A CONSTRUCTIVE HEURISTIC FOR THE MULTI-COMPARTMENT VEHICLE ROUTING PROBLEM: AN APPROACH FOR A FUEL DISTRIBUTION COMPANY

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ABSTRACT

In this paper, we suggest a Decision Support System (DSS) for route planning. This DSS was developed in a real context in a fuel distribution company. This company distributes three types of fuel through multi-compartment vehicles with limited capacity, and satisfying delivery time windows imposed by the customers. Two approaches for this problem were considered: the first one considers the route planning without replenishments while the second one considers the multi-trip case. The solution method is based on a Clarke and Wright savings algorithm incorporating all the constraints referred to above. Both approaches were tested using real instances. The savings for the company, in terms of the distribution process, were identified in the computational results. The DSS may provide an effective support to a complex decision problem.

Keywords: Vehicle Routing Problem, Multi-compartment, Multi-trip, Decision Support System

1 INTRODUCTION

The competition growth in the industrial sector is creating new challenges for the companies. It is essential for companies to boost their operational efficiency. In this paper, the focus is given to the distribution sector, namely the fuel retail distribution.

Naim, Potter, Mason and Bateman[1] cited that transportation is a key function in the supply chain as it acts as a physical link between customers and suppliers, enabling the flow of materials and resources. According to Reimann, Doerner and Hartl [2] goods distribution contributes approximately 20% to the total average costs of a product. This is caused by the fact that transportation occurs between any two subsequent members of a goods' supply chain and also between the chain and the final consumers. Both companies and academic researchers have recognized the huge potential for optimization in this area.

Finding efficient vehicle routes is a representative logistics problem which has been studied for the last 50 years. Formally, the majority of problems in the domain of goods distribution can be analyzed as Vehicle Routing Problems (VRP). Generically, the objective of the VRP is to find a set of routes that minimize the total distance traveled, starting and ending at the same depot and satisfying all the customers' requirements. The number of customers with geographical locations and demands are previously known. The total demand of all costumers on a route must not exceed the vehicle capacity and each customer is visited just once, referred by Reimann et al.[2].

This paper deals with a real VRP, and it was developed in an industrial environment of a Portuguese company. Its core business is the fuel stations and the fuel resale. This company delivers to the customer three types of diesel: road, agricultural and heating fuel.

This company belongs to a group of small and medium enterprises. Usually, these companies have more access difficulties to DSS, rather than big companies. The high acquisition costs or lack of internal know-how to develop such tool in-house are the main reasons. These reasons motivated the development of this project aiming to provide support in developing improved daily distribution plans for the company.

This paper is organized as follows. Section 2 presents a literature review on VRP and particularly the VRP with fuel distribution. Section 3 presents the real company problem. Section 4 describes the solution method. Section 5 presents the developed DSS and the computational experiments. Results are discussed in Section 6. Finally, Section 7 reports the main conclusions and final considerations regarding future developments.

2 LITERATURE REVIEW

Laporte, Gendreau, Potvin and Semet [3] define the VRP mathematically as graph $\mathrm{G} = (\mathrm{V}, \mathrm{E})$ where $\mathrm{V} = \{0, \dots, \mathrm{n}\}$ is a vertex set and $\mathrm{E} = \{(\mathrm{i}, \mathrm{j}) : \mathrm{i}, \mathrm{j} \in \mathrm{V}, \mathrm{i} \neq \mathrm{j}\}$ represents an edge set. Vertex 0 is a depot while the remaining are the customers. To each vertex of $\mathrm{V} \backslash \{0\}$ is associated a demand $\mathrm{q_i}$ and to edge (i, j) is associated a cost or length $\mathrm{C_{ij}}$, since $q_i, C_{ij} \geq 0$. The VRP consists in designing m vehicle routes, each one starting and ending at the same depot, such that each customer is visited exactly once. In some versions of the problem, m is fixed *the beginning*, while in others, it corresponds to a decision variable.

