

A Two-Stage Heuristic for a Real Multi-compartment and Multi-trip Vehicle Routing Problem with Time Windows

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Abstract. This paper addresses the multi-compartment and multi-trip vehicle routing problem in a fuel distribution company. A decision support system (DSS) to automatically produce daily routing plans was developed. The company delivers three fuel types using a heterogeneous fleet of multi-compartmented vehicles with a maximum capacity expressed in fuel liters. Additional and real constraints are imposed, such as time windows and compulsory breaks. A constructive heuristic based on the Clarke and Wright savings algorithm was adapted in order to embed all business constraints. This constructive heuristic was developed in three steps. In the first step, all the previously mentioned constraints were taken into account. In the second version of the algorithm, the multi-trip case was incorporated. In order to improve the quality of the solution, an exchange of compartments mechanism and two local search procedures were developed. One of the local procedures was based on local search movements within each route, while the other one was based on movements between distinct routes. Solutions are displayed using a georeferenced-based platform allowing for a spatial representation of data to be analyzed. The achieved results show that the total traveled distance can be reduced by approximately 14%. The main contribution of this work is to offer the company a DSS for route planning without any additional cost that may enable fast and efficient planning of the entire company's distribution sector.

Keywords: Vehicle routing problem · Multi-compartment · Multi-trip · Decision support system · Fuel distribution

1 Introduction

Nowadays, and in the scope of the Industry 4.0, companies are exploring the use of Information and Communication Technologies (ICT). This exploration will allow higher efficiency and better effectiveness of their operations while

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enhancing the organization's faster adjustment to the current dynamic environment. One of the areas where these technologies should be developed is the distribution [21].

In the distribution field, the Vehicle Routing Problem (VRP) plays an important role. Generally, the objective of VRP is to build a set of routes that minimize transport costs, associating a vehicle and a driver to each route, starting and ending in the same depot, so that all customers are served, taking into account that their demand is previously known. However, several constraints are inherent to the real problems that depend mainly on the nature of the products to be transported, the quality of service required, and the features of customers and vehicles. Such issues may significantly increase the complexity of these problems [2].

In this paper, we present a real-world problem context arising from the distribution sector. More precisely, we address the case of a Portuguese retail fuel distribution company. Usually, this type of company has restricted access to any decision support systems, using basic procedures to deliver a set of tours for each vehicle. Typically, the quality of routing solutions highly depends on the previous experience of the planner operator and/or vehicle drivers. Such approach lacks systematization and does not ensure the efficiency of produced solutions or acceptable levels of service. These facts strongly motivated our approach: the overall objective of this paper is to provide a decision support system to the distribution problem of a company in the fuel retail distribution sector. The motivation of this paper is to deepen the promising results of a previous work presented in [19]. In that contribution, the authors only addressed two constructive approaches: one of them considers the route planning without replenishments, and the other one considers the multi-trip case instead.

Additionally, we suggest another constructive approach and a local search method based on two neighborhood structures. Furthermore, a decision support system was developed using *Microsoft Excel* (under *Visual Basic Language platform*) combined with an interactive interface providing several functionalities to allow daily planning operations such as the record of new customers, new orders processing, and the design of a set of routes to be performed by the existing resources in a predefined slot of time. Additionally, the integration with a geographical information system and the inclusion of optimization procedures provides efficient solutions and, at the same time, allows the production of several reporting features to improve the overall performance of the distribution system.

This paper is organized as follows. Section 2 presents a brief state of art concerning VRP and, particularly, VRP with fuel distribution. Section 3 presents the definition of the real problem at the company. The solution methods are presented in Sect. 4. Section 5 describes the DSS developed at the company. Section 6 shows computational experiments, and the obtained results are discussed. Finally, Sect. 7 reports the main conclusions and final considerations regarding some possible future developments.

