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# Dynamic VRP in pharmaceutical distribution – a case study

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**Abstract** In recent years, the pharmaceutical sector has gone through deep changes, partially due to the ageing of the population and to the increasing of costs in health care services. With margins that are getting lower and lower, the drug distribution problem to pharmacies has become much more important, particularly in large metropolitan areas.

As pharmacies demand 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 pharmacies and may, in some cases, be quite inefficient for distributors.

In this work, a case study has been carried out and a change of the traditional approach is proposed, by adopting a system of variable routes that are dynamically designed, based on orders that are constantly arriving along the day.

A dynamic algorithm is therefore proposed, meant to be run several times a day. It has four phases: first, a clustering of the orders is performed; second, potential routes are constructed; third, a route is selected for operation; and finally, that route is subject to an improvement process. The selection of the next route to be launched may be postponed in order to take advantage of subsequent information. The algorithm has been tested in the case study, by simulating one week of operation, and by comparing the results with the plan produced by the traditional way.

**Keywords**: Dynamic Vehicle Routing Problem; Dynamic Routing Planning; Heuristics; Pharmaceutical Distribution.

# 1. Introduction

Transportation and distribution are responsible for a significant part of the Gross Domestic Product (GDP) of many developed countries. As an example, a study conducted in 1978 by the National Council of Physical Distribution, estimated that part as 15% of the GDP of the United States of America (Ball et al 1995). Recently, Larsen (2000) has estimated this value to be between 10% and 15%, for a large number of countries. This economic significance leads to a growing use of Operational Research techniques in order to improve the efficiency in people transportation and goods distribution.
In recent years, issues related to lead-times are becoming more and more critical. Companies are not only cutting their logistic costs but also competing by the differentiation in quality of service. Besides, the interest in just-in-time environments is increasing. The time dimension has therefore to be incorporated in the Vehicle Routing Problems (VRP) as time windows imposed by customers, or as maximum service times to be guaranteed by distributors.
An important part of the research in this domain has been done assuming static conditions. This means that the problem is solved a priori, with static data. But, in many real problems, these static conditions are not applicable, namely because not all relevant data are available at the beginning of the planning process.
A large number of dynamic problems are being formulated and solved as static problems, but relying on stochastic data. However, in many cases, some routes, defined a priori, could collapse if the initial conditions were not verified. For this reason dynamic approaches are needed to solve this kind of problems.
Moreover in a context where problems tend to be dynamic, pharmaceutical distribution has a particular importance, since stock management is usually done with a just-in-time policy. In densely populated urban areas, the shop area of pharmacies is getting smaller and smaller, the number of items is increasing, as well as the cost of capital invested in stocks. Pharmacies tend therefore to place multiple orders to the distributors during a single day, some of them of small quantities, and thus pushing the stocking activity to the distributors. Those facts force distributors to be more efficient and to assure a quick response to pharmacies, thus assuring availability and quick delivery of orders.
This paper is organised in five more sections. The next section presents the case study, describing the way the company operates. The third section presents a brief literature survey. The fourth section describes the model developed in this work and the algorithm designed to solve it. The fifth section presents the results obtained with the model, and in the last section we draw some conclusions and present some ideas for future research.

# 2. Case study

The work described in this paper was developed for a cooperative distributor of pharmaceutical goods operating in the North and Centre of Portugal. To explain the distributor's activity model, we start by briefly presenting the path followed by each order, since it is triggered by the client until its delivery. This model comprises three phases: 1) ordering; 2) picking; and 3) delivery. Figure 1 briefly describes the whole ordering process.

