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OPTIMIZATION OF VEHICLE ROUTES: AN APPLICATION TO LOGISTIC AND TRANSPORT OF THE FUEL DISTRIBUTION

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ABSTRACT: *Fuel distribution companies serve their customers with fleets of vehicles which have several compartments, each compartment being dedicated to one product. Each customer has his own time period and only during this period the service can be accepted. The demand of each customer can be contain one or more products. The objective is to determine a set of routes that respect all capacity and time constraints, serve all customers and minimize the number of vehicles and total distance traveled of all routes. According to this real world problem, a mathematical model is established for the multi-compartment vehicle routing problem with time windows (MC-VRPTW). A Tabu search method is developed to solve this problem. The proposed method has been tested on Solomon's VRPTW instances and on real data provided by the company.*

KEYWORDS: *Logistic, Tabu Search, VRPTW, Optimization, Supply Chain, Fuel Delivery.*

1 INTRODUCTION

The fuel distribution VRP problem is a complex combination optimization problem. It consists to optimize the delivery of several fuel products to a set of fuel stations over a given planning horizon. More specifically, one must determine, for each day of the planning horizon, with which transportation asset and at what time each of the products will be delivered to each station, how to load these products into vehicle compartments and how to plan vehicle routes. In a deployed road network region, knowing the fuel type (Gasoline, petroleum and Kerosene), geographical positions of depots and fuel stations and the quantity for each fuel demand, we need to distribute the fuel to each fuel station by choosing as far as possible few vehicles under the time and compartment constraints, and the high secure conditions. The objective is to optimize the delivery of fuel products to a set of fuel stations using a limited fleet of vehicles (tank-trucks). More specifically, one must determine the assignment of fuel products to the available vehicles, delivery routes and schedules. The problem intensifies from a practical perspective when the fleet is hired, that is, the vehicles do not constitute company assets. In such cases, effective planning is a critical success factor for operational efficiency and for the resulting service level, since non-company resources are responsible for the physical interface with the final customer.

Nowadays, many companies subcontract the replenishment of their fuel distribution stations to private fuel transport companies. For companies that have a large number of deliveries, hiring vehicles may be more expensive per unit distance traveled, but maintenance costs do not occur. The latter is the main reason why more and more companies use hired fleet or allocate the distribution function to third party logistic providers.

The objective of this paper is to solve fuel distribution problem over a given geographical territory including one depot and set of fuel stations. The depot stores the different fuel types which must be delivered to fuel stations by a fleet of vehicles. The vehicles are heterogeneous and have several compartments, each compartment can bring any product, but different products must not be mixed in one compartment. The products ordered by each fuel station are known and can be delivered by only one single vehicle. The service at any customer starts within a given time interval, called a time window. A major difference between this problem and most fuel distribution VRP problems is the handling of both compartments and time windows constraints and taking into account accessibility restrictions, that is, some fuel stations cannot be served by some vehicles. Therefore, to the best of our knowledge, this problem is studied for the first time.

This problem is motivated by a real case faced by the biggest fuel company in Algeria, which has sixty (60) depots located in Ten (10) Districts, all over the country, that deliver several fuel type to more than two thousand (2000) customers (fuel stations) using around nine hundred (900) vehicles, not necessary belong to the company, that deliver more than ten (10) million cubic meters at year. The project started with an agreement between the university and the company to evaluate their fuel distribution operation. In terms of distribution, the company has made various efforts to improve efficiency, one of which is to do a leasing system in the management of vehicles for fuel delivery. With this leasing system, the company leases vehicles from a third party, whereas the operation of these vehicles in the process of distributing fuel from depots to fuel stations is managed by the company. However, the effort to increase efficiency is not followed by good transportation management.

To optimize the distribution activity, it is necessary to design a system that can assist the company, in a daily basis, in determining the assignment and routes of the fleet in distributing the fuel products to each fuel station. The determination of routes and scheduling of fuel delivery to the fuel stations can be modeled as a variant of vehicle routing problem with time windows, called the Multi-Compartment Vehicle Routing Problem with Time Windows (MC-VRPTW), which in this study will be completed by the Tabu Search algorithm.

