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# INNOVATIVE PROCESSES IN THE FOOD INDUSTRY TO PROTECT HEALTH AND ECO-COMPATIBILITY

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# *INNOVATIVE PROCESSES IN THE FOOD INDUSTRY TO PROTECT HEALTH AND ECO-COMPATIBILITY*

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# Sommario

L’industria alimentare rappresenta uno dei più grandi settori dell’industria nel mondo. Studi sul settore alimentare hanno chiaramente dimostrati che esso è fra i più prolifici consumatori di energia e di conseguenza esso apporta un significativo contributo al riscaldamento globale, all’acidificazione, alla formazione di ozono fotochimico e l'eutrofizzazione.

I governi e gli organi di regolamentazione stanno prestando sempre più attenzione all’impatto ambientale delle attività economiche forzando i produttori ad essere responsabili dei loro prodotti.

Allo stesso tempo, i clienti dei paesi sviluppati hanno iniziato a considerare dei criteri ecologici ed etici nella selezione dei cibi, chiedendo prodotti sani, di elevata qualità e con ridotto impatto ambientale.

Di conseguenza, una delle principali sfide dell’industria alimentare è legata allo sviluppo di approcci per ridurre le emissioni di anidride carbonica durante le fasi di produzione, impacchettamento, trasporto e gli altri processi legati ai prodotti alimentari.

Questo induce il concetto di " Green supply chain management " (GrSCM), definita come l'integrazione delle problematiche ambientali nel SCM, compresa la progettazione dei prodotti, l’approvvigionamento e la selezione delle materie prime, la selezione dei processi di produzione, la consegna del prodotto finale ai consumatori, nonché la gestione del prodotto al termine della sua vita utile (Srivastava, 2007).

In questo contesto, la presente tesi è focalizzata sull'attività logistica legata alla catena di approvvigionamento dell’industria alimentare e le sue finalità sono:

- Per quanto riguarda la decisione a lungo termine, introdurre una metodologia innovativa per la progettazione di reti distributive di tipo chiuso nelle quali siano garantite sia la sostenibilità economica che quella ambientale.
- Mentre, considerando le decisione a breve termine, in primo luogo mettere in evidenza i vantaggi derivanti dall’apprendimento degli autisti nell’ottimizzazione dei percorsi distributivi. Questa parte del lavoro è stata sviluppata nel corso di un periodo di studio in Danimarca, presso la Technical University of Denmark. Inoltre, questa ricerca si propone di presentare il modello di stima delle emissione di $CO_2$ e di presentare una formulazione del problema di routing sostenibile. Lo

studio mette in evidenza come la familiarità degli autisti con i territori serviti permette di ridurre le emissioni dei gas serra. Infine, è stata considerata la parte terminale della catena alimentare, la raccolta dei rifiuti. Con l'intento di garantire la sostenibilità economica e ambientale, si è introdotto un modello innovativo di vehicle routing integrato con i dai raccolti in tempo reale.

Tutte queste attività sono associate con applicazioni software appropriate. La tesi, dopo una breve introduzione, è suddivisa, in base alla distinzione delle decisione di lungo e breve termine, in due parti principali

- progettazione catene distributive sostenibili;
- pianificazione di catena distributive sostenibili.

# Abstract

The food industry is one of the world's largest industrial sectors. Studies of the food sector clearly demonstrate that it is one of the most prolific energy users, and thus a significant contributor to global warming, acidification, photochemical ozone formation, and eutrophication.

Governments and regulations are paying more and more attention to the environmental impacts of the economic activities forcing manufacturers to be responsible for their products.

At the same time, customers in developed countries are starting to consider ecological and ethical criteria in selecting food products demanding safe food of high quality produced with the minimal environmental impact.

Therefore, how to reduce carbon emissions during food raw material production, processing, packaging, transport and other processes and how to develop low-carbon food are the main challenges of the food industrial sector.

This induces the concept of the "Green supply chain management" (GrSCM), defined as the integration of environmental thinking into SCM, including product design, raw materials sourcing and selection, manufacturing process selection, delivery of final product to the consumers as well as end of life management of the product after its useful life (Srivastava, 2007).

In this context, the present thesis is focalized on the logistics activity related to the food supply chain and its purposes are:

- With regard to long term decision, introducing an innovative closed loop supply chain design methodology where both economic and environmental sustainability are guaranteed.
- Facing with the short term decision, firstly highlighting the benefits derived from the driver learning in the routing optimization. This part of the work was developed during a period of study in Denmark, at the Technical University of Denmark. Then, this research aims to present the $CO_2$ estimation model and to propose a sustainable routing problem formulation. The study points out how the drivers' familiarity with the served territories allows to reduce the greenhouse gasses emission. Finally, it is considered the last part of the food supply chain, the

waste collection. With the intent of guaranteeing the economical and environmental sustainability, it is introduced an innovative vehicle routing model integrated with the real time traceability data.

