UNIVERSIDAD CARLOS III DE MADRID

working papers

ROUTING DESIGN FOR LESS-THAN-TRUCKLOAD MOTOR CARRIERS USING ANT COLONY TECHNIQUES[♦]

Lucía Barcos [1], Victoria M. Rodríguez[2], Mª Jesús Álvarez [3] and Francesc Robusté [4]

Abstract

One of the most important challenges for Less-Than-Truck-Load carriers consists of determining how to consolidate flows of small shipments to minimize costs while maintaining a certain level of service. For any origin-destination pair, there are several strategies to consolidate flows, but the most usual ones are: peddling/collecting routes and shipping through one or more break-bulk terminals. Therefore, the target is determining a route for each origin-destination pair that minimizes the total transportation and handling cost guaranteeing a certain level of service.

Exact resolution is not viable for real size problems due to the excessive computational time required. This research studies different aspects of the problem and provides a metaheuristic algorithm (based on Ant Colonies Optimization techniques) capable of solving real problems in a reasonable computational time. The viability of the approach has been proved by means of the application of the algorithm to a real Spanish case, obtaining encouraging results.

Key words: Distribution, Logistics, Ant Colony Optimization

[♦] Corresponding author: Dra. Lucía Barcos, Universidad Carlos III, C/Madrid 126, 28903 Getafe (Madrid), Spain. FAX: 34 – 91 624 96 07. Email: lbarcos@emp.uc3m.es
[2, 3] Universidad de Navarra. Dpto. de Organización Industrial, Tecnun. Spain
[4] Universidad Politécnica de Cataluña. ETS de Ingenieros de Caminos de Barcelona. Spain

1. Introduction

In a wide variety of large scale delivery systems, a firm must sheep goods on a network between many origin and destination pairs. This is the case of less-than-truckload (LTL) motor carriers and package carriers. A key to cost-effective shipping for these companies is to consolidate loads for different customers in order to travel with full or nearly full vehicles. In order to accomplish this, carriers use regional consolidation centers (en-of-line terminals, EOL terminals) and break-bulk-terminals (or hubs). But cost-effective shipping is not the only challenge for carriers since they have to ensure a certain level of service in terms of delivery time or service frequencies.

Freight originating in a region is picked up by "small" trucks and is delivered to EOL terminals (local transportation) where it is consolidated and loaded onto a trailer for the long-haul transportation. When the load arrives to the destination EOL terminal it is unloaded and moved into delivery trucks for final delivery. Break bulk terminals (or hubs) act as intermediate transshipment points where freight from many EOL terminals is unloaded, sorted, consolidated and reloaded onto other long-haul trailers which will take the freight to another break bulk terminal or to the destination EOL terminal.

Carriers working in Spain and Portugal usually offer a delivery time of 24 hours for most of their services (or 48 hours when this is not possible). Normally, the freight generated in a region is collected in the evening, meanwhile local deliveries are made in the morning.

This paper concerns the long-haul transportation between EOL terminals. Therefore, for the purposes here, it is possible to view the EOL terminals as origination and destination points. Long haul transportation between EOL terminals may be carried out directly between origin and destination. However, although this is the fastest method, in many cases it is not the most cost-effective one, since there is not enough

freight to fill or even nearly fill a truck. For this reason, other routing alternatives are used for consolidating freight. One way of doing this is to make multiple stops for collecting or delivering freight (collecting/peddling routes), as shown in Fig. 1, or else to ship freight through break bulk terminals. Normally hubs act as terminals with high expectations of freight consolidation, and play a very important role in this type of logistic network.

Collecting route

collection   destination

Peddling route

oigin   distribution
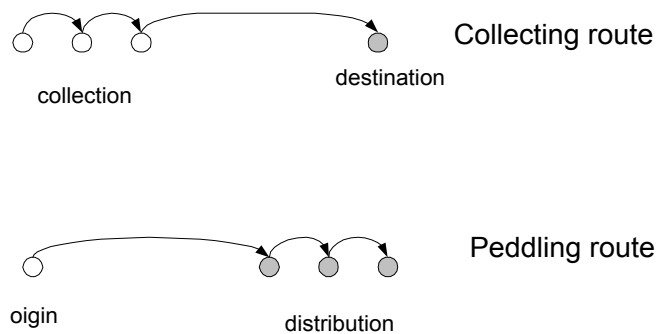
Fig. 1: Peddling and collecting routes

As such, the design of routes for these systems involves deciding if the freight for each origin-destination pair (origin EOL terminal – destination EOL terminal) should be transported directly, using a peddling/collecting route, or if consolidation should be carried out in one or several hubs. These decisions must also be taken bearing in mind the services conditions offered by the carrier. Which alternative is best? If the transportation has to be carried out using a peddling/collecting route, which stops should be made? If it has to be done via hubs, how many and which hubs should be used? Each option has its own cost and delay measures, but the choice does not depend solely on the situation of the origin and the destination and the volume moved between the two points, but also on the demand throughout the entire network and the configuration of the logistic costs of the system; these decisions have network-wide

impact and are complexly interconnected (Crainic and Roy, 1988); this is an overall problem and optimization requires an integrated approach.

This is a tactical problem in which a routing design which satisfies the regular demand (which is known to have a high degree of certainty) and which is valid for a medium to long period of time is sought.

A constant characteristic of any freight transportation system is the need to move empty vehicles. This follows from the imbalances that exist in demand in certain regions of the area of activity; there are zones which generate more freight than that which is received, and vice versa. To correct these differences, empty vehicles must be sent from the areas in which an excess of empty vehicles has been created to the place which needs them, to be able to perform the following day's activities. As such, the design of routes must also take this aspect into account and the most cost effective way of moving these vehicles must be sought.

2. State of the art

The type of problem considered is known as a *many-to-many* problem (i.e. several origins to several destinations in which each terminal acts simultaneously as origin and destination) unlike other classic problems such as the Vehicle Routing Problem or the Traveling Salesman Problem which are considered to be *one-to-many* problems (Daganzo, 1996)

The exact mathematical approach to this type of problem is usually non-viable for solving real-life problems. This fact is reflected in papers by, for example, Powell (1986), Powell and Sheffi (1983 and 1989) and Leung et al. (1990). In Barcos (2002),

a mixed-integer formulation of the problem is made (without considering the level of service), but its use for resolving real life problems involves the use of an unmanageable number of variables and restrictions and a prohibitive computation time. Consequently, heuristic algorithms which can provide solutions within a reasonable computational time are generally used.

