Strategies for an Integrated Distribution Problem

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ABSTRACT

Problems arising in the logistics of commercial distribution are complex and involve several players and decision levels. One of the most important decisions is the design of the routes to distribute the products in an efficient and inexpensive way but also satisfying marketing objectives such as customer loyalty. This chapter explores three different distribution routing strategies. The first strategy corresponds to the classical vehicle routing problem where total distance or cost is minimized. This one is usually an objective of the Logistics department. The second strategy is a master route strategy with daily adaptations where customer loyalty is maximized, which is one of the objectives of the Marketing department. We propose a third strategy which takes into account the cross-functional planning between the Logistics and the Marketing department through a multi-objective model. All strategies are analyzed in a multi-period scenario. A metaheuristic algorithm based on the Iterated Local Search is proposed and applied to optimize each strategy. An analysis and comparison of the three strategies is presented through a computational experiment. The cross-functional planning strategy leads to solutions that put in practice the coordination between the two functional areas of Marketing and Logistics and better meet business objectives in general.

INTRODUCTION

The growing number of problems that firms are facing nowadays in relation to the distribution of their products and services has lead Logistics and Marketing to be of primary concern to many industries. An important aspect of the logistics management task is to coordinate the activities of the traditional distribution functions together with purchasing, materials planning, manufacturing, marketing and often R&D. One important aspect of the integration process is cross-functional planning, which consists of coordinating different areas inside the firm, allowing for cost reductions and service improvement (Christopher, 1998).

The motivation of our work arises in the context of integration of logistics functions with other functions of the firm. In our case, we will focus our study on two key areas: Distribution and Logistics management and Marketing management. One source of competitive advantage for many firms is the development of an integrated relationship between the firm's marketing and logistics functions, as this integration has the ability to further enhance the firm's customer focus. This integration can be obtained by doing an integrated and coordinated planning of the logistics

operations. In our case we focus on the distribution strategies. On one hand, the importance of good distribution strategies in today's competitive markets cannot be overstressed. In many industries, an important component of distribution systems is the design of the routes of vehicles to serve their customer's demand. On the other hand, as pointed out by some industry leaders, new trends in supply-chain management include, "…better customer service...greater customer sophistication" (Partyka & Hall, 2000). Customer service is becoming more important. Customers demand more than a product. They demand a product arriving on time via an easy ordering system or just-in-time distribution.

In this work, we will study integrated distribution management from a strategic point of view. The logistics distribution problem consists of deciding how to assign customers to vehicles and how to design the routes made by each vehicle minimizing a transportation cost function. This is the well-known Vehicle Routing Problem (**VRP**) (Toth & Vigo, 2002b). The transportation cost represents a large percentage of the total logistics costs, so it makes sense to try to reduce this cost. Having the products arrive on time is also an important objective of the logistics department when planning distribution.

However, after interviews with several retailing companies, we realized that many of them do not consider minimizing transportation cost as the prime objective, but rather place greater importance on the customer relationship and customer service in the designing of distribution routes (Ribeiro, 2004). Marketing and Sales departments argue that drivers also perform sales activities and have responsibilities for promotion and the introduction of new products. So, if a driver is assigned always to the same customers this creates a good relationship and it leads to a sales increase.

We thus identified the two different primary strategies in the design of distribution routes: the Logistics department wants to minimize transportation costs and the Marketing and Sales department wants to maximize customer relationships, i.e. assign the same driver to each customer every day or most days.

This led us to the following question: What is the best strategy for an efficient distribution? On the one hand we have the classical VRP minimizing a transportation cost function. On the other hand, we have the strategy to always assign the same driver to the same customer to maximize customer loyalty. Beyond evaluating these two strategies, we propose a third one based on a bi-objective approach that tries to balance the two previous ones. This last strategy involves the implementation of integrated distribution processes.

The motivation for the present work arose from distribution problems faced by the food and beverage industry. In these industries, the tendency is to have lower inventories and higher delivery frequencies. Please note that the objective of this work is not to provide a system to optimize a particular distribution problem, but to study and analyze what is the best planning strategy for the distribution of a product among a set of customers.

In the next section, we present in detail the different distribution strategies proposed:
1. the classical VRP strategy, where the objective is to minimize the transportation costs;
2. the master routes strategy, where the main objective is maximizing the number of customers assigned to the same driver for a set period of time;
3. the new bi-objective strategy we propose that considers the integration between the marketing and logistics departments.

In third section, we present a brief literature review, followed by a section where we present the mathematical models for the three strategies proposed. Next section presents the tool designed to

optimize the routes. This tool is based on Iterated Local Search Heuristics, and we use the same tool to optimize the routes in order to be able to make a fair comparison. In the results section, we analyze the results and, in particular, the impact on integrated decision-making between the logistics and marketing departments. Finally, in the last section, we present the conclusions of the work.

THE DISTRIBUTION STRATEGIES

Distribution strategy has a great impact on the firm's performance, in particular in the retailing area. Frequently, this strategy is defined by the Logistics department, but sometimes the decision is made by the Marketing department. The objectives when defining this distribution strategy can be very different depending on the department involved. In this work, we will define and analyze three different distribution strategies that reflect different potential distribution policies in an organization.

The first strategy (Strategy 1) has a distribution policy that minimizes distance or transport costs. The objective consists in minimizing total routing cost, measured in distance units as in the classical VRP. This is a well-known problem and there exist a very large number of articles published on this subject. However, the objective function of this problem is often an object of criticism by users and planners, since it does not take into consideration other concerns of the company, for example, customer service and customer loyalty. The second strategy (Strategy 2) tries to implement a marketing policy based on customer service and loyalty. In an increasingly competitive environment, many firms adopt strategies of tight relationships with their customers where loyalty and friendship play a key role, through the delivering agents (Baker, Cronin, & Hopkins, 2009). By this strategy, routes are predefined so that each delivering agent or driver is associated with a specific set of customers. The third strategy (Strategy 3) is the one that considers marketing and distribution objectives at the same time, in an integrated manner.

The distribution strategies correspond to different situations and concerns inside the firm. By comparing them, we can analyze the effect that integrating two areas can have on the distribution policies. The objective of this analysis is to provide a set of possible alternative solutions to the decision maker, who, with the use of additional information on each particular distribution problem, can then make a good choice.