2 Literature Review

A huge number of variants and extensions can be found in the literature. We will give focus to the most common ones, and the most related one to the problem addressed in this paper, as follows:

- Capacitated Vehicle Routing Problem (CVRP): It is the basic version of the VRP. The name derives from the constraint of having vehicles with limited capacity Q. Customer demands are deterministic and known in advance. Deliveries cannot be split, and thus an order cannot be served using two or more vehicles. The vehicle fleet is homogeneous, and there is only one depot [22,24];
- Vehicle Routing Problem with Time Windows (VRPTW): In this VRP variant, the capacity constraint still holds and each customer i is associated with a time window $[a_i, b_i]$ and with a service time s_i. The nature of the time windows could be soft or hard. In the first case, the customer may be served after the upper bound of the time window, but a penalty is set for the service. In the second case, the same is not possible. If the vehicle arrives at a customer earlier than a_i, the vehicle must wait until the service is possible [16,22,24];
- Multi-Compartment Vehicle Routing Problem (MCVRP): In this variant, vehicles are compartmented in order to deliver products that are incompatible [15] or if their contact may be unstable or even dangerous. On the other hand, different types of products may need different conditions. The most common real-world examples are the trucks for selective waste collection or the petroleum distribution systems that deliver different types of fuel to retailers using multi-compartmented vehicles;
- Multi-Trip VRP (MTVRP): In this variant, the focus is given to the distribution of low quantities of products, and thus, several routes may be performed by each vehicle [5].

Note that the main goal is to minimize the overall cost or the traveled distance in all variants. According to [23], the data requirements and the complexity of urban planning and transportation problems have caused a growing interest in the use of decision support systems at the operational, tactical, and strategic planning levels. The significance and ability to use DSS to assist in fleet management on a daily or weekly basis has been widely recognized. Once adequate graphical interfaces are very important to represent solutions in routing problems given their strong spatial component. ICT can also play an important role in constructing user-friendly tools embedding algorithms, graphical interfaces, and access to remote data through the Internet [14,23].

The VRP was introduced in [12], exactly for the fuel transportation problem. Since then, this problem has awakened the interest of several researchers. Thus, in the last decades, several versions of the VRP for fuel transportation have been developed. In this section, a brief review of the literature contributions in this area is presented. Table 1 summarizes the main research works and dimensions addressed in the context of the fuel distribution problem.

The station replenishment problem is closely related to MCVRP, due to the different types of fuel that these companies transport. In [12], multi-compartment vehicles or the heterogeneous fleet variant are not considered. However, the authors recognized that it was important to include these variables.

Most of the contributions referred to in Table 1 tackled the multi-compartment VRP variant. However, only two approaches took into account time windows, and just three approaches considered the multi-trip case. The contribution presenting the highest number of variables is presented in [8]. However, the number of customers visited on each trip was limited to six since each compartment could only load one order. The last two contributions gave great importance to inventory management too. Additionally, due to the complexity of this type of problem, only three exact approaches were presented.

Table 1. Main characteristics of fuel distribution VRP problems, adapted from [8,19].

Ref.	Unlimited fleet	Homogeneous fleet	Multi-compartment	Time windows	Customers (each route)	Multi-trip	Exact approach
[12]	Yes	Yes	No	No	Several	No	No
[3]	No	No	Yes	No	Several	Yes	No
[1]	No	No	Yes	No	Several	No	Yes
[18]	No	No	Yes	No	Several	No	Yes
[9]	Yes	No	Yes	No	Up two	No	Yes
[10]	No	No	Yes	No	Up two	No	No
[11]	No	No	Yes	Yes	Up four	Yes	No
[8]	No	No	Yes	Yes	Up six	Yes	No
[20]	Yes	Yes	Yes	No	Up three	No	No
[25]	Yes	Yes	Yes	No	Up four	No	No
[26]	Yes	No	Yes	No	Several	Yes	Yes

3 Problem Description

This paper addresses the case of a Portuguese fuel retailer in the north of the country. Due to its chemical characteristics, fuel is included in the group of dangerous goods [4]. For this reason, it is guided by stricter legislation when compared to ordinary goods.

Three types of fuel are delivered (road, agricultural, and heating diesel) from a warehouse to several customers geographically dispersed in the north of Portugal (approximately 25 customers). The company has a heterogeneous fleet of four vehicles with multiple compartments of different capacities for fuel distribution: one vehicle has five compartments, the other two vehicles have two compartments and, the smallest vehicle has one compartment.

The company receives several orders to be performed on the following day. Each order is composed of the product type, product quantity, an interval of time

in which the delivery may occur (time window), the address of the customer, and the road access constraints if any.