There are studies which approach this type of problem with a high level of aggregation. In Daganzo (1996), the problem is analyzed from the perspective of Continuous Approximations; working with the lowest level of detail possible in the data and trying to provide solutions in terms of design rules. In Hall (1987) and Hall (1989), various shipment strategies via hubs are also analyzed (shipping through the hub closest to the origin or closest to the destination, shipping through the hub that offers the minimum travel distance, shipping first through the hub closest to origin and second through the hub closest to the destination, and other hybrid strategies). An attempt is made to identify different scenarios in which each of these strategies may be the most beneficial.

Powell (1986) and Powell and Sheffi (1983 and 1989) address the Load Planning Problem, which is defined as the specification of how freight should be routed (and consolidated) over the network, given a set of direct services between terminals. The authors implemented a heuristic procedure based on the hierarchical decomposition of the problem into a "master problem" and several subproblems. The "master problem" is a network design problem in which direct services offered by the carrier are established, with a minimum service frequency imposed. The total system cost is computed for each given configuration of selected services. Each time a modification is made in the network (adding or dropping arcs), a routing subproblem and another empty balancing subproblem must be solved. To solve the first subproblem, shortest-path type

procedures are used, while the second subproblem is solved using a minimum cost transshipment formulation with adjusted supply and demand.

In Leung et al. (1990) a problem-solving method also based on the decomposition of the problem into two inter-related subproblems is developed. The first subproblem considers de assignment of a first and a last break bulk terminal on the route for every origin-destination pair. A preselection can be made within all the possible assignations, eliminating the assignations which violate the service-time restrictions (delivery within a certain time). The second subproblem seeks a minimum cost routing of the aggregated flow of goods among the break bulk terminals (note that the routing problem is restricted to the hub network, which is significantly smaller than the overall network). This is a procedure which iterates between both subproblems, where the routing subproblem constitutes an evaluation mechanism for a certain assignation. Lagrangian Relaxation and shortest-path procedures have been used to approach these problems

Crainic and Rousseau (1986) proposed a general modeling framework for the medium-term planning problem of multimode, multicommodity freight transportation system, which was first used to solve a rail application (Crainic, 1988) and later adapted for LTL problems (Roy and Delorme, 1989). They develop a model named NETPLAN which is intended to assist motor carriers in making decisions about designing the service network, routing freight, and balancing empty vehicles. It is formulated as a non-linear mixed-integer programming problem, where service frequencies as well as the volume of freight moving on each route through the network are the main decision variables. NETPLAN explicitly considers the trade-offs to be made between operating costs and both speed and reliability of service at the objective function level. The original method described by Crainic and Roussseau (1986) combines a heuristic model (based on finite differences in the objective function) that iteratively decreases

frequencies from initial high values, with a convex network optimization procedure to distribute the freight.

In Robusté et al. (1996), the authors design a system intended to assist in restructuring decisions to be taken on the logistic network of an express carrier company working within Spain, developing a decision-making tool based on efficient design guidelines.

In this study, a solution methodology based on Ant Colony Optimization is proposed. Fundamental aspects of Ant Colony Optimization are sumnmarised in section 4 of this paper.

3. Definition of the problem and objective setting

Up to now, we have described in a general way the problem with which this study is concerned. However, before approaching it in more detail, different aspects of this problem must be specified and the objectives set out clearly.

The main objective is to develop a process for solving routing design problems which will be viable when applied to real life problems. To this end, we have developed a metaheuristic algorithm using Ant Colonies techniques.

The aim is also to test the viability of this algorithm when applied to real problems in a practical situation. This implies analysing the performance of the algorithm when it is applied to a real LTL carrier company working within Spain and Portugal.

The concrete problem which will be approached considers a freight delivery system with a set of EOL terminals which potentially act concurrently as freight origins and destinations. Some of these EOL terminals operate as *break bulk terminals (hubs),* and the number and location of these hubs is previously determined. The determination of the number and location of hubs within the system is an important strategic problem which requires deep consideration and lies outside the scope of this paper. A comprehensive study and review of this problem can be seen in Rodríguez (2002).

For each origin-destination pair within the network , there is a load flow (volume of freight per day) that must be transported from the origin to the destination. The problem consists of selecting, for each origin-destination pair, the routing strategy which produces de least total cost for the system, while ensuring a certain level of service . It is assumed that the LTL carrier guarantees the delivery of the freight within 24 hours, or within 48 hours at the latest. The routing strategies considered are the following:

- Shipping directly

- Shipping via the hub which, of the two closest to origin, generates the least costly route.

- Shipping via the hub which, of the two closest to destination, generates the least costly route.

- Shipping through two hubs (the two mentioned above)

- Shipping through the hub which generates the least costly route

- Using a collecting or peddling route, with no predetermined limit on number of stops. The possibility of mixing deliveries and collections in the same route is not considered, since this would imply the need to reorganize the load within the vehicle, which in many cases would be costly and difficult (see Daganzo,1996).

These routing strategies are based on efficient design guidelines and appear in various papers on the subject, e.g. Daganzo (1996), Hall (1987), Hall (1989) and Robusté et al (1996). Due to restrictions from the service level existing within the real system to which the algorithm will be applied, routes which pass through more than two hubs will not be considered: three transfers of freight would take up too much time and would make it difficult to provide the level of service demanded. However, the algorithm could consider any other type of routes which may be common in the concrete case to which it is to be applied.

The choice of a routing strategy for each origin-destination pair should be dependent on the restriction in the level of service. These restrictions demands the existence of a minimum percentage of freight (or dispatches) served in 24 hours, and the rest of the freight must be served within 48 hours. For a solution, the time in which each of the origin-destination pairs will be served must be calculated. To this end, driving time, the time used for peddling or collecting stops, handling time in hubs and the delay that occurs while waiting in the hubs for an outbound trailer to fill up with the load that must be consolidated prior to dispatch must all be taken into account. When the delivery time for each origin-destination pair is calculated, the level of service corresponding to the solution can be found.

An unlimited fleet with homogeneous capacity is assumed (with trailer trucks being considered for the concrete case of application, as is normal for long haul transport between terminals). All freight to be transported between each origin-destination pair should follow the same route, unless the load exceeds vehicle capacity, in which case as many vehicles as are full are sent directly to the destination, and an attempt is made to consolidate the rest of load. This is usual practice for Less-than-

Truckload carriers, such as the Spanish company which will be used as an example for the application of this paper, and other companies as can be seen in Leung et al. (1990).

With regard to system costs, the following three types are considered:

- Cost associated with the distance covered by each vehicle R (€/Km).

- Cost associated with stops made by vehicles to collect or deliver freight P (€ per vehicle stop)

- Handling cost in hubs, c_r , where r is the hub involved, expressed in € per unit of freight handled. This endows the hubs with a hierarchy, such that, for the same routing distance it may be preferable to transfer loads in hubs where load processing is cheaper.