Rizzoli, Montemanni, Lucibello and Gambardella [4] referred that the elements that define each model of the VRP are: the road network, as it describes the connectivity among customers and depots; the vehicles because they transport goods between customers and depots on the road network and the customers, which place orders and receive goods. However, in real-cases, these elements can represent some VRP's constraints. Combining several elements of the problem, we can define a whole family of different VRPs. The most common variants of VRP are the *capacitated vehicle routing problem* (CVRP), Rizzoli et al. [4], Toth and Vigo [5], and the *vehicle routing problem with time windows* (VRPTW), Rizzoli et al. [4], Toth and Vigo [5], Mester and Bräysy [6]. Additionally, in this context it is important to address the following variants:

- According to Mendoza, Castanier, Guéret, Medaglia and Velasco[7], when products are incompatible and must be transported in independent vehicle compartments we have a *multi-compartment vehicle routing problem* (MCVRP). This variant usually arises in the collection of different types of milk, petroleum companies also deliver different types of fuel to outlet retailers using multi-compartment vehicles, the use of trucks with compartments to perform selective waste collection, and food companies distribute groceries that require different levels of refrigeration in compartmentalized vehicles.
- Several times for small deliveries or distribution in the city center, for example, small vehicles are generally preferred. Because of this capacity limitation, they daily perform several short tours. This problem is also a variant of classic VRP, and it is generally referred to as the multi-trip VRP (MTVRP), as it was cited by Cattaruzza, Alsi, Feillet and Vidal [8].

Note that in all variants the main goal is to minimize overall cost or traveled distance.

2.1 Solution Methods

VRPs are usually modeled using graphs or networks and formulated as mixed-integer programs (MIPs). Regarding solution methods, there are two fundamental approaches: exact and heuristics, cited by Drexl [9].

The exact approach is based on mathematical programming algorithms and, theoretically, guarantees to find an optimal solution, if one exists. The most successful exact algorithms for VRPs are *branch-and-cut-and-price* methods. However, this approach typically requires too much time and memory for large instances, Drexl [9]. According to Drexl[9] real-world instances with many complex constraints and a realistic number of requests are still intractable with exact methods.

According to Laporte el al. [3] and Drexl [9], heuristics do not offer an optimal guarantee, but they are able to find close-to-optimal solutions in short time, even for very large instances. The heuristic method can be divided into two classes: constructive and improvement methods. The first one is used to compute an initial feasible solution. The most well-known constructive heuristics are Nearest Neighborhood Search algorithm and Clarke and Wright savings algorithm. The improvement heuristics try to improve a given solution by the modification of the current solution iteratively by performing local searches for better neighboring solutions. These methods perform a relatively limited exploration of the search space and generally produce good quality solutions, within reasonable computing time. Moreover, most of them can be easily extended to account for the diversity of real-world situations. Therefore, they are widely used in commercial packages. The use of metaheuristics has emerged since they are superordinate procedures that control the search processes performed by constructive and improvement heuristics, specifically exploring the most promising regions of the solution space. Normally, they produce the solutions with higher quality than the ones obtained by heuristics. However, the computing time can be increased.

2.2 Fuel transportation

Several versions of the VRP applied to the fuel transportation petrol have attracted the interest of researchers over the last decades, mainly associated with the station replenishment problem. In this section, we present a brief review of the published literature dealing with this problem.

Table 1 - Main characteristics of fuel distribution VRP problems, adapted from Cornillier, Boctor and Renaud[11].

Contribution	Limited Fleet	Homogeneous fleet	Time-windows	Depots Number	Customers visited by route	Multi-trip	Exact Approach
Brown and Graves[12]	Yes	No	No	Several	Several	yes	No
Avella, Boccia and Sforza[13]	Yes	No	No	One	Several	No	Yes
Ng, Leung, Lam and Pan[14]	Yes	No	No	One	Several	No	No
Cornillier, Boctor, Laporte and Renaud[15]	No	No	No	One	Up two	No	Yes
Cornillier, Boctor, Laporte and Renaud [16]	Yes	No	No	One	Up two	No	No
Cornillier, Laporte, Boctor and Renaud[17]	Yes	No	Yes	One	Up four	Yes	No
Cornillier et al.[11]	Yes	No	Yes	Several	Up six	Yes	No

The first author to address the VRP applied to a fuel transportation problem was Dantzig and Ramser [10] in 1959. This was also the first VRP publication followed by a huge number of contributions in this field. Table 1 summarizes main contributions in the area, highlighting problem main characteristics. These issues are commonly addressed in real-case problems in this field.