The work that this distribution carries out can be shown as follows: each depot receives the fuel from refinery; store it to be delivered by a fleet of vehicles to customers, which locate in the same district as the depot. Before every delivery, each customer must call the scheduler at the plant where it belongs, to order the fuel for the next days, with the corresponding temporal restrictions. Based on this information, the schedular determines determine the routes for the delivery of all the demanded products, assign these routes to vehicles, determine the time schedule for each of the vehicles, determine the quantities to be delivered by each route, and how to assign these quantities to the compartments of the vehicle selected for the route. This process is repeated until the end of the day, where the scheduler has a final delivery program for the next day, which includes vehicle availability and load assignment. For the customer, this demands calendar becomes a contractual agreement that fixes the quantities ordered of each product, dates and times during which it must be served. The depot uses these agreements to develop the supply plan, which is not imposed in the proposed version. Moreover, it's from this latter plan and considering these demands calendars of customers that the distribution plan can be established.

The rest of this paper is organized as follows. In Section 2, we present a brief review of the literature related to fuel station replenishment problems. In section 3, we describe the mathematical model of the fuel distribution problem. Section 4, present the Tabu Search Algorithm and its components. Then, we report computational results for the real data and Solomon's VRPTW instances test sets in section 5. Finally, we present our conclusions and discus some further research in 6.

2 LITERATURE REVIEW

While many extensions of the classical vehicle routing problem (VRP) were studied extensively in the literature like time windows, distance constraints, backhauls or variants involving pickups and deliveries leading to the research area termed as rich vehicle routing problems, published research regarding compartments and time windows is quite rare.(Derigs et al., 2010) mentioned the published papers concern the vehicle routing problem with compartments and its usage over practical applications, like the distribution of food or fuel, waste collection. Also, (Mendoza et al., 2008),(Mendoza et al., 2009) and (Mendoza et al., 2010) mentioned comprehensive surveys on multi-compartment VRPs and solution methods.

Most of these published papers concern fuel distribution, i.e. the compartments are tanks which can receive different fuel types. In this section, we present a brief review of the published literature dealing with the different versions of the fuel distribution problem in a chronological order.

One of the first papers was published by (Brown and Graves, 1981), who have considered the problem of direct deliveries (i.e. single-customer trips) and time windows, while (Brown et al., 1987) have developed a computerized assisted dispatch system for Mobil Oil Corporation in the United States. The dispatching procedure used by the system was an extension of the one presented by (Brown and Graves, 1981), but allowed visiting more than one customer per trip. (Van der Bruggen et al., 1995) solved the single period version of the problem as part of a broader study aimed at optimizing the distribution network of a large oil company operating in the Netherlands. They suggested some simple models to assign clients to depots, to determine the fleet size and composition and to restructure the depots network. Several greedy heuristics followed by simple improvement procedures for the multi-period problem have been proposed by (Taqa allah et al., 2000). They proposed two heuristics for constructing fuel station replenishment plans for the case in which there is only one depot, an unlimited homogeneous tank truck fleet, and no time windows.

In 2002, (Ben Abdelaziz et al., 2002) have presented a real-life routing problem in which a variable neighborhood search heuristic was applied to solve a single period fuel products delivery problem using a heterogeneous fleet of compartmented tank trucks.

(Malépart et al.,2003) have generalized this problem by allowing the delivery of more than one station in a same trip. They proposed four heuristics for constructing replenishment plans over a horizon of several working days. Their heuristics were tested using some real-life problems obtained from a transport company in eastern Quebec. Also, (Rizzoli et al.,2003) has described a software tool, based on an ant colony heuristic, which assists dispatchers during the different stages of fuel distribution.

(Avella et al.,2004) have proposed a heuristic and an exact algorithm based on a route generation scheme and a branch-and-price algorithm to solve a similar problem. They studied a fuel replenishment network involving one depot, heterogeneous tank truck fleet, and no time windows.

(Ng et al. 2008) studied two small fuel distribution networks in Hong Kong. They proposed a model for simultaneously assigning trips to trucks and stations.