The choice of routing strategies for each origin-destination pair allows the calculation of the freight volume (and as such, the number of vehicles) which must travel daily through each network arc, and the freight volume which must be processed in each hub. This allows the total cost of the system associated with each solution to be calculated. For a better understanding and deeper analysis of the cost structure used, see Barcos (2003) and Daganzo (1996).

Determination of empty vehicle movements is made using linear programming formulation of a classic transport problem, in which empty vehicles travel from the place where an "excess" of vehicles is created to where there is a "lack" of vehicles in order to satisfy the demand for the following period.

Since the method proposed in this paper is based on Ant Colony Optimization techniques, a summary of this methodology will be provided below.

4. Ant Colony Optimization

ACO (Ant Colony Optimization) algorithms are models inspired by the behavior of real ant colonies. Studies have been made to show how ants, which are almost blind, are capable of following the shortest route paths from their colonies to feeding sources and back. This is due to the ants' capacity for transmitting information between themselves, since each of them, as it goes, deposits a pheromone trail along the chosen path. In this way, while an isolated ant moves essentially at random manner, the "agents" of an ant colony detect the pheromone trail left by other ants and tend to follow that trail. These ants then deposit their own pheromone along the path, thus reinforcing it and making it more attractive. So, it can be said that the process is characterized by a positive feedback loop, in which the probability of an ant choosing a path increases with the number of ants which have previously used the same path.

The first algorithm based on Ant Colony Optimization (AS algorithm) was applied to the Traveling Salesman Problem (Dorigo et al, 1996), from which quite promising results were obtained. Improved versions of this algorithm have been developed, which have been applied not only to the Traveling Salesman Problem (TSP) but also to other Combinatorial Optimization problems, such as the Vehicle Routing Problem (VRP) and the Quadratic Assignment Problem (QAP). For more information, refer to: Dorigo et al. (1999), Gambardella et al. (1999), Colorni et al. (1994), Gambardella and Dorigo (1997), Bullnheimer et al. (1999), Stützle and Dorigo (1999a) and Stützle (1997). In this research paper, we have developed a heuristic based on one of these improved algorithms called the Max Min Ant System (MMAS), which was first applied to the TSP (see Stützle and Hoos, 1997)

In ACO algorithms, artificial ants act as computational agent which transmits information in some way. The ACO algorithms are iterative processes. In each iteration, each one of the artificial ants which make up the colony constructs a solution to the problem. These agents construct the solutions in a probabilistic manner, being guided by an artificial pheromone trail and by data which has been heuristically calculated a priori, i.e., the virtual ants are not totally blind; instead they are capable of including heuristic information in the construction of solutions. Therefore, when these algorithms are applied to the resolution of a problem, the pheromone trail which the ants will deposit must be determined, as must the heuristic information which will be worked with. The probabilistic rule followed by the ants to construct solutions must be defined taking these two elements into account.

When an ant has constructed a solution to the problem, this solution may be improved by applying a local search algorithm. For example, *3-opt local search* was used for the TSP and short runs of Tabu Search for the QAP, as shown in Stützle and Dorigo (1999a and 1999b).

When all the ants of the colony have constructed a solution, the pheromone trails deposited by the virtual ants must be updated, for which a pheromone updating rule must be defined. This updating rule may take into account the evaporation which the pheromone undergoes over time,

After updating the pheromone, the process is iteratively repeated until a termination condition is given (e.g. a maximum number of iterations or a given CPU run time). The solution provided by the algorithm will be the best solution found in the whole iterative process.

In general, all the ACO algorithms follow a specific algorithmic scheme

Step 1: Set parameters and initialize pheromone trails

Step 2: Construct a solution for each virtual ant

Step 3: Improve each solution applying local search

Step 4: Update pheromone trails

*Step 5*: If continuation is allowed go to Step 2, otherwise Stop.

5. Proposed method

The information regarding the freight transportation system, which must be entered to the algorithm as inputs, is summarized bellow:

- Network configuration: EOL terminals, break bulk terminals and distances between terminals.

- Load flows: the elements of the matrix Q^0 represent the load flow (volume of freight per day) that must be regularly transported between each origin-destination pair

- Fleet of vehicles : as mentioned in Section 3, we assume an unlimited fleet with homogenous capacity C.

- Cost structure: R, P and handling costs in each hub, c_r

- Travel time and service level: speed of the vehicles, stopping times in the EOL terminals for delivering or collecting freight (there is a fixed time and another time proportional to the load), load reorganization time in the hubs and level of service demanded.

With regard to the loads to be transported between each origin-destination pair, it may be that some of them exceed the capacity of the vehicles. In this case, the algorithm first determines the full vehicles which will travel directly from origin to destination (see Section 3) and then recalculates the new load flows (matrix Q) with

which it is going to work for consolidation; so for, it can be said, without lost of generality, that $q_{ij} \leq C$, where q_{ij} is the new load to be transported between origin i and destination j. See Fig. 2 for a better understanding of the process.
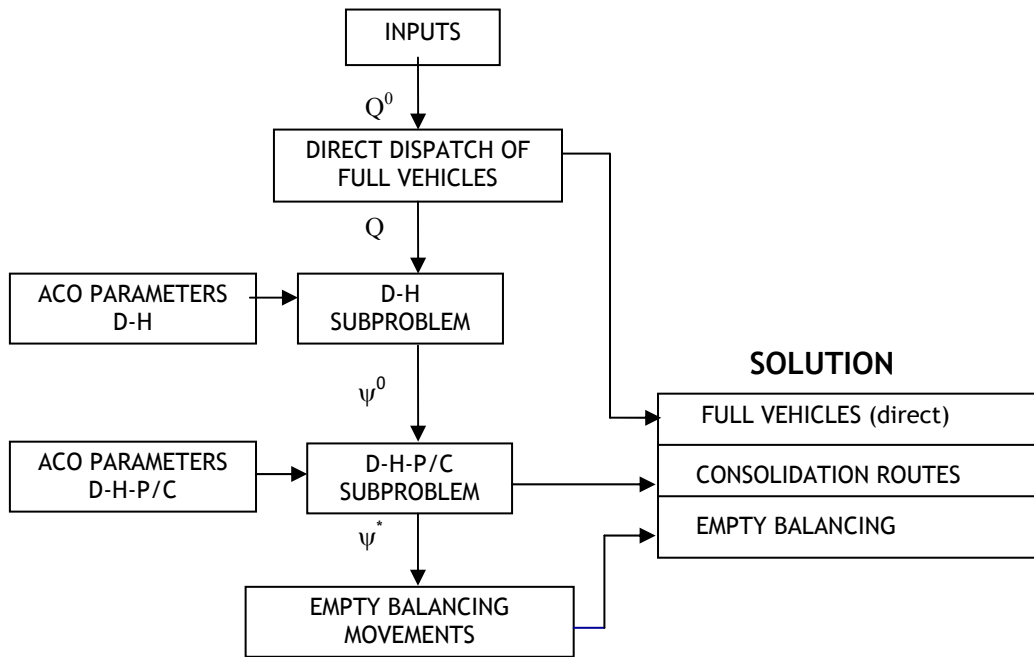
Fig.2. General scheme of the algorithm