The strategies are evaluated for a planning horizon of a week, five working days. The choice of this period is based on the need for a strategic perspective; we want to study the impact of a sequence of decisions on different objectives. As a consequence, we need several periods to analyze the marketing effect and a week seems to be a reasonable choice since in many industries, the behavior of the orders for a customer follows a weekly pattern (examples are the Beverage & Food industry). In any case, this assumption could be relaxed and the problem could be extended to a larger number of periods.

Strategy 1: Distance Minimization

In this strategy, the distribution policy is constructed based on routing cost or distance. Cost reduction is one of the biggest concerns in transportation and distribution management, but not the only one as we will see later. We want to find the route for each of the vehicles that will pass through the demand points in such a way as to satisfy all the demand with the smallest transport cost or distance. The classical VRP considers only one period at a time and chooses the optimal routes for that period. Strategy 1 corresponds to the classical Vehicle Routing Problem (VRP) repeated for each day of the planning horizon.

Strategy 2: Master Routes

The second strategy is based on marketing principles, and the distribution strategy is based on service measures. An important source of value to the firm can be obtained from a close relationship between the firm and its customers. Drivers see customers regularly, and perform sales activities and have responsibilities for promotions and the introduction of new products. Therefore, it is believed by the Marketing department that if the same driver is assigned always to the same customer this can create a good relationship and leads to increased sales.

This marketing policy is giving emphasis to the personal relationship between drivers and customers as a way to improve customer service. One of the identified advantages of this customer relationship management policy is that it makes it more difficult for a customer to switch to another provider. It is known that relationships require a time investment from both the customer and the provider (Simchi-Levi, Kaminsky, & Simchi-Levi, 2003). These marketing strategies allow the firm to obtain more information on customer needs. And, at the same time, it becomes easier to introduce new products, define promotions and even speeds up the delivery process due to experience effects on both sides. In the marketing literature, we can find several studies of relationships between firm employees and customers that lead to an improvement in customer satisfaction and loyalty, see for example (Baker et al., 2009), (Guenzi & Pelloni, 2004), (Chao, Fu, & Lu, 2007) and (Barroso-Castro, Armario, & Marin-Ruiz, 2004). These authors mention that maintaining a long term relationship between employees (in our case drivers) and customers may improve customer perceptions of the quality of services received, and consequent company performance.

In this strategy, each driver will serve always the same customers. So, master routes are designed considering all customers and an average daily demand, and then these routes are adapted daily so the driver always visits the same customers and he or she only visits customers with demand. Capacity constraints are also taken into account.

Strategy 3: Multi-Objective

The third strategy is the integrated distribution management model, which consists of taking into account in the decision process the concerns of the Logistics department and Marketing department i.e. the reduction of transportation costs and the emphasis on the personal relationship between driver and customer. We propose a multi-objective model with two objectives, each objective corresponds to a different function. The first is the transportation cost and the second a marketing function. This strategy tries to include in the same model the objectives of the two previous strategies. The best solution for the transportation problem might not always be the best solution for the marketing objective. In some cases, these two objectives may conflict and that is the main justification for a trade-off analysis between these two objectives. We need to find a solution (or several solutions) that integrate marketing and logistics objectives.

In the next section, we will present a brief literature review. In following section, we will present the well-known mathematical model for the VRP that serves as the basis for the models of the different strategies, and also present the mathematical model for each strategy.

LITERATURE REVIEW ON VRP

The classical VRP model is behind the models for the three distribution strategies. This problem is an NP-hard problem, which implies a non-polynomial increase in the size of the solutions space when the number of nodes is increased. A significant amount of research effort has been dedicated to VRP. See the survey articles on VRP by (Laporte & Osman, 1995), (Laporte, 1992), (Bodin, Golden, Assad, & Ball, 1983), (Christofides, Mingozzi, & Toth, 1981), (Fisher, 1995), (Crainic &

Laporte, 1998), (Cordeau, Gendreau, Laporte, Potvin, & Semet, 2002), (Laporte, 2007), (Golden, Raghavan, & Wasil, 2008) and (Juan, Faulin, Ruiz, Barrios, & Caballé, 2010). An extensive list of VRP research papers can be found on http://www.imm.dtu.dk/ ~orgroup/VRP_ref/. Although this problem has been studied for decades, (Laporte, 2009), it still gets the attention of many researchers.

Although the VRP is an important problem, the main contribution of this chapter is not regarding the VRP but rather Strategic Distribution Decisions. After several interviews with different Food & Beverages Companies we realized that in decision making about distribution routes, it was not only cost that was important, but also customer service and customer loyalty. We found that the Operations Research literature focuses mainly on minimizing transportation cost or distance, whereas Marketing literature has continuously emphasized the importance of human interactions and relationships in the process of delivery goods.

Several studies indicate that good relationships between firm employees and customers lead to greater customer satisfaction and loyalty. Baker, Cronin & Hopkins (2009) conclude that higher levels of involvement lead to greater levels of consumer loyalty. Guenzi & Pelloni (2004) mention that building customer loyalty is increasingly a major goal for a large number of companies and, also that a strong relationship between front-line employees and customers positively affects customer satisfaction and loyalty to the company. Chao, Fu & Lu (2007) say that customer orientation and interpersonal relationships may reinforce the quality-loyalty linkage. Barroso-Castro, Armario & Marin-Ruiz (2004) analyzes the effect that service company employee behavior has on customer perceptions of the quality of service received, and consequent company performance.

Therefore the proposed distribution strategies are based not only on the classical VRP, but also on a multi-period and multi-objective vehicle-routing problem. As far as we know there are no studies on routing problems with multiple periods and this type of marketing oriented objective function. There are some multi-objective VRP that consider other types of objectives. Hong & Park (1999) consider the minimization of customer waiting time as the second objective function, in a VRP with time windows constraints. Lee & Ueng (1999) developed an integer linear model that searches for the shortest travel path and balances driver's load simultaneously. The objectives are related to travel and loading time. Pasia, Doerner, Hartl, & Reimann (2007) present a population-based local search for solving a bi-objective vehicle routing problem. The objectives of the problem are minimization of the tour length and balancing the routes. Muller (2010) presents an approximate method to the bi-criterion Vehicle Routing Problem with soft time-windows. Jozefowiez, Semet, & Talbi (2008) surveys the existing research related to multi-objective optimization in routing problems. It examines routing problems in terms of their definitions, their objectives, and the multi-objective algorithms proposed for solving them.