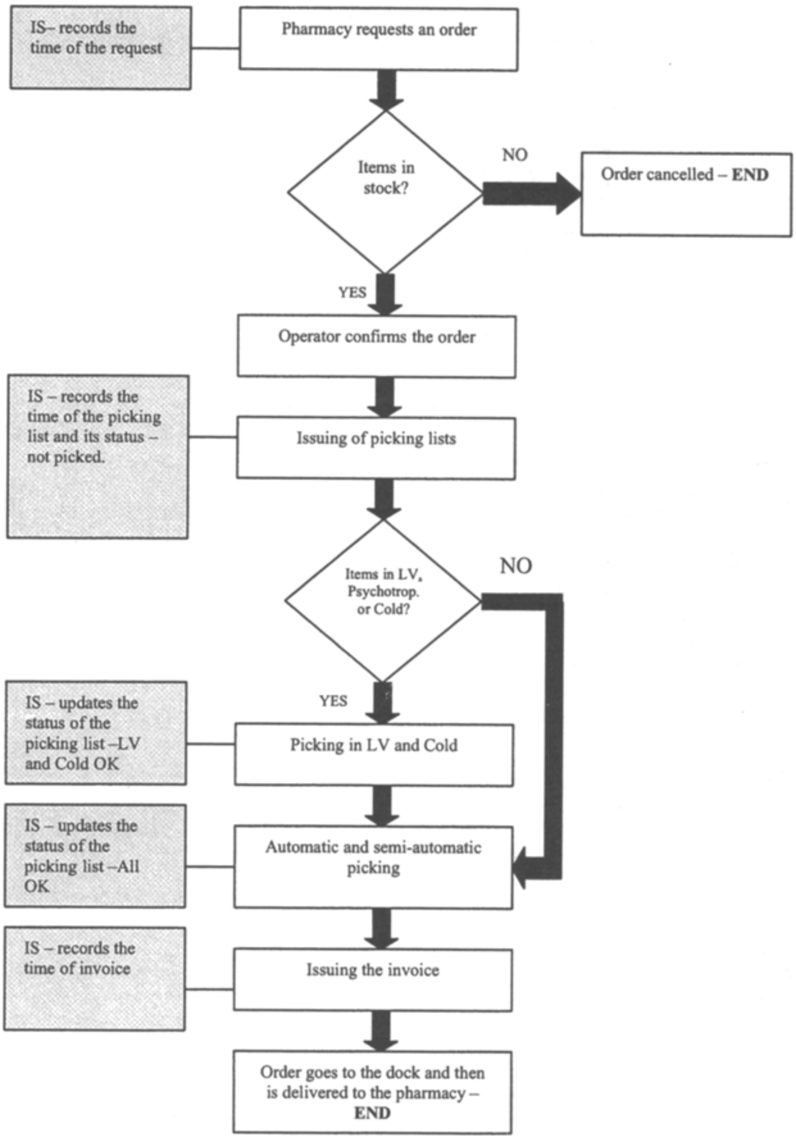


Figure 1 – Ordering process

## Ordering

All pharmacies have software applications that enable them to place the orders directly to the distributor Information System (IS) by modem.
When a distributor receives an order from a pharmacy, a human operator confirms the order by phone, checking if the pharmacy does not want to order any other item, or if they want to take advantage of any eventual

promotion. From this moment the order is ready to be filled by the warehouse. All orders are accepted except if the drugs are not available.

### Picking

In the warehouse, items are classified in 4 categories, according to the area where they are stored: Automatic / Semi-Automatic (A); Cold (C); Psychotropic (P); and Large Volumes (LV).
The Large Volumes area stores veterinary, cosmetic, chemical, bottled and large sized items. In this area one also fulfils the orders containing a large number of items, called "large quantity orders". In the Cold area, the items that need to be kept under low temperatures are stored. The psychotropic items, as well as other items that need special control, are kept in a station with controlled access. In these 3 areas picking is manual and the items are packed in card or plastic boxes, or in plastic bags.
The other items are stored in the Automatic area, where picking is done automatically by a robot, and in the Semi-Automatic area where picking is manual but packing is automatic. These areas store the most saleable items representing near 60% of the company's income. These items are packed in standard plastic boxes with 30 litres of capacity.
Once the order is confirmed, the IS issues a picking list. This list is divided in some sub-lists according to the place where the items will be picked. The sub-list is fulfilled in the following sequence: 1) Large Volumes; 2) Cold; 3) Psychotropic; 4) Automatic / Semi-Automatic. The IS records the time of fulfilment of each sub-list, thus being able to provide, at any time, the status of the order.
When picking is completed, the IS issues an invoice and records the moment of that event. At that time, the order is completed and the box is taken to the dock from where it will be delivered to the client.

### Delivery

Orders are distributed in own or in outsourced vans. The number of vehicles in the fleet is constant but the capacity is not the same for all vehicles. Currently each pharmacy is assigned to a specific (fixed) route according to the weekday and to a pre-defined service level. This means that one pharmacy may have several potential deliveries during the day. These routes have been defined after an initial study and are slightly adjusted from time to time.
However, the company started understanding that the routes for urban areas did not fulfil all the requirements and could in general be considered unsatisfactory. This lack of quality is mainly due to having routes fixed *a priori*, thus not taking into account the actual conditions of the system. Moreover, quite often those *a priori* routes are not fully accomplished, and sometimes vehicles leave the company only to deliver one or two orders.
In more practical terms, distributor would like to know, at any moment:
1) which orders to deliver;
2) when should they be delivered and
3) what vehicle will deliver those orders.
In fact, pharmacies are constantly placing orders during the day, which means that at each moment there are different groups of orders to be delivered. It also means that during one single day, some pharmacies are served three or more times.
Therefore, and given this operation environment, the main objective of the company turned out to be the development of a procedure to define vehicle

routes, in order to achieve a reduction of the lead-time without significantly increasing current delivery costs.