Recently, Cornillier, Boctor, Laporte and Renaud published three articles about the fuel station replenishment problem with one depot. In the first article, an exact algorithm was proposed to solve the single period case with unlimited heterogeneous truck fleet but without time windows (Cornillier et al., 2008a). In the second article, heuristics for the multi-period case with limited heterogeneous truck fleet and no time windows were proposed (Cornillier et al., 2008b). In the third article, two heuristics were proposed for the problem in which a limited heterogeneous fleet of tank trucks is used to replenish a set of stations with specified time windows (Cornillier et al., 2009).

3 MATHEMATICAL MODEL

In order to obtain the most cost/time efficient manner of transporting fuel to customers, we will need to solve the Multi-compartment Vehicle Routing Problem with Time Windows (MC-VRPTW). The model satisfies: (1) Single depot: every vehicle starts and returns to this depot. (2) Vehicles have several compartments: each compartment is dedicated to one product. (3) All products delivered on a route must be assigned to compartments of the vehicle, (4) Consider the vehicle and compartment capacities constraints, (5) Consider the possibility to bring the different products ordered by a customer using several vehicles, (6) when a vehicle arrives at a customer location before its earliest service time, the vehicle must wait until the service is possible. If the vehicle arrives late, a penalty for lateness is incurred. The problem considers as the primary objective the minimization of the number of vehicles and secondarily the minimization of total distance traveled of all routes.

To simplify the problem, we define the sets, parameters and variables used in the problem formulation as follows:
N: Number of customers.
$V = N \cup \{0\}$ Where 0 represents the depot.
K: Number of vehicles that can be used.
P: Number of products.
Q: Number of compartments.
c_{qk}: Capacity of compartment q for the vehicle k.
C_k: Capacity of vehicle k.
d_{ip} : Demand of customer i for the product p.
s_i: Service time at customer i.
t_{ijk}: Travel time of vehicle k from customer i to customer j.
a_i : Earliest start time for servicing the customer i.
b_i : Latest start time for servicing the customer i.
d_{ij} : Distance between the customer i and customer j.
C_{ijk} : Cost spent by the vehicle k from customer i to customer j.
x_{ijk} : Equals 1, if i precede j in the route of vehicle k, 0 otherwise.
y_{ikp} : The 0-1 variables take value 1 if and only if customer i receives product p from vehicle k.
z_{pqk} : The binary variables indicate whether product p is assigned to compartment q on vehicle k.
s_i : Specifies the arrival time at i when serviced by vehicle k. In case of vehicle k doesn't service customer i. s_i has no meaning and consequently its value is considered irrelevant.
With this notation, constraints and the objective function of the mathematical model can then be formulated as follows:

3.1 Constraints and Interpretations

3.1.1 The Delivery Constraints

All customers must be served at most once by each route, i.e:

$$\sum_{i \in V} x_{ijk} \leq 1, \forall j \in N, \forall k \in K \tag{1}$$

The continuity of each route is ensured as follows:

$$\sum_{i \in V} x_{ijk} = \sum_{i \in V} x_{jik}, \forall j \in N, \forall k \in K \tag{2}$$

3.1.2 The Vehicle and Compartment Constraints

A vehicle can only be loaded up to its capacity, i.e:

$$\sum_{p\in P}\sum_{i\in N} d_{ip} \sum_{j\in V} x_{ijk} \leq C, \forall k \in K \quad (3)$$

The products loaded into compartments on a given vehicle do not exceed the compartments capacities:

$$\sum_{i\in N} d_{ip} y_{ikp} \leq \sum_{q\in Q} c_q z_{pqk}, \forall k \in K, \forall p \in P \quad (4)$$

Each compartment is dedicated at most to one product by each route:

$$\sum_{p\in P} z_{pqk} \leq 1, \forall k \in K, \forall q \in Q \quad (5)$$

Each product ordered by customer is brought by one single vehicle:

$$\sum_{k\in K} y_{ikp} = 1, \forall i \in N, \forall p \in P \quad (6)$$

If the customer i is not visited by vehicle k, we set the variable to zero for each product p, as follows:

$$y_{ikp} \leq \sum_{j\in V} x_{ijk}, \forall i \in N, \forall k \in K, \forall p \in P \quad (7)$$

