

Modelization of Time-Dependent Urban Freight Problems by Using a Multiple Number of Distribution Centers

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Abstract The aim of the paper is to model urban distribution vehicle routing problems by means of hubs in large cities. The idea behind the urban distribution center (DC) is to provide buffer points where cargo and packages which are to be delivered to shops and businesses can be stored beforehand. At these centers, there will be other kinds of routing problems corresponding to other fairly similar distribution problems. In this paper, a new vehicle routing model (based on the known *Time-Dependent Vehicle Routing Problem with Time Windows*, TDVRPTW) has been carried out and a change in the traditional approach is proposed, by adopting a system in which some customers are served by urban DCs while remaining customers are served by traditional routes. This study is also motivated by recent developments in real time traffic data acquisition systems, as well as national and international policies aimed at reducing concentrations of greenhouse gases emitted by traditional vans. By using k DCs, the whole problem is now composed of $k+1$ problems: one special VRPTW for each DC in addition to the main problem, in which some customers and k DC are serviced. The model has been tested by simulating one real case of pharmaceutical distribution within the city of Zaragoza.

Keywords Modelization · Vehicle routing problem with time windows · Time-dependent · Distribution centers

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1 Introduction

As time goes on and because of population increase in large cities, the problems generated by urban freight distribution are getting more and more complicated due to traffic flow, traffic congestion, illegal parking, just-in-time delivery, time constraints, e-commerce and, above all, pollution and environmental impact. Although the literature on solving routing and scheduling problems is very extensive nowadays, almost no models exist that take hubs into account, and so, from the point of view of research, it is still necessary to find ways of resolving the negative effects caused by the above-mentioned points, through an analysis of new delivery strategies and algorithms.

The aim of the paper is to model urban distribution vehicle routing problems by means of hubs in large cities. Hubs are very well known in the literature; they are often used in many scheduling problems and strategy models, like air traffic models, logistic models, etc. Over the last few years, new distribution centers (called Urban Distribution Centers, UDCs or DCs) have appeared within the cities. Finnegan et al. (2005), present a study evaluating sustainable freight distribution in the city center of Dublin, focusing particularly on urban distribution centers and managing the last mile delivery.

The idea behind the urban distribution center is to provide buffer points where cargo and packages which are to be delivered to shops and businesses, can be stored beforehand. At these centers, there will be other kinds of routing problems corresponding to a fairly similar distribution problem. The comparison between both distribution systems is shown in Fig. 1.

One of the main objectives of these centers is related to reducing traffic congestion (caused by the large number of delivery trucks on the streets and because it is not possible to create enough parking places), in zones where problems such as illegal parking lead to reductions in traffic flow. As shops and businesses demand shorter and shorter delivery times, vehicle routing and scheduling problems become harder for distributors. It is recognized that the traditional system based on fixed routes does not fulfil the expectations of trade and may, in some cases, be quite inefficient for distributors.

In this work, a new vehicle routing model (based on the known Time-Dependent Vehicle Routing Problem with Time Windows, TDVRPTW, Huey-Kuo et al. 2006)

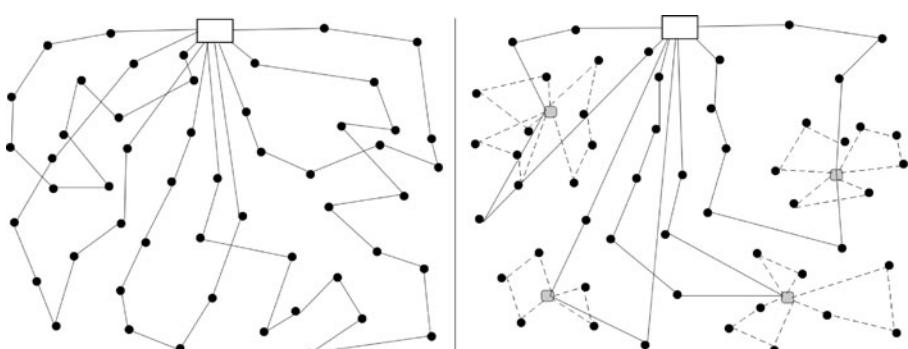


Fig. 1 Direct Delivery vs Delivery using DCs

has been developed and a change in the traditional approach is proposed, by adopting a system in which some customers are served by urban distribution centers (to be more specific, by using, for example, hybrid vehicles) while the remaining customers are served by traditional routes. This study is also motivated by recent developments in real time traffic data acquisition systems, as well as national and international policies aimed at reducing concentrations of greenhouse gases in the atmosphere emitted by traditional vans.

Due to the fact that the density of shops differs greatly in central districts of a city compared to the outskirts, not all shops are serviced by routes starting at the hub. For this reason, it is suggested that the DCs be located in areas where there is a high density of shops and that in other areas, deliveries be made directly through conventional distribution methods (Fig. 1).