# 3. Literature survey

There are a large number of real distribution problems that can be modelled as vehicle routing problems. These include the pick up and delivery of goods and services, scheduling of vehicles and crews, and fleet definition (Ball et al 1995). According to their variety and specific features, these problems can be classified in many different ways. For example, the general problems we are interested in here, consider a network with customers as nodes and road connections as arcs, the delivered service being performed at the nodes (node routing).
Moreover, the type of data that are available play an important role in the classification of these problems. The uncertainty and the variability of data along the planning horizon are crucial factors in practice. If there is no uncertainty, problems are classified as deterministic. If uncertainty is present, problems are stochastic. If data vary along the planning horizon problems are said to be dynamic, if data does not vary, problems are considered to be static (Teixeira et al 2004).
The problem tackled in this work and presented above can clearly be viewed as a dynamic problem.

### The Dynamic Vehicle Routing Problem

Psaraftis (1988) defines the dynamic VRP by comparing it with the classic VRP, as follows: the VRP is static (or classic) if the result of a given formulation is a set of predefined routes which will not be reoptimized nor recalculated if data change along time. The problem is viewed as dynamic if the result is not a set of routes, but rather a procedure establishing how the routes should be constructed according to the data that could be changing along the planning horizon. In this classification the time dimension obviously plays an important role.
This definition is complemented by Bianchi (2000) who states that a problem is not dynamic if changes in data along the planning horizon, could be predicted by the decision maker. This means that if data are not deterministic but the problem can be solved based on some probabilistic assumptions, the problem should not be considered as dynamic.
It should also be noted that in recent years, the growing interest in logistics for just-in-time environments along with the advances in information technologies, allow the practical use of large quantities of data in real time (see Larsen 2000).

One way to approach and solve Routing Problems with uncertainty about available data, consists in establishing an *a priori* solution, based on probabilistic information about future events. This uncertainty can obviously be related with several aspects of the problem, namely the moment of ordering, the size of orders, travel times and distances, among others.
In this group of problems, we should include the Probabilistic Travelling Salesperson Problem (PTSP) (Jaillet 1988), the Probabilistic Vehicle Routing Problem (PVRP) (Bersitmas et al 1996), and the Stochastic Vehicle Routing Problem (SVRP) (Gendreau et al 1996).

However, another way to face this kind of problems is to develop dynamic approaches that tackle problems through real-time procedures. The Dynamic Travelling Repairman Problem (DTRP) is a well known problem that has been repeatedly approached by real-time strategies. This problem was introduced by Bertsimas and Van Ryzin (1991). The Time Dependent Vehicle Routing Problem (TDTRP) is another problem that deals with dynamic issues of real situations (Ichoua et al 2003). Also recently other authors have introduced some partially dynamic approaches to tackle this type of problems (Bent et al 2004 and Larsen et al 2002).

Another problem in this broad class is the Home Delivery problem for grocery goods acquired through the internet. Traditional home delivery systems like mail (normal or express) are not adapted to this problem, but it is also clear that creating a dedicated supply chain involves large investments and risks. Punakivi and Saranen (2001) simulate four delivery strategies used by home delivery companies and compare the results with the traditional way of buying grocery goods (visiting the store). The main results suggest that the home delivery systems could be globally cheaper than the traditional one.
Finally, Campbell and Savelsbergh (2002) state that it is common practice, in these models, that the client and the distributor (or seller) make an agreement about the time slot to deliver the goods. Usually, for each time slot the distributor accepts orders in a "first in first out" strategy. There is a bound on the number of orders that can be assigned to each time slot, and once this bound is reached, no more orders are assigned to it. The authors conclude that: 1) for orders in a given time slot, the closer the delivery locations are, the easier it will be to schedule the deliveries and the cheaper it will be to carry them out; 2) the closer the deliveries are in a given time slot, the more deliveries can be accepted and effectively handled, thus reducing average delivery cost and increasing profitability. The approach is based on building a set of routes for a specific day. The requests for that day arrive in real time and are considered up to a certain cut-off time, that precedes the execution of the planned routes. Each request is accepted or rejected as it arrives. It is assumed that each request, if accepted, consumes some vehicle capacity and results in revenue. The calculation of this revenue takes into account the probability of other clients making requests before the cut-off time.