All these activities are associated with appropriate software applications.

The dissertation, after a brief introduction, is divided, in accordance with the distinction of long and short decision, into two main parts

- Sustainable supply chain design;
- Sustainable supply chain planning.

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# 1 INTRODUCTION

## 1.1. PURPOSE

Climate change becomes a global issue and a common concern to the international community, as well as the most serious global environmental problem facing mankind. Global scientific research shows that climate change is primarily depending on human activities and the tremendous energy use, which causes excessive emissions of carbon dioxide ($CO_2$), methane ($CH_4$) and nitrous oxide ($N_2O$) and other greenhouse gases to the atmosphere (Ma et al., 2010).

The food industry is one of the world largest industrial sectors (Roy et al., 2009). Studies of the food sector clearly demonstrate that it is one of the most prolific energy users, and thus a significant contributor to global warming potential (GWP). The European study on the Environmental Impact of Products (EIPRO) showed that the "food and drink" sector involves 20-30% of the total environmental impacts of EU consumption, with regard to global warming, acidification, photochemical ozone formation, and eutrophication (Tukker et al., 2006; Cellura et al., 2012). Therefore, how to reduce carbon emissions during food raw material production, processing, packaging, transport and other processes and how to develop low-carbon food are the main challenges of the food industrial sector.

Producers and supplier are nowadays assuming more and more responsibility as regards placing their products on the market mainly motivated by the strong pressure they are subject to as a result of customer expectations and governmental regulations (Gonzalez-Torre et al., 2004). Indeed, there is an increasing awareness that the environmentally conscious consumer of the future will consider ecological and ethical criteria in selecting food products. Consumers in wealthy countries demand high quality, safe food that is produced with minimal environmental losses (De Boer, 2002).

Furthermore, new government regulatory measures address the disposal of waste products. Governments are implementing a concept called Extended Producer Responsibility (EPR) which places the responsibility of disposal on the producer. Financially, and/or physically, the producer is legally required to recover the product from the consumer and to dispose of it in an environmentally-responsible manner. The most direct form of EPR implementation is take-back legislation and packaging was the first major implementation of it. The legislation’s goal was to minimize weight and volume of packaging, encourage recycling or reuse, and use environmentally-safe materials (Williams et al., 2000).

It is worthy of note that the food industry, of all the manufacturing industries, makes the largest demand on packaging, whether it be paper/board (including laminates), plastics, glass or metal. Indeed, the food industry is responsible for around two thirds of the total industrial usage. Finding ways to reduce this packaging quantity and its subsequent waste is one of the primary activity for reducing food environmental impact (Lillford et al., 1997).

Packaging waste was legislated by the European Packaging and Packaging Waste Directive‘94 (European Parliament and Council, 1994/62/EC) and revised ten years later (Directive 2004/12/EC). This Directive aims to harmonize national measures in order to prevent or reduce the impact of packaging and packaging waste on the environment. It outlines how to manage packaging and packaging waste so that less packaging waste is sent to landfill. The directive promotes the re-use of packaging and the recovery and recycling of packaging waste. Producer responsibility is outlined in Directive 2004 for packaging and packaging waste so that there is a responsibility on the producers of packaging to consider what is going to happen to the packaging at the end of its life cycle (Dixon-Hardy and Curran, 2009).

All these aspects induce the concept of the “Green supply chain management” (GrSCM), defined as the integration of environmental thinking into SCM, including product design, raw materials sourcing and selection, manufacturing process selection, delivery of final product to the consumers as well as end of life management of the product after its useful life (Srivastava, 2007). Different from a conventional supply chain, planning a green supply chain requires an additional function of recycling and thus, a closed-loop chain is a necessary infrastructure for a material flow. Moreover, as affirmed in Tsoulfas and Pappis (2006), “transportation and the consequent environmental effects can be significantly limited if the recovery of used products can occur at the same time or in combination with the distribution of new products”.