The method used consists of extending the traditional *VRPTW* by giving further consideration to total delivery costs and the influence of arrival times at each DC.

The paper is organized as follows: after this introductory section; a review of time dependent models is presented in the next section; then the model formulation is introduced in two parts—a problem description and a mathematical model. After introducing the model, which is the focus of this paper, the solution algorithm is presented once the concept of latest possible departure time is explained in detail. The general scheme of the solution procedure is shown as well. At the end of this paper, in section 5, a case study involving a pharmaceutical distribution is presented to show the method and computational results. Finally, several findings and future work are discussed.

2 Literature review of time-dependent VRP models

Before proceeding to the description of the new model, some brief general concepts of *Time Dependent Vehicle Routing Problems* (TDVRP) are introduced. It is not necessary to explain the VRP models because they have been largely studied.

The Time Dependent Vehicle Routing Problem (TDVRP), another variant of the classic Vehicle Routing Problem, consists of optimally routing a fleet of vehicles of fixed capacity when travel times are time dependent, in the sense that the time employed to travel each given arc depends on the time of day that the travel starts from its originating node. It is motivated by the fact that in urban contexts, variable traffic conditions play an essential role and cannot be ignored if a realistic optimization is to be achieved. An optimization method consists in scheduling, planning and finding solutions that minimize three hierarchical objectives: number of routes, total travel time and cost.

Mitrović-Minić et al. (2004) proposes the use of a rolling time horizon for the standard solution methodology for the dynamic PDPTW. When assigning a new request to a vehicle, it may be preferable to consider the impact of a decision on both a short and a long-term horizon. This way, in particular, better managing of slack time in the distant future may help reduce routing costs. On the other hand, Hashimoto et al. (2007), uses a local search to determine the routes of the vehicles. When evaluating a neighbourhood solution, they compute an optimal time schedule for each route. This sub-problem can be efficiently solved by dynamic

programming, which is incorporated into the local search algorithm. The neighbourhood of the local search contains slight modifications of the standard neighbourhoods called 2-opt, Cross Exchange and Or-opt. The final aim is an algorithm that evaluates solutions in these neighbourhoods more efficiently than those that compute the dynamic programming from scratch, as these utilise information from past dynamic programming recursions in order to evaluate the current solution. Another recent work can be found in Donati et al. (2008) wherein the time space in a suitable number of subspaces is discretised with a multi-ant colony system. Regarding urban environment, Friesz et al. (2008) discusses a model of dynamic pricing of freight services that follows the paradigm set in the field of revenue management for nonlinear pricing in a dynamic, game theoretic setting. They propose three main entities: sellers, transporters and receivers. Each competing agent's extremal problem is formulated as an optimal control problem and the set of these coupled optimal control problems is transformed into a differential variational inequality representing the general Nash equilibrium problem.

Ando and Taniguchi (2006) presents a model for minimising the total costs incorporating the uncertainty of link travel times with the early arrival and delay penalty at customers who set up designated time windows. This paper presents calibration of the Vehicle Routing and scheduling Problems with Time Windows-Probabilistic. Casceta and Coppola (2003) review and classify models according to basic assumptions on the flow structure. Regarding locations of DCs, Silva and Serra (2007) propose a metaheuristic to solve a new version of the Maximum Capture Problem. The MaxCap problem seeks the location of a fixed number of stores belonging to a firm in a spatial market where there are other stores belonging to other firms already competing for clients. Yamis et al. (2003) present a simple simulation of road growing dynamics that can generate global features as belt-ways and star patterns observed in urban transportation infrastructure.

Hsu et al. (2007) carries out a study focused on determining the optimal delivery routing, loads and departure times of vehicles, as well as the number of vehicles required for delivering perishable food to many customers from a DC. Features related to delivery of perishable food were considered, such as the time-window constraints of customers and the stochastic characteristics of travel time and food preservation. Time-dependent temperatures, travel time and soft time-windows with penalty costs were further discussed, and modifications were accordingly made to both the objective functions and the constraints in the mathematical programming models.

Regarding scheduling, one important aspect of this type of problem (Mitrović-Minić and Laporte 2004) lies in analysing two simple waiting strategies, Drive-First (DF—a vehicle leaves its current location immediately), and Wait-First (WF—a vehicle waits at its current location for as long as is feasible). The other two strategies introduced are Dynamic Waiting (DW—the vehicle drives as soon as is feasible while serving close locations; when all such locations are served, then the vehicle has to serve the next furthest location) and Advanced Dynamic Waiting (ADW—propagate the total waiting time available on the route along the entire route), which are combinations of the two simple strategies.

3 Model formulation

In this section, the model based on the time-dependent vehicle routing problem with time windows is formulated.