# 4. Models and algorithms

In general terms, the main objective of the company is to improve the quality of the service to customers, i.e. to decrease the delivery time, without significantly changing the current costs that are roughly related to the driving distances.
Basically the problem the decision-maker faces is: given a set of orders and a set of available vehicles, determine: 1) what orders are going to be delivered next; 2) when are they going to be delivered; 3) by which vehicles and in which order. The decision process is triggered each time a vehicle becomes available. In the meanwhile, several orders may have been placed.
For a given set of picked orders and available vehicles, the procedure should decide whether a given vehicle leaves immediately to perform a route, or whether it is better to let the vehicles wait some time for the arrival of new orders, so that the routes can be improved. In the case that a route is

launched, the procedure will also indicate what orders are going to be delivered and in what sequence.
Based on the above ideas, our case can be approached as a VRP, with two levels. The first level is the assignment or clustering phase, where the customers to be served are grouped. The second level is concerned with scheduling, and handles the construction of the routes for each cluster of customers as defined in the previous phase.
As it has been mentioned before, at the beginning of the day, only a small part of the information related to the orders for the day, is available. Orders arrive along the whole day, and each time the planner makes a decision, he/she only has access to information about the orders that are already ready to dispatch or that are in the picking process. In this context, it may obviously be interesting to partially postpone decisions, delaying the construction of routes, to wait for the arrival of more orders.
The solution approach proposed in this work divides the problem in several phases or steps that somehow reflect the current management model of the company. This partition of the problem sets the ground for an algorithm, that is structured around four phases: first, a clustering of the orders is performed; second, potential routes are constructed; third, a route is selected for operation; and finally, that route is subject to an improvement process.
Being an "extension" of already difficult routing problems, the problem is naturally NP-hard. A heuristic approach, structured in four phases, has therefore been adopted. This approach, as well as the decisions made along the process, is schematically depicted in Figure 2.

Next we describe the heuristics designed to tackle each of these four phases.

### Phase 1 – Clustering

The goal of this phase is to create groups of pharmacies (clusters) that will potentially form good routes. The creation of these groups tries to tackle two basic issues: the first is related to the total load of each cluster, and the second is related to the geographical dispersion of the customers in the cluster.
Each cluster cannot contain more load than the capacity of the vehicle, and should not be too much spread in physical terms. On the other hand, due to reasons of an operational nature (involving an easier control), solutions with routes that cross or routes that are inside other routes, are not desirable.
For these reasons, a traditional k-median approach cannot be adopted. An alternative approach has therefore been designed to initialize the clusters. This is performed by a constructive procedure based on a space filling curve, as a way to partition the total intervention area (Bersitmas and Van Ryzin 1991, 1993). The depot is the centre, and each cluster is a sector. Each sector is determined by satisfying two constraints: the total order of the pharmacies belonging to one sector should not exceed the vehicle capacity, and a predefined limit is imposed on the size of the sector angle. Table 1 and Figure 3 illustrate this procedure.