Also, some work on periodic VRP has been done. Baptista, Oliveira, & Zúquete (2002) present a period vehicle routing problem based on the assignment problem and the vehicle routing problem. Collection days have to be assigned to each customer and vehicle routes have to be designed for each day of the period (time horizon) so that the total distribution cost is minimized. Francis, Smilowitz, & Tzur (2006) present a variation of the periodic VRP in which service frequency is a decision of the model. Mourgaya & Vanderbeck (2007) propose a column generation-based heuristic for the periodic VRP. Hemmelmayr, Doerner, & Hartl (2009) propose a new heuristic for the Periodic Vehicle Routing Problem (PVRP) based on variable neighborhood search.

The main contribution of this work is to present a new model and new method to solve a multi-period and multi-objective vehicle-routing problem, but the most important contribution is to

analyze three different alternative distribution strategies that can be adopted in a firm when planning their routing and evaluate the consequences of adopting each one of them.

THE MODELS FOR THE DISTRIBUTION STRATEGIES

The most well known model for routing is a basic VRP. This model considers a set of nodes, representing retailers or customers, at a known location, that must be served by one depot. Each node has a known demand. A set of vehicles, with equal capacity is available to serve the customers. The routes must start and finish at the depot. The objective is to define the set of routes to serve all customers with minimal cost.

For each pair of nodes, a fixed known cost is associated. We assume this cost matrix is symmetric and can represent a real cost, distance or time. The main constraints of the problem are that all the demand must be satisfied and the vehicles' capacity cannot be exceeded.

The basic VRP is a generalization of the Traveling Salesman Problem, where more than one vehicle is available, for TSP references see for example (Lawler, Lenstra, Rinnooy Kan, & Shmoys, 1985). There are several formulations of the classical VRP in the literature, for some of these formulations see (Fisher & Jaikumar, 1978), (Fisher & Jaikumar, 1981), (Kulkarni & Bhave, 1985), (Gouveia, 1995)and (Toth & Vigo, 2002a).

The classical model of the VRP can be formulated as an integer linear programming and this is the formulation we will use throughout later chapters.

Consider the following data:

$I = 1,..., n$, set of nodes, that correspond to the different locations of the customers, node 1 corresponds to the depot.

$K = 1,..., m$, set of vehicles;

Q, capacity of each vehicle;

q_i , demand of customer i, $i =1,...,n$;

c_{ij} cost of going from i to j, $i =1,...,n$; $j = 1,...,n$.

This formulation considers two types of variables:

$$x_{ijk} = \begin{cases} 1, & \begin{array}{l} \text{if vehicle } k \text{ visits customer } j \\ \text{immediatly after customer } i \end{array} \\ 0, & \text{otherwise} \end{cases}$$

The formulation of the problem is:

Objective Function:

$$Min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} \sum_{k=1}^{m} x_{ijk}$$

1

Subject to:

$$\sum_{k=1}^{m} y_{ik} = 1, \ \forall \, i = 2,...,n$$

2

$$\sum_{k=1}^{m} y_{1k} = m$$

3

$$\sum_{i=2}^{n} q_i y_{ik} \leq Q, \ \forall \, k = 1,...,m$$

4

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{ijk} = y_{ik}, \ \forall \, i = 2,...,n; k = 1,...,m$$

5

$$\sum_{j,i \in S} x_{ijk} \leq |S| - 1, \ \forall S \text{ non} - \text{empty subset of } \{2,...,n\}; k = 1,...,m$$

6

$$x_{ijk} \in \{0,1\}; y_{ik} \in \{0,1\}, \ \forall i = 1,...,n; k = 1,...,m$$

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Constraint (2) ensures that each customer is visited by one vehicle only. Constraint (3) guarantees that all vehicles visit the depot. Constraint (4) represents the vehicle capacity constraint. For each vehicle k, we guarantee that the sum of the demand of the nodes that the vehicle covers is less than or equal to its maximum capacity. Here we assume that none of the customers has a daily demand that exceeds Q. The constraint (5) ensures that if a vehicle visits a customer it also has to leave that customer. Constraint (6) is the sub-tour elimination constraint. This constraint implies that the arcs selected contain no sub-cycles. It states that for every vehicle, the following holds: for every non-empty subset S of {2,..,n}, the number of arcs that are in the route of this vehicle, with both nodes belonging to S, has to be less than or equal to the number of elements of S minus 1. The last constraint (7) defines the variables x and y as binary. The objective function is minimizing the total cost of the routes.

The TSP is a sub-problem of the VRP, the TSP belongs to the class of NP-hard (non-deterministic polynomial time) problems, and so do the basic VRP and extensions. This means that the computational complexity of the problem grows exponentially with its size, i.e., it grows exponentially with the number of customers.

In this section we will present the mathematical models associated with the three strategies. First of all, we describe the assumptions of the model.

We assume that the firm is responsible for the distribution of its own products. Therefore, there are no questions of outsourcing to be handled. These firms face the pressures of a competitive market making them concerned about both consumer satisfaction and internal efficiency.

The classical VRP considers only one period and chooses the optimal routes for that period. Here we will introduce more periods by considering a week-long analysis. Each day we have a different set of customers to serve and different corresponding quantities to deliver. Reduction of inventory levels, and increasing frequency of orders are tendencies in many businesses to lower stock handling costs.

Other assumptions of the model are:
- All the demand is satisfied on the same day that it is required and not on any other day of the week.

- Only unloading is done at each customer.

- The number of vehicles is fixed and there are no fixed costs associated with the use of the vehicles. They all have the same capacity. Moreover, the number of vehicles available is enough to satisfy all the demand.

- Each vehicle is assigned to a driver. We consider that each driver works every day of the period in question.

- One vehicle can only be used once a day and the time it takes to deliver the full capacity is less than a working day.

Next, we will present the model in detail. The following data is considered in the mathematical formulation:

$i, I,$ index and set of nodes, $I=1,...,n$ where 1 is the depot and 2 to n are the customers locations;

$k, K,$ index and set of vehicles, $K=1,...,m;$

$t, T,$ index and set of days which represent the period, $T=1,...,p;$

$T_i,$ set of days where customer i has a demand that is greater than zero, $i = 2,...,n;$

$q_i^t,$ demand of customer i on day t, $i = 1,...,n$ and $t = 1,...,p;$

$c_{ij},$ the cost of going from i to j, this is a fixed matrix , $i=1,...,n$ and $j=1,...,n;$

$Q,$ capacity of a vehicle.