Before this work, the routes were planned in the early morning for each day. It is important to note that before the DSS implementation for route planning, this planning was empirically performed by a distribution manager, and the routes were defined by drivers. In the first phase, the employee responsible for the operational management of this area distributes orders by available drivers. In a second phase, the drivers create routes empirically based on their experience. If a new customer in an unknown area arises, the drivers use Google Maps to help to achieve the new location. Therefore, it was a disaggregated planning process involving several people and with a low level of control.

Frequently, the same driver returns to the depot to reload the vehicle, and it performs a new route. Therefore, the multi-trip variant must be considered.

The objective function is the sum of all traveled distances. However, there is a set of issues related to the level of service that will be analyzed.

4 Solution Method

Due to the complexity of the addressed problem, we suggest a two-stage heuristic that guarantees a global solution. The first stage consists of the application and adaptation of the well-known Clarke and Wright savings algorithm [6] as it was proposed in [19] for this problem. In the second stage, a local search approach is suggested. In order to make our paper self-contained, we present the two constructive heuristic approaches from [19], followed by the presentation of our newly developed procedures. Note that the authors considered first the relaxed algorithm version without considering the multi-trip variant. Therefore, and since the vehicle's compartments have different capacities, a mechanism was embedded to increase the efficiency of the solutions through the exchange of products among each compartment. We called it the exchange of compartments mechanism.

Constructive Heuristic without Multi-Trip – V1 [19]. The Clarke and Wright savings algorithm [6] has two versions: the parallel and the sequential version. In our constructive approach, the parallel version is used due to its performance. The algorithm was implemented in the following steps:

Step 1. For each pair of customers (i, j), a saving is computed by $S_{ij} = C_{i0} + C_{0j} - C_{ij}$ with $i, j = 1, \ldots, n$ and $i < j$, where C_{ij} represents the cost of traveling from i to j.
Step 2. Create n routes $(0, i, 0)$ for $i = 1, \ldots, n$ where n is the number of customers.
Step 3. Order the savings in decreasing order.
Step 4. Order the vehicles in decreasing order of capacity.
Step 5. Starting from the first saving, and for each saving S_{ij}, test if there are two routes, one starting with $(0, i, \ldots, 0)$ and other ending with $(0, \ldots, j, 0)$ that can be feasibly merged. Whenever two routes are combined, $(0, i, 0)$ and $(0, j, 0)$ are deleted and the arc (i, j) is introduced. This process is repeated while $S_{ij} \geq 0$.

When two single customers are merged, the first available vehicle (starting from the vehicle with the largest capacity) is assigned to the route. A feasible merge is performed when all capacity constraints and time windows are satisfied. The product load is distributed by the vehicle compartments. If the time windows are not feasible initially, the feasibility of the route is verified in reverse order. A solution with unvisited customers was considered as a feasible solution since the company makes the same assumption. If this happens, the customer is assigned to the next plan, providing that the time window constraint is always satisfied.

Constructive Heuristics with Multi-Trip Case – V2 [19]**.** In a second step, the replenishments were incorporated into the algorithm, i.e., the multi-trip case. Each vehicle performs a set of trips $T_b = \{1, \ldots, |T_b|\}$, in each planning period.

New Constructive Heuristics with Multi-Trip and an Exchange of Compartments Mechanism – V3. In this version of the algorithm, an exchange of compartments mechanism was incorporated. The aim of this mechanism is to improve the quality of solutions generated by the constructive heuristic through the load exchange between every two compartments, whenever it is possible. In Fig. 1, an order of 600 liters of heating diesel must be introduced into the vehicle. As it can be seen, in the initial phase, it is not possible to introduce 600 liters of heating diesel into the vehicle. So, the exchange of compartments mechanism starts by testing the load exchange between compartments 1 and 2. However, Fig. 2 shows that this exchange is not possible since the load in compartment 1 is larger than the capacity of compartment 2. Thus, the exchange is not performed. Thereafter, the load exchange between compartments 1 and 3 is tested. However, this movement does not enable the introduction of the order since the heating oil compartment remains the same, as shown in Fig. 3. Once again, the movement is not performed. The last movement tested is the load exchange between compartments 2 and 3. As it can be seen in Fig. 4, this movement allows the introduction of the order (600 liters of heating diesel) into the vehicle. Thus, this exchange is performed. The final solution is presented in Fig. 5. This mechanism finishes when a better feasible solution is found or when all movements are tested.