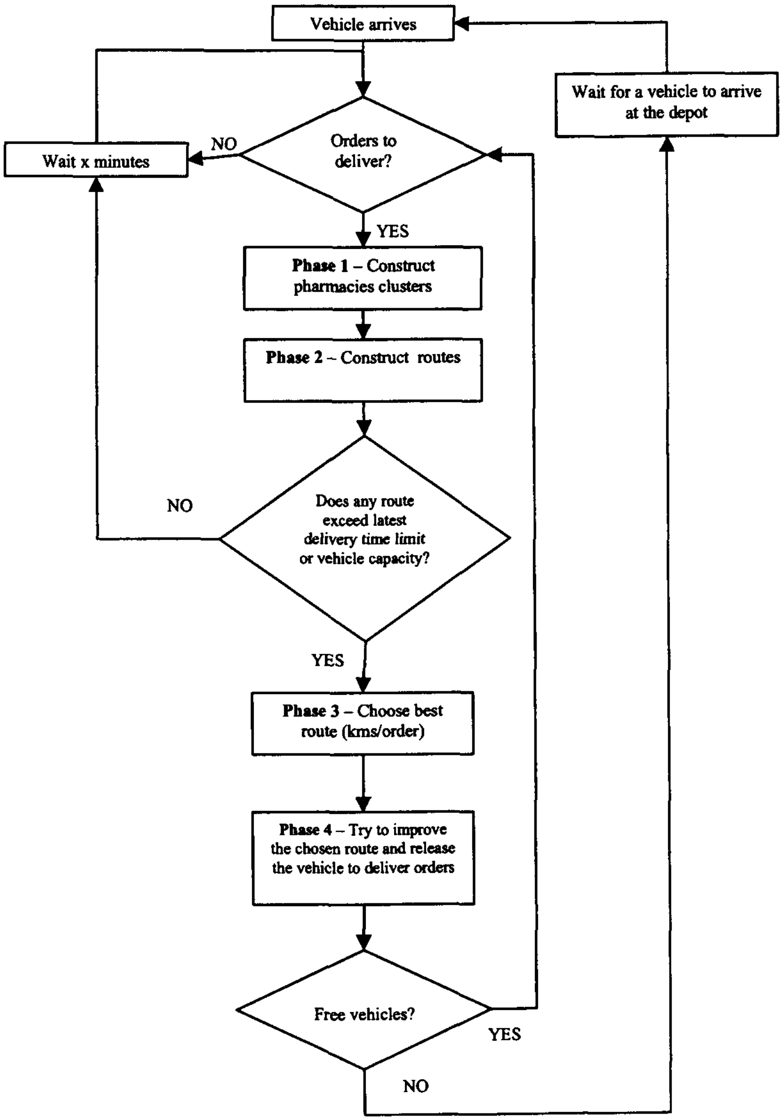


Figure 2 – General Heuristic Approach

```
Sorting the pharmacies by their angle to the boundary ray
Minimum_angle=0
Available_capacity = vehicle_capacity
Current_cluster = 1
i = 1
While i ≤ number_of_pharmacies
      If available_capacity – volume_of_orders_of_pharmacy i ≤ 0 or
      angle (i) – minimum_angle ≥ limit
            current_cluster = current_cluster + 1
            cluster (i) = current_cluster
            available_capacity = vehicle_capacity – volume_of_orders_of_pharmacy (i)
            minimum_angle = angle (i)
      else
            cluster (i) = current_cluster
            available_capacity = vehicle_capacity – volume_of_orders_of_pharmacy (i)
      End if
      i = i + 1
End While
```

Table 1 – Initial procedure to construct the clusters

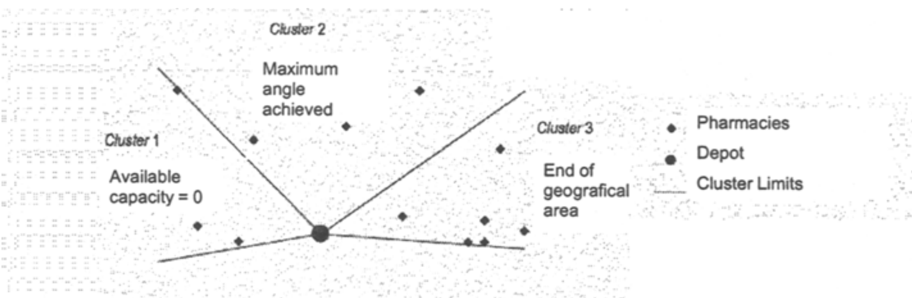


Figure 3 – Initial construction of clusters

Taking into account the conditions imposed for constructing the routes, namely those concerning the type of undesirable routes (the "crossing" or "interior" routes, as mentioned), computing the centre of the cluster should not be done in the traditional way i.e. using the average of the coordinates. Alternatively, we have chosen to compute the average of the angles that the pharmacies form, with the depot as the vertex, and the boundary ray (cluster limits) (Table 2). The reassignment procedure is shown in Table 3. Note that, as a result of this procedure, we get the centre of the cluster as an average angle of different pharmacies in the cluster.

According to Hair Jr et al (1995), the final result of a clustering process is strongly dependent on its initialization. In order to minimise this effect, the area is covered twice: clockwise and counter-clockwise. The clustering procedure starts from a fixed boundary ray that contains a pharmacy. The border may also be a natural limit such as the sea or a river. Two different boundary rays may be used for the clockwise and for the counter-clockwise case.

```
Sorting the pharmacies by their angle to the boundary ray
While i ≤ number_of_pharmacies
    number_of_pharmacies (cluster (i)) = number_of_pharmacies (cluster (i)) + 1
    centre (cluster (i)) = centre (cluster (i)) + angle (i)
    i = i + 1
End while
For j = 1 to number_of_clusters
    centre (cluster (j)) = centre (cluster (j)) /number_of_pharmacies (cluster (i))
End For
```