3.1.3 The Scheduling Routes Constraints

The relationship between the vehicle departure time from a customer and its immediate successor is established as follows:

$$x_{ijk}(s_{ik}+t_i+t_{ij}-s_{jk}) \leq 0, \forall i \in V, \forall j \in V, \forall k \in K (8)$$

This constraint can be linearized as:

$$s_{ik}+t_i+t_{ij}-M_{ij}(1-x_{ijk}) \leq s_{jk}, \forall i \in V, \forall j \in V, \forall k \in K (9)$$

The large constants M_{ij} ($M_{ij} > 0$) can be replaced by $max\{b_i+t_i+t_{ij}-a_j, 0\}, i, j \in N$.When $max\{b_i + t_i + t_{ij} - a_j, 0\} = 0$, these constraints are satisfied for all values of s_{ik}, s_{jk} and x_{ijk}.

3.1.4 The Time Window Constraints

The time window constraints are formulated as follows:

$$a_i(\sum_{j\in V} x_{ijk}) \leq s_{ik} \leq b_i(\sum_{j\in V} x_{ijk}), \forall i \in N, \forall k \in K \ (10)$$

$$a_0 \leq s_{0k} \leq b_0, \forall k \in K \quad (11)$$

3.1.5 The Integrity and non Negativity Constraints

Constraints (12) - (15), define the decision variables, which are all binary except for the variables s_{ik}.

$$x_{ijk} \in \{0,1\}, \forall i \in V, \forall j \in V, \forall k \in K \quad (12)$$

$$y_{ikp} \in \{0,1\}, \forall i \in N, \forall k \in K, \forall p \in P, d_{ip} \neq 0 \quad (13)$$

$$z_{pqk} \in \{0,1\}, \forall p \in P, \forall q \in Q, \forall k \in K \quad (14)$$

$$s_{ik} \geq 0, \forall i \in N, \forall k \in K \quad (15)$$

3.2 Objective Function

The proposed model minimizes the sum of the travel costs over all routes, as follows:

$$min \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_{ij} x_{ijk} \quad (16)$$

Subject to: (1)→(15)

4 DESIGN OF ALGORITHM

Due to the complexity of solving the MC-VRPTW, the Tabu search algorithm is proposed to tackle the fuel distribution problem in practice. A Tabu search method is an iterative heuristic procedure for solving complex combinatorial optimization problems, based on the idea of moving step by step, from an initial candidate solution towards a solution giving the minimum value of some objective function, with a special feature designed to avoid being trapped by local minima. Tabu search was initially proposed by (Glover, 1989). The memorization of the visited solutions is simply performed by memorizing the sequence of applied moves. This is a characteristic aspect of Tabu search methods, whose main novelty is the use of flexible memory systems, taking advantage of the history of the search. The previously described memory is the so-called short-term memory. A second kind of long-term memory can also be implemented. Two important main long-term memory concepts that can be considered are intensification and diversification mechanisms. Intensification mechanism is based on the idea to encourage move combinations and solution features historically found to be good, returning towards attractive regions to search them thoroughly. Diversification mechanism, on the other hand, is designed to drive the search into new promising regions. A simple approach to perform this is to measure how many times a move has been chosen during the search, i.e. measuring the absolute frequency of a move. Summing up, the performance of Tabu search depends on a proper choice of the neighbor of a solution, on the number of iterations for which a move is kept as Tabu, on the best combination of short and long-term memory and on the best balances of intensification and diversification mechanism.

4.1 The Construction Routes Heuristic

The proposed Tabu search starts from one initial feasible solution and improve it. This solution is built by using the construction routes heuristic inspired by the nearest neighborhood principle.