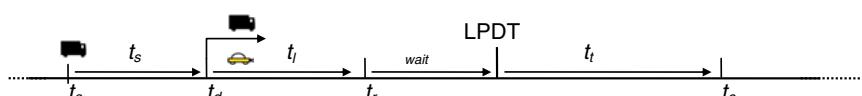
3.1 Problem description

Solving a problem modelled as a VRPTW deals with calculating a solution based on a set of routes and a scheduling of the same; therefore, one only has to solve a single problem. However, by using k DCs, the whole problem is now comprised of $k+1$ problems: one special VRPTW in each DC besides the main problem in which some customers and k DCs are serviced (Fig. 1).

Each special VRPTW involves a subset of customers which are serviced by vehicles (these may be hybrid vehicles) starting from the DC. From now on, the routes and vehicles starting from the depot and the routes and vehicles starting from the DCs, will be identified by *first and second level routes and vehicles* respectively. These two important remarks need to be discussed in more detail, as follows:

- (a) From the point of view of the dispatching center at the depot, each DC is considered in the light of another customer, with demands of its own in addition to the demands of its associated customers. However, its time window is not a trivial issue as will be explained later. Therefore, apart from a reduction in the number of locations/customers, the original problem has yet another variant with respect to the original problem: the DC costs must be taken into account and added to the original costs.
- (b) Once the first level vehicles have serviced demand for one DC, the second level vehicle can already be loaded and, thereafter, can depart. At this point, note that the information data of the customers never changes and hence delivery is transparent for the customers associated with the DC; that is to say, these customers do not need to know whether the second level vehicles left from the depot or from the DC.

Figure 2 depicts the variables used in the model on a temporal line. When a first level vehicle arrives at the DC at time t_a , this is serviced during the time service, t_s . Next, the second level vehicle is loaded during a load time, t_l , and after a determinate



¹ t_a = arrival time of the first level vehicle at DC;

t_s = service time of the first level vehicle at DC.

t_d = departure time of the first level vehicle at DC and start loading.

t_l = load time of the second level vehicle

t_r = ready time of the second level vehicle

LPDT = latest possible departure time. Start time of the routes.

t_t = travel time of the second level vehicle

t_e = end time, the second level vehicle has just arrived at DC.

Fig. 2 Time variables at the DCs¹

waiting time, until the *latest possible departure time* (Mitrović-Minić et al. 2004), the vehicle can already leave the DC. The LPDT concept will be explained later and widely detailed in section 4.1. All customers of the DC will be serviced by time, t_e . At this time, the second level vehicle has just returned to its DC. Note also that, although at time t_r , all second level vehicles have already been loaded and are ready to leave, it does not imply that they all have to leave the DC at the same time. Each vehicle must wait until its particular LPDT, so a vehicle may have arrived at a customer while another vehicle is still standing at the DC.

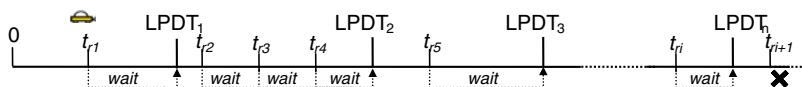
The concept of the latest possible departure time (LPDT) is used in order to achieve the lowest cost objective and calculate the DC time window for a given feasible route. Suppose a first level vehicle has left the depot at time 0, has arrived at a DC at time t_a , has serviced the demand and, at the end, has left for another customer at time t_d (Fig. 2). At that precise moment, it is already possible to calculate this particular VRPTW in order to achieve an optimal solution and begin the service using a DF strategy. However, the model uses the travel time in the cost function (section 3.2) and therefore a WF strategy is used. So, once a solution has been calculated, the second level vehicle is required to wait at DC for as long as is possible, i.e. it leaves at the LPDT. Thus, this waiting time (LPDT minus t_r) is not computed in the cost function. Because of the delay in the departure of the second level vehicle, this model permits the first level vehicle to have a wider time window (the due time at DC will be higher).

For a better understanding of the LPDT, consider Fig. 3. Let c_1 be the solution cost at DC at t_{r1} . In this case, the second level vehicle must wait until $LPDT_1$. According to Fig. 3, if the first level vehicle had arrived a few units of time later, the second level vehicle would have been ready at t_{r2} and would have been waiting until $LPDT_2$. However, if this vehicle had been ready at either t_{r3} or t_{r4} , the vehicle would also have had to wait until $LPDT_2$ before departing, c_2 being the cost solution (c_{12}). Thus, the best solution is for a second level vehicle to be ready just at $LPDT_1$; if not, one must be ready just at $LPDT_2$, and so on. The number of LPDT is finite; suppose n LPDTs (Fig. 4, the DC cost function is a piecewise linear function):

$$c_{LPDT_i} < c_{LPDT_j} \forall i, j \in [l, n], \quad i < j \quad (1)$$

The $LPDT_n$ (the last *latest possible departure time*) directly influences the DC time window. If a second level vehicle is ready at time $t_{ri+1} > LPDT_n$, the problem will have no solution. Therefore, the time window $[e, l]$ of a DC is:

- (a) One of the functions of the DCs is to store goods for a long time before their distribution. So, it is assumed that the start of the time window is 0; $e = 0$. The first level vehicles can deliver goods at the DCs anytime from time 0.