The variables of the model are:

$$x_{ijk}^t = \begin{cases} 1, & \begin{array}{l}\text{if vehicle } k \text{ visits customer } j \\ \text{immediatly after customer } i \text{ on day } t\end{array} \\ 0, & \text{otherwise} \end{cases}$$

$$y_{ik}^t = \begin{cases} 1, & \text{if customer } i \text{ is visited by vehicle } k \text{ on day } t \\ 0, & \text{otherwise} \end{cases}$$

Strategy 1: Distance Minimization

The objective function minimizes routing costs, for all customers during the week period. This strategy corresponds to repeating a classical VRP for each day of the week.

The formulation of this objective will be the same as the one used for the classical model but with a new parameter, t, representing the day of the week.

Objective function:

$$Min \sum_{t=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ij} x_{ijk}^t \qquad \textbf{8}$$

Strategy 2: Master Routes

This strategy and the associated model are very close to common practice in many companies. It consists of: first defining "master routes" and, afterwards performing daily adjustments depending on the demand of the customer and on the capacity of the vehicle. To obtain the "master routes" we consider a VRP model, where all customers are in the input data and the demand of each customer depends on the average daily demand. To adjust the daily routes we consider other constraints such as capacity and number of vehicles. The requirement that a customer will always be served by the same driver may have to be sacrificed but we will try to enforce this at least for the best customers. Therefore, the idea is: the better the customer, the more interest we have in maintaining the same driver.

The mathematical formulation for this strategy is identical to the one for the classical VRP for one period, but in this case all customers are considered for the "master routes".

Strategy 3: Multi-Objective

In this strategy, we propose a multi-objective model with two objectives: minimization of routing costs and maximization of service levels that reflect an integration of the strategies of the Logistics and Marketing departments.

In most cases of multiple objectives it is unlikely that the problem is optimized by the same alternative parameter choices. Hence, some trade-off between the criteria is needed to ensure a satisfactory design.

In the multi-objective optimization an important relation is the dominance relation. Let (z_1) and (z_2) be two solutions of a multi-objective minimization problem with R objectives. We say that: Solution (z_1) **dominates** (z_2) if $z_{1r} \leq z_{2r}$ for all objectives r in $\{1,...,R\}$ and $z_{1r} < z_{2r}$ for at least one r and $(z_{1r}) \neq (z_{2r})$. A feasible solution is **efficient** if it is non-dominated. Based on this concept we will optimize the two objective functions to find non-dominated solutions.

Ideally, we would like to find the solution that would be optimal for both objectives at the same time. In multi-objective programming, this solution point rarely exists. So, we would like to find solutions that are close to this ideal point.

Mathematically, all non-dominated solutions are equally acceptable. It is the decision maker who is responsible for choosing the final solution. The decision maker is someone who has a deep knowledge of the problems, the relationships and the implications of each solution. The choice among these non-dominated solutions is determined by the decision maker's preferences among the multiple objectives.

The two objective functions considered within the integrated strategy are:

Objective A: Minimizing Cost

The formulation of this objective will be the same as in equation (8), the one used for the model of strategy 1.

$$Min \sum_{t=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} c_{ij} x_{ijk}^{t}$$

Objective B: Marketing Objective

In terms of mathematical formulation, the second objective works as follows: For each customer i we have a set of pairs of days with positive demand, T_i, for each pair of days (g, h) in T_i (with $g \neq h$) we want to minimize the difference in the assignment to a vehicle k. The objective is to minimize $\left| y_{ik}^g - y_{ik}^h \right|$.

The importance is given by the total demand for the period, therefore a weight is introduced: the total amount ordered by each customer. The objective function becomes:

$$Min \sum_{i=1}^{n} \sum_{k=1}^{m} \sum_{\substack{g,h \in T_i \\ g<h}} \left[\left(\sum_{t=1}^{p} q_i \right) \times \left| y_{ik}^g - y_{ik}^h \right| \right]$$

The importance of a customer is measured in terms of sales. In some cases other measures could be used to classify the goodness of a customer, for example, frequency of orders, credit history, etc. This function is non linear.

Considering a multi-period model is an essential aspect of our study. Since objective B is not static but measures decisions across more than one period, it only makes sense to consider a multi-period base.

In the integrated strategy the objective is to find a set of non-dominated solutions and give the decision maker the possibility to choose not only between strategies but also between solutions.

The constraints of the model for strategy 1 and 3 are:

$$\sum_{k=1}^{m} y_{ik}^t = 1, \quad \forall i = 2,...,n; t \in T_i \tag{9}$$

$$\sum_{k=1}^{m} y_{ik}^t = m, \quad \forall t \in T_i; i = 1 \tag{10}$$

$$\sum_{i=2}^{n} q_i^t y_{ik}^t \leq Q, \quad \forall k = 1,...,m; t = 1,...,p \tag{11}$$

$$\sum_{j=1}^{n} x_{ijk}^t = \sum_{j=1}^{n} x_{jik}^t = y_{ik}^t, \quad \forall i = 2,...,n; k = 1,..,m; t = 1,...,p \tag{12}$$

$$\sum_{k=1}^{m} y_{ik}^t = 0, \quad \forall i = 2,...,n; t \notin T_i \tag{13}$$

$$\sum_{j,i \in S} x_{ijk}^t \leq |S| - 1, \quad \forall \, S \, nonempty \, subset \, of \, \{2,...,n\}; k = 1,..,m; t = 1,...,p \tag{14}$$

$$x_{ijk}^t \in \{0,1\}; y_{ik}^t \in \{0,1\}, \quad \forall i = 1,...,n; k = 1,..,m; t = 1,...,p \tag{15}$$

Constraints (9) to (15) are similar to the ones in the basic model, but for each day of the period in question. Constraint (9) ensures that on the days where a customer has a positive demand, that customer is visited by only one vehicle. Constraint (10) imposes that each day all vehicles go to the depot. Constraint (11) ensures that, the daily loading of a vehicle does not exceed its capacity. Constraint (12) guarantees

that if the vehicle enters a node, on day t, it also has to leave that node, on the same day. Constraint (13) prohibits a vehicle from visiting a customer on a day where that customer has zero demand. Finally constraint (14) avoids sub-tours, but now not only for each vehicle but also for each day. The sub-tour elimination constraint represents an exponential number of constraints. The last constraint (15) defines all variables as binary.

