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A Heuristic Approach to Support Route Planning for Delivery and Installation of Furniture: A Case Study

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Abstract: The number of variants of the vehicle routing problem (VRP) has grown rapidly in the last decades. Among these, VRPs with time window constraints are among the most studied ones. However, the literature regarding VRPs that concerns the delivery and installation of products is scarce. The main aim of this study was to propose a heuristic approach for the route planning process of a company whose focus is on furniture delivery and assembly and, thus, contributing to the research around the Delivery and Installation Routing Problem. The case study method was used, and two scenarios were compared: the current scenario (showing the routes created by the company worker); and the future scenario (representing the routes created by the heuristic). Results show that the proposed heuristic approach provided a feasible solution to the problem, allowing it to affect customers and teams without compromising the teams' competencies and respecting all constraints.

Keywords: last-mile delivery; heuristics; vehicle routing problem; delivery and assembly routes; logistics

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1. Introduction

E-commerce has gained increased importance in several countries worldwide, and online initiatives have proliferated across different industries and sectors [1,2]. This has led to a change of priorities and requirements in the overall logistics [3], resulting in the need for organizations to innovate their ways of creating value for their final customers by performing additional services in addition to the delivery of items, such as the collection of items [4] or installation or assembly service according to the items received [5].

Last-mile delivery, defined by [6] as the last trip the product takes before the final customer, represents one of the most critical activities for companies. Even though there are several definitions, a widely agreed one is that last-mile delivery refers to all logistics activities related to the distribution of shipments, i.e., parcels with items ordered by private customers to their houses in urban areas [7]. The adequate management of the processes behind the last-mile delivery affects the reliability, effectiveness, efficiency, and level of service of the delivery made to the final customer [8]. Considering the diversity of services, the rising number of orders, the higher customer expectations, and the low operation efficiency [9], it is critical that companies can manage human resources, fleets, and routes, among others, to guarantee a certain level of service. The level of service offered by an organization is assumed to depend on several factors related to the characteristics of the items sold, such as price, promotions, delivery, or assembly. Thus, it is expected that companies aim to increase their level of service to increase their profits [10].

Logistics is highlighted by [11] as a group of different activities that involve planning, implementing, and efficiently and effectively controlling the storage and flow of goods, services, and related information from the point of origin to the point of consumption to achieve the end customer requirements. Logistics services have a critical role within an e-commerce business and must implement innovative technologies in their logistics activities [12]. According to [13], even though they can provide the organization's end consumers with a better purchase experience, logistics services can additionally bring other challenges to organizations. One of the most critical challenges that logistics companies whose focus activity is on the delivery and collection of goods face is related to the vehicle routing problem (VRP) [14]. The VRP emerged from the traveling salesman problem [15], and in the classic VRP, vehicles perform deliveries from the depot, visiting one or more customers and then going back to the depot [16]. While the traveling salesman problem is made up of only one vehicle that visits multiple customers, the VRP is a problem made up of more than one vehicle [17]. As emphasized by [18], the VRP can be defined as the problem of designing the least costly delivery routes from a depot to geographically dispersed customers, subject to a set of rules and constraints.

Since the early 2000s, the number of VPR variants has grown fast [19], which shows the diversity of its applications [20], and among these variations, Capacitated Vehicle Routing Problem (CVRP) or Vehicle Routing Problem with Time Window (VRPTW) are the most cited in the literature [18,21]. On the one hand, as emphasized by [22], in the CVRP, goods need to be delivered to a set of customers with established demands, originating and terminating at a depot with the minimum-cost vehicle routes. On the other hand, VRPTW extends CVRPs by adding a time window associated with customers' different variations of the VRP, such as Distance-Constrained Vehicle Routing Problem, Vehicle Routing Problem with Backhauling [23], and Vehicle Routing Problem with Pick-up and Delivery [5,23]. Moreover, authors, such as [5], highlighted that the generalization of the VRP with time windows and driver-specific times or VRP with multiple synchronization constraints could be designated by the Delivery and Installation Routing Problem (DIRP).

Hence, route problems or VRPs are one of the most studied combinatorial problems due to the issues arising in numerous real contexts [24] and, additionally, due to their significant contribution, at a theoretical level, to the area of combinatorial optimization [25]. Transportation tasks have become progressively complex, and according to [26], there is a need to find a general system that can model the many variants of transportation tasks. In [23], it was highlighted that finding solutions to VRPs may reduce the overall transportation costs within an organization, representing a reduction of about 10% to 20% of the organization's total costs.

The conditions and restrictions on routes developed for VRPs will vary widely from organization to organization and according to their activity [27]. Restrictions on routes can be determined by the nature or type of products to be transported, by the characteristics of the end customer, by the features of the fleet, or by the level of service [23]. When it comes to companies that use vehicles to serve customers, decisions are based on experience and tacit knowledge of the service to be provided [28]. In this sense, heuristics can help make quick decisions without the need to spend much time searching and analyzing information [24]. However, although heuristics can "speed up" problem-solving, they can introduce errors and make it challenging to perceive alternative solutions [29]. Using heuristics to solve route problems and their variants has gained interest and attracted researchers due to the possibility of obtaining solutions using few resources and reducing costs [15,30].

A particular case of last-mile delivery occurs in the furniture industry, where a customer can tailor the products by selecting the parts and components needing assembly and installation at their own house. In Ref. [5], the authors emphasized that issues concerning the minimization of the total cost of having separated and synchronizing delivery from assembly/installation have been receiving increasing interest. Route planning problems were introduced by Dantzig and Ramser in 1959 through a real problem of gas delivery to several gas stations [31]. However, since then, problems related to route planning with a time window and stochastic service times [32,33], route planning with stochastic service [25] and travel times [32,34,35], or route planning with a heterogeneous fleet [36] have been found in the literature. Some examples of the application of heuristics to VRPs dealing with time windows, heterogeneous fleets, or DIRPs found in the literature are described in Table 1.

Table 1. Summary table of the papers with an application of heuristics to problems of deterministic route planning.

Paper ID	Description	Problem Characteristics	Methods	Observations
[5]	Exploratory case Investigates a distribution strategy where two fleets of deliverymen and installers are used to deliver and install home appliances and furniture	- Delivery and installation routing problem - VRP with multiple synchronization constraints - VRP with time windows and driver-specific times	Mixed-integer linear programming model and tailored adaptive large neighborhood search heuristics	Results show that even though flexibility is included in a model, it generates better costs but also has more potential for computational burden. With the developed algorithms several issues related to VRP with multiple synchronization constraints and VRP with time windows and driver-specific times are solved optimally in shorter times and new lower bunds and some best-known solutions are observed
[37]	Exploratory case Investigates a Deterministic–Annealing-based approach to solve VRPTW and to model constraints related to shipments and heterogeneous vehicles	- VRPTW with aspects of routes and schedules and VRPTW with heterogeneous fleet - Assignment of priorities to customers - Scheduling and route planning restrictions	Deterministic Annealing Heuristic	- Unlimited scheduling resulted in between 15% to 20% of shipments not being collected - Capacity-constrained scheduling resulted in 30% of shipments not being collected - Scheduling with multiple restrictions resulted in 29% of shipments not being collected - Planning routes with time window resulted in 18% of shipments not being collected
[38]	Study case Investigates a company that provides repair services for office machines and that has 20 technicians that must do around 70 repairs daily, located in Chile	- VRPTW - Priority restrictions assigned to customers	Constrained programming based on column generation through an algorithm of Branch-and-Price.	Results show that the developed model allowed to improve performance, with improvements obtained between 15% and 45% in terms of total travel time and total time-window violation
[39]	Exploratory case Investigates a parallel route construction heuristic to deal with VRPTW	VRPTW	Route construction heuristic with an adaptive parallel scheme	- The algorithm allowed to have larger vehicle capacity and longer scheduling horizon - The average total travel distances were shorter with the algorithm - The proposed heuristic was confirmed to be effective and efficient for routes construction
[40]	Exploratory case Investigates an efficient heuristic method to reduce the number of routes in VRPTW	VRPTW	Heuristic-based on the powerful insertion, ejection pol and guided local search strategies	The proposed method performed the best heuristic that has been applied to Gehring and Homberger's benchmark in terms of the number of routes