¹The last *latest possible departure time* ($LPDT_n$) is the latest time to begin departure from the DC and is in relation to the latest time window as regards first level distribution. If a first level vehicle is not ready until $LPDT_n$, the route will not be feasible.

Fig. 3 Time window of the DC and waiting times until the LPDTs¹

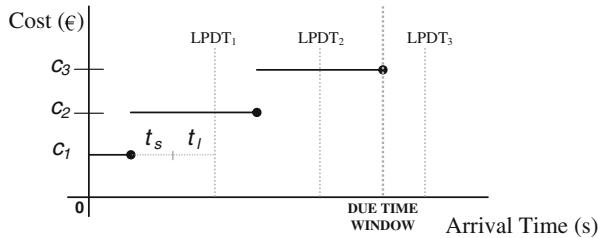


Fig. 4 DC cost function dependent on the arrival time of first level vehicle

- (b) Once the $LPDT_n$ is known, the deadline of the time window, l , will be calculated as follows:

$$l = LPDT_n - t_l - t_s \quad (2)$$

3.2 Mathematical model

The whole problem can be modelled in both cases (direct delivery and delivery via DCs) as a *Vehicle Routing Problem with Time Windows* (VRPTW). The mathematical definition of the problem is as follows (Cordone and Wolfson-Calvo 2001).

Let $G = (N, A)$ be a directed graph, where $N = \{0, 1, \dots, n\}$ constitutes a group of nodes of the problem and $A = \{(i, j) : i, j \in N \text{ and } i \neq j\}$ is the group of arcs that connect the nodes. The node 0 represents the depot and $N' = \{1, \dots, n\}$ is the group of nodes that has to be visited. Each node i demands a quantity of product q_i that requires a time s_i to be served. In addition, each node i has a fixed hard time window $[e_i, l_i]$ within which delivery must be performed. All the vehicles have the same capacity Q . In urban delivery the group of arcs A are defined by a non-symmetric array distance $[D]$ and by a non-symmetric travel time array $[T]$, defined by traffic flows. Temporal and capacity restrictions are defined by Cordone formulation (Cordone and Wolfson-Calvo 2001). Cost functions have been used as objective functions in both cases. For direct delivery, Eq. (3) is used as a cost function.

$$\min \left(\sum_{(i,j) \in A} (cd + cm)d_{ij}x_{ij} + \sum_{(i,j) \in A} (ct)t_{ij}x_{ij} + (ci)m \right) \quad (3)$$

where

- cd : cost by unit of distance travelled during direct delivery.
- cm : cost by unit of distance travelled due to green urban taxes.
- ct : cost by unit of travel time during direct delivery.
- ci : indirect cost per vehicle and delivery.

m : number of vehicles used for delivery.

x_{ij} : function that is equal to 1 when arc (i,j) is used and 0 otherwise.

For delivery via DCs Eq. (4) is used as a cost function:

$$\min \left(\left(\sum_{(i,j) \in A} (cd + cm)d_{ij}x_{ij} + \sum_{(i,j) \in A} (ct)t_{ij}x_{ij} + (ci)m \right) \right) \\ + \sum_{K=1}^{DCs} \left(\sum_{(i,j) \in A_k} (c'd)d_{ij}\delta_{ij}^k + \sum_{(i,j) \in A_k} (c't)t_{ij}\delta_{ij}^k + (ci)m_k + cf_k + (c't)tl_k \right) \quad (4)$$

where

$c'd$: cost by unit of distance travelled from DCs (second level routes).

$c't$: cost by unit of travel time of routes from DCs.

ci : indirect cost per vehicle and delivery from DCs.

m_k : number of vehicles used for delivery in DC k .

cf_k : fixed cost per delivery due to the use of DC k .

tl_k : total load time in DC k .

δ_{ij}^k : function that is equal to 1 when arc (i,j) of DC k is used and 0 otherwise.

The hard time windows of the DCs are defined by the time windows of their customers as explained in the previous section. Violations of time windows are not permitted; in such cases the solution would not be feasible.

4 Solution algorithm

Because of the NP-hardness and the high complexity of the TDVRPTW, it is difficult to solve the problem within a reasonable time scale by an exact algorithm, especially for large problems. Considering both the computational efficiency and the k+1 special VRPTW requirement, a heuristic comprising route construction, route reduction and route improvement based on the *Variable Neighbourhood Search and Tabu Search* is proposed for the TDVRPTW.