SOLUTION APPROACH

The main objective of this work is to make a fair comparison of the three distribution strategies therefore we will use the same solution technique to optimize each strategy. As mentioned, the proposed problems are NP-hard, so they require an heuristic methodology in order to solve large instances. A heuristic algorithm is a solution method that does not guarantee an optimal solution, but in general has a good level of performance in terms of solution quality and convergence. Heuristics may be constructive (producing a single solution), local search (starting from one given random solution and moving iteratively to other nearby solutions) or a combination of the two. Heuristics for VRP have been extensively studied. Cordeau et al. (2002) summarize the most important classical and modern heuristics for the VRP.

Local search is the most powerful general approach for finding high quality solutions to hard combinatorial optimization problem in reasonable time. It is based on the iterative exploration of neighborhoods of solutions trying to improve the current solution by local changes. The type of local search that may be applied to a solution is defined by a neighborhood structure.

Our proposal is to use a metaheuristic algorithm that has proven to give quite good results for other problems and that is easy to implement, modify and adapt to different strategies: the Iterated Local Search (ILS).

The Iterated Local Search for the VRP

ILS is a simple and generally applicable meta-heuristic which iteratively applies local search to modifications of the current search point. For more detailed information on ILS see (Lourenço, Martin, & Stützle, 2003), (Lourenço, Martin, & Stützle, 2010) and (Stützle, 1998). At the start of the algorithm a local search is applied to some initial solution. Then, a main loop is repeated until a stopping criterion is satisfied. This main loop consists of a modification step ("perturbation"), which returns an intermediate solution corresponding to a modification of a previously found locally optimal solution.

Next, local search is applied to yielding a locally optimal solution. An "acceptance criterion" then decides from which solution the search is continued by applying the next "perturbation". Both, the perturbation step and the acceptance test may be influenced by the search history. ILS is expected to perform better than if we just restart local search from a new randomly generated solution.

The architecture of the ILS is as follows:

Architecture of the ILS Algorithm

Procedure ILS:
s^0 = GenerateInitialSolution
s^* = LocalSearch(s^0)
Repeat
s' = Perturbation(s^*, history)

s*′ = Local search(s′)
s* = Acceptance Criterion(s*, s*′, history)
Until termination condition met
End

The proposed ILS heuristics is based on the ILS metaheuristic developed by (Stützle, 1998)and (Kunz, 2000) to solve the classical VRP. The ILS used for the VRP is the following:

ILS for the VRP

Step 1. Savings Heuristic - Initial Solution
Step 2. ILS for TSP on each tour:
Step 2.1. Local Search for TSP
Step 2.2. Perturbation for TSP
Step 2.3. Acceptance criterion
Step 3. ILS for the VRP
Step 3.1. LS for the Assignment Problem
Step 3.2. Perturbation for VRP
Step 3.3 Acceptance Criterion
Step 4. ILS for the TSP on the new routes

We will now present the implementation of each step of the above algorithm in more detail.

Savings Heuristic
This is a greedy heuristic to construct an initial solution, (Clarke & Wright, 1964). It has been proved that starting from a random solution gives worse results (Stützle, 1998)). This savings heuristic obtains the initial solution.

ILS for the TSP
On each of the tours obtained in the savings heuristic, we apply an ILS. At this step of the algorithm, we ignore any relation between routes.

LS for TSP: The LS used was a 2-opt local search. The 2-opt move can be defined as follows: on one tour, 2 connections are removed and two others are included, since there is only one possibility for reconstructing the tour. We tested for all combinations. Only when a complete run without improvements finishes has one reached a 2-opt solution.

Figure 1: Example of a 2-opt move for the TSP

Searching in a complete 2-opt would not be efficient. So, to reduce the search space, some techniques are introduced that quicken the process whilst still generating good quality solutions: a list of candidates and "don't look bits". One "don't look bit" is associated with each node. Initially, all "don't look bits" =0, if for a node no improving move can be found, then "don't look bit" is

turned on (set to 1) and is not considered as a starting node in the next iteration. If an edge incident to a node is changed by a move, the node's "don't look bit" is turned off again - reduces to O(n).

Perturbation (Kick-move) for TSP: On the local minimum that has been reached, we apply the kick-move and arrive at a new start solution. The goal here is to escape from local optima by applying perturbations to the current local minimum.

For the LS on the TSP we use a "double bridge" move. This perturbation cuts four edges and introduces 4 new ones.

Figure 2: Example of a Double Bridge move

Acceptance criterion: The acceptance criterion used at this step is 'better'; this means that the new tour is accepted if it has a lower cost.

ILS for the VRP
The ILS for the VRP is implemented considering the initial solution for the routes obtained from the ILS of the TSP.

LS for the assignment problem: The local search for the VRP is a 2-opt and again a list of candidates and "don't look bits " techniques are applied to restrict the search.

We have two possibilities for a 2-opt: A customer of a tour is postponed until a later tour or a customer trades with another customer from another tour. First, if capacity restrictions allow and it reduces costs, a city is inserted in the tour. Only if it cannot be inserted do we check if an exchange with another tour improves the solution.

Figure 3: Example of a 2-opt move for the VRP

The same techniques as those used in LS for the TSP are used: "don't look bit" and list of candidates.

Kick-moves: "Numb-crosser": This perturbation consists of exchanging a group of customers from 2 tours. In this case, 1/3 of the customers of the tour are exchanged.

Acceptance criterion: 'Best', the same as the acceptance criterion for the TSP.

ILS for the TSP on the new routes
Repeats the ILS procedure for the TSP.

The ILS for each strategy

The ILS for the VRP is now adapted to solve the 3 models for the different strategies. Next we will describe in detail the ILS for each of them.

Strategy 1: Since in this strategy we have a classical VRP model, for each day we apply the ILS to find the best daily routes, according to the capacity of the vehicle and the daily demand. The algorithm is repeated for several runs and chooses the best solution for each day.

Let L be the total number of loops:

Structure of the algorithm for Strategy 1

Step 1: Set loop = 0
Step 2: Set day = 1
Step 3. Savings Heuristic - Initial Solution
Step 4. ILS for TSP on each tour
Step 5. ILS for the VRP
Step 6. ILS for the TSP on the new routes
Step 7. Set day = day + 1; Repeat Step 3 to 6 until day = 5;
Step 8. Set loop = loop + 1
Step 9. Repeat Step 2 to 8 until loop = L

Strategy 2: In this strategy, we have considered a classical VRP model to obtain the "master routes", where all customers are taken into account based on average demand. Therefore, to obtain the master routes we apply an ILS. Afterwards, the routes for each day of the week are obtained in the following way: consider the master routes for each day and eliminate from these the customers that have no demand on that day. If on any of the routes the capacity constraint is violated, we identify the least important customer, and we delete it from this tour and insert it on another tour. This tour is chosen in such a way as to minimize routing costs within capacity constraints.