In real systems, a large part of the freight is shipped through one or several hubs, since these terminals provide high expectations for consolidation. Taking this into account and for greater simplicity, it was decided to break down the general routing problem into two subproblems: the D-H subproblem and the D-H-P/C subproblem. Both are solved using ant colony optimization techniques. The **D-H** subproblem consists of finding the optimal solution to the general problem while ignoring the possibility of making peddling/collecting routes (only **D**irect routes or via **H**ubs are considered). The point of departure for the **D-H-P/C** subproblem is the solution found for the D-H subproblem. This second phase attempts to refine and improve the solution by introducing **P**eddling/**C**ollecting routes.

When the solution is found for the general problem, the algorithm solves the empty balancing using linear programming formulations, as mentioned in section 3.

5.1. Resolution of the D-H subproblem using Ant Colony Optimization

Before starting to explain the procedure used for solving this subproblem, it should be made clear that both the formulas used in this algorithm and the methodology followed have been adapted from the Max Min Ant System, which has already been applied to other problems such as the TSP or the QAP (Stützle and Dorigo ,1999a and Stützle and Dorigo 1999b)

In each iteration of the resolution process there is a colony of virtual ants, each of which constructs a solution to the D-H subproblem. The construction of these solutions is based on the probabilistic choice of a routing strategy for each origin-destination pair within the system. The routing strategies considered in this subproblem are the first five set out in Section 3 (i.e. peddling and collecting routes are excluded).

The process for exploration and exploitation of solutions is directed by a pheromone trail and a heuristic information parameter, which are assigned to each routing option and for each origin-destination pair. Let *Z* be the set of five routing strategies considered for each origin-destination pair, and *z* the indicative corresponding to each of the elements of this set. Let *P* be the set of all origin-destination pairs *(i, j)*.

$\tau_{ij}^{z}(t)$ = *pheromone trail for the pair (i,j) and routing option z in iteration t*

η_{ij}^{z} = *heuristic information parameter for pair (i, j) and routing option z*

The probability with which an ant from the colony chooses the routing strategy *z* for the origin-destination pair *(i, j)* in iteration *t* is:

$$P_{ij}^{z}(t) = \frac{\left[\tau_{ij}^{z}(t)\right]^{\alpha_1}\left[\eta_{ij}^{z}\right]^{\beta_1}}{\sum_{z \in Z}\left[\tau_{ij}^{z}(t)\right]^{\alpha_1}\left[\eta_{ij}^{z}\right]^{\beta_1}}$$ (1)

where α_1 and β_1 are two algorithm parameters which determine the relative influence of the pheromone trail and the heuristic information.

Each of the solutions constructed by the ants involves a cost which must be calculated taking into account the costs structure set out in section 3 of this paper. It must be clarified that for simplicity's sake, no local improvement of the solutions found by the ants has been made in this subproblem.

After all ants have constructed a solution, the pheromone trails are updated according to

$$\tau_{ij}^{z}(t+1) = (1-\rho_1)\tau_{ij}^{z}(t) + \Delta\tau_{ij}^{best1} \qquad (i,j) \in P, z \in Z$$ (2)

$$\Delta\tau_{ij}^{best1} = \begin{cases} 1/\text{cost}\left(\psi^{best1}\right) & \text{If z is chosen for (i, j) in solution } \psi^{best1} \\ 0 & \text{Otherwise} \end{cases}$$

where $0 \le \rho_1 \le 1$ corresponds to the pheromone evaporation rate; $\text{cost}(\psi^{best1})$ means the cost of the solution ψ^{best1}; ψ^{best1} may be either the *iteration-best* solution ψ^{ib1} or the best solution found during the run of the algorithm, the *global-best-solution* ψ^{gb1}. Experience shows it is convenient to use ψ^{ib1} and ψ^{gb1} alternatively in pheromone updating; in general, best results are obtained by gradually increasing the frequency of choosing ψ^{gb1} for the trail update.

The heuristic information parameter used in solution construction is the following

$$\eta_{ij}^z = \frac{1}{C_{\min}^z(q_{ij})} \qquad (i,j) \in P, z \in Z \qquad\qquad (3)$$

When z corresponds to the strategy of direct shipping, $C_{\min}^z(q_{ij})$ is calculated as the total cost of the route. If z corresponds to a routing strategy which passes through hubs (remember that four possibilities of shipping via hubs were considered), then $C_{\min}^z(q_{ij})$ corresponds to the cost which can be proportionally imputed to q_{ij} when all the vehicles covering the route travel full. In this sense, $C_{\min}^z(q_{ij})$ is the **minimum** cost which can be imputed to the load when it is transported following the routing strategy z.

Up to now we have defined all the information involved in this Ant Colony Optimization procedure. Figure 3 shows the flow chart of the ACO algorithm for the D-H subproblem.
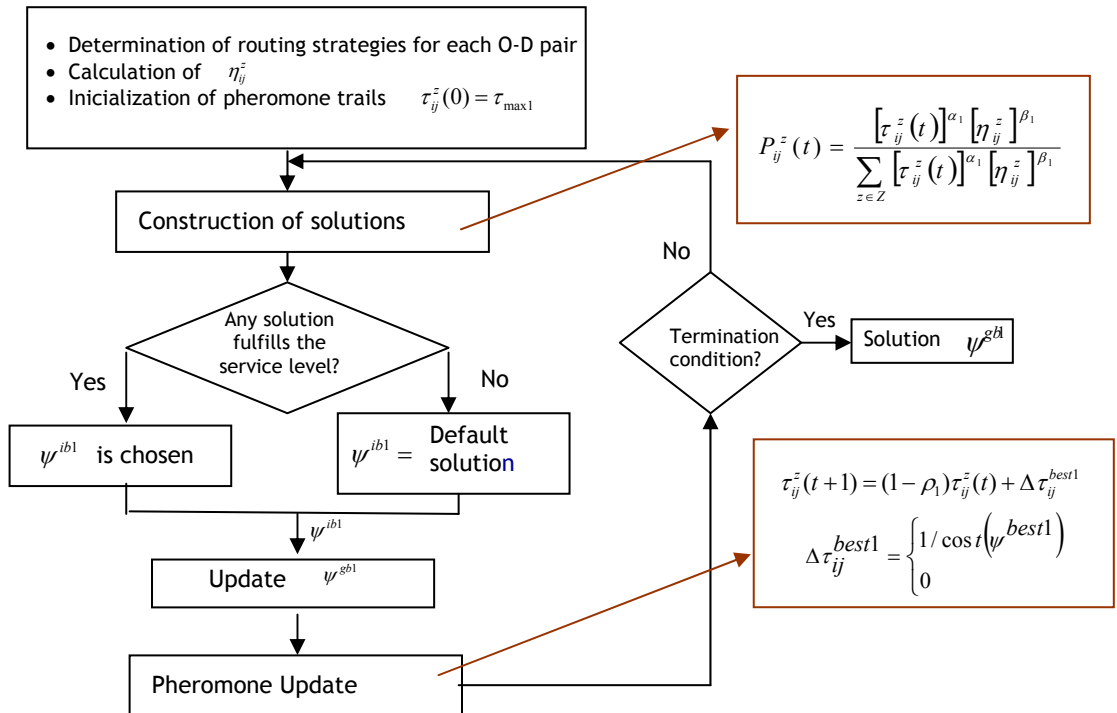
Fig.3. Iterative process for the D-H subproblem