Subsequently, two local search procedures were implemented, aiming to improve the quality of solutions. The first one is based on movements within each route, while the second one is based on movements between two routes. Both mechanisms are presented below.

Intra-Route Local Search – V3,1. For each iteration, this local search mechanism tests the exchange of positions between two customers in the same route. If the objective function is minimized and the solution remains feasible, the movement (exchange of positions between the customers) is made. This process is repeated for all pairs of customers in all the routes generated by the constructive heuristic. For the sake of clarity, an example is provided in Fig. 6: it is possible to observe that movement $(C1, C2)$, starting from an initial route

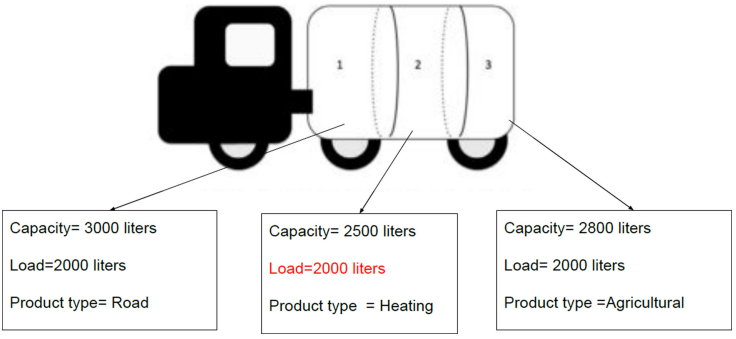

Fig. 1. Exchange of compartments: initial phase (adapted from [7]).

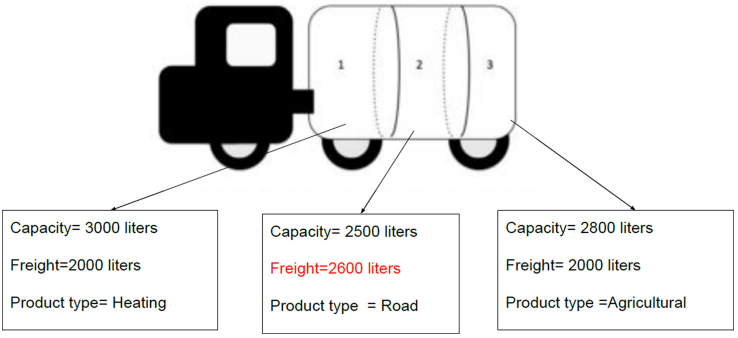

Fig. 2. Exchange of compartments: movement 1 (adapted from [7]).

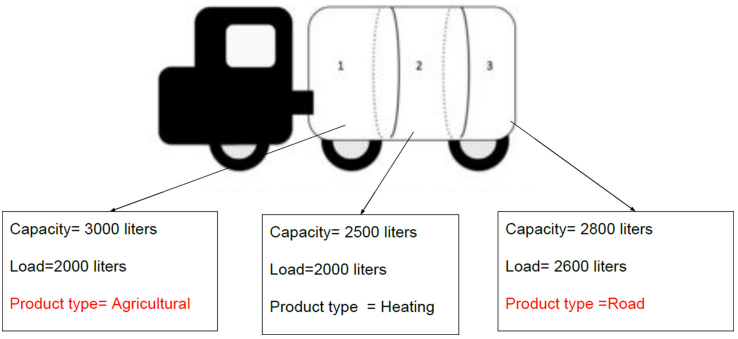

Fig. 3. Exchange of compartments: movement 2 (adapted from [7]).

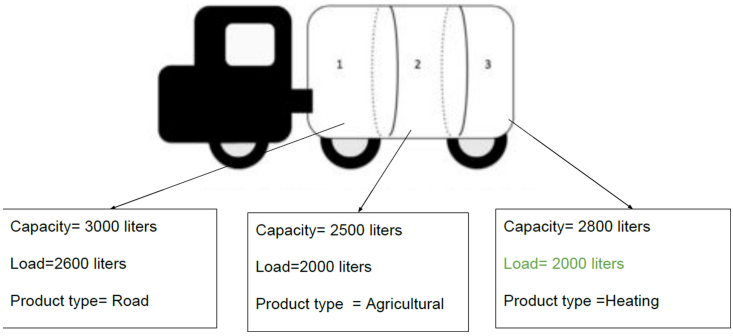

Fig. 4. Exchange of compartments: movement 3 (adapted from [7]).