Structure of the algorithm for Strategy 2

Step 1: For all customers do
Step 1.1. Savings Heuristic - Initial Solution
Step 4. ILS for TSP on each tour
Step 5. ILS for the VRP
Step 6. ILS for the TSP on the new routes
Step 2: Set day = 1
Step 3: For each tour eliminate customers with zero demand
Step 4: For each tour, if capacity constraints are violated remove customer with lowest total demand
Step 5: ILS for the TSP on the new routes
Step 6: Set day = day + 1
Step 7: Repeat Step 3 to 6 until day = 5;

Strategy 3: In this strategy we face a multi-objective combinatorial optimization problem (MOCOP). Ehrgott & Gandibleux (2002) provide an annotated bibliography on MOCOP.

Two main approaches can be found in the metaheuristics for the MOCOP: methods of local search (LS) in object space and population based methods. In the LS methods, we start from an initial

solution and the procedure approximates a part of the non-dominated frontier corresponding to the given search direction. A local aggregation mechanism of the objectives, based on the weighted sum, produces the effect to focus the search on a part of the non-dominated frontier. The principle is repeated for several search directions. In the population-based methods, the whole population contributes to the evolution process toward the non-dominated frontier. Here we will use the first approach, i.e. methods based on local search.

In this case, after having decided the routes for the first day, the program takes into consideration objective B, through a weighted function of both objectives. To do this, we calculate the effect of a move in the weighted function of the objectives. Then, the acceptance criterion determines that a new solution is accepted if the weighted function has improved. The algorithm is repeated for several different sets of weights. All the non-dominated solutions are retained during the run of the algorithm.

An objective function Z is used as the weighted function. Z is the weighted sum of the single objectives A and B.
Let f_r be the single objective function of objective r,

$$Z = \sum_{r=1}^{2} w_r f_r \text{ and } \sum_{r=1}^{2} w_r = 1$$

The solution is very sensitive to the weights that have been defined. The problem lies also in having objectives with different variables and scales. In our case, for example, we are adding costs and quantities. Notation:

w_a = weight for *Objective A*, with $0 \leq w_a \leq 1$;

w_b = weight for *Objective B*, with $0 \leq w_b \leq 1$;

and

$w_a + w_b = 1$

$$Z = w_a(ObjectiveA) + w_b(ObjectiveB)$$

Structure of the algorithm for Strategy 3

Step 1: Set $w_a = 1$ and $w_b = 0$
Step 2: Set day = 1
Step 3. Savings Heuristic - Initial Solution
Step 4. ILS for TSP on each tour
Step 5. ILS for the VRP
Step 5.1. LS for the Assignment Problem
Step 5.1.1 For each move calculate the effect on objective A
Step 5.1.1 Accept only if the new z is smaller
Step 5.2. Perturbation for VRP
Step 5.3. Repeat Step 3.1
Step 5.4 Acceptance Criterion
Step 6. ILS for the TSP on the new routes
Step 7. Set day = day + 1; Repeat Step 3 to 6 until day = 5;

Step 8. Set $w_a = w_a - 0.1$ and $w_b = w_b + 0.1$
Step 9. Repeat Step 2 to 8 until $w_a = 1$ and $w_b = 0$

ANALYSIS OF THE RESULTS

The main objective of this experiment is to evaluate the three strategies and analyze the effect of each objective on the solutions. With this purpose, we applied the above algorithms to several sets of randomly generated examples. The results are expressed in terms of the values of the objectives and total number of vehicles needed. For each strategy two values were calculated: the Routing Cost and the Marketing (or service) Value. The first is measured in distance and the second can be interpreted as the unit cost for the distributor for not serving a customer with the same driver, working in a similar way as a penalty cost. Next we will explain the data used and analyze some important results of this experiment.

The data

For the computational experiment, we have generated several sets of examples concerning the total number of customers (50,100,200,400). Also, we have examples with two types of demand (low variation and high variation) and two types of vehicles capacity, high and low.

To obtain the demand, we have used a normal distribution with mean 50 and standard deviation 20 for the case where demand has a high variation and a standard deviation of 5 for the examples with low variation. The probability to obtain a negative value is very small, and we have never found one. On each day, on average, 25% of the customers have zero demand. This implies that for a problem with 100 customers, there will be about 375 deliveries to make during the 5 day week. The customer locations are uniformly generated in a 100×100 square with the depot located in the centre with the coordinates (50, 50).

Truck capacity is 300 for problems with 50, 100 and 200 customers and 700 for problems with 400 customers. We also run cases with 200 customers and a truck capacity of 500. In total, we have studied 30 examples for each strategy, therefore we will consider 90 problems per run.

All data is available ot the first author's web page: http://www.econ.upf.edu/~ramalhin/. A standard personal computer, Intel ® Core™ 2 Duo CPU T9300 @ 2.50 GHz and 3 GB RAM, was used to solve all instances.

Analysis of the results

In this section, we will present the results obtained for each example in terms of the objective function values, the number of vehicles used, the non-dominated solutions and the run times.

We can illustrate the aim of the different strategies by looking at a small example with 2 days and a few customers: in Figure 4 we have the routes for two days, for strategies 1, 2 and 3. Strategy 1 has fewer and more efficient routes in terms of distance, Strategy 2 has more routes, but the routes are the same for each day. And, Strategy 3, has a solutions that is not completely efficient in terms of distance, but allowing for a better service level.

Figure 4: Routes for Strategies 1, 2 and 3

Table 1 (1.1, 1.2 and 1.3) shows the results for each example and for each strategy. Strategy 1 tries to find lowest cost, strategy 2 the best service level and strategy 3 the set of non-dominated solutions with respect to the integrated strategy. Note that objective (a) can be decimal due to the calculation of the distance based on the coordinates, however objective (b) is always an integer value. We can observe that, as expected, strategy 1 will always give us the solution with the lowest objective A and the highest objective B when compared with strategy 2. For strategy 2, we have much lower marketing values but the cost of routes increases significantly.

