_3	357.17	36.60	73.22	331.61	7.35	95.56	280.13	7.67	30.86
	r25_3_4	284.37	29.41	112.34	274.89	8.34	121.42	254.11	11.21	31.50
	r25_3_5	395.15	41.95	49.10	381.09	17.92	67.04	318.74	5.97	30.52
	r25_3_6	375.00	28.24	57.72	344.08	10.19	86.40	286.24	9.07	30.61
	r25_3_7	343.67	30.72	77.94	319.36	7.60	103.86	272.19	7.03	32.43
	r25_3_8	263.91	17.77	124.92	272.38	7.44	134.60	250.67	9.36	32.49
	r25_3_9	352.53	26.28	56.82	341.33	10.76	79.62	285.86	11.79	30.54
	r25_3_10	325.70	29.20	74.58	300.20	7.84	94.56	266.81	14.89	30.65
	r25_3_11	326.09	29.99	80.66	305.31	10.51	101.04	255.35	11.23	31.49
	r25_3_12	279.84	39.48	100.98	248.15	8.66	130.84	242.88	10.27	32.59
50	r50_3_1	1238.11	66.62	284.66	1234.20	44.99	171.02	1043.90	27.07	122.55
	r50_3_2	1257.79	101.16	305.68	1082.78	48.46	240.32	928.96	12.49	119.01
	r50_3_3	1158.92	155.55	446.30	916.23	33.29	310.52	846.11	21.47	118.38
	r50_3_4	1067.64	111.08	584.86	804.39	40.51	480.58	822.05	30.86	115.30
	r50_3_5	1251.80	81.35	200.58	1144.72	55.01	168.32	988.17	25.11	116.37
	r50_3_6	1204.22	115.91	297.08	1030.90	44.72	232.74	920.01	24.38	111.20
	r50_3_7	1134.73	126.78	436.32	899.99	39.85	331.82	870.59	28.57	113.61
	r50_3_8	1085.62	122.97	544.00	788.34	32.37	512.06	841.80	33.18	117.75
	r50_3_9	1245.75	103.36	200.68	1056.64	35.44	181.00	898.47	29.47	110.75
	r50_3_10	1156.13	95.65	267.60	998.06	45.67	212.82	917.38	39.96	112.82
100	r100_3_1	3217.75	163.13	988.88	2959.41	98.62	707.82	2634.96	58.72	397.32
	r100_3_2	3010.34	243.96	1207.06	2496.54	91.85	1241.44	2457.43	59.51	393.39
	r100_3_3	2627.79	173.99	1727.04	2200.64	99.99	1546.28	2246.53	98.21	399.38
	r100_3_4	2240.21	115.45	3799.78	1932.28	64.63	2171.92	2159.23	66.61	410.37
	r100_3_5	3197.04	157.74	767.36	2833.05	101.60	730.58	2607.26	56.85	392.36
	r100_3_6	2953.05	217.49	1335.36	2423.52	91.42	1219.56	2337.40	80.01	384.46
	r100_3_7	2603.03	177.52	1800.94	2162.49	88.99	1576.56	2180.11	75.83	391.04
	r100_3_8	2191.85	130.92	4149.24	1886.96	59.33	2230.52	2110.78	58.49	393.81
	r100_3_9	3056.98	176.51	956.02	2706.84	90.47	793.64	2530.86	37.09	390.98
	r100_3_10	2852.15	206.34	1171.50	2452.96	93.26	966.90	2308.79	48.83	378.20

5.3. Priority Considerations

With the objective of analyzing the effects of priorities on the preferences of the customers, an experiment with a 25-customer instance was run. The priorities were established by means of sorting the different options using an integer number. In the case of three possible options, maximum priority was linked with number 1, and minimum priority would be number 3. Since $\alpha + \beta = 1$ represents the relative preference of the decision maker, the evolution of objective function (9), the cost, and the average priority are represented by different combinations of α and β. The results are shown in Figure 1. When $\alpha = 1$ and $\beta = 0$, the priorities of the customer are not taken into account, so the problem is considered to be a VRPTWDO problem with no priorities. At the other extreme, when $\alpha \rightarrow 0$ and $\beta \rightarrow 1$, the algorithm will select all of the first priorities, turning the problem into a traditional VRPTW problem whose time windows correspond to those set as priority 1.

Figure 2 represents the solution of a problem with 25 customers and 3 possible options of delivery. We can observe how the increase in the possibilities of deliveries lets the planner look for better solutions more efficiently. In this problem, the first preference is satisfied for 80% of customers, the second preference for 16% of them, and the last preference for 4% of the customers. The algorithm tries to prioritize consumer preferences, and only when not attending to these preferences results in significant cost savings are other options considered.