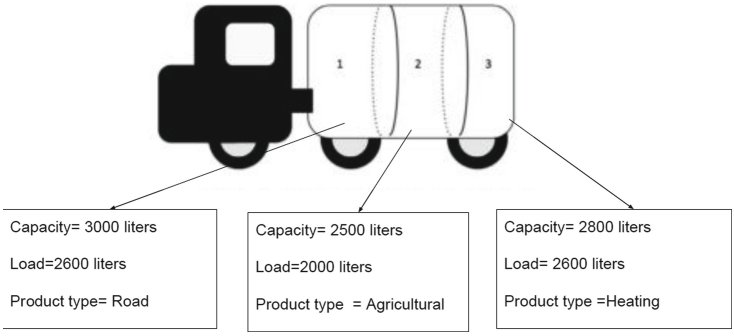

Fig. 5. Example of the exchange of compartments mechanism – final solution (adapted from [7]).

R_i. If the movement produces a decrease in the value of the objective function, the movement is performed, and the process is restarted with the new obtained route (new R_i). If the movement does not minimize the value of the objective function, no change is made to the original route, thus advancing to the next movement (C1, C3). This process must be repeated until all movements for all routes are tested.

Local Search Between Two Routes – V3,2. The second mechanism of local search introduced in the algorithm is based on relocate movements applied in [17]. Each movement requires the specification of two stops. For each customer, a neighbor list is built. The maximum size of the neighbor list is three. The neighbor list is composed of the three nearest customers in a different route. The movement (C3, S2) is presented in Fig. 7: two movements are tested: the first one is the insertion of customer S2 in the position immediately before C3, and the second movement tests the insertion of S2 in the position immediately after C3.

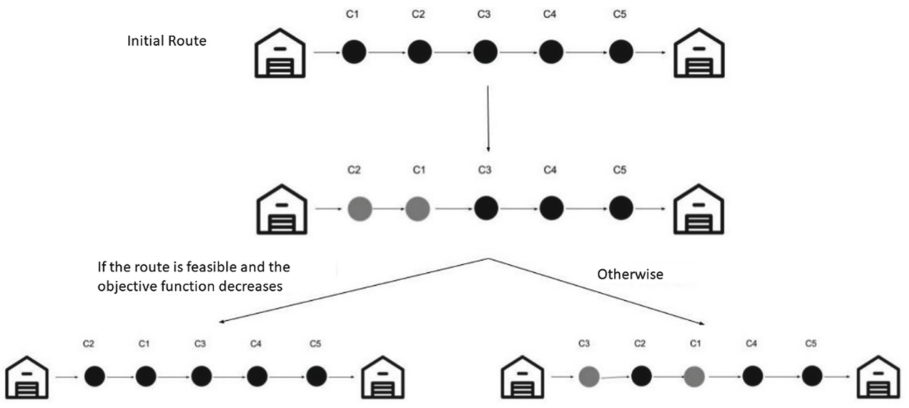

Fig. 6. Example of intra-route local search.

5 Decision Support System

A decision support system was developed using *Visual Basic Language* from *Microsoft*, using the VRP Spreadsheet Solver [13] as a starting platform. *Microsoft Excel* was considered by the company as the most convenient solution since the company is already familiar with this software. The architecture of the DSS is illustrated in Fig. 8.

Any process is made up of an input, output and a rule set, which limits the process. The DSS also works as a process. The inputs for this DSS are:

- Depot, opening hour and loading time;
- Data set of orders: customer ID number, name and address, delivery address, quantity, type of product, time windows, service time, and access restrictions;
- Set of available vehicles.