Latest possible departure time choice is essential at each DC, as described in Section 4.1. An efficient Variable Neighbourhood Search is proposed for route improvements and is elaborated in Section 4.2. In Section 4.3, a general solution procedure embedding both optimizations on each DC and TDVRPTW algorithm, is illustrated.

4.1 Latest possible departure time

This section explains how to calculate the latest possible departure time for a given feasible route so that travel time is minimized. Since the route is given, the variables that should be considered are the time windows, service times and travelling times. This process is graphically shown in Fig. 5. The latest possible

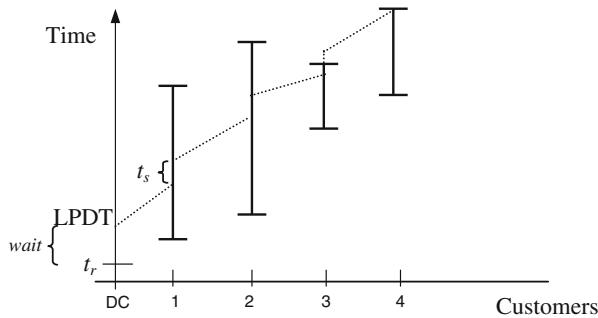


Fig. 5 The latest possible departure time¹

departure time (LPDT) may be calculated by the following formulas by means of a recurrence process:

$$l_{n+1} = l_0 \quad (5)$$

$$LPDT_x = \min[l_x l_{x+1} - t_{x,x+1} - ts_x] \quad \forall x \in \{1, \dots, n\} \quad (6)$$

$$LPDT = LPDT_1 - t_{0,1} \quad (7)$$

where

- n = number of customers.
- $[e_i, l_i]$ = time window at customer i . $\forall i \in \{0, 1, \dots, n\}$, $0 = DC$.
- $t_{x,x+1}$ = travel time between x and $x+1$. $\forall x \in \{0, 1, \dots, n\}$, $n + 1 = DC$
- ts_x = service time at customer x

4.2 Variable neighbourhood search and tabu search

A Variable Neighbourhood Search and Tabu Search algorithm (Millán 2006; Escuin et al. 2007) is used to solve the problem which was implemented in C++. The algorithm developed to solve the VRPTW comprises three differentiated calculation phases as follows:

4.2.1 Route construction

In this phase a quick, initial, feasible solution is built based on the problem data, but is not optimised. The algorithm used is based on patterns used by Yepes (2002).

4.2.2 Route reduction

Once there is an initial solution to the problem, the process of reducing the number of routes begins. For this purpose, a route elimination algorithm has been developed

based on the movement and study of chains of clients between routes, based on the ideas of Injection Trees (Braysy 2003; Braysy et al. 2003) and Ejection Chains (Glover 1992). This process is divided into two methods termed 2i–1e Reduction and Ni-Me Reduction (Millán 2006). The “i” value refers to “insertions”, (inserting customer chains), and “e” stands for “eliminations”, or the elimination of customer chains. In this way, Ni-Me is a procedure which aims to eliminate routes based on N insertions and M eliminations of chains (or segments) of customers. The value of N is known as “level” (the maximum value of the process depth) and it is true provided that $N = M + 1$. The 2i–1e case is a special case of Ni-Me in which an attempt is made to eliminate complete routes and, if this is not possible, the customers from the starting route are removed one by one, following a 2 insertions and 1 elimination pattern.

4.2.3 Local improvement and meta-heuristics

The mechanisms for the generation of customer movements between routes used in this algorithm are the well-known “Intraroute Operators” (Or 1976; Braysy 2003), and the “Interroute Operators” ICROSS and 2-OPT* (Potvin and Rousseau 1995). Furthermore, the latter operator has been implemented, generalizing 2-OPT* movement, so that the interchange of ending customer segments between two routes of a general maximum length L is brought about (said interchanged segments being equal or, as is generally the case, different), and they are inserted in all of the possible positions on the other route in its original and inverted form.

With all operators it is possible to use the “Best Movement” (*global best—GB*) acceptance criterion or the “First Feasible Movement” criterion (*first-best—FB*). Once a solution has been obtained with a reduced number of routes using the aforementioned operators, the solution is optimized in terms of distance or cost using a metaheuristic. With the objective of adding diversity to the process of improving the solution in terms of distance, an innovative hybrid deterministic metaheuristic termed “VNS-TS” (Millán 2006) has been developed. VNS-TS combines the metaheuristics “General Variable Neighbourhood Search” (VNS-G) and “Tabu Search” (TS). The basic idea behind the “Variable Neighbourhood Search” is the systematic change of neighbourhood within a local search (Hansen et al. 2003). The “Descending Variable Neighbourhood Search” (VND) consists of iteratively replacing the current solution with the result from the local search, while there is an improvement. Every time a local minimum is reached, there is a deterministic change in the structure of neighbourhoods.