(c)

Figure 1. Effects of preference between cost (α) and priority (β): (**a**) objective function; (**b**) cost; (**c**) priority.

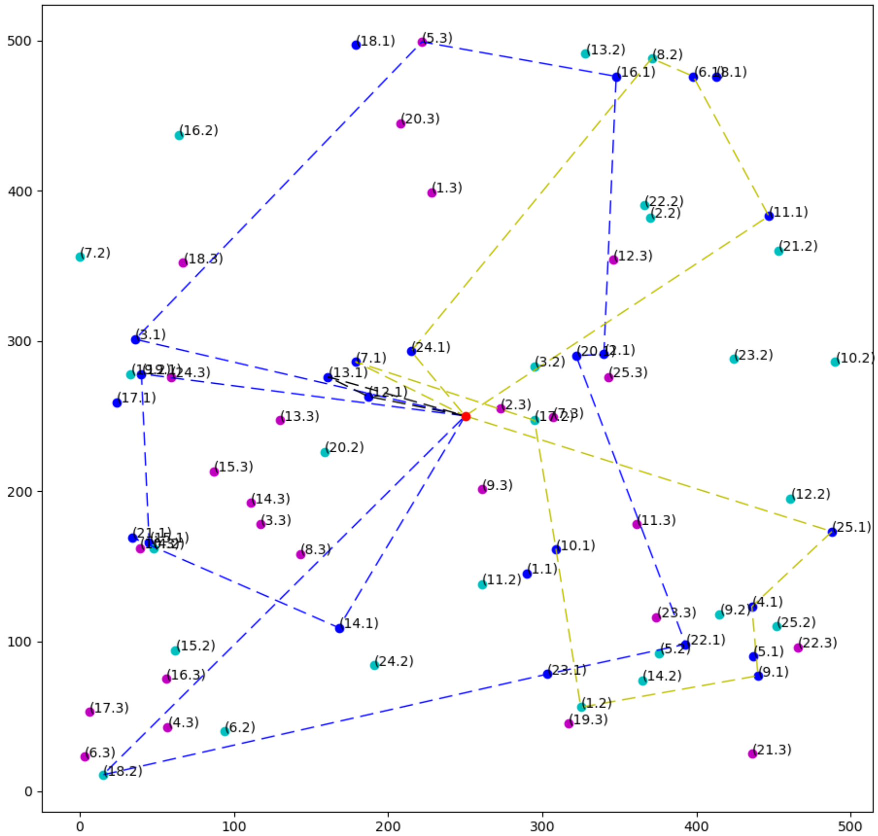


Figure 2. Example of routes for a problem with 25 customers and 3 possible options.

Table 4 shows the results obtained by the evolutionary procedure (EP) for three simulation batteries (25, 50, and 100 customers) where priorities were declared by the customers. Every instance was run 50 times. The table shows the best value, the average value of the fitness values obtained (OF), the cost, and the priority. The gap between the average value and the best value is shown to demonstrate the convergence of the procedure.

Table 4. Results of the EP with priority considerations.

Customers	Instance	OF			Cost			Priority		
		Avg.	Min	Gap	Avg.	Min	Gap	Avg.	Min	Gap
25	r25_3p_1	424	413	2.66%	5223.09	5014.87	4.15%	1.036	1	3.60%
	r25_3p_2	413	388	6.44%	5195.87	4505.05	15.33%	1.064	1	6.40%
	r25_3p_3	428	419	2.15%	5245.62	5115.03	2.55%	1.028	1	2.80%
	r25_3p_4	408	393	3.82%	5530.29	5304.27	4.26%	1.008	1	0.80%
	r25_3p_5	411	402	2.24%	5197.58	4998	3.99%	1.004	1	0.40%
	r25_3p_6	411	405	1.48%	5251.48	5160.81	1.76%	1	1	0.00%
	r25_3p_7	407	394	3.30%	5223.87	4967.22	5.17%	1.032	1	3.20%
	r25_3p_8	431	418	3.11%	5614.3	5066.46	10.81%	1.108	1	10.80%
	r25_3p_9	385	370	4.05%	4574.93	4363.56	4.84%	1	1	0.00%
	r25_3p_10	398	387	2.84%	4815.47	4533.15	6.23%	1.02	1	2.00%
50	r50_3p_1	356	346	2.89%	8533.94	8260.79	1.80%	1.006	1	0.60%
	r50_3p_2	364	355	2.54%	8607.28	8347.22	1.89%	1.03	1	3.00%
	r50_3p_3	365	351	3.99%	9037.99	8165.41	3.94%	1.022	1	2.20%
	r50_3p_4	363	347	4.61%	9190.26	8131.28	5.58%	1.022	1	2.20%
	r50_3p_5	345	329	4.86%	8228.71	7767.57	3.43%	1	1	0.00%
	r50_3p_6	357	348	2.59%	8941.46	8528.38	2.42%	1.012	1	1.20%
	r50_3p_7	349	337	3.56%	8553.5	8177.82	3.42%	1.014	1	1.40%
	r50_3p_8	365	355	2.82%	9369.44	8771.76	3.26%	1.012	1	1.20%