In this scenario the aims of this PhD thesis are:

- To point out the necessity to adopt an integrate approach in the supply chain design, instead of model separately direct and reverse flows.
- To introduce an innovative closed loop SC (CLSC) design methodology based on a linear programming model, where both economic and environmental sustainability are guaranteed.
- To provide an effective and flexible decision making tool to identify the best routing strategy for a given distribution network. The thesis investigates the possibility to apply a fixed routing strategy instead of a daily routing optimization strategy, analyzing the benefits derived from the driver familiarity with customers habits. This work was developed during a period of study in Denmark, at the Technical University of Denmark.
- To address to the solution of a new class of routing problem: the sustainable routing problem, where the objective is the CO2 emission minimization.
- To introduce an innovative vehicle routing model integrated with the real time traceability data to optimize the solid waste collection, in order to guarantee both economical and environmental sustainability.

## 1.2. THESIS OUTLINE

The research has been divided into two consecutive phases (figure 1.1), in accordance with the usual distinction between long and short term decision:

- *Sustainable Supply Chain Design*: this part of the thesis (Chap. 2) is dedicated to the strategic decisions. It aims to introduce an innovative closed loop supply chain design methodology, wherein, both economic and environmental sustainability are guaranteed, stressing the necessity to adopt an integrated approach in the supply chain design, instead of modelling separately the direct and reverse flows. The chapter firstly illustrates the state of the art related to the models developed for the supply chain design, starting from the classification of the supply chain structure. Furthermore, it is described the main relevant costs distinguishing traditional and environmental ones. Then, it describes the integrated CLSC design model developed in this research study, followed by a parametrical analysis.

- *Supply chain planning:* this part of the work (Chap. 3) is dedicated to the tactical decision. It aims to optimize not only the activity related to the food products distribution, but also the activity associated with the last part of the food supply chain, i.e. the waste collection. The research was made in order to assure the sustainability from both economical and environmental point of view. The chapter starts, as well as the previous one, from the analysis of the state of the art, in this case, related to the models developed for the supply chain planning. Then, it continues describing the innovations introduced by this research study, organized in three consecutive and related steps. The first one describes and compares the different routing models used in the daily routing optimization strategy and in the fixed routing strategy, and shows the advantages given by the driver learning effect. The second step defines the $CO_2$ estimation model and the sustainable routing problem. Moreover, it points out that the drivers' familiarity with the served territories is an important aspect for the $CO_2$ estimation model implementation. The last step introduces the heuristics model for waste collection starting from the description of the framework about the real time data traceability technology available on waste collection. It demonstrates that if it is possible to use real time data the routes can be optimized dynamically allowing the network sustainability.

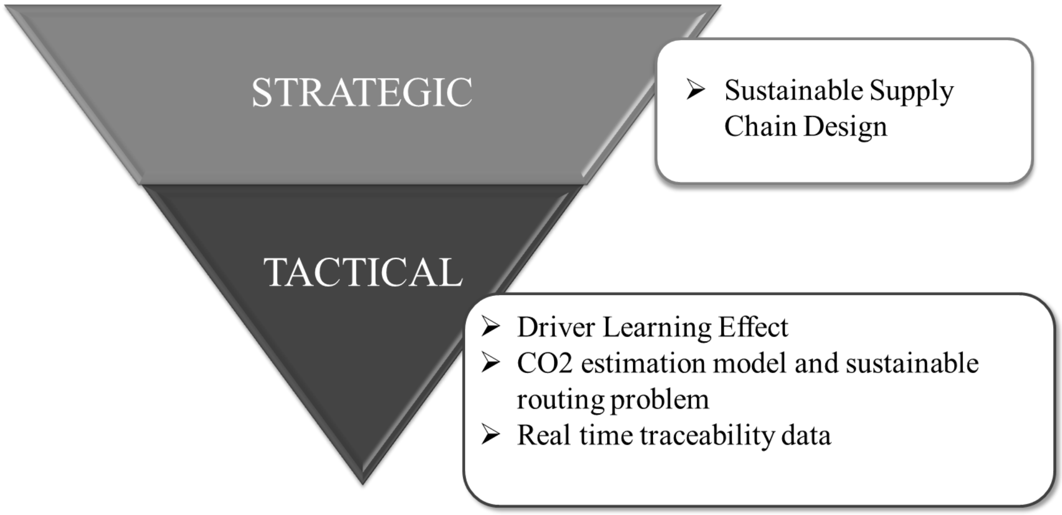



*Figure 1.1: Main relevant phases*

Finally, the last chapter of this dissertation (Chap.4), reports the conclusion of the present work summarizing the most important results of the study and the consequently recommendation in order to design and manage eco-compatible food supply chain.