This problem is closely related with MCVRP, due to the different types of fuel currently transported by these companies. It was observed that the majority of articles approach this VRP variant, although, only two takes into account time windows, and just three consider the multi-trip case. We can conclude that the contribution which includes the highest number of variables is Cornillier et al. [11]. However, the number of customers visited on each trip is limited to six. Additionally, due to problem complexity, only two papers present exact approaches to solve this problem.

3 PROBLEM DESCRIPTION

In this work, we address the case of a Portuguese company that delivers fuel in the north of Portugal. Three types of fuel are distributed using a heterogeneous fleet composed by 4 multi-compartment vehicles with different capacities.

The company receives daily orders to be scheduled for the next day. In these orders, the customer specifies the product type and the required quantity, the interval of time in which the delivery may occur (time-window) and the delivery location. Currently, the distribution plan is carried out for the next day but, very often, in the early afternoon, the plan is revised to accommodate new requests received during the morning period. This planning is empirically carried by a distribution manager and routes are defined by drivers.

Although the company has 4 vehicles, normally only two drivers are attached to the transport task. Frequently, the same driver returns to the depot to reload and start a new route.

In summary, the main issues of the problem are: 4 different vehicles with compartments; 3 types of products; 2 drivers; one depot and a set of customers, each one with a given geographical location, a given demand, and a given time window. Normally, the number of customers never exceeds the 25 in each planning. Thus, we can conclude that the problem has limited capacity, time windows, multi-compartment and multi-trip is considered.

4 SOLUTION METHOD

Due to the complexity of the problem, we suggest a constructive approach based on the well-known Clarke and Wright savings algorithm [18].

According to Cordeau, Gendreau, Laporte, Potvin and Semet[19], the Clarke and Wright [18] savings algorithm is one of the most well-known constructive algorithm and nowadays is still widely used. This algorithm scores very high on simplicity and speed, it has not parameters and it is easy to code.

4.1 Constructive heuristic

The Clarke and Wright [18] savings algorithm has two versions: the parallel and the sequential version. In our constructive approach, the parallel version is used due to its performance, as it was suggested by Cordeau et al.[19]. We consider the undirected case, i.e., $i < j$, where $C_{ij} = C_{ji}$. The algorithm was implemented in the following steps:

Step 1 Savings calculation: $\mathrm{S_{ij} = C_{i0} + C_{0j} - C_{ij}\ \ i, j = 1, \ldots, n \text{ and } i < j}$;

Step 2 Create *n* routes $(0, \mathrm{i}, 0)$ for $\mathrm{i} = 1, \ldots, \mathrm{n}$.

Step 3 Order the savings in a 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}, determine whether 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.

When two single customers are merged, the first free vehicle (starting from the vehicle with higher capacity) is assigned to the route.

A feasible merge is performed when all capacity constraints and time windows are satisfied.

Note that we assume a solution with no visited customers as a feasible solution, once the company as the same assumption. If this happens, the customer is assigned to the following plan, providing that the time window constraint is always satisfied.

5 DECISION SUPPORT SYSTEM

We developed a decision support system with VBA *Excel* using Visual Basic Language from *Microsoft*. The *Microsoft Excel* was considered by the company as the most convenient solution, once the company is already familiar with this *software*. The inputs of this DSS are the symmetric distance matrix with all customers identification; customers demand (quantity and product type); time windows; service and loading time, and vehicle data to be included in the plan (vehicle number, consumption, the number of compartments and their capacity).

The main output is a set of routes, each one assigned to a vehicle. However the developed DSS also returns a set of complementary information associated with each route, as the arrival and departure time for each customer and for the depot; waiting time in each customer; route length (in Kilometers); fuel consumption (in Liters); route time; quantity and type of product assigned to each compartment of each vehicle and the vehicle usage.

5.1 Computational Results

In order to validate solutions produced by the DSS, data from the case study was collected for 10 days, from January 30th to February 9th 2017 (February 5th was a Sunday and therefore there were no deliveries). During these days, the drivers reported the traveled routes, the used vehicles, and the traveled distance. Using this information and the list of deliveries for each planning period, it is possible to compute all parameters.