N	Example	Strategy 1		Strategy 2		Strategy 3	
		a	*b*	*a*	*b*	*a*	*b*
50	1	14,344.15	36,840	17,018.93	3,306	14,510.34	32,327
						14,344.15	36,840
	2	13,589.47	38,538	16,304.18	4,590	13,755.11	35,826
						13,697.92	38,148
						13,589.47	38,538
						13,680.72	38,278
	3	13,225.97	40,284	15,744.37	4,997	13,289.63	36,178
						13,228.96	40,284
						13,278.06	40,140
	4	11,710.86	32,341	15,597.20	5,950	11,850.30	25,753
						11,811.55	31,776
						11,710.86	32,341
						11,788.70	32,289
	5	13,452.19	38,084	16,832.34	3,012	13,541.62	30,733
						13,462.15	38,426
						13,473.14	38,198
						13,485.40	37,925
						13,534.13	37,952
100	6	22,970.35	75,096	28,356.94	8,368	23,240.29	64,967
						23,033.35	75,012
						22,971.54	75,096
						23,162.88	74,404
						23,153.66	74,601
	7	21,999.94	73,497	27,755.47	7,209	22,045.08	61,244
						22,041.77	73,416
						21,999.94	73,497
	8	21,839.25	74,834	26,873.79	10,264	21,907.99	63,623
						21,839.25	74,834
	9	20,638.13	70,492	24,874.82	5,045	20,836.26	59,365
						20,820.51	69,385
						20,612.55	69,987
	10	22,383.01	76,252	27,892.60	5,987	22,632.56	63,871
						22,467.32	76,110
						22,493.46	75,632
						22,462.16	76,252

Table 1.1: Routing Cost (a) and Marketing Level (b) for Strategies 1, 2 and 3

N	Example	Strategy 1		Strategy 2		Strategy 3	
		a	b	a	b	A	b
200	11	40,438.90	152,536	52,738.09	19,418	40,682.92	132,320
						40,438.90	152,536
						40,484.58	152,292
	12	40,420.19	152,564	52,089.76	9,967	40,757.39	134,118
						40,420.19	152,564
	13	38,484.12	151,187	49,881.28	19,803	38,498.67	131,916
						38,423.14	150,677
	14	38,481.27	148,056	47,837.33	9,999	38,681.92	129,944
						38,601.73	148,056
						38,502.60	148,186
						38,581.57	148,113
						38,624.36	147,863
						38,457.64	148,254
						38,649.81	147,718
	15	40,047.94	130,399	50,744.95	15,778	40,047.94	130,399
						40,028.26	151,554
200*	16	28,589.23	152,040	35,849.68	8,375	28,883.37	132,744
						28,782.42	151,361
						28,780.13	151,569
						28,686.55	151,883
						28,551.03	152,164
						28,630.92	152,040
	17	28,675.59	150,844	34,171.20	2,096	28,814.46	130,891
						28,711.49	150,542
						28,704.59	150,844
	18	27,350.06	149,576	33,919.54	9,715	27,511.87	130,867
						27,474.54	149,315
						27,255.56	150,108
						27,503.72	149,261
						27,397.52	149,435
						27,371.86	149,576
	19	27,674.99	147,608	33,632.54	9,637	27,676.81	128579
						27,613.74	147754
	20	27,836.23	152,388	34,002.28	9,320	28,035.45	130,763
						27,896.09	151,456
						27,824.33	151,509
						27,990.09	151,355

* Truck capacity =500

Table 2.2: Routing Cost (a) and Marketing Level (b) for Strategies 1, 2 and 3

N	Example	Strategy 1		Strategy 2		Strategy 3	
		a	b	a	b	A	b
400	21	40,013.36	304,388	49,637.55	9,607	40,120.90	260,814
						40,101.29	304,184
						40,023.38	304,388
	22	39,758.16	308,956	47,691.43	9,401	39,961.71	270,449
						39,845.07	308,604
						39,842.23	308,956
	23	39,576.78	300,057	47,635.00	6,954	39,658.17	255,775
						39,584.53	299,568
						39,579.08	300,084
	24	39,949.22	302,980	47,978.58	9,525	40,022.79	266,906
						39,956.93	303,057
						39,970.21	302,980
	25	39,552.16	299,976	46,682.14	9,538	39,593.30	264,664
						39,583.25	299,976
50 (low stdev)	26	12,606.09	37,756	15,118.07	2,396	12,870.39	33,258
						12,716.23	37,124
						12,606.09	37756
						12,867.78	36802
	27	13,752.04	37,759	16,724.64	3,329	13,861.01	34,403
						13,715.64	37,757
						13,855.72	37,428
	28	12,723.78	39,888	14,507.04	777	12,820.79	33,940
						12,781.62	39,888
	29	12,468.30	32,983	14,737.70	1,335	12,571.04	25,854
						12,489.20	32,330
	30	12,687.26	36,396	15,024.22	1,894	12,765.22	31,287
						12,657.08	36,504
						12,685.23	36,352
						12,747.45	36,043

Table 3.3: Routing Cost (a) and Marketing Level (b) for Strategies 1, 2 and 3

Concerning Strategy 3, we can say that, in almost every example, we can find more than one non-dominated solution. In case 4, for example, we have 4 non-dominated solutions and it would be the responsibility of the decision maker to decide between the alternatives.

Figure 5: Example 4 - set of dominated and non-dominated solutions for Strategy 3

In Figures 5 and 6 we can see the set of all solutions obtained after 22 iterations of the strategy 3 heuristic for examples 4 and 30 with 50 customers. The diamonds correspond to the dominated solutions and the squares correspond to non-dominated solutions.

Figure 6: Example 30 - set of dominated and non-dominated solutions for Strategy 3

The number of vehicles needed for each solution strategy also varies and this is reflected in the total distance cost. In Table 2, we can observe these differences. The master routes approach always requires a much higher number of vehicles each week. This is due to the route design procedure. The routes are constructed considering all customers, and then for each day eliminating the ones with no demand. When constructing the "master routes" we have used the daily average demand of each customer. The higher the values used for the demand associated with each customer, the higher the number of vehicles used in the "master routes" and the lower the marketing values.

Comparing the number of vehicles for Strategy 1 and Strategy 3 we observe that, on average, Strategy 3 has the same or a higher number of vehicles. This is due to the existence of the second objective, which introduces a preference for service rather than just distance. To achieve better service we need to sacrifice the routing efficiency and this can require the use of an additional vehicle.