This DSS has a database with information about customers, with the ID number, name, address, geographical coordinates, and access constraints. The customer information is automatically inserted just by filling in the customer ID number. If the customer is not on the database, the user will be informed, and the customer data may be inserted into the database before introducing the order. The geographical coordinates of the customer address can be introduced by the user or be computed by the DSS. Additionally, the DSS also has a database with information about vehicles, with the license plate, fuel consumption per 100 km, number of compartments, and capacity. This database can also be edited. If all data is inserted, the user can generate planning through the selection of this option. The main output is a set of routes, each one assigned to a vehicle. Furthermore, the developed DSS also returns a set of complementary information associated with each route, such as the arrival and departure time for each customer and the depot; waiting time at each customer; route length (in Kilometers); fuel consumption (in Liters); route time (in hours); quantity and

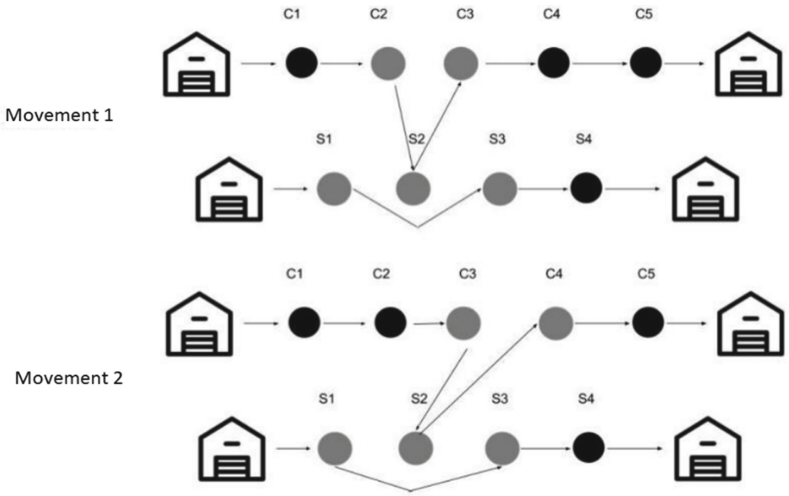

Fig. 7. Local search between two routes adapted from [17].

type of product assigned to each compartment and the vehicle usage. A table is generated for each route with the information referred to above. Additionally, the set of routes can be visualized on a map, as seen in Fig. 9. In this example, the starting point is the warehouse 20 and 7 customers are visited through three routes.

Finally, the user can analyze the generated routes. Then, he/she can validate all routes or eliminate one or more routes. In the end, the main data of each validated route are added to a database, with the generation date, vehicle's license place, starting and ending time, fuel consumption, the number of customers, and quantity of each type of fuel transported. So, the KPIs (Key Performance Indicators) are updated. The measured KPIs are the number of routes, the traveled distance, the fuel consumption, the visited customers, the quantity loaded of each type of product.

Additionally, this information is also presented in a set of charts, which are related to the different parameters analyzed by a period of time that can be defined by the user Fig. 10, such as: bar chart of traveled distance; bar chart of fuel consumption; bar chart of the number of visited clients; bar chart of the amount of each type of loaded fuel; bar chart of the number of visited clients per vehicle; Pie chart of the quantity loaded of each type of product. This feature allows the graphical visualization of performance indicators, referred to above, and it is constantly updated. So, the developed DSS takes into account the capacity of each compartment, time windows, and customers' access constraints. Additionally, the DSS also considers that different types of products cannot be mixed. The DSS needs internet access to operate since the real distances among customers, the distances between customers and the depot, and the geographical coordinates are calculated through *Bing Maps*.