The shaking process of the VNS-G algorithm has been replaced by the downgrading of the current solution in searching for a new solution following the “Tabu Search” metaheuristic (Glover and Melián 2003). This has been carried out with the objective of eliminating randomness in the search process and establishing a system to diversify the exploration region, avoiding the rapid decrease in local minimums and/or allowing the current solution to be taken out of these minimums to search for better solutions. The “Tabu Search” allows the process history to be used to continually establish new search directions. In this case, this has been carried out via the use of a calculation process history matrix (matrix H) in which recent movements are stored (Tabu movements) to avoid undoing them during a set number

of variable iterations during calculation, except in the event of aspiration criteria (an active Tabu movement allows a previously unexplored solution to be reached).

4.3 General scheme of model solution

For solving the model developed, the solution process has been divided into two parts. The first part consists of calculating the special VRPTW applied in each DC. Once all special problems have been calculated, TDVRPTW is computed by a Variable Neighbourhood Search and Tabu Search algorithm, as explained in the previous section. The steps of the general scheme are shown in Fig. 6.

The first task is to distribute all customers into their corresponding DCs; the second is to begin calculating each special VRPTW. To carry out these simulations, two variables are introduced, A_{DC} and B_{DC} . Due to the fact that each DC cost depends on the arrival time of the first level vehicle, it is necessary to analyse many simulations of each VRPTW with different departure times (from A_{DC} to B_{DC}). The aim is to obtain a matrix [AC] (*arrival-cost*) for each DC, which include all possible

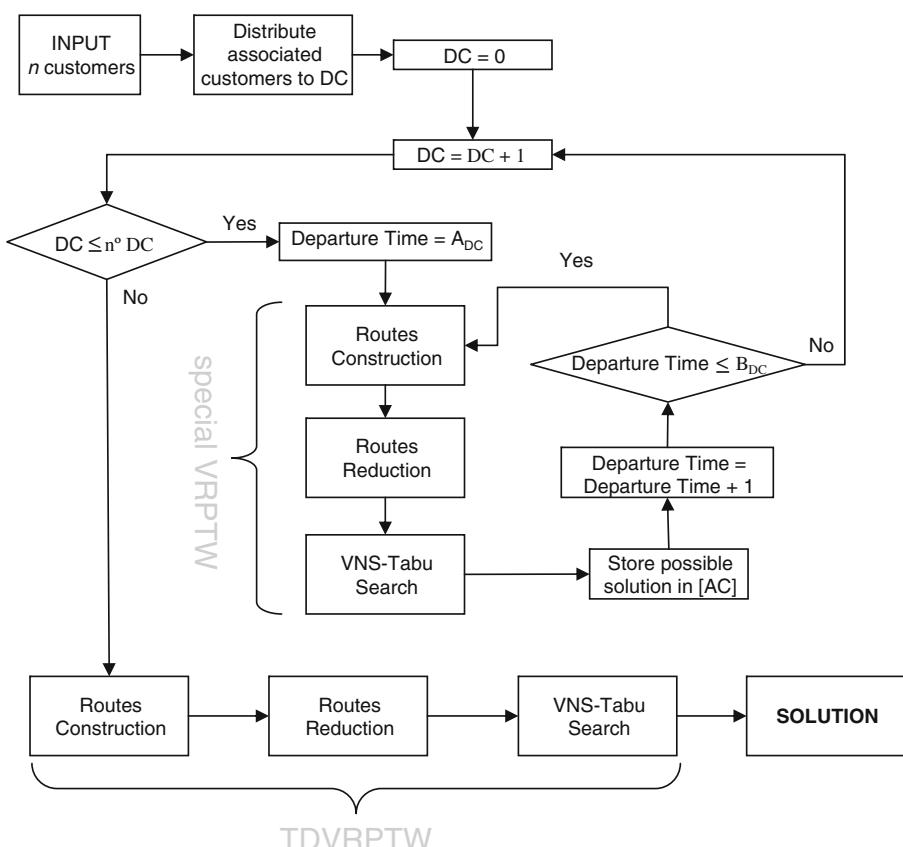


Fig. 6 General scheme of solution procedure

LPDTs, together with associated costs. This way, during the posterior TDVRPTW process, this algorithm will get the associated cost at each DC through knowledge of the arrival time. The arrival times usually depend on the travel times and the position of each DC on the ordered sequence of customers.

Both variables are calculated by means of the following formulas:

$$A_{DC} = \text{travel time between depot and DC } k \quad (8)$$

$$B_{DC} = \min[b_x] - t_{DC,\min[bx]} \quad \forall x \in \{1, \dots, n\} \quad (9)$$

where

n_{DC}	= number of customers in DC
b_x	= the ending time of time window at customer x
$t_{DC,\min}$	= travel time between DC and the customer whose ending time is the $\lfloor b_x \rfloor$ smallest

Note that the total computation time is not large because there are considerably fewer customers than in the original problem. Nonetheless, this total time depends on the number of DCs, the number of customers within them and the location of these customers.