In general, the scheme to be followed is similar to that already explained in Section 4 (although in this case no local improvement of the solutions constructed by the ants has been made). However, it is worth mentioning that after the construction of solutions, the service level corresponding to these solutions must be evaluated. The solution then selected is the most cost-effective of those which fulfill the service restrictions. This will be the *iteration-best solution* (ψ^{ib1}). If none of the solutions constructed by the ants fulfills the service restrictions, then ψ^{ib1} will be a solution chosen by default.

5.2 Resolution of D-H-P/C subproblem using Ant Colony Optimization

The point of departure for the solution of the D-H-P/C subproblem is the solution found for the D-H subproblem. In this second subproblem, we try to improve the initial solution by introducing peddling/collecting routes. As such, there will be loads which in the initial solution are transported directly or through hubs, and which in this second phase, will change to being transported by peddling/collecting routes.

The construction of peddling/collecting routes is complicated as there are too many possible combinations. To reduce the space of possible solutions, a *Set of Candidates for Peddling (S_{ij}^{P})* and a *Set of Candidates for Collecting (S_{ij}^{C})* is assigned to each *(i, j)* pair. With the aid of these sets only peddling/collecting routes with a quite high expectation of improving the initial solution can be constructed.

S_{ij}^{C} is made up of those loads q_{lj} so that if a route such as that described in the figure 4(a) was constructed, this route would have a high probability of improving the initial solution. Something similar can be said for the S_{ij}^{P} set (see Fig.4b).

q_{ij}

$q_{ij} + q_{lj}$ j

i   l

$$\forall q_{lj} \in S_{ij}^C \qquad \textbf{(a)}$$

q_{ij}

$q_{ij} + q_{ij}$ l   j

i

$$\forall q_{il} \in S_{ij}^P \qquad \textbf{(b)}$$

Fig.4: Sets of candidate loads for peddling/collecting

As such, the loads making up these sets and the routes constructed with them (as indicated in Fig. 4) must fulfill the following conditions:

- The loads involved in the peddling/collecting route must not exceed vehicle capacity

- The cost of the peddling/collecting route must be not more than the **minimum cost** attributed to the two loads (for this concept see section 5.1) when transported according to the initial solution

- The delivery time (24 or 48 hours) of the loads involved in the peddling/ collecting route should be the same as or better than the delivery time of both loads in the initial solution

5.2.1 Pheromone trails and heuristic information

Since the D-H-P/C subproblem is also solved using an ACO approach, the *heuristic information* which will be used and the *pheromone trails* must be determined.
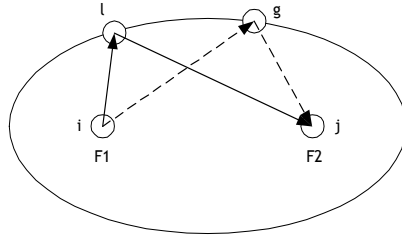
Pheromone trails $\qquad \tau_{ilj}^C(t) \quad \forall q_{lj} \in S_{ij}^C ; \qquad \tau_{ilj}^P(t) \quad \forall q_{il} \in S_{ij}^P \qquad$ (4)

Heuristic information (Utility) $U_{ilj}^C \qquad \forall q_{il} \in S_{ij}^C ; \qquad U_{ilj}^P \quad \forall q_{il} \in S_{ij}^P \qquad$ (5)

The heuristic information chosen for this subproblem is given by the ***Utility*** parameter. This parameter is a measure of the profitability of a route such as those

described in Fig. 4. *Utility* can be calculated using the formulas (6). These formulas confer greater *Utility* on those routes which fill the vehicle more and deviate less from the main direction of travel. For two routes with equal detours (candidate loads located in the ellipse in Fig.5) these formulas allow greater *Utility* to be conferred on the route which has the origins closest to each other (for the case of a collecting route) or the destinations closest to each other (for the case of a peddling route).

$$U_{ilj}^C = \frac{q_{ij} + q_{lj}}{\dfrac{d_{il} + d_{lj}}{d_{ij} + d_{lj}}} \quad \forall q_{lj} \in S_{ij}^C \qquad\qquad U_{ilj}^P = \frac{q_{il} + q_{ij}}{\dfrac{d_{il} + d_{lj}}{d_{il} + d_{ij}}} \quad \forall q_{il} \in S_{ij}^P \qquad (6)$$

Fig. 5: Routes with equal detours from main direction of travel

However, the formulas (6) can be modified to use costs instead of distances in the denominator, permitting a more realistic calculation. This is how we have proceeded in the development of the algorithm, with "corrected" formulas being used for determining *Utilities*.

5.2.2 Construction of a solution for the D-H-P/C subproblem

Artificial ants construct solutions for the D-H-P/C subproblem, departing from the solution found for the D-H subproblem, and improving on it by adding peddling/collecting routes. The flow chart corresponding to this process is shown in Fig. 6.