Table 2 – Procedure to calculate the centre of the clusters

```
Sorting the pharmacies by their angle to the boundary ray
While i ≤ number_of_pharmacies
    new_cluster = cluster whose centre is closest to the ray containing pharmacy (i)
    If new_cluster ≠ cluster (i)
        If available_capacity (new_cluster) < volume_of_orders_of_pharmacy (i)
            cluster (i) = new_cluster
            available_capacity (new_cluster) = available_capacity (new_cluster)
            – volume_of_orders_of_pharmacy (i)
        End if
    End if
End While
```

Table 3 – Procedure to reassign the pharmacies to clusters

### Phase 2 – Route construction

Once the clusters have been created, the customers assigned to each cluster are sequenced. This sequence represents the order in which they are going to be visited, i.e. the vehicle route. The algorithm uses the least insertion cost as the criterion for constructing the route. The first point to be inserted in the route corresponds to the pharmacy whose ray creates the smallest angle with the cluster centre, as calculated above (Table 4 and Figure 4).

```
For j from 1 to number_of_clusters
    While pharmacies_in_cluster ≠ 0
        minimum_insertion_cost = major
        For k from 1 to number_of_pharmacies (j)
            For m from 1 to number_of_pharmacies_in_route
                calculate the insertion cost between m and m +1 (cost_m)
                cost_m = d_m,k + d_k,m+1 – d_m,m+1
                If cost_m < minimum_insertion_cost
                    minimum_insertion_cost = cost_m
                    x = k
                    y = m
                End if
            End (For m)
        End (For k)
        Insert the pharmacy x in position y
    End While
End (For j)
```

Table 4 – Construction of routes

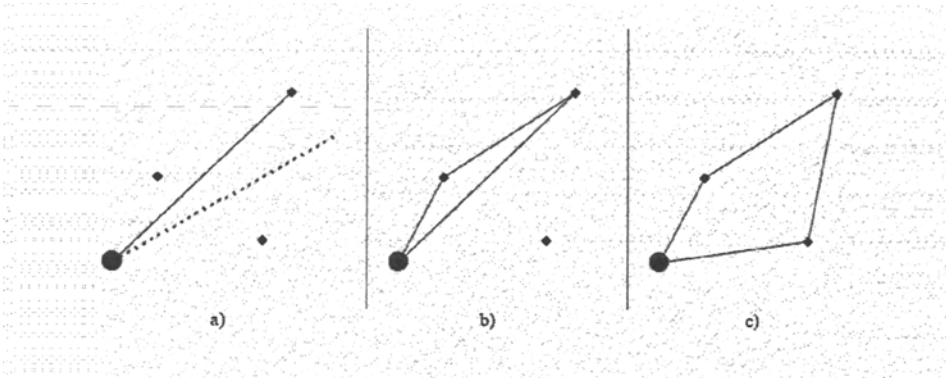


Figure 4 – Construction of routes in sequence a, b and c (the dotted line is a cluster centre)

**Phase 3 – Choice of the route to be performed**

Once the routes have been constructed, the following global values are computed for each of the orders already sequenced: 1) total completed distance; 2) average delivery time; 3) maximum delivery time; 4) number of delivered orders; 5) ratio between the total completed distance and the number of delivered orders. The delivery time is computed as the difference between order placement time and expected delivery time.

Once these parameters have been calculated for all routes, one per sector, the decision-maker will hopefully choose one of the following actions: either he/she assigns one of the routes to the vehicle under analysis, or he/she forces it to wait, thus postponing the actual decision.

The decision to launch a given route should be made based on two criteria applied in sequence. From all constructed potential routes, we only consider those routes having a maximum delivery time larger than a predefined threshold. If there is no such a route, the planner does not launch any route, but waits a certain time (x minutes, as shown in Figure 2) to run the algorithm again. Otherwise, he/she will choose the route with minimum ratio between the total completed distance and the number of delivered orders.

**Phase 4 – Route improvement**

Once a route has been chosen, a local optimisation procedure is run, to improve the route length. For this purpose we have adopted a "2-opt" exchanges procedure (Taillard et al 1997).

At the end, a report is produced with the route to be performed by the vehicle. If more vehicles are available, the whole procedure is repeated for another vehicle. Otherwise, the system waits for the arrival of a new vehicle, and the procedure is performed again.

## 5. Computational tests and results

Collecting and preparing data for assessing the proposed approach was a quite difficult task, because in many cases they were not available or they were not reliable (most records were written on paper and hard to read).