Table 1. *Cont.*

Paper ID	Description	Problem Characteristics	Methods	Observations
[41]	Study case Investigates a real distribution problem, related to a company that supplies goods for several supermarkets distributed in Brazil	Heterogeneous fleet VRPTW and split deliveries	Two constructive heuristics to generate the initial solution of scatter search	- The approach allowed decreasing the number of trucks used - The algorithm shows that it could offer a better solution in terms of costs distribution
[22]	Exploratory case Investigates a cohesive heuristic that can solve five different variants of the VRP	Five variants of the VRP: CVRP; VRPTW; the multi-depot vehicle routing problem; the side-dependent vehicle routing problem; and the open vehicle routing problem	Adaptive large neighbourhood search heuristic for the pick-up and delivery problem with time window	- The algorithm was able to improve 183 best-known solutions out of 486 benchmark tests - The heuristic has shown promising results for a large group of VRP with backhauls
[42]	Study case Investigates professional logistics company located in Taiwan	Real-time time-dependent VRPTW	Anytime algorithm comprising route construction and improvement	- All customers could be served by six vehicles with seven routes - The total travelled time is shorter than the result of manual planning - The total waiting time for services was zero - Contrary to the traditional VRP, the model developed does not require a vehicle to the customer's location as soon as the service ends

There is a lack of studies that include historical data regarding product assembly [43], and only a few studies focus on the delivery and assembly of furniture, such as: [44] that analyzed delivery and assembly operations using discrete event simulation; ref. [45] explored home furniture delivery and assembly services using times series forecasting methods, such as the Holt–Winters method, ref. [46] developed a performance measurement system for a home furniture delivery and logistic assembly provider; and [47] that used a SCOR-based performance framework for last-mile delivery of home furniture items.

To the best of our knowledge, ref. [5] is the first to deal with a delivery problem with such a flexible setting for installation services. This paper aims to provide more insights into the literature around DIRP. It focuses on the problem where a company needs to find a way to determine last-mile routes for the delivery, assembly, and installation of furniture. The case study was used to develop a heuristic approach that received input data, resulting in a set of routes with a specific order to visit the final customers that should be possible to execute within the established time window. Two scenarios are analyzed: the current scenario (representing the company's current state of route planning, which is not an automated process) and the future scenario (considering the route planning developed through a heuristic). A set of performance indicators is used to assess the heuristic and compare the scenarios.

The results show that the proposed heuristic is a feasible solution, which allows to allocate customers to the teams without compromising the team's skills and competencies to serve the customers and respecting all constraints, including the time window.

This paper is structured as follows. After the first introductory section, Section 2 highlights the materials and methods, where the case study is presented in detail, along with the development of the prosed heuristic and the rules underlying it. Section 3 presents the main results and discussion and suggests future research venues, followed by Section 4, which contains the main conclusions.

2. Materials and Methods

According to [48], the case study methodology allows an understanding and explanation of more complex problems. Given the still limited amount of research that concerns VRPs with delivery and furniture assembly, the case study methodology was used since it allowed to adapt to the problem, as it had a high level of flexibility compared to other qualitative methods [49]; this study was also considered an exploratory investigation [50]. Similar to [51] or [52], a single case study was chosen, considering its potential to be used as a base for future multiple case study approaches. In this case study, the unit of analysis considered is the process of route planning for customers that request the delivery, assembly, and installation of furniture at their homes.

The company under study delivers, assembles, and installs furniture and other products for the IKEA brand. Operating in mainland Portugal, this study includes the company's routes carried out within the area of Lisbon and the Tagus Valley.

At the time of this research, in the company under study, the route creation process was not automated. It was performed manually by a company worker. This may result in routes with very long service times or, on the other hand, in routes that may have reduced service times. Consequently, there is a need to reschedule the team allocated to a specific route. From the end customer side, the customers may refuse to receive the items outside the established time window. In this sense, there is a need to find alternative solutions that support the process of route planning. Thus, the main aim of this case study is to develop a heuristic approach that supports the process of route planning, considering the delivery, assembly, and installation of furniture.

All routes' starting point is the company's warehouse, and the ending point is the last customer inserted in the route.

Each route is executed by a single team, selected from a set of available teams with different skills:

- Each team has a vehicle with a specific transport capacity;
- The customers time window must be respected;
- Constraints must be respected.

The research comprised four main phases that are presented and described in Figure 1: (1) Problem characterization; (2) Data collection; (3) Development of the heuristic approach; (4) Validation of the heuristic approach. The following subsections describe in detail each one of these phases.

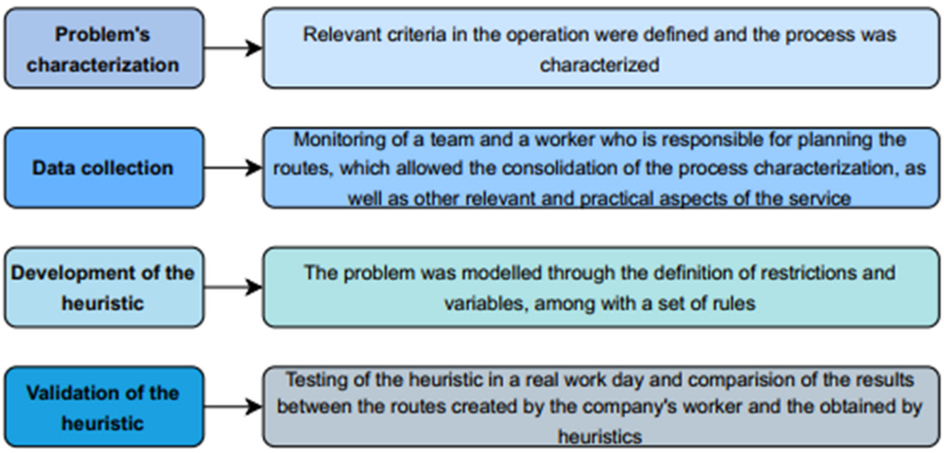

Figure 1. Research phases.

2.1. *Problem Characterisation*

2.1.1. Product Categories

Some IKEA products can be relatively easy to assemble, such as chairs, tables, desks, benches, lamps, and shelves, among others. On the other hand, other products can be more complex, such as those concerning storage systems, such as PAX wardrobes. PAX wardrobe, or PAX, is a storage system that usually includes the assembly of the wardrobe and its components, designated by "KOMPLEMENT". Table 2 presents several IKEA categories of products, divided and classified into three main groups considering the product complexity in assembly and installation: PAX, Assembly (includes all the categories of products), and Mixed types (less complex products). The most complex products to be assembled and installed are the PAX wardrobes; the company measured the customer orders by using the number of linear meters of PAX that needed to be assembled and installed. In the other product types, it used the quantities of items ordered.

Table 2. Product categories classified by type of items.

Product Category	Item Type		
	PAX	Assembly	Mixed
Accessories		X	X
Sideboard/Showcase		X	
Dressers		X	X
Banks		X	X
Hanger		X	X
Chairs		X	X
Beds		X	X
Beds/Bunk Beds		X	
Add-ons	X	X	
Hinges	X	X	X
Bookcases		X	X
Structures	X	X	
Drawers	X	X	X
General		X	X
Lighting	X	X	X
Knobs/Handles/Feet/Legs	X	X	X
Tables		X	X
Extending tables		X	
Tables + Chairs		X	X
Panels		X	X
Doors	X	X	X
Shelves	X	X	X
Closets		X	X
Closets +		X	
Sofas		X	X

In this sense, the company classifies its customers according to the type of products to be assembled and installed in their homes: "PAX customers", "Assembly customers", and "Mixed customers". This way, assigning customers to teams becomes easier.