Firstly, the algorithm constructs a list (L) with all the origin-destination pairs within the system and arranges them in a decreasing order according to direct distances between origin and destination. The first pair of the list is taken and the availability of candidate loads for peddling or collecting is checked. If there are candidates, then the ant chooses among them in a probabilistic manner according to the formulas:

$$P_{ilj}^{C}(t) = \frac{\left[\tau_{ilj}^{C}(t)\right]^{\alpha_2}\left[U_{ilj}^{C}\right]^{\beta_2}}{\sum\limits_{f|q_{fj}\in S_{ij}^{C}}\left[\tau_{ifj}^{C}(t)\right]^{\alpha_2}\left[U_{ifj}^{C}\right]^{\beta_2} + \sum\limits_{f|q_{if}\in S_{ij}^{P}}\left[\tau_{ifj}^{P}(t)\right]^{\alpha_2}\left[U_{ifj}^{P}\right]^{\beta_2}}$$ (7)

$$P_{ilj}^{P}(t) = \frac{\left[\tau_{ilj}^{P}(t)\right]^{\alpha_2}\left[U_{ilj}^{P}\right]^{\beta_2}}{\sum\limits_{f|q_{fj}\in S_{ij}^{C}}\left[\tau_{ifj}^{C}(t)\right]^{\alpha_2}\left[U_{ifj}^{C}\right]^{\beta_2} + \sum\limits_{f|q_{if}\in S_{ij}^{P}}\left[\tau_{ifj}^{P}(t)\right]^{\alpha_2}\left[U_{ifj}^{P}\right]^{\beta_2}}$$ (8)

Given the pair (*i,j*), $P_{ilj}^{C}(t)$ refers to the probability with which the ant chooses the load $q_{lj} \in S_{ij}^{C}$ to make a collecting route according to the *i-l-j* sequence in the iteration *t* (see Fig. 4a); $P_{ilj}^{P}(t)$ corresponds to the probability with which the ant chooses the load $q_{il} \in S_{ij}^{P}$ to make a peddling route according to the *i-l-j* sequence (Fig. 4b). After this choice is made, the load chosen must be eliminated from the list L and from the sets S_{ij}^{C} and S_{ij}^{P}. Then, an attempt is made to introduce more stops into the peddling/collecting route which is being constructed, until one of the following conditions is produced, in which case the route is said to be *saturated:*

• There is insufficient space in the vehicle to introduce another load

• The route becomes so long that it affects the delivery times of the loads involved

To introduce new stops in a collecting route, loads from S_{lj}^{C} are chosen, with q_{lj} being the last load introduced into the route. In the case of a peddling route, a load is chosen from those in S_{il}^{P}, with q_{il} being the last load introduced into the route (note that in S_{lj}^{C} and S_{il}^{P} there will only be loads which have not been used up to that moment). This choice will also be made in a probabilistic manner, using very similar formulas to (7) and (8).

When a route is saturated, a new route begins to be constructed with the next origin-destination pair available in list L. It should be said that this advance throughout the list is done in a probabilistic way, which causes a higher exploration of solutions.

When no more pairs are available in L, the construction process for the solution is completed, which will be formed of:

- the peddling/collecting routes constructed by the ant
- direct routes and routes via hubs, since the loads not involved in these peddling/collecting routes are transported according to the initial solution (the solution obtained for the D-H subproblem)

5.2.3 Local improvement and pheromone update

Until now, we have explained how each of the ants in the colony constructs solutions for the D-H-P subproblem. However, the optimization process is iterative and follows the general scheme set out in section 4. In this case, a local improvement for solutions constructed by the ants has been made. In order to avoid excessive running time, this local improvement has been only applied to the *iteration-best* solution. With this process, more efficient consolidation is sought for loads which are transported directly or through hubs. Alternative routes for some loads are evaluated, with the aim

of avoiding nearly empty vehicles and taking advantage of gaps in other partially full vehicles.

For the pheromone updating, similar formulas to those already used in the resolution of the D-H subproblem have been followed.
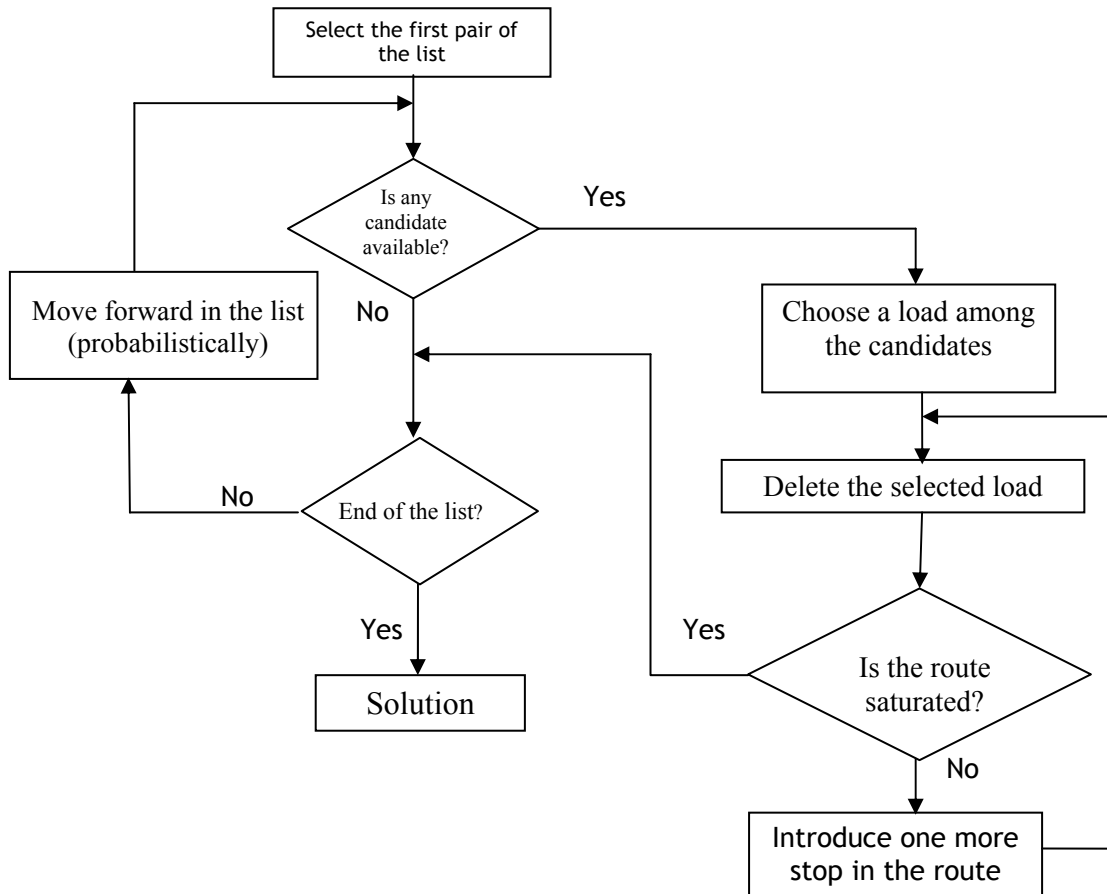
Fig.6: Construction of solutions for the D-H-P/C subproblem

6. Application of the algorithm to a real case

One of the main objectives of this paper was to test the viability of our algorithm in the resolution of real-life problems. With that purpose, the algorithm was implemented in C language and was applied to the real case of a LTL carrier operating in Spain and Portugal.