Therefore, in order to make the process feasible and sound, some simplifications have been made, and some values have been corrected or estimated, based on assumptions discussed with the planners.
The validation and evaluation of the algorithm was based on comparing the results obtained with those that have been actually implemented through the current manual procedures. One given week of operation was chosen for performing this assessment. Two basic criteria have been used that are related to the completed distance, and to the quality of service.
The criterion adopted to evaluate distance was the ratio between the total number of kilometres of the route and the total number of delivered orders. Concerning quality of service, indicators have been used, that are related to the time of delivery when compared with time of order placement. These indicator are: 1) average delivery time; 2) percentage of orders delivered in 1 hour; 3) percentage of orders delivered in 2 hours; 4) percentage of orders delivered in 3 hours; 5) percentage of orders delivered in 4 hours; 6) percentage of orders delivered the following day.

## 5.1. Comparison of results

In this section, we compare the results obtained by the proposed approach with those obtained by the manual procedure currently in use. For each of the considered criteria, we present graphics and tables comparing the values of the two situations, highlighting the differences.
With respect to the completed distance, the suggested criterion is the ratio between the actual completed distance and the number of delivered orders. As Table 5 shows, although the total distance is larger in the solution of the new algorithm, that ratio is slightly smaller. This clearly results from the fact that the total number of delivered orders is significantly larger.

| Day | Current manual procedure | | | Proposed algorithm | | | Difference % |
|---|---|---|---|---|---|---|---|
| | Total distance | Number of orders | Km/ order | Total distance | Number of orders | Km/ order | |
| 1 | 823 | 286 | 2,88 | 687 | 313 | 2,19 | 24,0 |
| 2 | 817 | 375 | 2,18 | 915 | 434 | 2,11 | 3,2 |
| 3 | 764 | 414 | 1,85 | 914 | 404 | 2,26 | -22,2 |
| 4 | 820 | 458 | 1,79 | 867 | 455 | 1,91 | -6,7 |
| 5 | 911 | 445 | 2,05 | 834 | 450 | 1,85 | 9,8 |
| **Avg** | **827** | **396** | **2,09** | **844** | **411** | **2,05** | **1,9** |

Table 5 – Comparison of distance values

In the obtained results, there is a slight gain (1.9%) in the distance for each delivered order. However it should be noted that these results are better for some days, and worse for others.
For the criterion "average delivery time for pharmacies", Table 6 presents the results obtained for each day. We can observe that on average the proposed algorithm improves this time in 8.1%. This improvement occurs in all the days of the study.

| | Current manual procedure | Proposed algorithm | Difference |
|---|---|---|---|
| Day | Average delivery time | Average delivery time | % |
| 1 | 1:58 | 1:34 | 20,3 |
| 2 | 1:44 | 1:41 | 2,9 |
| 3 | 1:47 | 1:44 | 2,8 |
| 4 | 1:53 | 1:44 | 8,0 |
| 5 | 1:56 | 1:45 | 9,5 |
| **Average** | **1:51** | **1:42** | **8,1** |

Table 6 – Comparison of delivery time

Concerning the "delivery time for pharmacies", we can still compare the accumulated number of orders, as a function of their delivery time (see Table 7).

| Average delivery time | Number of orders | | Difference | |
|---|---|---|---|---|
| | Current manual procedure | Proposed algorithm | Absolute | % |
| Until 1h | 641 | 598 | -43 | -6,7 |
| Until 2h | 1333 | 1430 | 97 | 7,3 |
| Until 3h | 1627 | 1912 | 285 | 17,5 |
| Until 4h | 1737 | 2023 | 286 | 16,5 |
| **Total** | **1 978** | **2 056** | | |

Table 7 – Comparison of delivered orders

Finally, a comparison can be performed between the number of orders delivered in a given day and those delivered in the following day. Again, Table 8 compares the results obtained by the new algorithm with those obtained in the manual procedure. Note that the orders delivered in the same day for days 2, 3, 4 and 5 include postponed orders placed previous day.

| | | Current manual procedure | | | Proposed algorithm | | | |
|---|---|---|---|---|---|---|---|---|
| Day | N° of Orders | Same day | Next day | % | Same day | Next day | % | Gain (%) |
| 1 | 389 | 286 | 103 | 26,5 | 313 | 76 | 19,5 | 26,2 |
| 2 | 448 | 375 | 176 | 39,3 | 434 | 90 | 20,1 | 48,9 |
| 3 | 385 | 414 | 147 | 38,2 | 404 | 71 | 18,4 | 51,7 |
| 4 | 544 | 458 | 233 | 42,8 | 455 | 160 | 29,4 | 31,3 |
| 5 | 368 | 445 | 156 | 42,4 | 450 | 78 | 21,2 | 50,0 |
| **Total** | **2134** | **1978** | **815** | **38,2** | **2056** | **475** | **22,3** | **41,7** |