Once k matrixes are calculated, the TDVRPTW algorithm is executed. A Driver-First strategy is used for leaving the depot as soon as possible.

5 Case study: pharmaceutical distribution

This section presents an application of the explained urban distribution model, by simulating a hypothetical case of the DCs being used according to a real case. The real case proposed deals with the pharmaceutical distribution of products (buckets) to 211 pharmacies in the city of Zaragoza. The current delivery system consists of a range of from nine to 12 fixed routes which are carried out in each daily service, although not all pharmacies are serviced; there are between 130 and 150 pharmacies in each service. This distribution system has very similar characteristics to the proposed model.

First, it is necessary to geographically locate the DCs in strategic positions within the city, by covering the greatest possible number of pharmacies. The ideal DC would be one that contained not only a large concentration of pharmacies, but one that also had similar time windows. This would allow both the fixed costs of using the DC and the conventional distribution costs in the area covered by the DC to be reduced.

The elaborate process of locating the DCs is not a topic of this article; therefore, only the final map is shown in Fig. 7. At the end of this process, six DCs have been established covering a total of 139 customers (around 65% of the total number).

The model developed has been tested in the case study, by simulating 2 days of operation and by comparing the results with the plan produced in the traditional way. Day 1, originally with 131 customers, now becomes a new problem with 57 customers, six of which are DCs. On the other hand the second day, initially with 139 customers, now has 60 customers, of which six are DCs as well.

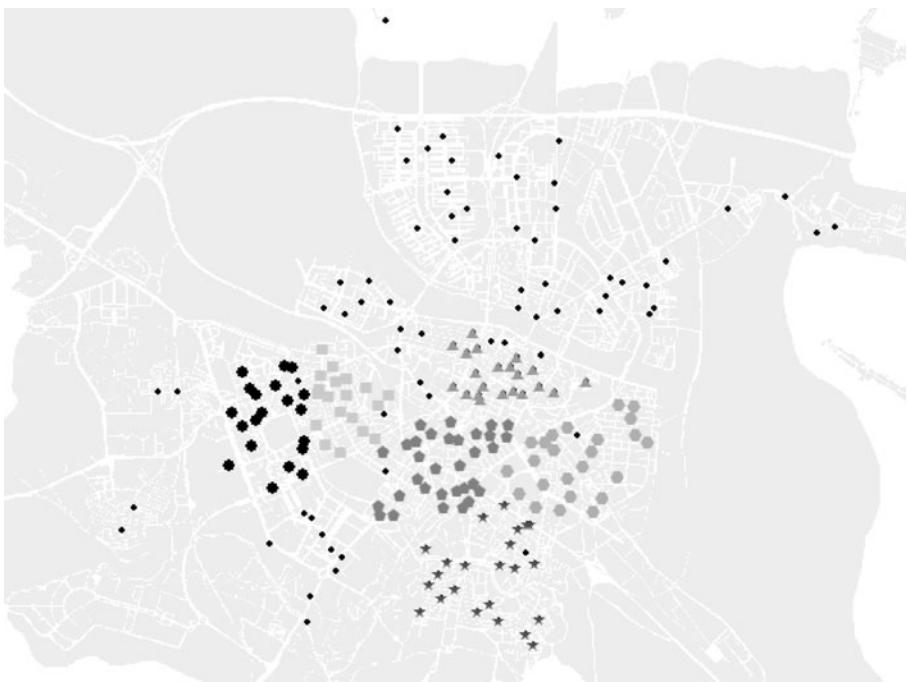


Fig. 7 Set of customers located in the DCs¹

One of the most important points has been to consider both the service time and the load time values. Since both variables are not known for the moment in our model, time service, t_s , is imagined as calculated as follow:

$$ts = \frac{45s * Nbuckets}{5 \text{ buckets per wheelbarrow}} \quad (10)$$

and the load time, t_l , is imagined as dependent on the number of second level vehicles to be loaded, n , as follow:

$$ts = \frac{45s * Nbuckets}{5 \text{ buckets per wheelbarrow}} \quad n = 1 \quad (11)$$

$$tl = \frac{45s * Nbuckets}{5 \text{ buckets per wheelbarrow}} + \frac{2s * Nbuckets}{n} = \frac{11s * Nbuckets}{n} \quad n \geq 2 \quad (12)$$

These formulas have been obtained according to the following suppositions: (a) each wheelbarrow is loaded with five buckets; (b) the elapsed time between loading and unloading at the pharmacy is imagined as 45 s for each wheelbarrow; (c) classification time is imagined as 2 s for each bucket and vehicle.

Base values for the parameters in the total cost function (Eqs. (3) and (4)) were estimated by interviewing the DC operator and by analyzing the routes scheduled on

both days, as listed in Table 1. cm (cost by unit of distance travelled due to green urban taxes) and cf_k (fixed cost per delivery due to the use of DC k) have not been included for purposes of simplicity (Tables 2 and 3).