The principle behind this heuristic is that, every route is started by finding the un-routed customer that is closest to the depot. The closeness relation tries to take both temporal and geographical closeness of the customers into account. At every subsequent iteration the customer closest to the last customer added to the route is considered for insertion to the end of the route presently generated. Before adding a customer to the route, the heuristic checks the constraints of vehicle capacity and the requirement of time window. When the search fails a new route is started. Note that the insertion costs are evaluated in terms of distance and service time.

In the following, for the sake of clarity, we summarize the main steps of the proposed heuristic:

0. *Initially, the customers are collocated according to their earliest times* a_i.
1. *For each vehicle* $k \in K$ *do:*
2. *Search one un-served customer i witch satisfy:*
2.1. *The least early time* a_i *.i.e.*

$$a_{min} = Min_{i \in N}\{a_i\}. \tag{17}$$

2.2. *The arrival time at i must be:*

$$a_i \leq s_i = s_{i-1k} + t_{i-1} + t_{i-1i} \leq b_i. \tag{18}$$

2.3. *The least distance to the last customer added to the route.*
3. *Add this customer to the route and adjust the set of customers* $N = N \setminus \{i\}$.
4. *While not violate the capacity constraints, go to step* 2.
5. *When all customers are arranged, finish the process. Otherwise, return to step* 1.

4.2 The Neighborhood Structure

After obtaining an initial feasible solution, the neighborhood search procedure is proposed to improve it by exploring the solutions space. At each iteration, the best non-tabu move in the neighborhood $N(S)$ is selected to move from the incumbent solution S to the best solution $S*$.

Neighborhood search improvement procedure applies 2-Opt* and Or-opt methods with slight modifications. The 2-Opt* neighborhood is applied in the inter-route improvement and uses a neighbor list to prune the neighborhood search heuristically. The list is determined on the basis of distance. The Or-opt neighborhood is applied in the intra-route improvement.

In Section 4.2.1, we describe the neighbor lists that take into account the time windows, and in Section 4.2.2, the details of the neighborhoods are described.

4.2.1 The Neighbor List

The interest of having a neighbor list for each customer i is that the set of customers preferable to visit immediately after i can be used by the neighborhood search procedure when we move from a solution to another. Our approach uses the *neighbors-customer heuristic* described bellow, to computes these values once at the beginning and stores the best $N(i)$ customers as a neighbor list of i.

Neighbors-Customer Heuristic:

1. *Repeat step 2 for each customer* $i = 1, ..., N$.

2. *Do :*

2.1. *Find the average distance :*

$$\overline{d_i} = \sum_{j \in N, j \neq i} \frac{d_{ij}}{N-1}. \tag{19}$$

2.2. *Find the variance :*

$$\delta_i^2 = \sum_{j \in N, j \neq i} \frac{(d_{ij} - \overline{d_i})^2}{N-1}. \tag{20}$$

2.3. *Deduce the standard deviation :*

$$\delta_i = \sqrt{\sum_{j \in N, j \neq i} \frac{(d_{ij} - \overline{d_i})^2}{N-1}}. \tag{21}$$

2.4. *Deduce the parameter* a_i*:*

$$a_i = \overline{d_i} - \frac{\delta_i}{2}. \tag{22}$$

Where $\overline{d_i}$ is the average distance of the customer i, d_{ij} the distance between i and j and δ_i is the standard deviation of the customer i.

In this section, we aim at providing a distance associated to the neighborhood search procedure. The proposed distance, is defined on the basis of the measures of dispersion. This definition verifies the mathematical conditions:
• $d_{ij} \geq 0, \forall i, \forall j$
• $d_{ij} \leq a_i, \forall i, \forall j$
Where the parameter a_i is defined as the half of the interval $[\overline{d_i} - \delta_i, \overline{d_i}]$ which is equal to: $a_i = \overline{d_i} - \frac{\delta_i}{2}$.

With this parameter, the neighborhood $N(S)$ of a solution S defined by the exchanges procedures can be described as the set of all the solutions which are at a distance less than or equal to its value. So, The best choice of such value a_i from this interval is very important to define the neighborhood for a given customer.