Table 8 – Comparison of the orders delivered the same day with the orders delivered next day

The results reported here show that the new algorithm does not present a clear advantage in terms of the completed distance. However, as mentioned before, when the case study was described, the main objective of the company is to improve the quality of service, measured by the delivery time

to pharmacies, keeping the increase in the distance within an acceptable value. The proposed algorithm improves the average delivery time in about 8%, from 1h51 to 1h42.
An analysis of the accumulated number of deliveries as a function of the delivery time, allows us to identify three distinct situations.
In the first situation, up to 1 hour of delivery time, we notice that in the current manual procedure there are a larger number of deliveries than with the new algorithm. This is due to the fact that the algorithm keeps vehicles waiting when the delivery time is not larger than 2 hours. By keeping vehicles waiting, it is natural that the number of deliveries up to 1 hour is smaller than in the current manual procedure. In the second situation, up to 2 hours of delivery time, the number of deliveries performed by the new algorithm was 7.3% larger than in the current manual procedure. In the third situation, up to 3 hours of delivery time, the improvement is still higher. The number of deliveries performed by the new algorithm was 17.5% larger than in the current manual procedure.
In terms of the number of orders that are delivered in the following day, the algorithm drastically reduces their number, with more than 40%. However this gain is not considered to be vital by the company, given that some pharmacies do prefer to have deliveries made early in the next morning rather late in the evening the day the order is placed.

# 6. Conclusions and further research

The algorithm proposed in this work has been evaluated by the simulation of the company's operation during one week, having as a reference, the plan designed and executed using the current manual procedure. Results show that the adopted strategy leads to solutions that are implementable in practice, and that we should expect to achieve significant improvements in the quality of service (evaluated by delivery times) for almost the same completed distance.
The model adopted for this problem can be viewed as a particular case of a dynamic vehicle routing problem. However, it has not been possible to directly adopt any approach from the literature, given the specific features of the problem, the existence of particular constraints, and the need to take operational management requirements into account (for example tackling the difficulty in establishing reasonably stable demand patterns or the difficulty to predict the availability of the vehicles during the day).
Improvements in the order of 8% have been achieved, concerning the average delivery time, with no changes to the currently available fleet and by roughly completing the same distance.
It should also be noted that a set of non-tangible benefits have been obtained, that are directly related to the automation of the process. For example, the planner knows, at any time, the status of each order and whether it is being picked in the automatic zone. This clearly increases the flexibility of the decision-maker as he/she becomes able to construct routes taking into account orders that have not yet been completely picked. Moreover the company has been able to restructure some of its management processes, as more reliable information becomes available on the actual routes and simplifications have been introduced.
In order to make this application a real and useful Decision Support System (DSS), a couple of additional developments are still needed, involving the reinforcement of its integration with the company's main information system, and the design of a more effective and user-friendly graphical

interface. This will naturally require the integration with a Geographical Information System, thus improving the way solutions are presented to the planner.
It should also be noted that the heuristics used in this work will easily encompass further practical requirements, resulting e.g. from the consideration of time windows for some specific pharmacies. Trough simple, easy to implement modifications, we will hopefully be able to adapt those heuristics to the specific features of real situations.
Moreover such a DSS, together with a more thorough information collection and management, will enable the realization of studies and analysis of a more tactical nature, supporting for example the definition of some algorithm parameters such as the limit angle or bounds on the waiting time. "What-if" analysis could then be performed to assess the impact of changes in the whole distribution policies. Changing these policies may involve issues such as moving late deliveries to the next day (early morning).
As mentioned above, many pharmacies do not place their orders at fixed times during the day. However, some pharmacies do in fact use this policy. Collecting more information about these different behaviours might lead to the identification of some behavioural "patterns" for a considerable number of pharmacies. These patterns might then be used to anticipate demand and to create a set of a priori fixed routes, to which variable routes would be dynamically added, according to the incoming orders. A new method based on this idea would in fact be an adaptation of the one already proposed by Campbell and Savelsbergh (2002). This would lead to some kind of "hybrid" approach, merging real time and a priori methods, that would hopefully be configurable to accommodate the requirements of each specific company.

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