# 2 SUSTAINABLE SUPPLY CHAIN DESIGN

*This chapter aims to point out the necessity to adopt an integrate approach in the supply chain design, instead of modelling separately the direct and reverse flows. Furthermore, it is introduced an innovative closed loop supply chain design methodology, wherein, both economic and environmental sustainability are guaranteed.*

## 2.1 INTRODUCTION

Recent legislation, social responsibility, corporate imaging and customer awareness are forcing manufacturers not only to provide more environmentally friendly products, but also to take back used products at their end of life. Moreover, there is an increasing consciousness that recovery of used products after the end of their life cycle is a mean for environmental protection and a source of business profit through their handling (Daniel et al., 2003). This has heightened the importance of reducing the utilization of materials by reusing and remanufacturing used products. Consequently, manufacturers have turned to a better design of their products for maximum material reuse and recycle, that induce the concept of the “green supply chain” design. According to Tsoulfas and Pappis (2006), the “green supply chain” design is influenced by different principles of environmental sustainability: product design, packaging, collection and transportation, recycling and disposal, greening the indoor and outdoor environment and other management issues. Respect to the classical supply chain, planning a “green supply chain” requires an additional function of recycling and thus, reverse logistics is a necessary infrastructure for material flow (Wang and Hsu, 2010). In fact, as Tsoulfas and Pappis (2006) affirmed, “transportation and the consequent environmental effects can be significantly limited if the recovery of used products can occur at the same time or in combination with the distribution of new products”. However, if returned products are not handled/transported efficiently, manufacturers incur in larger costs that can increase the cost of the new products. Therefore, the design and management of the reverse flow is an important issue for the companies (Mutha and Pokharel, 2009). Considering the whole product life cycle (production, distribution, warranty, remanufacturing, recycle, disposal, etc.) and all the relative logistic flows (forward and reverse), the SC design methodology changes significantly respect to the classical approaches.

Due the relevance of these concepts this PhD thesis aims to present an integrated methodology in a closed-loop network design, based on mixed-integer programming. This work starts from the study of Faccio et al. (2011), that address the possibility to apply different supply chain (SC) design approaches in presence of reverse flows, analysing the network structure where the considered flows are exclusively forward flow, or forward and reverse flows, or integral closed-loop flows. The analysis points out that, only if the quantity of reverse flows is limited and the capacity constrains at the intermediate levels of the SC (DCs, distributors) are relaxed, the structure of a forward SC can be implemented for reverse flows without requiring major changes in existing production–distribution networks. If such conditions are not satisfied, the introduction of a reverse flow drastically alters the SC structure. The authors presented an integrated methodology in a closed-loop network design, considering as inputs the most important drivers such as: the fixed and variable costs (installation, transportation, handling, inventory and production), the facilities attributes (type, location, capacity and costs), the stochastic customer demand. The proposed closed-loop SC (CLSC) design methodology has been validated through a real industrial application. Furthermore, their study developed a comparison between different SC design approaches, highlighting that an integral approach in designing SC, where shipping is combined and forward and reverse flows have the same route, incurs in costs that are always lower or equal to those of a sequential design, in which each forward and reverse shipment is dedicated and singularly optimized.

This thesis proposes an evolution of the Faccio et al. CLSC design methodology, where environmental sustainability is guaranteed by the complete reprocessing of an end-of-life product, the re-use of components and the disposal of unusable parts, sent directly from the manufacturers, in a closed loop transportation network that maximizes transportation efficiency. Then, by means of a parametrical study, the economical sustainability of the proposed CLSC model are compared with the classical forward supply chain model

(FWSC) from two perspectives: Case 1, the ‘traditional company perspective’, where the SC ends at the customers, and the disposal costs are not included in the SC, and Case 2, the ‘social responsibility company perspective’, where the disposal costs are considered within the SC.

The work has been developed starting from the analysis of the state of the art, that has allowed to identify the main types of SC networks and the more relevant design models. Then, the principal costs that impact on the supply chain networks have been investigated, distinguishing traditional and environmental ones, and described in section 3. At this point was evaluated the importance to apply an integrate supply chain design approach, instead of modelling separately the direct and reverse flows. Section 4 describes the integrated CLSC design model developed followed by the parametrical study, while section 5 reports the observation of this first part of the thesis.

## 2.2 SUPPLY CHAIN NETWORKS AND DESIGN MODELS

In the last decades, the design and management of supply networks have been fully studied in the scientific literature. The supply chain management (SCM) is the process of planning, implementing and controlling the operations of the supply chain in an efficient way. It encompasses all goods, movements and storage, including raw materials, work-in-process inventory and finished goods from the point of origin to the point of consumption (Melo et al., 2009). Another significant definition of the supply chain was reported by Lambert et al. (1998) “the integration of key business processes from end-user through original supplier, that provides product, service, and information that add value for customers and other stakeholders.”