2.1.2. Time Window

The delivery time window is considered flexible, as the service can start before or after the end of the time window, as long as the customer accepts it, without penalty [33,53].

In route planning, the time window must be respected. This means that customers with the first-time window (9 a.m.–1 p.m.) must first be inserted into the route of each team and, only after, the second-time-window customers (2 p.m.–6 p.m.) should be tended to. Therefore, even if customers are located closer to the last customer inserted in the route, the time window must be checked, and then the customer with the correspondent time window should be served (even if it means traveling a greater distance).

2.1.3. Teams Classification

Companies have heterogeneous teams due to their teams having different levels of performance. Teams' performances are dependent on the products they can deliver and install, travel times (that consider that customers must be rotating to shorten travel times), and service times (that assume that each customer has a specific service time, according to the service requested and with the items purchased).

Due to the diversity of items, assembly, and installation teams are divided into different types and categories. Three main types of teams exist:

- PAX (P) type, serving customers whose contract includes items of the PAX type;
- Assembly (M) type, serving customers whose contract comprises all kinds of items;
- Mixed (S) type, only serving customers whose contract includes less complex items.
- In total, the company has 29 teams:
- M and S-type teams, representing a total of 26 teams, are divided into the first, second, and third categories. Customers should be assigned to teams considering their type and category. As such, customers are first allocated by teams within the first category, then by those within the second category, and finally, by those within the third category.
- There are three P-type teams in total, and thus, they are not divided into categories, and each one has a maximum limit on the number of linear meters of PAX to serve per route.

When allocating teams to customers, there are several constraints to be considered: (i) maximum weight to be transported in kilograms; (ii) minimum commodity value, i.e., the value of goods to be transported) in euros; (iii) time window associated with the customer (i.e., the time interval in hours); and (iv) number of PAX linear meters (only applicable to teams of P and M types). Constraints (i), (ii), and (iv) are determined according to the team's type and category. On the other hand, the customer determines the constraint (iii). The types of teams and their categories, as well as constraints, are depicted in Table 3, except for the restriction associated with the time window depending on the customer.

Table 3. Teams classification and constraints.

Type of Team	Team ID	Category	N° of Teams	Commodity Value (€)	Weight (kg)	N° of Linear Meters PAX (m/Route)	Type of Customers
PAX	E_{pi}	N/A	1	N/A [(a)]	N/A [(b)]	14	PAX, Assembly and Mixed
		N/A	1	N/A [(a)]	N/A [(b)]	10	PAX, Assembly and Mixed
		N/A	1	N/A [(a)]	N/A [(b)]	7	PAX, Assembly and Mixed
Assembly	E_{m1i}	1st	11	≥1500	1200	3 to 4	PAX, Assembly and Mixed
	E_{m2i}	2nd	11	≥1500	1200	2 to 3	PAX, Assembly and Mixed
Mixed	E_{s1i}	1st	2	>500	1000	N/A [(c)]	Mixed
	E_{s2i}	2nd	1	>500	1000	N/A [(c)]	Mixed
	E_{s3i}	3rd	1	>500	1000	N/A [(c)]	Mixed

Notes: N/A—not applicable. [(a)] does not have a limit on the commodity value to transport. [(b)] does not have a limit on the weight to carry. [(c)] does not have the capacity to serve PAX-type customers.

2.1.4. Travel and Service Time

It is important to consider travel times as they may vary due to factors such as traffic, weather conditions, obstacles, changes in speed, and others [54].

To create routes and respect time windows, knowing the service time associated with each team is essential. Service time is defined by the team's vehicle total time at the customer's location. Therefore, it results from the various components that are included in the service performed by the company. This includes loading time (concerning the time that it takes to transport all items from the vehicle to the customer's home) and also the installation time (corresponding to the time that the team needs to assemble and install the items purchased by the customer). For this study, the time was considered to be deterministic.

2.2. Data Collection

One of the most important and driving phases for the success of the case study was the collection of data, which allowed the consolidation of all the relevant criteria for creating routes. Primary and secondary data were collected using the different data sources presented in Table 4. The team's mode of operation, loading time, assembly time, and problem restrictions were collected as primary data. Additionally, the current process of route creation was analyzed for one week. The research team performed ethnographic observations and unstructured questions to the worker responsible for this task.

Table 4. Primary and secondary data sources.

Type of Data	Data Designation	Collection Method	Time Horizon
Primary Data	Team Operating Modus	Observation of how the team execute operations and organises the daily work	Duration: 2 weeks
	Loading Time	Collected using the timing technique while monitoring the team at the customer's house	
	Assembly Time	While monitoring the team, some products' assembly times were collected using the timing technique. Other products' assembly times were estimated	
	Problem Restrictions	Observed and discussed while observing the worker creating the routes manually	Duration: 1 week
Secondary Data	List of products delivered and assembled in 2019	Obtained through the database, available in the company's software Imoovit	Duration: 4 weeks
	Information about IKEA products	IKEA website	
	Team Classification	Company internal document	
	Team Restrictions	Company internal document	
	Travel Time	Obtained through Google Maps	
	Planned routes by the collaborator	Software Imoovit query for the following fields: customer in route; team's name assigned to the route; weight to carry; volume; commodity value; number of linear meters PAX. These were copied to an Excel worksheet	

As secondary data, the list of items delivered and assembled by the company in 2019 was used; information relevant to the items, classification of teams, team restrictions, travel times, and the routes created by the worker should be further used as a comparison to the solution obtained through the proposed heuristic.

2.3. Proposed Heuristic

Heuristics based on constructive strategies or local search have been proven to deliver the best trade-offs between solution quality and computation time [24]. To develop heuristics, it is necessary to define a set of rules and an objective to be achieved and define variables and constraints.

For the case under study, the heuristic to be developed needs to consider all the characteristics mentioned above of the route planning process of the company under study, highlighted in sub-Section 2.1. The proposed heuristic aims to promote a higher level of performance of teams in terms of the number of assembled PAX linear meters, the number of visited customers inside of the time window, and the commodity value transported by each team. Thus, to develop the heuristic, the following constraints were defined: (i) the total number of routes to be carried out on a given day must not be higher than the number of teams available for that day; (ii) the sum of service, travel and trip times for the last customer in route, within the same time window, must not exceed the upper limit of the time window; (iii) the goods to be transported during a route cannot exceed the capacity defined for each team, to avoid unnecessary trips to the warehouse; (iv) the commodity value must be higher than the minimum value established by the team; (v) the number of PAX linear meters must not exceed the capacity of the teams that are competent to carry out the assembly; and (vii) each team must be devoted to the customers they have the competence to serve, according to Table 4.

The notation used in the heuristic and the rules embedded in it are shown in Tables 5 and 6, respectively.

Table 5. Notation used for the purposed heuristic.