N	Strategy 1	Strategy 2	Strategy 3
50	36	44	36
100	68	84	68
200	135	167	135
200(cap=500)	81	99	81
400	114	141	114
50 (low stdev)	36	43	36

Table 2: Average number of vehicles needed per week, for Strategies 1, 2 and 3

The running time should not be overemphasized. The first and third strategies are the ones that take more time to compute. But, since we are referring to strategic planning, it does not seem impractical for a firm with a network of 400 customers to spend one hour run prior to strategic decision making each week. Table 3 summarizes running times. For Strategies 1 and 3 we have done the same number of iterations. The magnitude of the difference in running time for strategy 2 is due to the fact that we only run the VRP once for the master case. For the other two strategies we have to run the VRP for each day of the planning period several times.

N	Strategy 1	Strategy 2	Strategy 3
50	39.62	0.69	39.68
100	106.98	1.97	104.16
200	294.63	4.53	290.01
200(cap=500)	394.25	5.60	388.28
400	899.01	7.70	746.59
50 (low stdev)	42.42	0.67	0.67

Table 3: Average run time in seconds, per problem size, for Strategies 1, 2 and 3

Finally, in Table 4 we show the results of the other versions of the algorithm for strategy 3. In version 2 we have introduced more iterations for each weight. And, in version 3 we have done more iterations for the ILS for each day, and kept the same number of iterations per weight. From the results we can conclude that by allowing more running time, the algorithm of version 2, on average, gives more non-dominated solutions in 3 of the 5 problems. In version 3, on average the number of non-dominated solutions is smaller than in the other versions but we are able to improve the solutions, when comparing with version 1 and 2.

N	Example	Startegy 3, version 1		Startegy 3, version 2		Startegy 3, version 3	
		a	b	a	b	a	b
50	1	14,510.34	32,327	14,510.34	32,327	14,372.34	32,327
		14,344.15	36,840	14,376.34	36,570	14,251.39	36,840
				14,318.05	36,840		
	Run Time	40.59		103.29		110.75	
	2	13,755.11	35,826	13,589.45	38,538	13,631.61	38148
		13,697.92	38,148	13,644.05	38,376	13,657.49	35826
		13,589.47	38,538	13,680.72	38,278	13,629.26	39450
		13,680.72	38,278	13,697.92	38,148		
				13,755.11	35,826		
	Run Time	40.92		99.03		105.43	
	3	13,289.63	36,178	13,289.63	36,178	13,235.85	35,668
		13,228.96	40,284	13,224.70	40,284	13,229.69	40,148
		13,278.06	40,140			13,183.31	40,284
	Run Time	41.75		106		112.48	
	4	11,850.30	25,753	11710.85523	32,341	11812.68164	25,393
		11,811.55	31,776	11751.11426	32,062	11676.1062	31,848
		11,710.86	32,341	11805.80127	31,416	11641.05762	32,182
		11,788.70	32,289	11850.29736	25,753		
	Run Time	34.46		88.04		93.06	
	5	13,541.62	30,733	13,452.19	38,084	13,515.69141	30,336
		13,462.15	38,426	13,485.39	37,925	13,411.3667	37,662
		13,473.14	38,198	13,541.62	30,733	13,364.65	38,084
		13,485.40	37,925			13,441.13	36,998
		13,534.13	37,952				
	Run Time	40.69		103.7		109.28	

Table 4: Routing Cost (a) and Marketing Level (b) for the non dominated solutions of Strategy 3, for 3 different versions of the algorithm

SUMMARY AND CONCLUSIONS

In this chapter, we have explored different distribution strategies to analyze an integrated distribution problem. The strategies cover a week-long planning horizon and reflect different ways of looking at the distribution problem. The first strategy is the classical VRP approach, which

reflects only transportation cost: For each day of the planning horizon the routes are designed minimizing routing costs. The second strategy is a more customer oriented strategy based on customer relationship management principles, where master routes are constructed to ensure a marketing policy where each customer is always served by the same driver. The third strategy is a multi-objective combinatorial optimization problem with two objectives: minimizing cost and improving customer service. This third strategy results from the integration of the two other strategies and brings together two areas of great importance in many industries: Distribution and Marketing. The idea was to compare this new approach with the other two strategies.

For each of the above strategies we have presented a mathematical model and a heuristic procedure, based on the ILS, to solve the problems. Then, the three algorithms were applied to a set of randomly generated instances.

The main conclusion is that the multi-objective model gives several non-dominated solutions that can be seen as a good balance between optimizing the transportation cost or customer service and loyalty. The decision maker has to choose the solution that best meets business needs, since cost minimization is not the only concern in distribution management.

There are several possible extensions of this work, one is in the area of the metaheuristics and here it would be interesting to develop multi-objective population based metaheuristic to solve the multi-objective model and to perform a comparison with the current approach. The second extension would be to include other objectives that would reflect different business needs, as for example, the one of balancing the routes. This is particularly interesting if we assume that driver's remuneration can be related to truck loading. In this case, we would be studying the integration of decisions of the Human Resources department.

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KEY TERMS & DEFINITIONS

Cross-functional planning at distribution: consists of coordinating different areas inside the firm, as marketing and logistics for example, allowing for cost reductions and service improvement.

Iterated Local Search (ILS): ILS is a simple and generally applicable meta-heuristic which iteratively applies local search to modifications of the current search point. At the start of the algorithm a local search is applied to some initial solution. Then, a main loop is repeated until a stopping criterion is satisfied. This main loop consists of a modification step ("perturbation"), which returns an intermediate solution corresponding to a modification of a previously found locally optimal solution.

Local Search Methods (LS): Local search is the most powerful general approach for finding high quality solutions to hard combinatorial optimization problem in reasonable time. It is based on the iterative exploration of neighborhoods of solutions trying to improve the current solution by local changes. The type of local search that may be applied to a solution is defined by a neighborhood structure.

Multi-Objective Combinatorial Optimization Problem (MOCOP): Combinatorial problems are characterized by the consideration of a selection or permutation of a *discrete* set of "items" or by an assignment among these. The MOCOP are combinatorial optimization problems with several objective functions.

Savings Heuristic: This is a greedy heuristic to construct an initial solution based on the saving calculations and tour construction. This savings heuristic (Clarke & Wright, 1964), obtains the initial tour for the VRP problem.

Traveling Salesman problem (TSP): Given a collection of cities (or points) and the cost (or distance) of travel between each pair of them, the traveling salesman problem is to find the cheapest way of visiting all of the cities and returning to your starting point.

Vehicle Routing Problem (VRP): This problem considers a set of nodes, representing retailers or customers, at a known location, that must be served by one depot. Each node has a known demand. A set of vehicles K, with equal capacity is available to serve the customers. The routes must start and finish at the depot. The objective is to define the set of routes to serve all customers with minimal cost.