Table 4. *Cont.*

Customers	Instance	OF			Cost			Priority		
		Avg.	Min	Gap	Avg.	Min	Gap	Avg.	Min	Gap
	r50_3p_9	367	346	6.07%	8577.33	8020.42	4.00%	1.054	1	5.40%
	r50_3p_10	357	348	2.59%	8821	8526.94	2.03%	1	1	0.00%
100	r100_3p_1	353	341	3.52%	16,851.63	16,159.34	3.55%	1.028	1	2.80%
	r100_3p_2	353	334	5.69%	16806.4	15,673.85	4.45%	1.007	1	0.70%
	r100_3p_3	353	343	2.92%	17,144.93	16,683.24	2.15%	1.036	1	3.60%
	r100_3p_4	351	336	4.46%	17,229.21	16,397.92	2.82%	1.014	1	1.40%
	r100_3p_5	343	331	3.63%	16,270.05	15,392.24	4.25%	1.028	1	2.80%
	r100_3p_6	354	327	8.26%	16,716.27	15,018.89	5.36%	1.042	1	4.20%
	r100_3p_7	362	341	6.16%	17,520.29	15,962.86	5.97%	1.069	1	6.90%
	r100_3p_8	355	349	1.72%	17,191.82	16,492.24	2.90%	1.048	1	4.80%
	r100_3p_9	365	343	6.41%	17,151.35	15,961.33	3.02%	1.028	1	2.80%
	r100_3p_10	348	335	3.88%	16,610.44	15,859.48	3.70%	1.025	1	2.50%

5.4. Discussion of Results

Increasing the possibilities of delivery locations, with defined time windows at each location, would favor successful deliveries. However, this new perspective of the last-mile logistics leads to an increase in the mathematical complexity of this type of NP-hard problem. Despite this, it is possible to find solution methods that present admissible solutions in real-world implementations.

From the economic point of view, this strategy provides cost savings in the scheduling of trips in most cases (see Table 1). As the distribution company has more possibilities for deliveries, they can use this method to adapt the deliveries to their needs.

In the case of stated user preferences regarding locations, where the different location–temporal window pairs are prioritized by the customer, the proposed methodology achieves high levels of compliance with these preferences, only using the lowest preferences when there is a strong economic justification (see Table 4).

Increasing customers' options would increase customer satisfaction, especially if the number of failed deliveries is reduced. This latter aspect would increase customer loyalty.

6. Conclusions

With increasing volumes of e-commerce transactions and subsequent home deliveries, the economic benefits of logistical operators depend on the reduction in costs without affecting the perceived level of service. Allowing the customer to choose a preferred time slot for the delivery increases that service quality, but at the cost of concentrating most of the deliveries during the evening hours, resulting in growing imbalances between peak and valley demands, and larger and more infra-used fleets.

The possibility of asking customers to provide different locations or places—each one associated with a different time window—for the delivery day thus represents an opportunity for carriers to increase the balance between peak and valley hours, providing flexibility to manage their operations without damaging the level of service. The problem of scheduling a vehicle fleet under requirements of time and location is thus relevant from the point of view of operational research, and with a clear industrial application. We have presented the mathematical formulation of the problem and tested the performance of different heuristics and metaheuristics on different problem instances, obtaining the best results with the application of a technique based on evolutionary optimization. Given the characteristics of the problem, where the degree of complexity depends not only on the number of customers, but also on the number of different locations and time windows associated with each of them, the use of numerical methods proves to be a necessary tool.

Further research may be focused on gaining methodological insight, testing additional solution techniques, and improving the performance of algorithms, but our interest lies also in the applicability of the concept. Dynamic variants—in order to develop techniques to re-plan routes when a time window is missed—or cost-based analyses—estimating the tradeoffs between total distance, number of vehicles used, penalties for missing time windows, and total driving plus waiting time—are two of the most promising directions for future research efforts.

This work has been developed based on simulated data and assuming that more delivery possibilities, where customers identify their availability at each location, decreases the rate of failed deliveries. The analysis of the real cost of externalities due to missed deliveries, as well as the objective calculation of how this approach can reduce the rate of missed deliveries, are avenues for future research.

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