Notation	Designation
C_{ti}	Set of Customers For PAX-type Customers: $t = p$ $i = 1, 2, 3, \ldots, N$, sequential index that runs through all PAX-type customers For Assembly-type Customers: $t = m$ $i = 1, 2, 3, \ldots, N$, sequential index that runs through all Assembly-type customers For Mixed-type Customers: $t = s$ $i = 1, 2, 3, \ldots, N$, sequential index that runs through all Mixed-type customers
E_{tck}	Set of Teams For Assembly-type Teams: $t = m$ $k = 1, 2, 3, \ldots, N$, sequential index that runs through all Assembly-type teams c = 1, 2 and 3 for 1st, 2nd, and 3rd categories for Assembly-type Teams For Mixed-type Teams: $t = s$ $k = 1, 2, 3, \ldots, N$, sequential index that runs through all Mixed-type teams c = 1, 2 and 3 for 1st, 2nd, and 3rd categories for Mixed-type Teams
E_{pk}	Set of PAX-type Teams $k = 1, 2, 3, \ldots, N$, sequential index that runs through all PAX-type teams
b_{ti}	Time window upper limit for customer i of type t
PE_{tck}	Weight to carry, in kilos, for a team k of type t (i.e., m or s type) with category c
PE_{pk}	Weight to carry, in kilos, for a team k of PAX-type
$PESOE_{tck}$	Weight to carry upper limit, in kilos, for a team k of type t with category c
VA_{ti}	Commodity value, in euros, transported to a customer i of type t
VAE_{tck}	Commodity value, in euros, transported by a team k of type t with category c.
VAE_{pk}	Commodity value, in euros, transported by a team k of PAX-type.
VOL_{ti}	Volume, in m^3, occupied by orders of a customer i of type t
$VOLE_{tck}$	Volume, in m^3, transported by a team k of type t with category c
$VOLE_{pk}$	Volume, in m^3, transported by a team k of PAX-type
$V_{ti,\, ti+1}$	Travel time, in minutes, between a customer $i+1$ of type t and a customer i of type t Travel time from the depot to a customer i of type t, $V_{0,\, ti}$, is 0 min, given that it was assumed that the team arrives at the first customer at the beginning of the time window, so the travel occurs before the time window starts. Therefore, the travel time for the first customer is not included in the total travel time of the route.
S_{ti}	Total estimated service time, in minutes, for a customer i of type t
D_{ti}	Loading time of products to a customer i of type t If $t = p$, PAX-type customer For M_{pi} between 0 to 3 linear meters—then D_{pi} = 15 min; For M_{pi} between 3 to 6 linear meters—then D_{pi} = 30 min For $M_{pi} \geq 6$ linear meters—then D_{pi} = 40 min. For the other types of customers, a fixed time of 10 min was considered.
$T_{ti,\, tck}$	Arrival time at a customer i of type t, for a team k of type t with category c
TTE_{tck}	Total estimated route time, in minutes, for a team k of type t with category c
M_{pi}	Number of linear meters, in meters, to be assembled at a customer i of PAX-type
ME_{tck}	Number of linear meters, in meters, to assemble for a team k of type t with category c
ME_{pk}	Number of linear meters, in meters, to assemble for a team k of PAX-type
$METROSE_{tck}$	Number of linear meters upper limit, for a team k of type t with category c
$METROSE_{pk}$	Number of linear meters upper limit, in meters, for a team k of PAX-type

Table 6. Rules considered to define the heuristic.

Type of Team	Team Selection	1st Customer to Insert	Next Customer to Insert	After the Allocation of All Teams
Pax Team (P-type)	Criteria:"Highest PAX linear meter capacity" First the team with highest capacity	Start with the first time window: Select the "PAX customer" with the highest number of PAX linear meters to be assembled. After the customer selection, calculate the number of linear meters available for the team. Once the first PAX team's capacity reaches 0 or there are no more "PAX customers" to serve in the first time window, go to the second time window.	If the first team has capacity available, select the "PAX customer" with the zip code more similar the last customer inserted.	If there are still "PAX customers" to allocate, once the teams have all been used, add the "PAX customers" to the route with the lowest ratio between the allocated number of linear meters and the maximum number of linear meters available for the team.
Assembly Team (M-type)	Criteria: "Team category" First the first category teams	Start with the 1st time window: If there are "PAX customers" to allocate, start with them. Select the "PAX customer" with the highest number of linear meters to assemble. After that, calculate the number of linear meters available for the team, the weight to carry, and the commodity value. If there are no "PAX customers" to allocate, start with the "Assembly customers". Select the "Assembly customer" with the higher estimated service time, weight to carry, and commodity value. After that, calculate the time available in the time window. If there are no "Assembly customers", start with the "Mixed customers". Select the "Mixed customer" with the highest estimated service time. After that, calculate the time available in the time window, weight to carry and commodity value. Once the team reaches the weight to carry limit, the number of linear meters to assemble limit or cannot get to the next customer inside the time window interval, or there are no more customers to serve in the first time window, go to the second time window.	If there are still "PAX customers" to allocate and the team has capacity available in linear meters, select the "PAX customer" with the zip code more similar to the last customer inserted. If there's still a "PAX customer" to allocate, but the team does not have enough capacity in linear meters and has time available in the time window, select the "Assembly customer" with the zip code more similar to the last customer inserted. If the team still has time available in the time window and there is still "Assembly customers" to allocate, select the "Assembly customer" with the zip code more similar to the last customer inserted. If the team still has time available in the time window and there are no "Assembly customers" to allocate, select the "Mixed customer" with the zip code more similar to the last customer inserted.	If there are still "Assembly customers" to allocate, once the teams have all been used, add the "Assembly customers" to the route with the lowest estimated total time to be completed.
Mixed-type Team (S-type)	Criteria: "Team category" First the first category teams	Start with the first time window: Select the "Mixed customer" with the highest estimated service time. After that, calculate the time available in the time window, the weight to carry and the commodity value. Once the team cannot get to the next "Mixed customer" inside the time window interval, or there are no more customers to serve in the first time window, or the team reaches its limit of weight to carry, go to the second time window.	If the team has time available in the time window and if there is still a "Mixed customer" to allocate, select the Mixed customer with the zip code more similar to the last customer inserted.	If there are still "Mixed customers" to allocate, once the teams have all been used, add the "Mixed customers" to the route with the lowest estimated total time to be completed.

2.4. Illustrative Example—M-Type Teams Heuristic in Pseudocode

To illustrate how the rules presented in Table 7 were used to develop the heuristic, an example using the details to affect customers of M- type teams is described in Figure 2.

M-type teams can serve all types of customers, thus resulting in a more complex heuristic that needs to consider all possible scenarios. To facilitate the operation of the heuristic, customers are divided into lists: one for PAX customers; one for Assembly customers; and one for Mixed customers.

To allocate customers to M-type teams, first, the PAX customers (the ones that were not allocated to a P-type team) are screened, then the Assembly customers, and finally, the Mixed customers are selected. In addition, customers must be selected considering the chosen time window. Hence, firstly, PAX customers within the first-time window are affected. If the team cannot serve more PAX customers but still has time available within the time window, Assembly customers within the first-time window should be affected. Only when the first-time window does not have any more available time should it advance to customers within the second-time window.

In summary, whenever there are PAX customers to be affected, the heuristic should start with them unless teams no longer have available PAX linear meters capacity. After assigning PAX customers, Assembly customers are affected. The mixed customers are affected only when there are no more Assembly customers to affect when or teams do not have available time within the time window for any more Assembly customers.

Appendix A presents the algorithm concerned with the assignment of customers to M-type team, considering the first-time window (9 a.m.–1 p.m.). For the second time window, the rationale is similar.

Table 7. Performance indicators for all types of teams in the current and future scenarios.