From the point of view of material flows, it is possible to classify three basic network structures (Kannan et al., 2010):

*Forward supply chain (FSC)*

> A FSC is a network of facilities and distribution options that performs the functions of materials procurement, transformation into intermediate, production of goods and distribution of these finish products to customers.

*Reverse supply chain (RSC)*

RSC focuses on the backward flow of materials from customer to supplier (or alternate disposition) with the goal of maximizing the value of the returned item or minimizing the total reverse logistics cost.

RSC networks consist of the reverse channel only, i.e., the reverse activities, collection, inspection, sorting, disassembly, reprocessing/recycling and disposal operations, and the reverse flows.

*Closed-loop supply chain (CLSC)*

A CLSC consists of both the FSC and the RSC. The FSC involves mainly the movement of goods/products from the upstream suppliers to the downstream customers, whereas the RSC involves the movement of used/unsold products from the customer to the upstream supply chain, for possible recycling and reuse.

It is possible to distinguish between two different CLSC designs: the sequential CLSC, in which the reverse flow is independent of the forward flow, and the integral CLSC, in which the route in the reverse flow is the same as the one in forward flow, including the same transportation model, in order to optimize transportation costs (Fleischmann et al., 2001).

Part of the planning processes in SCM aims at finding the best possible supply chain configuration (Melo et al., 2009). It defines, given a set of spatially distributed customers:

- the location of new facility, like production and assembly plants, as well as warehouses and distribution centres;
- the allocation of the demand of each customer, i.e. which customers should be served by which facility;
- the configuration of the transportation network.

The problem of locating facilities and allocating customer covers the core components of distribution system design (Klose and Drexl, 2005). The so-called location–allocation problem is not new to the operations research community and has inspired a rich, colorful and ever growing body of literature. Klose and Drexl (2005) and ReVelle et al. (2008) suggested a classification that would distinguish between continuous location and network location models, discrete location or mixed-integer programming models and their applications. They defined:

*Continuous location models*

In the continuous location models the solution space is continuous, this means that the facilities can be located anywhere in the service area. Moreover, distance is measured with an appropriate metric, like Manhattan or right-angle distance metric, the Euclidean or straight-line distance metric.

The classic model in this area is the Weber problem, which aims to locate a single facility to serve $m$ demands with coordinates $(x_i, y_i)$ with $i=1, \ldots, m$ and demands (weights) $w_i$, $i=1, \ldots, m$. Distances in the Weber problem are often taken to be straight-line or Euclidean distances. The objective is to locate a single facility with coordinates $(x_0, y_0)$ to minimize the demand-weighted total distance. The corresponding optimization problem is

$$v(SWP) = \min \sum_{i=1}^{m} w_i d_i(x_0, y_0) \text{ where } d_i(x_0, y_0) = \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}$$

can be solved efficiently by means of an iterative procedure.

An extended version of the problem, called multi-source Weber problem, requires to locate p, $1 < p < |K|$ facilities and to allocate demand to the chosen facilities.

The Weber problem and its extension have been widely investigate in literature. Example of these models were discussed in Canbolat and Wesolowsky (2010), where the authors considered the problem of locating a single facility in the presence of a line barrier that occurs randomly on a given horizontal route. The authors distinguished three categories of barriers. The first category considers forbidden regions where no facility placement is allowed or possible; however travelling through these regions is not restricted. The second category considers congested regions, that is a region where placement of a facility is forbidden but travelling through it is possible with some penalty. The third category deals with barrier regions, where neither travel through these regions nor placement in a region is possible. Example of these barrier regions can be mountains, lakes, military zones, existing facilities, railroads, highways etc. Other interesting studies on the Weber problem were proposed in Bischoff and Klamroth (2007) and Bischoff et al. (2009), which dealt with the problem of locating new facility with respect to a given set of existing facilities and the presence of convex polyhedral barriers.

*Network location models*

The network location models deal with a graph where a set of arcs connect the notes which represent the potential facility sites and the demand points. The network location model corresponding to the continuous multi-source Weber model is called *p*-median problem. In the *p*-median problem *p* facilities are to be selected to minimize the total (weighted) distances for supplying customer demands. This model assumes that all candidate sites have the same costs of opening a new facility. A variant of the *p*-median problem is presented by the p-center problem, which aims to locate *p* facilities such that the maximum distance is minimized.

*Discrete location models*

The discrete location models assume that there is a discrete set of demand points, *I*, and a discrete set of potential facility sites, *J*. Most of such problems are NP-hard on general networks. They are often formulated as integer or mixed integer programming problems. Differently from the network location models, which explicitly take the structure of the set of potential facilities and the distance metric into account, the mixed-integer programming models just use input parameters without asking where they come from.