This value of a_i was taken on the basis of our knowledge that if we add and subtract two standard deviations from the mean, we should find that nearly all of the scores (which are customers in our study) will fall between those two numbers $[\overline{d_i} - \delta_i, \overline{d_i} + \delta_i]$. Furthermore, The variance poses a slight problem, because when we are using variance we are dealing with squares of numbers. That makes it a little hard to relate the variance to the original data. The way most statisticians choose to do this is by taking the square root of the variance. When this brilliant maneuver was made the great statistics gods named the new measurement standard deviation. With this new measurement, the information derived through the variance can much more easily be applied to the original data.

4.2.2 The Neighborhood

We use the 2-Opt* and Or-opt neighborhoods with slight modifications, wherein we restrict the 2-opt* neighborhood by using the neighbor lists. A 2-opt* operation removes two edges from two different routes (one from each) to divide each route into two parts and exchanges the second parts of the two routes.

The 2-opt* operation always changes the assignment of customers to vehicles. We also use an intra-route neighborhood to improve individual routes, which is a variant of the Or-opt neighborhood. An intra-route operation removes a continuous segment of customers of length $L_{segment}$ (a parameter) and inserts it into another position of the same route, where the position is limited within $L_{insertion}$ (a parameter) from the original position.

Sometimes, solutions generation violate the capacity and time constraints. In the aim of to enlarge the search space by visiting these infeasible solutions, the capacity and time violations are multiplied by two coefficients and the penalized term added to the objective function. The resulting new evaluation function $F'(S)$ is inspired by the one proposed by Gendreau et al. for the VRP (Gendreau et al., 1994):

$$F'(S) = F(S) + \alpha C(S) + \beta T(S). \tag{23}$$

Where $F(S)$ is the routing cost of solution S, $C(S)$ and $T(S)$ are the total over-capacity and overtime of all routes respectively and α, β are two penalty factors. Initially set equal to 1, these parameters are periodically divided by $1 + \rho$ ($\rho \in]0, 1[$) if all previous ϕ solutions were feasible, or multiplied by $1 + \rho$ ($\rho \in]0, 1[$) if they were all infeasible. This way of proceeding produces a mix of feasible and infeasible solutions which acts as a diversification strategy.

4.3 The Tabu List

Tabu list is one of the key factors that determine the quality of a Tabu search algorithm. The most popular Tabu list is constructed by those recently visited solutions, or the moves to a solution. If the size of the Tabu list is too large, it will spend more time to compare with the current solution one by one, but if the size of the Tabu list is too small, it will be very hard to escape from local optima.

In this paper, the Tabu list is implemented as an upper triangular matrix L of $K \times K$ dimensions where each element $L(k, k^{'}), (k, k^{'} = 1, ..., K, k < k^{'})$ is associated to pair of routes k and $k^{'}$. Each element $L(k, k^{'})$ contains a set of attributes able to characterize the solution and also records the iteration in which the arc (i, j) has been removed from the route k to the route $k^{'}$. An arc removed at iteration t is forbidden to be reinserted in the solution until iteration $t + \theta$.

When an exchange between the routes k and $k^{'}$ is accepted, we just change information corresponding to the line k and the column $k^{'}$. Thus, we avoid calculating information above the other pairs of routes which not contain neither k nor $k^{'}$.

The size of Tabu list θ takes its values in $[\theta_{min}, \theta_{max}]$ starting from θ_{init}. The parameter θ is updated according to the quality of the solutions obtained during the recent moves. After each improvement of the current objective function, θ is updated as $\theta = max(\theta - 1, \theta_{min})$, with the aim of intensifying the search around this solution. Otherwise, after ϕ_{LT} consecutive moves deteriorating the value of the visited solutions, the size of the tabu list is updated as $\theta = min(\theta + 1, \theta_{max})$.

4.4 Diversification and Intensification

To make the search strategy fully effective in our Tabu search method, we have included the diversification and intensification features. The purpose of diversification is to widen the set of solutions considered during the search. Intensification consists of accentuating the search in promising regions of the solution space.