Team ID	Ratio of the Commodity Value to Be Transported in Relation to the Minimum Value		Vehicle Occupancy Rate by Weight		Vehicle Occupancy Rate by Volume		Ratio of Linear Meters to Be Transported in Relation to the Maximum Value		Average Travel Time between Customers (min)		Rate of Customers Visited within the Time Window	
	Current State	Future State	Current State	Future State	Current State	Future State	Current State	Future State	Current State	Future State	Current State	Future State
E_{p1}	N/A	N/A	N/A	N/A	N/A	N/A	0.57	0.96	12	21	N/A	N/A
E_{p2}	N/A	N/A	N/A	N/A	N/A	N/A	0.68	0.93	7	15	N/A	N/A
E_{p3}	N/A	N/A	N/A	N/A	N/A	N/A	1.54	1.00	11	9	N/A	N/A
E_{m11}	4.78	1.61	91%	28%	95%	20%	0.00	0.88	8	15	100%	100%
E_{m12}	3.24	1.25	86%	35%	49%	10%	0.00	0.88	4	11	100%	100%
E_{m13}	3.28	1.86	93%	48%	81%	27%	0.00	0.95	12	10	100%	100%
E_{m14}	2.85	2.09	99%	71%	36%	19%	0.25	1.00	5	15	57%	100%
E_{m15}	2.56	1.69	89%	84%	34%	23%	0.00	0.50	5	3	75%	100%
E_{m16}	1.24	2.37	46%	55%	11%	38%	0.38	0.00	10	11	100%	100%
E_{m17}	3.99	2.78	112%	68%	31%	34%	1.25	0.00	7	21	20%	100%
E_{m18}		3.23		93%		42%		0.00		13		100%
E_{m19}	3.31	1.61	96%	47%	41%	12%	1.32	0.75	15	4	33%	100%
E_{m110}	5.10	3.15	141%	82%	59%	44%	0.00	0.00	10	13	47%	100%
E_{m111}		2.79		97%		35%		0.00		12		100%
E_{m21}		3.01		93%		52%		0.00		10		100%
E_{m22}	2.08	1.75	81%	50%	33%	14%	0.56	0.00	6	16	100%	100%
E_{m23}		2.72		71%		23%		0.00		26		100%
E_{m24}	1.48	1.74	37%	57%	7%	33%	0.00	0.75	7	18	50%	100%
E_{m25}		1.74		58%		28%		0.00		16		100%
E_{m26}	2.19	1.16	116%	29%	37%	15%	0.00	0.00	7	11	75%	100%
E_{m27}		1.36		28%		15%		0.00		19		100%
E_{m28}	1.31	1.34	40%	30%	9%	28%	0.38	0.00	14	15	67%	100%
E_{m29}	1.87	0.80	66%	32%	25%	14%	0.00	0.00	9	17	67%	100%
E_{m210}	1.04	0.69	22%	13%	4%	8%	0.38	0.00	8	13	60%	100%
E_{m211}	3.68	0.56	87%	26%	51%	6%	1.50	0.00	2	10	67%	100%
E_{s11}		0.50		15%		4%	N/A	N/A		9		100%
E_{s12}		0.33		5%		8%	N/A	N/A		0		100%
E_{s21}		0.00		0%			N/A	N/A				
E_{s31}	1.91	0.00	40%	0%	23%		N/A	N/A	3		100%	

Note: N/A—not applicable. Colored in blue are the cells for teams that were not used to affect customers.