These models can be classify in function of relevant aspect like:

- The presence of capacity constraints. The models, that take into account these restrictions, consider the maximum demand that can be supplied from each potential side, while, models without capacity constraints do not restrict demand allocation;
- Number of stages covered by the distribution system. It permits to distinguish single-stage models from multi-stage models;
- Number of products supplied. If demand, cost and capacity for several products can be aggregated to a single homogeneous product, than single-product models can be analyzed, otherwise multi-product models have to be studied.
- Number of period covered. Static models try to optimize system performance for one representative period. Instead, dynamic models evaluate system in which the

parameters (cost, demand, capacities, etc.) change over time within a given planning horizon.

- The presence of uncertain data. It is possible to have deterministic models if input is (assumed to be) known with certainty or probabilistic models if input is subject to uncertainty.
- The combination with the routing models. Some models consider the necessity of delivering the products through tours, that start from the facility location and supply more than one customer. In these cases delivery cost cannot be calculated separately for each pair of supply and demand points; consequently the routing models must be combined with the location allocation models.

Considering these features it is possible to distinguish:

*Uncapacitated, single-stage models*

The simple plant location problem (SPLP) or uncapacitated facility location problem (UFLP) is the simplest model of this category. It considers the tradeoff between fixed operating and variable delivery cost. The UFLP is similar to the *p*-median problem. In both of them each customer is allocated to the open facility that minimizes his assignment cost. While in the *p*-median problem the number of facilities is fixed and the cost of opening a facility is the same in all locations, in the UFLP the number of open facilities is part of the solution and set up costs are not the same among the different sites. One of the most important extensions of the UFLP is the aggregate capacity plant location problem (APLP), in which an additional constraint ensures that facilities open in a feasible solution have enough capacity in order to satisfy the customers' demand.

*Capacitated, single-stage models*

The Capacitated single-stage models (CFLP) is a further extensions of the UFLP, in this case the additional capacity constraint introduced impose that the maximum amount of material handled in each facility are less than the capacity of the facility considered.

An interesting example of this problem is proposed in Amiri (2006), where the author proposed a mixed integer programming model for selecting the optimal location of the production plants and of the distribution warehouses and defining their capacity in order to satisfy the customers' demand with the minimum costs. Other remarkable examples of this problem were proposed in Wu et al. (2006) and in Harkness and ReVelle (2003). The first one presented an extension of the capacitated facility location problem, in which the general set-up cost was considered. In particular in their study the authors take into consideration two types of setup costs: site setup costs and facility setup costs. The site setup cost is a fixed cost associated with opening a site and independent of the facilities located in it. The facility setup cost is a function of its size. Instead, Harkness and ReVelle (2003) introduced a new type of facility location model, that is an hybrid of the well-studied simple uncapacitated and capacitated facility location models. The distinguishing feature of their study is that output from any given facility is unconstrained, but beyond a certain point, incremental output can only be achieved at additional costs. Thus, it introduces a capacity constraint that is not ''hard'' but ''soft'' in the sense that the producer is not strictly forbidden from exceeding it, but pays a penalty if she/he does.

*Multi-stage models*

The CFLP can be generalized in the two-stage capacitated facility location problem (TSCFLP), if additional variables are considered, such as, different types of facility (e.g., plant and warehouses) and the flow of material between them. These models contemplate the structure of the distribution system as a network of facility with several hierarchical levels. Each set of facilities of the same type and with the same role is usually denoted by an echelon, thus define a level of the hierarchy of facilities. In an equivalent manner to the CFLP also the UFLP can be generalized into a model at multiple levels.

*Multi-product models*

These models are applied when the capacity of production, storage and shipment is different for the various products, and it is not possible to consider aggregations of demand, production etc.. In this case it is necessary to apply multi-product models, which consider the facility's capacity, the demand and the flows separated into groups some homogeneous product groups. Some products require specific infrastructure or equipment that imply different fixed cost. Consequently, some models also consider if different types of facilities have to be distinguished in some locations and/or if fixed cost of locations depend on the product provided by a location. These models are respectively the multi-commodity and the multi-uncapacitated facility location problem (MUFLP).

*Dynamic models*

Several literature contributions distinguish three different levels of decision in a supply chain: strategic, tactical and operational (figure 2.1). The strategic level deals with long-term planning horizon, that considers problems of design and configuration of a generic multi-stage SC. These problems deal with the determination of the number of facilities, their geographical locations and capacity, and the allocation of customer demand. Instead, tactical decisions refer to both short and long-term planning horizons and deals with the determination of the best fulfillment policies and material flows in an SC, modelled as a multi-echelon inventory distribution system. The operational decisions introduce the time variable correlating the determination of the number of logistic facilities, geographical locations, and capacity of facilities to the optimal daily allocation of customer demand to retailers, DCs, and/or production plants (Manzini and Bindi, 2009).