According to the results obtained in the above tables, the principal conclusions that can be highlighted are:

- With realistic cost data, the DC operation permits a reduction of more than 15% in urban travel distance (over 35% in the case of first level diesel vehicles) and a reduction in travel time of more than 3% (also more than 35% in the case of first level diesel vehicles), although the total delivery time remains constant. Moreover, a greater percentage of both travel distance and travel time would have been reduced even if cm had been used.
- The total operational cost of using DCs is slightly higher than that obtained by direct delivery.
- The general and most important conclusion is that if this method became operative and was implemented on a large scale, these measures would allow for a significant reduction in environmental impacts in terms of the production of CO₂ and NO_x (including toxic emissions and high noise levels as well) in urban centers, caused by goods distribution and traffic congestion, especially in rush hours. However, because of fears of the perceived extra cost to the wholesaler (buying new vehicles, rerouting planning, etc), application of this method should be encouraged by public authorities rather than private companies.

6 Conclusions

This study has focused on determining a new model for urban distribution vehicle routing problems by means of DCs within large cities. These centers are areas whose objective is to provide buffer points where cargo and packages which are to be delivered to shops and businesses can be stored beforehand. The setting up of these centers is also motivated by recent developments in real time traffic data acquisition systems, as well as national and international policies aimed at reducing concentrations of greenhouse gases in the atmosphere caused by the use of traditional vans.

A new vehicle routing model (based on the well-known *Time-Dependent Vehicle Routing Problem with Time Windows, TDVRPTW*) has been carried out and a change in the traditional approach proposed, by adopting a system in which some customers

Table 1 Initial values of parameters

Parameter	Initial Value of 1° level vehicle
cd	0.0001353 €/m
ct	0.0047 €/s
ci	14.15 €/vehicle
cd	0.0000315 €/m
ct	0.0047 €/s
ci	9.00 €/vehicle

Table 2 Experimental results obtained on the first day of work

DAY 1	Vehicles number	Distance (km)	Service Time (s)	Load Time (s)	Travel Time (s)	Total Time (s)	Cost(€)
Without DCs	9	394.08	23,580	0	45,761	69,341	506.58
DC1	2	14.79	2,160	247	2,246	4,653	40.12
DC2	1	10.36	2,340	259	1,511	4,110	28.65
DC3	1	13.56	2,520	279	3,237	6,036	37.80
DC4	2	15.06	3,420	247	2,479	6,146	47.36
DC5	2	14.64	2,520	187	3,578	6,285	47.34
DC6	1	10.10	1,440	135	3,154	4,729	31.54
1 level Routes	6	251.42	11,032	0	28,172	39,204	303.19
With DCs	15	329.93	25,432	1,354	44,377	71,163	536.00
	66.67%	-16.28%	7.85%		-3.02%	2.63%	5.81%

are served by urban DCs while remaining customers are served by the traditional routes. By using k DCs, the whole problem is now composed of $k+1$ problems: one special VRPTW for each DC in addition to the main problem over how some customers and k DCs are serviced.

Time-dependent travel time and cost functions have been further discussed, as well as the constraints in the mathematical programming model and the latest possible departure time concept. To test the model, a hypothetical case of the DCs has been used according to a real case which deals with the distribution of pharmaceutical products to 211 pharmacies in the city of Zaragoza. The results obtained show a reduction of more than 15% in urban travel distance (over 35% in some cases) and a reduction of 3% in travel time (also more than 35% in some cases).

Future work should be aimed at including distribution center location problems within the proposed model. This is because location of distribution centers affects performance of the network. Another important point to consider is the economic impact in terms of CO₂ emissions when evaluating the model. Finally, the issue of soft time windows with penalty cost should also be addressed in order to add more flexibility to the model.

Table 3 Experimental results obtained on the second day of work

DAY 2	Vehicles number	Distance (km)	Service Time (s)	Load Time (s)	Travel Time (s)	Total Time (s)	Cost(€)
Without DCs	9	400.24	25,020	0	44,285	69,305	507.24
DC1	2	14.14	2,160	225	2,176	4,561	38.89
DC2	1	9.69	1,980	207	1,780	3,967	27.95
DC3	1	12.30	2,160	333	2,937	5,430	34.92
DC4	2	15.19	3,600	253	2,512	6,365	48.40
DC5	1	6.05	2,700	324	3,358	6,382	38.85
DC6	1	16.93	2,160	243	3,679	6,082	38.12
1° level Routes	6	250.66	11,691	0	25,196	36,887	297.12
With DCs	14	324.96	26,451	1,585	41,638	68,089	520.32
	55.56%	-18.81%	5.72%		-5.98%	-1.75%	2.58%

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