Three mechanisms are used for diversifying or intensifying the search of a Tabu search method. The first, described in Section 4.2.2, consists of biasing the evaluation of infeasible moves by adding to the objective function a penalized term.

The second mechanism consists of conducting a limited search on a small number of starting solutions. The full search then proceeds starting from the most promising solution. So, after γ_{max} iterations without improving the best solution found or after ϑ_{max} iterations since the last restart, the search is started with an empty tabu list. Note that the maximal number of restarts is fixed as η_{max}.

Finally, the search is accentuated around the best known solution by increasing or decreasing the size of the tabu list as explained in Section 4.3.

5 COMPUTATIONAL RESULTS

The proposed Tabu search approach is coded in C++ and has been tested on 2.0 GHz PCs with 2 GB memory running under windows XP.
The proposed Tabu search approach introduced relatively few parameters. These parameters values reported in table 1 are chosen after some tests.

Parameter	Value
$L_{segment}$	1
$L_{insertion}$	3
α	1
β	1
ρ	0.3
$\phi = \phi_{LT}$	10
θ_{init}	8
θ_{min}	5
θ_{max}	15
γ_{max}	500
ϑ_{max}	2000
η_{max}	50

Table 1: Parameters used in tabu search algorithm

To assess the effectiveness of our Tabu search algorithm we considered two alternatives solutions approaches for the proposed testing:

Firstly, as no published instances for the MC-VRPTW in the literature, we have tested the behavior of our algorithm for solving standard Solomon's VRPTW instances, i.e. we have interpreted VRPTW data sets as MC-VRPTW instances with one product type and one compartment which is a valid input for our algorithm. Hence, we considered thirty (30) Solomon's VRPTW instances with different characteristics. The instances are divided into six (06) groups (test-sets) denoted R1, R2, C1, C2, RC1 and RC2. Each of the test sets contains five (05) instances. Each instance has one hundred (100) customers. All these instances may be downloaded from (http://www.sintef.no/Projectweb/TOP/Problems/VRPTW/ Solomon-benchmark/).
Table 2 compares the results obtained by the proposed Tabu search algorithm with the best known Solomon's VRPTW solutions. Considering as the primary objective the minimization of the number of vehicles and secondarily the minimization of the total traveled distance, Table 2 shows that we are able to produce solutions with a deviation of distance and number of vehicles from the best-known Solomon's VRPTW solutions around -2.97(%) and -3.06(%) respectively. This is quite remarkable because our algorithm is not specially designed for the VRPTW and the best known VRPTW solutions reported in literature were obtained by using various metaheuristics and settings of parameters.

Secondly, we considered the actual data sets provided by the fuel logistic company. The tests were based on the orders delivered by the customers of Algiers's depot on thirty consecutive working days. The distance data needed in this paper are calculated by Dijkstra Algorithm. The time window of each customer is at in a certain interval in [7, 12], [12, 17], [17, 23] in the day. It's assumed that the service time at each customer is proportional to the amount of his demand. The average speed of vehicles is 60km/h. The plans produced by the human operator in the company were also obtained for each of these thirty days. These plans (referred to as manual plans) contained the orders, the routing sequences and the vehicle identities. The manual plans were not as detailed as the algorithm's plans, in that the arrival, departure and waiting times at each call were in the algorithmic schedules but not in the manual ones. The algorithm automatically hired vehicles if the company had insufficient but none were needed during the thirty days, either in the manual or in the algorithmic solutions.
Table 3 resumes the comparison between the algorithm and manual solutions over a testing period of thirty days.
A significant enhancement in the efficiency of the number of vehicles used can be noticed. Another interesting point is to observe that all the solutions obtained with the algorithm are better than those with the human operator. Moreover, The table 3 shows that the algorithm allows a reduction of 17.68(%) in cost of the traveled distance. We expect to obtain even better results in high demand periods, when the human operator is under pressure because of urgent deliveries and a much greater number of orders have to be delivered.