Problems about facility location deal with strategic decisions. Depots, distribution centers and transshipment points once established shall be used for a couple of periods. In literature generally strategic, tactical and operational decision are treated separately even if factors like customers demand (volume, regional distribution) and cost structures may change, and relocation and/or redimensioning of facilities can be quite costly. In order to cope with such issues dynamic location and allocation models have been developed and the three levels of decision are integrated focusing on the effectiveness of the whole system.

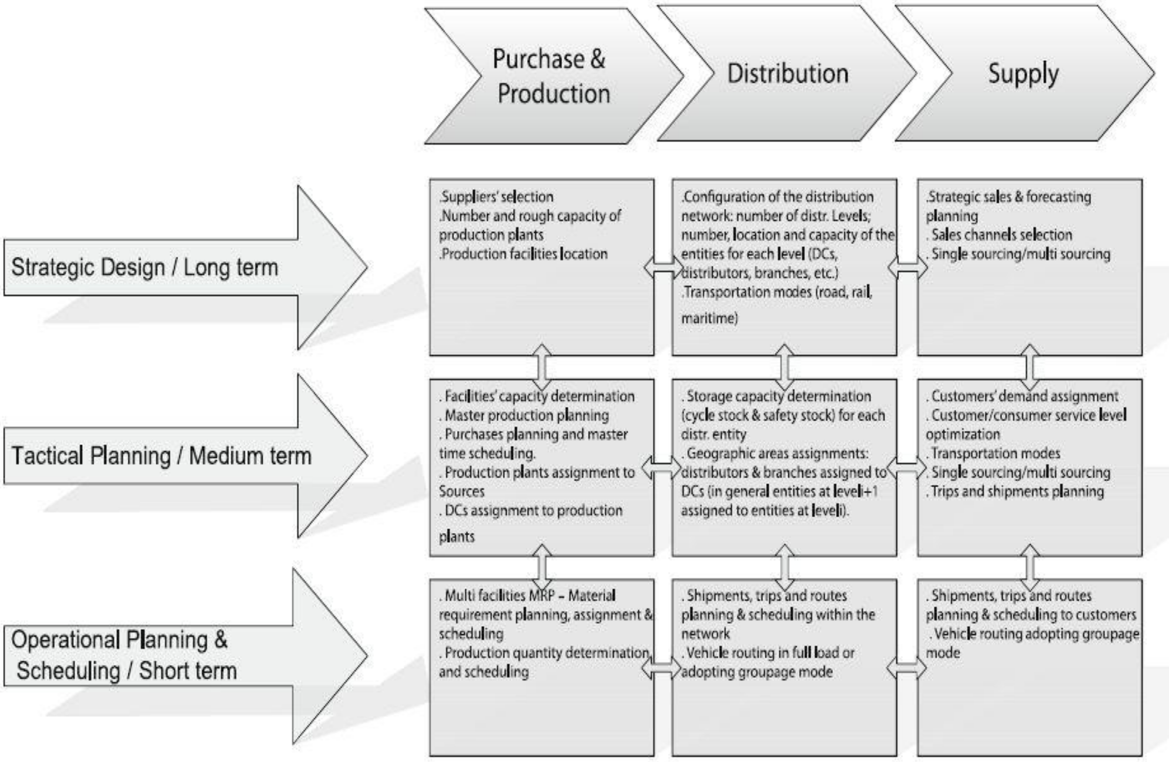



*Figure 2.1: Logistic issues & classification of decision (Manzini and Bindi, 2009)*

<u>*Probabilistic models*</u>

The uncertainty that often can be associated with some of the parameters, such as future customer demands and costs, involves the use of stochastic models. In order to use reliable values for the uncertain parameters, it is necessary to elaborate a large amount of data, so that empirically observed distributions can be adapted to theoretical ones. In general, these data are not available for the problems of location, then it is required a sensitivity analysis in order to observe the behaviour of the network designed in various situations.

<u>*Hub location models*</u>

The hub-and-spoke networks are represented in a graph with a set of node K and an indirect flow between each pair of nodes $i, j \in$ K. A subset of "central" nodes acts as transit points, hubs, other nodes, terminals or non-hub, are connected to the hub with an arc, spoke. The flow between a node and another is direct if at least one of them is a hub, and if there is a spoke that connects them.