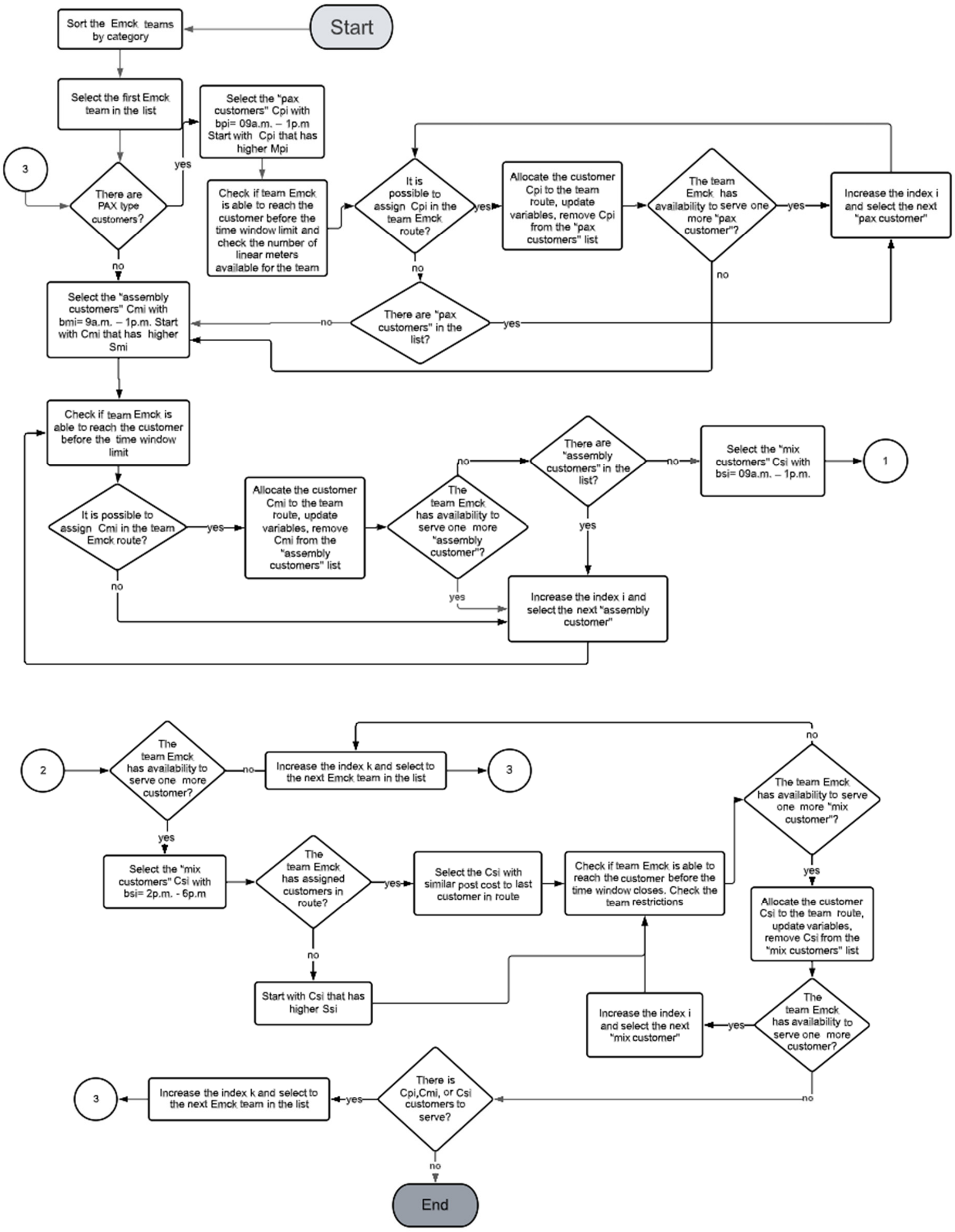

Figure 2. *Cont.*

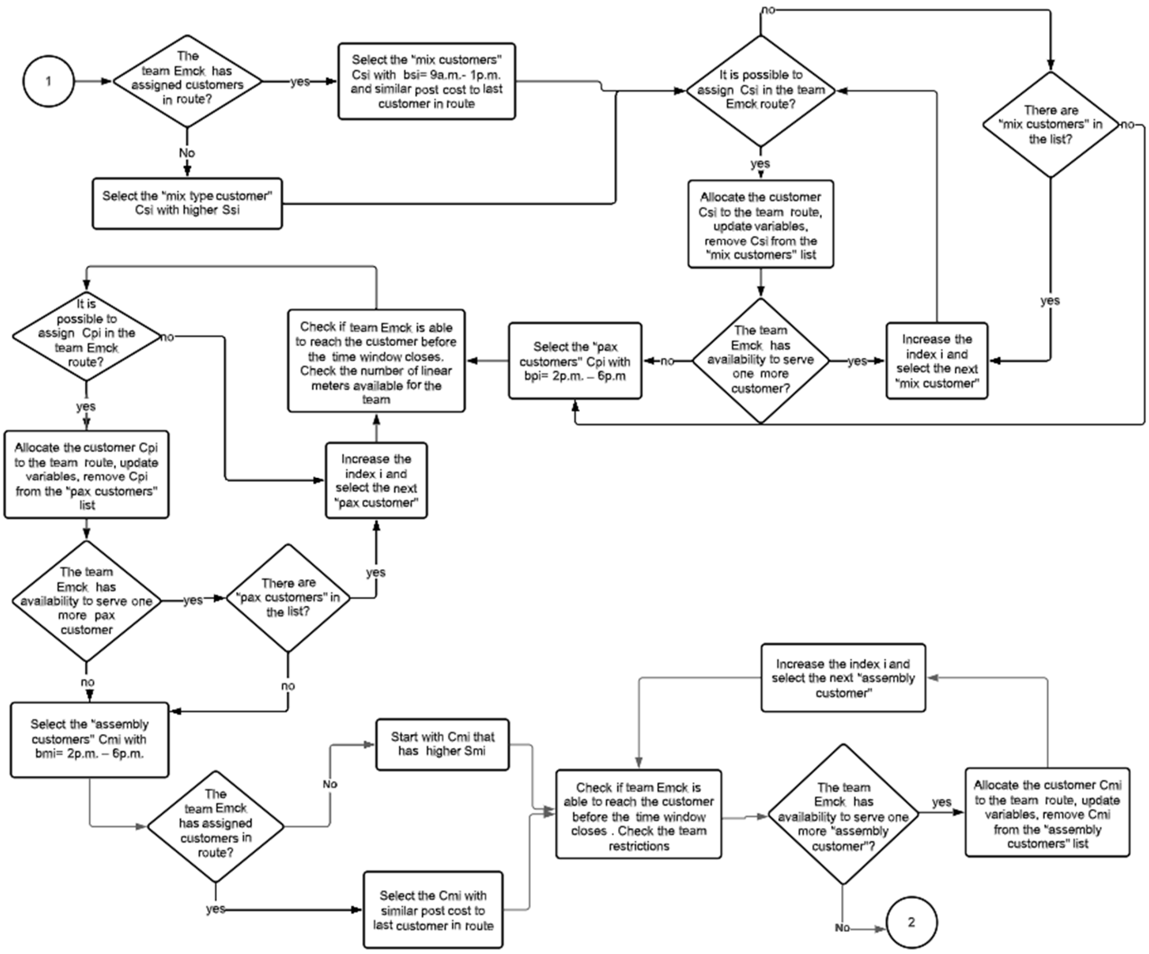

Figure 2. Heuristics graphic display.

3. Results

3.1. Results and Assessment of the Proposed Heuristic

This section analyses the results obtained by applying the heuristic, for Lisbon and the Tagus Valley, for one working day. The company databases were used to collect the input values (e.g., customers' orders, teams' categories, or service times). The data set was imported into an Excel spreadsheet, which was programmed to run the heuristics. Excel was chosen because it was already used by the collaborator responsible for daily route planning; therefore, it did not require any training. In addition, by using Excel, there is no time or cost to ensure the heuristic integration with existing software and infrastructure.

All the routes start at the depot point (the company warehouse). Here, all the materials necessary for satisfying the customer orders are loaded in each truck according to route planning and respective team allocation to customers. After satisfying the last customer en route, the teams do not need to travel back to the depot; so the last customer location corresponds to the route ending point. Through the application of the proposed heuristic, routes were obtained for P-type, M-type, and S-type teams.

Figure 3 provides the route planning for team E_{m11}, which is an assembly team with category 1; therefore, it can serve PAX and assembly-type customers. In this example, this team leaves the depot with all the materials necessary to serve four customers; two of them are PAX-type (i.e., C_{p14} and C_{p15}), and the other two are Assembly-type (i.e., C_{m47} and C_{m46}). Figure 3 represents the travel time between customers (i.e., $Vti, ti + 1$) and the service time (S_{ti}) in minutes, as well as the arrival instant at each customer (i.e., $T_{ti,\, Etck}$) and the total estimated route time in hours. There is a 1 h lunch break during a work day. The travel time from the depot to the first customer is not included in the route planning. In Appendix B, the results for M-type teams are presented.

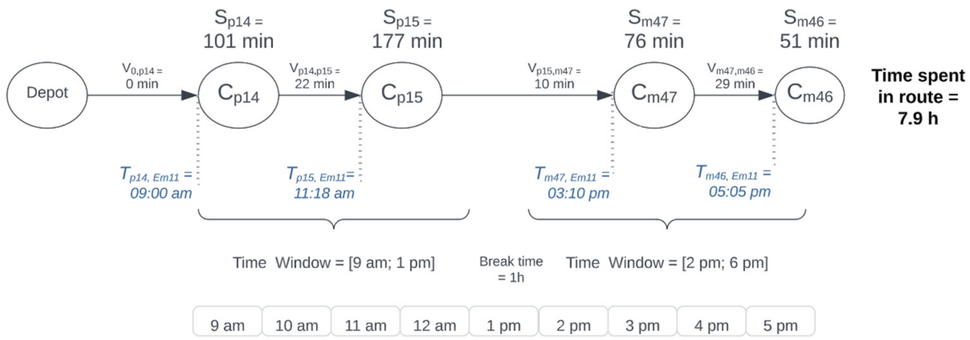

Figure 3. Route planning for the team E_{m11}.

After obtaining the routes for all types of teams and assessing the performance of the developed heuristic, a day of work for the teams under study was selected to apply it. The aim was to compare two different scenarios: the routes obtained through the proposed heuristics (which are designated by "future scenario") with the ones obtained through the current process, i.e., created by the worker of the company (and designated by "current scenario"), for the Lisbon and Tagus Valley area.

A set of performance indicators was selected to assess the proposed heuristic and compare the scenarios. The metrics used for each indicator are presented in the following Equations (1)–(6).

$$\text{Vehicle occupancy rate by weight} = \frac{\text{En route weight}}{\text{Maximum weight established for the team}} \times 100\% \tag{1}$$

$$\text{Vehicle occupancy rate by volume} = \frac{\text{Volume allocated en route}}{\text{Maximum vehicle volume}} \times 100\% \tag{2}$$

$$\text{Ratio of the commodity value to be transported in relation to the minimum value} = \frac{\text{Commodity value allocated en route}}{\text{Minimum value established for the team}} \times 100\% \tag{3}$$

$$\text{Ratio of linear meters to be transported in relation to the maximum value} = \frac{\text{Number of linear meters allocated en route}}{\text{Maximum value of linear meters established for the team}} \times 100\% \tag{4}$$

$$\text{Rate of customers visited within the time window} = \frac{\text{Number of customers visited within the time window}}{\text{Number of customers allocated en route}} \times 100\% \tag{5}$$

$$\text{Average travel time between customers} = \frac{\text{Team's total travel time}}{\text{Number of customers allocated en team's route}} \tag{6}$$

Table 7 provides the values obtained for each of the performance indicators considering both current and future scenarios for all types of teams within the company under study.

Regarding the ratio of the commodity value to be transported, Table 7 allows concluding that all teams, in the future scenario, have a lower ratio of the value of goods to be transported, except for the teams Em_{29}, E_{m210}, E_{m211}, E_{s11}, and E_{s12}. This can be explained because these teams were the last ones to be affected by customers, so they mainly serve Mixed-type customers, which usually results in a lower commodity value per customer. Furthermore, to ensure compliance with the time window, it was not possible to insert more customers within the route of these teams.

In what concerned the vehicle occupancy rate by weight, the future scenario resulted in a higher value for nine teams E_{m111}. Nevertheless, in the future scenario, only three teams will cross the 90% vehicle occupancy rate by weight (E_{m18}, E_{m111}, and E_{m21}). Thus, it appears that within this scenario, through the heuristic, teams do not carry too much weight; instead, the vehicle capacity is almost entirely used by these three teams. It is essential to highlight that the E_{s12} team only showed 5% of the vehicle occupancy rate by weight since this was the last team to which customers were affected.

The vehicle occupancy rate indicator in volume shows values below 100% for all routes, both in current and future scenarios. However, from Table 7, it is possible to conclude that the routes in the current scenario present, in general, a higher value for the vehicle occupancy rate in volume. Still, it is important to emphasize that the volume of a vehicle is hardly used entirely. This is because the items and their packaging have different arrangements and structures. Hence, there can be bulkier items, items longer than others, or more fragile than others, among other types of situations. As such, if the value of the vehicle's occupancy rate by weight is very high, the team will have more difficulty in organizing all the items they need to deliver inside the vehicle and during the execution of the route, as they will have to remove and reposition all the items during the day.