We considered the 49 main EOL terminals with which the company works in Spain and Portugal. Six of these terminals acted simultaneously as break bulk terminals. The service requirements introduced into the algorithm correspond to the levels provided by the company at the time in which the application was made (83.7% of the dispatches had a delivery time of 24 hours, the rest was delivered within 48 hours). We worked with a load flow matrix obtained from statistical studies on historical data provided by the company. It was also necessary to establish, in a parallel fashion, a kilometer distance matrix from a road map.

Cost parameters were determined from data provided by the company. Estimations could also be made for the time required for loading and unloading of freight for peddling/collecting and time spent in the reorganization of the freight in the hubs. A mean travel speed was assumed for all the routes, and the capacity of the vehicles was considered to be that equivalent of a trailer.

In addition, it was also necessary to set the value of the parameters intervening in the two ACO processes used in this paper. Numerous experiments were carried out on the real problem to determine the value of the parameters which lead, in general, to better solutions (see Barcos, 2003). These values are summarized in Table 1:

D-H	D-H-P/C
$\alpha_1 = 2$	$\alpha_2 = 5$
$\beta_1 = 23$	$\beta_2 = 20$
$\rho_1 = 0.6$	$\rho_2 = 0.2$
$\tau_{max1} = 0.01$	τ_{max2}
$\tau_{min1} = 0.0$	τ_{min2}
Number of ants in the colony : 150	Number of ants in the colony : 100
Number of iterations : 3000	Number of iterations = 1250

Table 1. Parameter setting

Initially, the values used for the pheromone limits had been calculated from the following formulas:

$$\tau_{\max} = \frac{1}{\rho} \cdot \frac{1}{\cos t(\psi^{gb})} \qquad\qquad \tau_{\min} = \frac{\tau_{\max}}{2n} \qquad\qquad (9)$$

where n is the number of origin-destination pairs in the system. These formulas had been adapted from those used in Stützle and Dorigo (1999a and 1999b). However, experience showed that the performance of the algorithm was better when values similar to those which appear in the table were used for $\tau_{\max 1}$ and $\tau_{\min 1}$. In the case of $\tau_{\max 2}$ and $\tau_{\min 2}$, the formulas (9) have been shown to be appropriate.

It has also been observed that, in general, the value of the parameters of the D-H subproblem substantially influence the results obtained, while the value of the parameters in the D-H-P/C subproblem appears to affect the solution to a lesser degree.

When all this information on the real problem and on the two ACO processes was entered into the algorithm, the algorithm was run multiple times. The best solution found with the application indicated cost savings of approximately 7% (including also the costs of empty vehicle movements). It must be made clear that the cost per unit of freight transported was used for this evaluation. Additionally, the computation time used by the algorithm was less than 40 CPU min (using a PC INTEL PIII with 1GHZ and 256MB), which is a very reasonable time even if the software has to be run frequently.

Fig.7. shows a convergence diagram of the solution provided by the algorithm. It can be observed how the introduction of peddling/collecting routes for solving the D-H-P subproblem represents a significant improvement in the result
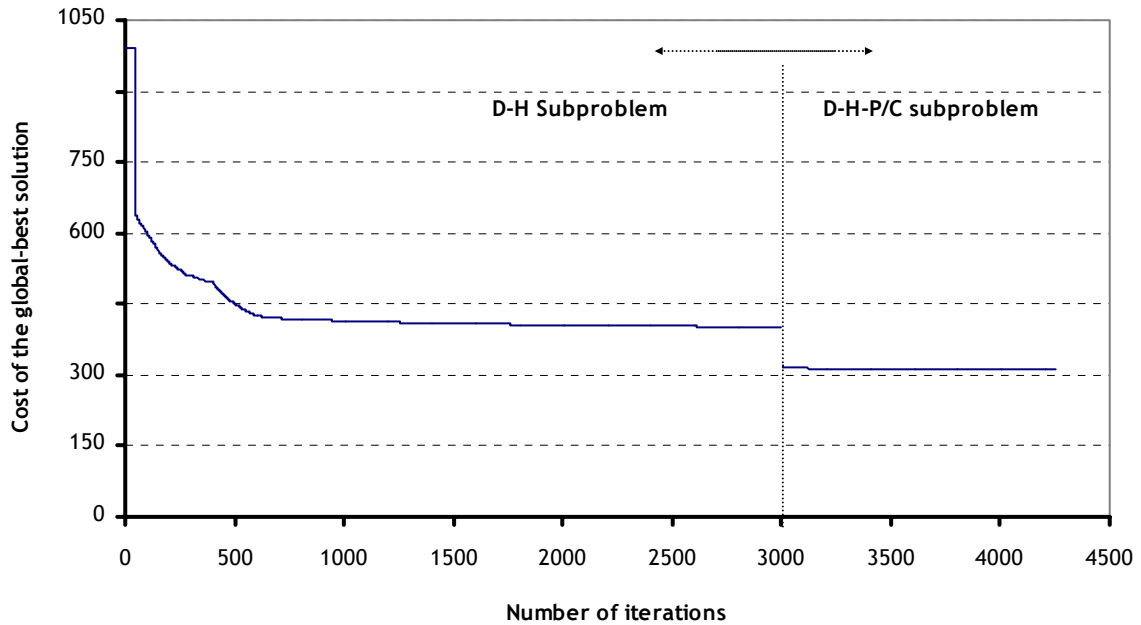
Fig.7: Convergence diagram for the algorithm for a typical run of the problem addressed in the application

7. Discussion of results and conclusions

Although the results obtained for the application provide a notable reduction in cost, it must be said that this is not the most outstanding aspect of this research paper, for the reasons explained below. The principal conclusion is that the results obtained show great consistency with reality and the proposed algorithm is viable for the resolution of real life problems. As a result, it can be said that the following aspects of our process are suitable for solving this type of problems:

- Division of the general problem into two subproblems (D-H and D-H-P)

- Use of ACO processes for solving both subproblems

- The way in which the ants construct the solutions and the information is transmitted by pheromone trails

- Heuristic information parameters defined for each subproblem

26

However, since this was a first attempt to find a solution to this real-life problem using mathematic models and optimization methodologies, the application has been carried out in a simplified manner. This means that the model may be improved by including other aspects of the real-life problem more in line with reality. Accordingly, for example, the possibility of using a fleet of non-homogenous vehicles was not considered in this paper (container trucks are usually used for long distances, but on some routes it may be appropriate to use vehicles with less capacity). Nor has the possibility of offering an intermediate delivery time of between 24 and 48 hours been considered (this practice is used by the company studied in the application, but infrequently). In addition, the model does not include capacity restrictions in the hubs, so there is the possibility that some hubs may be saturated and others underused. An effort must be made in future research papers to improve these and other aspects of the model, with the aim of refining even further the solution.