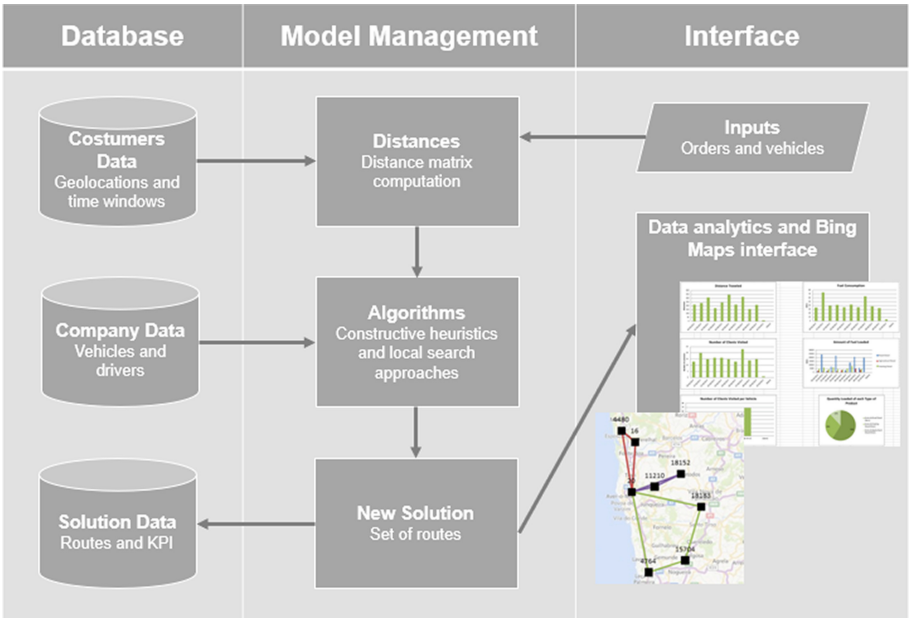

Fig. 8. Architecture of the DSS.

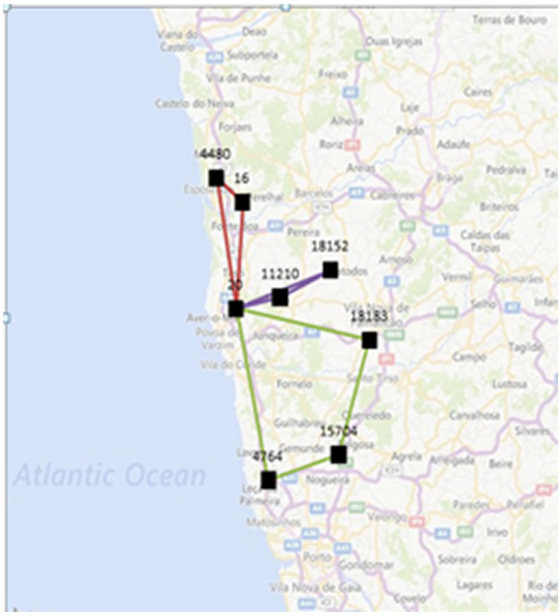

Fig. 9. Interface for visualization of routes on a map.



Fig. 10. Graphical representation of performance indicators accounted for by DSS.

6 Computational Results

In order to validate solutions produced by the DSS, data from the company was collected for 10 consecutive days (excluding Sunday). During these days, the drivers reported the traveled routes, the used vehicles, and the traveled distance. Combining this information with the list of deliveries for each planning period makes it possible to compute all parameters.

Five performance indicators have been used to assess the overall performance of the distribution system and to validate and compare obtained solutions: traveled distance (in kilometers); fuel consumption (in liters); time spent on distribution (in hours); average vehicle usage and the level of service. As for the level of service, the percentage of delivered orders was considered. In order to approach the real scenario, in each planning procedure it was considered: a set of vehicles used in the company; an average speed of 55Km/h; a loading time of 20 min; service time of 15 min and depot opening time from 8 a.m. until 7 p.m. Note that times and average speed are based on the collected data in the period referred to above. The five versions of the algorithm presented above were tested using real instances, and the results from computational experiments are shown in Table 2.

In the three first parameters (traveled distance, time spent on distribution, and fuel consumption), Table 2 shows that all versions of the algorithm present

Table 2. Results of real case and 5 versions of algorithm

Parameters	Real case	V1	V2	V3	V3,1	V3,2
Traveled distance (kilometers)	2828,5	2883	2621	2443	2428	2428
Time spent on distribution (Hours)	538,5	517,6	457,4	443,2	440,5	440,1
Fuel consumption	132,3	112,1	111,2	107,2	106,7	106,7
Level of service	93%	96%	97%	96%	96%	96%
Average vehicle usage	57%	66%	59%	56%	56%	57%

gradually better results with the increase of complexity of algorithms. Nevertheless, V1 presents a larger amount of traveled distance than the real case. However, this version also presents a higher average vehicle usage. The largest variations are found between V1 and V3. Both versions of V3 do not present a significant impact on the analyzed parameters. All versions present a higher level of service than the real case, but V2 has the best result for this parameter. The behavior of the traveled distance is shown in Fig. 11: V1 presents a traveled distance increase of 2% when compared to the real case. All other versions of the algorithm present a traveled distance in the overall solution that is lower than the one in the real case.