With regards to the ratio of the number of linear meters PAX to be transported in relation to the maximum number (i.e., 1), it can be observed that, in the current scenario, considering P-type teams, only the E_{p3} exceeds the value 1, surpassing the maximum number of linear PAX meters established. However, in the current scenario, all the remaining P-type teams present lower ratio values than those in the future scenario. Moreover, customer demand for PAX-type assembly service is higher than the company's offer, as the number of P-type teams is insufficient to respond to all customers. In this way, M-type teams are necessary to serve these clients, which P-type teams cannot. Table 7 shows that, in the future scenario, none of the M-type teams presents ratio values above 1, so the limits are respected. Still, the same does not apply to the current state for the M-type teams E_{m17}, E_{m19}, and E_{m211}, who exceed the maximum value. Thus, it can be concluded that the developed heuristic allowed to obtain better results for P-type teams when concerning the ratio of the number of linear PAX meters to be transported.

Table 7 also allows making conclusions about the average travel time per customer. The results show, for the future scenario, values higher than 20 min for E_{p1}, E_{m17}, and E_{m23} teams, when compared to the current scenario. This can be explained by the fact that these teams serve more distant customers. Another significant aspect concerns the E_{s12} team, which has an average travel time per customer of zero minutes. This is because this team only has one customer within their route, and the displacement until the customer occurs before the start of the time window. Thus, it was considered that the travel time for the only customer on the route corresponds to 0 min.

Moreover, concerning the rate of customers visited within the time window, it corresponds to a rate of 100% in the future scenario. This result contrasts with the results obtained for the current scenario, where eleven teams possess a rate of customers visited within the time window of less than 100%.

3.2. Discussion and Insights

To understand the main differences between the current and future scenarios, an overall comparison of both scenarios is presented in Table 8.

Thus, through the comparison of both scenarios, there are critical aspects to highlight. Even though the proposed heuristic did not allow to have better or worst results, when compared to the routes developed by the worker of the company, the proposed heuristic meets the following set of characteristics:

- It allows affecting customers to teams without compromising the competence of the team to serve the affected customer;
- All routes obtained through the heuristic are possible and achievable;
- It allowed affecting all customers to teams, without leaving any customer left to serve;
- All teams' constraints have been respected;
- The use of zip codes as the criteria for selecting the next customer to include in the route may not be the best criteria to improve the distances traveled between customers. Regardless, these criteria can be used;

– All time windows were respected, and this should have resulted in no reschedules of teams;
– The number of clients each team served was consistently affected, thus resulting in routes that did not serve a high number of customers nor a low number of customers. Only three teams have a higher number of clients to serve when compared to the others.

Table 8. Comparison between the current and future scenarios.

Item	Current Scenario	Future Scenario
Number of teams	22 teams	28 teams
Time window requirements	12 routes with the shortest estimated travel time	Although the routes have a higher estimated travel time, the routes comply with the established time window
Commodity Value/team	The commodity value reaches higher values in 15 routes	The routes have higher commodity value than the minimum limit
Weight to carry/team	3 teams have weight to carry higher than the maximum limit	The weight to carry is lower than the maximum limit
Number of linear meters PAX/team	4 teams have number of PAX linear meters to assemble above the maximum limit	The number of PAX linear meters respects the upper limit, being used in full for some teams

This study evidences the use of a heuristic as an alternative to support the route-creating process of a company whose focus is on the delivery and assembly of furniture providing insights into the literature regarding DIRP. As already highlighted by [21,39], this study supports the literature about the use of heuristics as a tool that generally yields near-optimal solutions which can efficiently deal with a large set of constraints and still produce near-optimal solutions. The results indicate that the proposed heuristic can affect customers to teams without compromising the team's skills and competencies to serve the customers and respecting all constraints, including time windows. Thus corroborating [37,38,41,55] emphasized the use of heuristics for solving VRPTWs in real-world situations. Moreover, through the use of performance indicators, this study developed and compared two scenarios (using the current manual method for route construction vs. the use of a heuristic) to assess the value of DIRP as a new delivery method [5].

Some major aspects of our findings are related to the process of developing a heuristic to support the route-creating process for the delivery and assembly of furniture and include:

- It is critical to understand how routes are developed since this process allows to define the predominant criteria used to create routes;
- There is a need to monitor the planning process to create routes. In this way, it is possible to understand how the workers responsible for this task operate and how they organize and affect different customers into teams;
- There is a need to carefully define the main objectives to achieve the proposed heuristic and to define decision variables and restrictions, as it is crucial to understand how to make decisions and the boundaries of the problem;
- General rules, as priority rules, are important to be defined, and all rules need to be clearly defined. Additionally, rules for unpredictable situations need to be defined;
- Finally, it is important to test the proposed heuristic through performance indicators to understand if it is adequate for the problem.

4. Conclusions

In this paper, we propose a heuristic for supporting the route-creating process of a company whose focus is on the delivery and assembly of furniture, as opposed to the current manual process planning performed by a company's worker. This problem can be formulated into a VRP with heterogeneous fleet and time window constraints.

We presented the development of a heuristic based on a set of rules for allocating the customers to delivery and assembly teams. Furthermore, to test the proposed heuristic, we applied it to the company under study and compared the routes obtained through the heuristic with the routes created by a worker. A set of indicators was used to compare both scenarios, such as vehicle occupancy rate by weight and volume, linear meters to be transported, and customers visited within the time window or average time between customers. For some of these indicators, such as the number of teams used or time window requirements (regarding travel times), the routes created by the worker provided better results. However, when considering the other indicators, routes created by the proposed heuristic allow for improving teams' performance.

Thus, the proposed heuristic provided a feasible solution that could automate the process of route planning for the delivery and assembly of furniture, allowing the worker of the company under study to be able to verify the viability of the routes created while having more time to spend on other tasks.

In this study, only one day of work was analyzed, and the proposed heuristic was not implemented. Thus, there is uncertainty on the routes created by the heuristic as these might be totally practicable and adequate to the requirements of the company under study. Therefore, future research that monitors the implementation of the proposed heuristic is needed as a means also to understand the fragilities within it. Additionally, it is suggested to develop a tailored software code to run the heuristic and integrate it within the company existing software. This will allow the company collaborator responsible for developing daily route planning to automatize this task and use their time to validate the solution and, if possible, to improve the solutions returned by the heuristics.

Since this study provides the description of a real case related to the DIRP, it opens future avenues to develop an optimization approach to this problem. It encourages the development of methodologies that include more than one objective and evaluation of the optimization model sensibility (and respective results) to the problem parameters. Since this is a multiple-objective problem, possible relationships and trade-offs among objectives should be investigated.