Problem	Optimal Solution		Our Solution	
	NV	DT	NV	DT
R101	19	1645.79	19	1672.91
R103	13	1292.68	13	1317.35
R105	14	1377.11	15	1388.95
R107	10	1104.66	10	1213.33
R109	11	1194.73	11	1240.96
C101	10	828.94	10	839.87
C102	10	828.94	10	840.01
C103	10	828.06	10	838.07
C104	10	824.78	10	831.29
C105	10	828.94	10	856.45
RC101	14	1696.94	14	1692.15
RC102	12	1554.75	13	1627.46
RC103	11	1261.67	11	1324.93
RC104	10	1135.48	9	1260.97
RC105	13	1629.44	13	1724.93
R202	3	1191.70	3	1198.12
R204	2	825.52	2	823.41
R206	3	906.14	3	930.13
R208	2	726.75	2	754.33
R210	3	939.34	3	940.19
C201	3	591.56	4	791.61
C202	3	591.56	4	593.38
C203	3	591.17	4	610.36
C204	3	590.60	4	613.54
C205	3	588.88	4	592.15
RC201	4	1406.91	4	1408.78
RC202	3	1367.09	3	1370.53
RC203	3	1049.62	3	1051.28
RC204	3	798.41	3	800.03
RC205	4	1297.19	5	1310.33
Deviation from optimality			**-3.06**	**-2.97**

Table 2: Results compared to best-known Solomon's VRPTW solutions

NV: Number of Vehicle used, DT: Distance Traveled

Day	Customers	Vehicle used		Distance (Km)		Cost (u)	
		I	II	I	II	I	II
1	75	12	09	1876	1655	178204	157252
2	68	8	07	1489	1398	141494	132766
3	88	14	11	1510	1416	143469	134499
4	91	14	12	1488	1361	141316	129305
5	56	08	06	999	843	94863	80091
6	61	13	09	1123	1068	106690	101415
7	19	05	03	530	498	50390	47292
8	71	13	09	1240	1107	117832	105137
9	64	13	10	1102	1001	104672	95125
10	59	10	08	1047	1002	99459	95163
11	95	18	15	1829	1724	173767	163782
12	78	17	13	1687	1541	160281	146387
13	73	14	12	1364	1227	129546	116547
14	23	06	04	459	305	43642	28964
15	58	09	08	994	805	94451	76468
16	62	07	05	1250	1032	118734	98007
17	51	08	06	1066	941	101228	89354
18	49	05	05	1113	1092	105772	103777
19	69	10	08	845	695	80277	66035
20	81	11	08	1131	961	107463	91326
21	15	04	03	476	339	45202	32158
22	104	17	13	1818	1469	172733	139522
23	98	13	10	1772	1443	168353	137124
24	84	10	07	1371	1005	130268	95454
25	92	14	12	1000	807	95012	76710
26	93	14	11	2042	1532	194004	145519
27	81	08	06	1932	1646	183584	156390
28	20	06	03	721	513	68488	48713
29	130	21	17	2407	1900	228653	180532
30	123	18	14	2455	1955	233241	185693
Average	**71**	**11**	**09**	**1338**	**1143**	**127103**	**108550**
Reduction							**17.09** (%)

Table 3: Algorithmic and manual solutions

I: Human operator, II: Approach Solution

6 CONCLUSION AND FURTHER RESEARCH

In this paper we considered the MC-VRPTW as a variant of the VRPTW constrained by a composition vehicles fleet (vehicles have several compartments), which is not yet studied in literature in spite of we believe that is a more realistic problem in logistics. A Tabu Search method has been proposed to solve it. The method was tested using two sets of problems. One obtained by adapting 30 known Solomon's VRPTW instances and the other by using real data provided by the company.

As no published method is available for comparison, the performance of our method is evaluated in two perspectives. Firstly, we showed that the method could be used to give good solutions for the standard VRPTW problem. Secondly, it is evaluated through real instances and compared with the plan made by the human operator. The results showed that it can be considered as an advanced logistic system for the fuel distribution. It is compact, fast and easy to use.

The possible extensions of this paper would be to (1) study other heuristics algorithms for comparing the solutions quality for this problem and their computational times (2) propose the parallel methods in the aim to centralize the fuel distribution management on all Districts.

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