The results of the final algorithm show a 14% reduction in traveled distance, an 18% reduction in fuel consumption, a 19% reduction in time spent on distribution, and an increment of 3% in the level of service. The average vehicle usage remains the same. During the analyzed period, 166 orders were collected. The computational times increased slightly with the increase of the algorithm complexity. However, just a few seconds are needed to have a solution.

The first version of the algorithm does not take into account the multi-trip case. However, after testing several daily plans, the computational results presented had worse performances when compared to the results of the real case in terms of traveled distance. This fact is due to the shortest planning horizon. In many cases, since the possibility of performing multi-trips was not considered, the first saving values (merges) were wasted due to the lack of capacity of vehicles or to the time windows constraints.

As expected, in the first three parameters (traveled distance, time spent on distribution, and fuel consumption), the overall solution quality increases with the complexity of the algorithms. Although V3,1 and V3,2 have a better global solution, it has very similar values in all parameters and close values to the V3. Therefore, the local search contribution did not have a major impact. Version V2 has the highest level of service. Nevertheless, all versions of the algorithm have a global solution better than the real case regarding this parameter. Table 2 shows that the best usage of vehicle capacity is performed by V1.

The potential savings of the proposed DSS consists of a reduction of up to 5900 km, 1700 Fuel liters, and 640 work hours per year. These values were calculated through an arithmetic average of 258 working days per year. This is the number of days of distribution in the company during a given year.

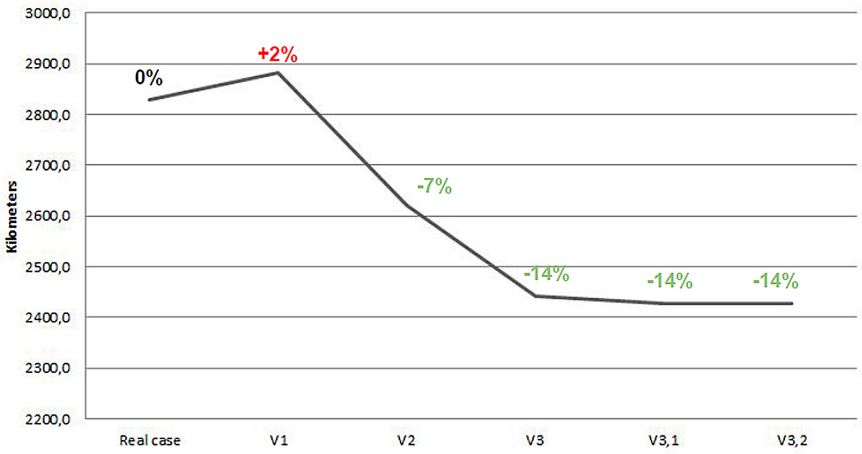

Fig. 11. Percentage changing in traveled distance parameter, compared to the real case.

7 Conclusions and Future Work

In this paper, a two-stage heuristic for a real-world multi-compartment VRP problem is proposed. Some real constraints are considered, such as the limited capacity, time windows, multi-compartments. Different approaches were developed: the first version without replenishments; the second one considers the multi-trip case; the third version also includes an exchange of compartments mechanism and finally, the last two versions of the algorithm with two local search procedures. The first one is an intra-route local search method, and the second one is a local search inter-route method. Generally, the last version of the algorithm (V3,2) is the most robust algorithm version. Therefore, this is the version to be incorporated into the DSS.

Despite positive results found in preliminary tests, the main contribution of this work is to offer to the company a DSS for route planning without any additional cost. This enables fast and efficient planning of the entire distribution sector. Currently, route planning is an automatic process that can be validated by the distribution manager. Real-world situations have a lot of unpredictable variables and, for this reason, any output of DSS may need human validation. Additionally, the DSS allows the company to monitor with detail the distribution activity.

Future work may include: the extension of the analyzed period to be used as an instance for computational experiments; the incorporation of multi-depot variant into the algorithm; the distinction between hard and soft time windows, and thus the user could choose if the time windows must be respected or if the time windows should be respected. The future work referred to above will increase the complexity of algorithms. Therefore, more efficient methods should be implemented to tackle that complexity.

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