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Appendix A. Algorithm A1

Algorithm A1

For all E_{mck} in List of Teams
If (List of PAX-type customers <> 0)
For all C_{pi} in List of PAX-type customers
For all C_{pi} with (b_{pi} = 09 a.m. – 1 p.m.)
$i = i$ from the C_{pi} with higher M_{pi}
If ($M_{pi} + ME_{mck} \leq METROSE_{mck}$)
Insert C_{pi} in E_{mck} route
Remove C_{pi} from List of PAX-type customers
$ME_{mck} = ME_{mck} + M_{pi}$
$VAE_{mck} = VAE_{mck} + VA_{pi}$
$PE_{mck} = PE_{mck} + P_{pi}$
$VOLE_{mck} = VOLE_{mck} + VOL_{pi}$
$TTE_{mck} = TTE_{mck} + S_{pi} + V_{p(i\text{-}1),\, pi} + D_{pi}$
If ($ME_{mck} < METROSE_{mck}$ AND $PE_{mck} < PESOE_{mck}$ AND TTE_{mck} < 240)
Go to the next C_{pi} with a zip code similar the last inserted customer and so on
Else
Go to the next type of customers, C_{mi}
End if
Else if
Go to the next PAX-type customer, with higher M_{pi} and so on
End if
End for
End for
For all C_{mi} in List of Assembly-type customers
For all C_{mi} with (b_{pi} = 09 a.m. – 1 p.m.)
If (E_{mck} route <> {})
$i = i$ of C_{pi} with zip code similar to the last inserted customer
If ($TTE_{mck} + V_{ti,\, mi} \leq 240$)
Insert C_{mi} in E_{mck} route
Remove C_{mi} from List of Assembly-type customers
$VAE_{mck} = VAE_{mck} + VA_{mi}$
$PE_{mck} = PE_{mck} + P_{mi}$
$VOLE_{mck} = VOLE_{mck} + VOL_{mi}$
$TTE_{mck} = TTE_{mck} + V_{ti}, m_i + S_{mi} + D_{mi}$
If ($PE_{mck} < PESOE_{mck}$ and $TTE_{mck} < 240$)
Go to the next C_{mi} with zip code similar to the last inserted customer and so on
Else
Go to the PAX-type customers with the next-time window
End if
Else
Go to the next type of customers, C_{si}
End if
Else
$i = i$ of C_{mi} with higher S_{mi}
If ($TTE_{mck} + V_{m(i\text{-}1),\, mi} \leq 240$)
Insert C_{mi} in E_{mck} route
Remove C_{mi} from List of Assembly-type customers
$VAE_{mck} = VAE_{mck} + VA_{mi}$

$PE_{mck} = PE_{mck} + P_{mi}$
$VOLE_{mck} = VOLEmck + VOLmi$
$TTE_{mck} = TTE_{mck} + V_{ti}, m_i + S_{mi} + D_{mi}$
If ($PE_{mck} < PESOE_{mck}$ **and** $TTE_{mck} < 240$**)**
Go to the next C_{mi} **with zip code similar to the last inserted customer and so on**
Else
Go to the PAX-type customers with the next time window
End if
End if
End if
End for
For all C_{si} **in List of Mixed-type customers**
For all C_{si} **with (**b_{pi} **= 09 a.m. – 1 p.m.)**
If (E_{mck} **route <> {})**
$i = i$ **of** C_{si} **with zip code similar to the last inserted customer**
If ($TTE_{mck} + V_{ti,\,mi} \leq 240$**)**
Insert C_{si} **in** E_{mck} **route**
Remove C_{si} **from List of Mixed-type customers**
$VAEmck = VAE_{mck} + VA_{si}$
$PE_{mck} = PE_{mck} + P_{si}$
$VOLE_{mck} = VOLE_{mck} + VOL_{si}$
$TTE_{mck} = TTE_{mck} + V_{ti}, m_i + S_{si} + D_{si}$
If ($PE_{mck} < PESOE_{mck}$ **and** $TTE_{mck} < 240$**)**
Go to the next C_{si} **with zip code similar to the last inserted customer and so on**
Else
Go to the PAX-type customers with the next time window
End if
End if
End if
End for
End for
End for
End for

Appendix B

Table A1. Routes Obtained for M-Type Teams through the Proposed Heuristic.

Team ID	Start Time	Finish Time *	Route	Time Spent in Route [h]
E_{m11}	09 a.m.	5.52 p.m.	$0 \rightarrow C_{p14} \rightarrow C_{p15} \rightarrow C_{m47} \rightarrow C_{m46}$	7.88
E_{m12}	09 a.m.	6.58 p.m.	$0 \rightarrow C_{p11} \rightarrow C_{p12} \rightarrow C_{m44}$	8.97
E_{m13}	09 a.m.	7.24 p.m.	$0 \rightarrow C_{p5} \rightarrow C_{p2} \rightarrow C_{p1} \rightarrow C_{m29} \rightarrow C_{m30} \rightarrow C_{m31}$	9.41
E_{m14}	09 a.m.	10.14 p.m.	$0 \rightarrow C_{p16} \rightarrow C_{p13} \rightarrow C_{p27} \rightarrow C_{m45}$	13.43
E_{m15}	09 a.m.	8.19 p.m.	$0 \rightarrow C_{m10} \rightarrow C_{p21}$	10.32
E_{m16}	09 a.m.	6.15 p.m.	$0 \rightarrow C_{m14} \rightarrow C_{m15} \rightarrow C_{m40} \rightarrow C_{m41}$	8.25
E_{m17}	09 a.m.	8.22 p.m.	$0 \rightarrow C_{m26} \rightarrow C_{m25} \rightarrow C_{m43} \rightarrow C_{s50}$	10.38
E_{m18}	09 a.m.	7.57 p.m.	$0 \rightarrow C_{m27} \rightarrow C_{m28} \rightarrow C_{m49}$	9.96
E_{m19}	09 a.m.	8.57 p.m.	$0 \rightarrow C_{m7} \rightarrow C_{m8} \rightarrow C_{m9} \rightarrow C_{p19} \rightarrow C_{p20}$	10.95
E_{m110}	09 a.m.	7.58 p.m.	$0 \rightarrow C_{m20} \rightarrow C_{m21} \rightarrow C_{m22} \rightarrow C_{m42}$	9.97
E_{m111}	09 a.m.	8.02 p.m.	$0 \rightarrow C_{m16} \rightarrow C_{m17} \rightarrow C_{m18} \rightarrow C_{m39}$	10.04
E_{m21}	09 a.m.	6.00 p.m.	$0 \rightarrow C_{m6} \rightarrow C_{m5} \rightarrow C_{m4} \rightarrow C_{m32}$	7.99

Team ID	Start Time	Finish Time *	Route	Time Spent in Route [h]
E_{m22}	09 a.m.	7.24 p.m.	$0 \rightarrow C_{m11} \rightarrow C_{m12} \rightarrow C_{m13} \rightarrow C_{m38}$	9.40
E_{m23}	09 a.m.	6.02 p.m.	$0 \rightarrow C_{m2} \rightarrow C_{m3} \rightarrow C_{m1} \rightarrow C_{m19} \rightarrow C_{m36} \rightarrow C_{m35}$	8.04
E_{m24}	09 a.m.	7.01 p.m.	$0 \rightarrow C_{m24} \rightarrow C_{m23} \rightarrow C_{s22} \rightarrow C_{s23} \rightarrow C_{p22}$	9.02
E_{m25}	09 a.m.	5.44 p.m.	$0 \rightarrow C_{s18} \rightarrow C_{s19} \rightarrow C_{s17} \rightarrow C_{s16} \rightarrow C_{m37} \rightarrow C_{m48}$	7.73
E_{m26}	09 a.m.	5.08 p.m.	$0 \rightarrow C_{s13} \rightarrow C_{s12} \rightarrow C_{s11} \rightarrow C_{s10} \rightarrow C_{s9} \rightarrow C_{s8} \rightarrow \rightarrow C_{s7} \rightarrow C_{s28} \rightarrow C_{s29} \rightarrow C_{s30}$	7.13
E_{m27}	09a.m.	4.25 p.m.	$0 \rightarrow C_{s2} \rightarrow C_{s3} \rightarrow C_{s4} \rightarrow C_{s5} \rightarrow C_{s6} \rightarrow C_{s14} \rightarrow C_{s31} \rightarrow C_{s32}$	6.43
E_{m29}	09 a.m.	7.06 p.m.	$0 \rightarrow C_{s27} \rightarrow C_{s1} \rightarrow C_{m33}$	6.84
E_{m211}	2 p.m.	5.56 p.m.	$0 \rightarrow C_{s36} \rightarrow C_{s37} \rightarrow C_{s38} \rightarrow C_{s39}$	3.94

Note: in column "Route" 0 represents the depot, C_{ti} is the customer designation, and the symbol "→" is used to describe vehicle movement between two consecutive points in the route. After the last customer the team does not need to return to the depot. * it includes 1 h for a breaktime.

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