Four performance indicators have been used to assess the overall performance of the distribution system and in order to validate and compare obtained solutions: distance traveled (in Kilometers); time spent on distribution (in Hours); the level of service and the average vehicle usage. As the level of service, we consider the percentage of customers' orders delivered. In order to approximate as close as possible to the real scenario, in each planning we consider: a set of vehicles used in the real scenario; an average speed of 55Km/h; a loading time of 20 minutes; service time of 15 minutes and depot opening time from 8a.m until 7p.m. Note that times and average speed are based on the collected data in the referred to above period.

Relatively to the algorithm in a first stage we develop a relaxed version of the algorithm, we consider time windows and multi-compartments. And in a second stage, we incorporate multi-trips into the algorithm. Algorithms were tested using real instances and results from computational experiments are compared and discussed in the next sections.

5.1.1 Version 1

In this version, successive planning was performed, with the not visited customers until all of them are assigned to a route, ensuring that time windows constraints are satisfied. Then we were able to compare the two sets of obtained results with the real instances.

Table 2 – Results of version 1 and comparison to the real-case.

Parameters	Real-case	Version 1	Absolute difference	Percentage difference
Distance traveled (kilometers)	2886,5	2911,8	25,3	1%
Time spent on distribution (Hours)	133,7	119,8	-13,9	-12%
Level of service	95%	95%	0%	
Average vehicle usage	57%	65%	8%	

As we can see in Table 2, the version 1 of algorithm presents a global solution close to the real results. The traveled distance is slightly larger, the level of service remained unchanged while the others parameters exhibit a somewhat better performance, time spent on distribution decreases 12% and average vehicle usage increase 8%.

5.1.2 Version 2

In the second version of the algorithm, successive planning may not be performed as in the previous version, since the vehicles may carry out several routes (multi-trip).Table 3 shows the performance of version 2 in comparison with real-case results.

Table 3 - Results of version 2 and comparison to the real-case.

Parameters	Real-case	Version 2	Absolute difference	Percentage difference
Distance traveled (kilometers)	2886,5	2655,5	-231,0	-9%
Time spent on distribution (Hours)	133,7	108,6	-25,1	-23%
Level of service	95%	97%	2%	
Average vehicle usage	57%	57%	0%	

This second version presents better performance in all parameters when compared to the real case, with exception of the average vehicle usage which is the same. However, the traveled distance decreases 9% and the service level increases 2%.

Note that the computation time was much reduced, providing results in milliseconds.

6 DISCUSSION

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 worse performance when compared to the results of real-case in terms of traveled distance. This is due to the shortest planning horizon. In many cases, as we did not consider the possibility performing multi-trips, the first saving values were wasted due to the lack of capacity or to the time windows constraints.

In general, as shown in Tables 2 and 3, the version 2 of algorithm presents better results in all parameters when compared with version 1 and with the results of real-case, with only one exception. The vehicle usage never increases in the second version. However, and during the analyzed period, an overall saving is found in this version. Thus, we can conclude that this is the best possible solution for the company, within the studied solutions.

The comparison period is short, so for a better perception of the effective savings that this tool can generate, we estimate the potential saving of the developed DSS in one year may be up to 5900 Kilometers, 1700 Fuel liters and 640 work hours. These values were calculated for 258 working days per year. This is the number of days of distribution in the company during the year 2016.

7 CONCLUSION

In this paper, a constructive heuristic for a multi-compartment VRP problem arising in the real world is suggested. Some real constraints are considered such as the limited capacity, time-windows, multi-compartments and two different approaches: one version without replenishments while the second one considers the multi-trip case.

The presented results show a better performance of the algorithm when considering multi-trip against the other version, and against the real-case. However, the main contribution is to offer to the company a DSS for route planning without any additional cost. This may enable a fast and efficient planning of the entire distribution sector. The route planning can now be an automatic process. However, the real-world situations have a lot of unpredictable variables and, for this reason, any output of DSS may need human validation.

As a future work, some improvements can be performed in the user interface before the implementation of the DSS at the company. Thus, it would be easily managed by the distribution manager. The incorporation of improvement heuristics into the algorithm may generate better results.

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