This application has also revealed the high sensitivity of the result to variations in the data with regard to the level of service (mean travel speed, reorganization times in the hubs, and time limit for arrival of the vehicles in the destination terminals). This implies that in future research papers, we must work with different travel speeds, depending on the route covered (remember that in this study a mean travel speed applicable to all the routes was used). In addition, all the information which can influence service time should be estimated as exactly as possible.

With regard to the optimization methodology, we must emphasize the large number of parameters involved, as this complicates the parameter setting process. Nevertheless, it has been observed that the result obtained is much less sensitive to the parameter values of the D-H-P/C subproblem than to those of the subproblem D-H. In

any case, the need to research efficient ways of setting the parameters has been clearly established.

As a final conclusion, it may be said that the results obtained justify continued research in this area. The model and the resolution process proposed appear to be viable when applied to real problems, although efforts must be made in order to improve both of them. There is no doubt that a lot of work remains to be done in this area.

References

Barcos, L., 2002. Optimización de rutas de transporte de carga de muchos orígenes a muchos destinos mediante Colonias de Hormigas, PhD thesis, Tecnun, Universidad de Navarra

Bullnheimer, B., Hartl, R.F., and Strauss, C., 1999. Applying the Ant System to the Vehicle Routing Problem. In: Voss, S., Martello, S., Osman I.H. Y Roucairol, C. (Eds.), Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization, Kluwer, Boston, pp. 285-296.

Colorni, A., Dorigo, M., Maniezzo, V. and Trubian, M., 1994. Ant System for Job-Shop Scheduling, Belgian Journal of Operations Research, Statistics and Computer Science, 34 (1), pp. 39-53.

Crainic, T.G., 1988. Rail Tactical Planning: Issues, Models and Tools. In: Bianco, L. and Bella, A.L., (Eds.), Freight Transport Planing and Logistics, Springer-Verlag, Berlin, pp. 463-509.

Crainic, T.G. and Rousseau, J.M., 1986. Multicommodity, Multimode Freight Transportation: A General Modeling and Algorithmic Framework for the Service Network Design Problem, Transportation Research B, 20B (3), pp.225-242.

Crainic, T.G. and Roy, J., 1988. O.R. Tools for Tactical Freight Transportation Planning, European Journal of Operational Research, 33, pp. 290-297.

Daganzo, C.F., 1996. Logistics Systems Analysis, Springer-Verlag, Berlin

Dorigo, M., Di Caro, G. and Gambardella, L.M., 1999. Ant Algorithms for Discrete Optimization, Artificial Life, 5 (3), pp. 137-172.

Dorigo, M., Maniezzo, V. and Colorni, A., 1996. The Ant System: Optimization by a Colony of Cooperating Agents, IEEE Transactions on Systems, Man and Cybernetics, 26B (1), pp. 29-42.

Gambardella, L.M., Dorigo, M., 1997. HAS-SOP: Hybrid Ant System for the Sequential Ordering Problem, Technical Report IDSIA-11/97, IDSIA, Lugano, Switzerland.

Gambardella, L.M., Taillard, É. and Agazzi, G., 1999. MACS-VRPTW: A Multiple Ant Colony System for Vehicle Routing Problems with Time Windows. In: Corne, D., Dorigo, M. and Glover, F. (Eds.), New Ideas in Optimization, McGraw-Hill.

Hall, R.W., 1987. Comparison of strategies for routing shipments through transportation terminals, Transportation Research A, 21A (6), pp. 421-429.

Hall, R.W., 1989. Configuration of an overnight package air network; Transportation Research A, 23A (2), pp. 139-149.

Leung, J.M.Y., Magnanti, T.L., Singhal, V., 1.990. Routing in point-to-point delivery systems: Formulations and solution heuristics, Transportation Science, 24 (4), pp. 245-260.

Powell, W.B., 1986. A local improvement heuristic for design of less-than-truckload motor carrier networks, Transportation Science, 20 (4), pp. 246-257.

Powell, W.B. and Sheffi, Y., 1.983. The load planning problem of motor carriers:

problem description and a proposed solution approach, Transportation Research A, 17A (6), pp. 471-480.

Powell, W.B. and Sheffi, Y., 1989. Design and implementation of an interactive optimization system for network design in the motor carrier industry, Operations Research, 37 (1), pp. 12-29.

Robusté, F., Almogera, J.M., Gargallo, X., Ardanuy, A., 1.996. Sistema de ayuda a la decisión para la reestructuración de la red logística de una empresa de transporte urgente. In: Actas del II Symposium de Ingeniería de los Transportes, Vol II, pp. 269-277, Madrid, Colegio de Ingenieros de Caminos, Canales y Puertos,.

Rodriguez, M.V., 2002. Metodología para determinar la ubicación de hubs con capacidad limitada, PhD thesis, Tecnun, Universidad de Navarra.

Roy, J. and Delorme, L., 1989. NETPLAN: A Network Optimization Model for Tactical Planning in the Less-than-Truckload Motor-Carrier Industry, INFOR 27 (1), pp. 22-35.

Stützle, T., 1997. An Ant Approach to the Flow Shop Problem. In: Proceedings of the 6th European Congress on Intelligent Techniques & Soft Computing (EUFIT'98), Vol. 3, pp 1560-1564, Verlag Mainz, Aachen.

Stützle, T. and Dorigo, M., 1999a. ACO Algorithms for the Quadratic Assignment Problem. In: Corne, D., Dorigo, M. and Glover, F. (Eds.), New Ideas in Optimization, McGraw-Hill.

Stützle, T. and Dorigo, M., 1999b. ACO Algorithms for the Traveling Salesman Problem. In Miettinen, K., Makela, M., Neittaanmaki, P., Periaux, J.(Eds), Evolutionary Algorithms in Engineering and Computer Science, Wiley

Stützle, T. and Hoos, H., 1997. The MAX-MIN Ant System and Local Search for the

Traveling Salesman Problem. In Baeck, T., Michalewicz, Z. and Yao, X. (Eds.), Proceedings of the IEEE International Conference on Evolutionary Computation, ICEC'97, pp. 309-314.