Likewise the *p*-median and the facility location models, the number of hubs can be fixed or part of the solution, the capacity constraint can be considered or neglected. Moreover, it is possible to consider the single allocation problem, if each terminal node has to be connected with exactly one hub node, or the multiple allocation hub location problem, if terminal nodes have access to more than one hub.

These problems were well analysed and classified in Alumur and Kara (2008).

*Routing location models*

These models consider the possibility of delivering to more customers simultaneously. Given a set of customers with known demand and a set of potential depot sites, the location routing problem aims to determinate the location of the depots and the vehicle routes from the depots to the customers that minimize the sum of the costs associated with locating depots and distribution to the customers. Each customer is assigned to a depot which will dispatch a vehicle to fulfil its demand. A vehicle route must start from and end at the same depot. This problem take into account fixed cost associated with opening a depot at each potential site, and a distribution cost associated with the routing of vehicles which includes the route setup cost and the transportation cost which is linear in the total distance travelled by the vehicles.

The choice of location and routing decisions are related but complex, for several reasons: First, the optimal solution is very complicated, this problem belongs to the class of NP-hard problems since it combines the facility location problem (FLP) and the vehicle routing problem (VRP), both of them are shown to be NP-hard (Lin et al., 2009). Second, the time horizon of the two decisions is different, the FLP is a strategic issue, while, the VRP is a short term decision. Third, the location of the facility requires to aggregate customers, while routing does not. Moreover, in addition to the variety of facility location models exist, there are also many of routing models, and so a huge number of combined models are possible.

Due to the complexity and the exponential growth of the problem size, several meta-heuristics approaches were proposed in recent studies. An interesting example of them was presented in Lin et al. (2009), where the authors described a simulated annealing-based heuristic for solving the location routing problem.

*Multi-objective location models*

> The strategic problem such as location-allocation are often multi-objective by nature. Possible objectives can be, for example, minimizing periodic distribution costs, minimizing investment in new facilities. These types of problem can be solved, firstly, reducing the cost in the objective function and, then, modelling the other objective as "soft constraint".

This classification was repeated in Melo et al. (2009), where the authors discussed the general relation between facility location models and strategic supply chain planning, and observed that the full integration of forward and reverse activities in SCM requires more attention. Other interesting surveys were developed in Meixell and Gargeya (2005) and Van der Vaart and van Donk (2008), where the authors described the decision support models for the design of global supply chains. The first one considered the fit between the research literature in this area and the practical issues of global supply chain design, whereas, the second highlighted the relationship between supply chain integration and performance.

## ***Forward Supply Chain Models***

The literature presents manifold studies that deal with the location allocation problem; most of them belong to more than one of the categories previous described. Erlebacher and Meller (2000) and Miranda and Garrido (2007) considered a two-stage distribution-inventory system, analysing the interaction between network design decision (facility location and customers demand allocation) and the optimization of the inventory service level. Both of them considered the design of a two-level supply chain, in which plants serve a set of warehouses, and these warehouses serve a set of end customers or retailers. While, Erlebacher and Meller (2000) defined the number and the location of the distribution centers, in order to minimize the total costs maintaining an acceptable service level. On the contrary, Miranda and Garrido (2007), firstly optimize the service level and then, as second step, tackle the location decision. Also, Nozick and Turnquist (2001) proposed an integrated approach, that considers the service responsiveness (the capability of providing a desired product where and when the customer wants it) and in addition combined the location problem with the routing problem. Other interesting approaches for the integrated problems relative to location, allocation, inventory and routing decision were proposed in Max Shen and Qi (2007) and Ambrosino and Scutella (2005).

These problem characteristics are also considered in studies dealing with the dynamic planning horizon. Gebennini et al. (2007) proposed an innovative cost-based models and solutions for the location–allocation problem with production rates and safety stock level determination and customer service level optimization in a dynamic planning horizon. Similarly, Melo et al. (2005), proposed a dynamic mathematic framework for the location-allocation problem in a dynamic planning horizon. The framework integrates network design issues with inventory, transportation and supply decisions in case of and storage limitations. Routroy and Maddala (2009) and Routroy and Sanisetty (2007) discussed a generic model for multi-echelon supply chain inventory planning, considering the total SC cost, which consists of SC inventory capital, SC ordering/set-up cost and SC stock out cost for a maximum allowable SC inventory. In Manzini et al. (2008), the authors introduced the basis of an innovative decision support systems platform, capable of integrating design, management, control and optimization activities for a supply chain system. The authors expanded their theories in Manzini and Bindi (2009), where they illustrate an original framework for the design and optimization of a multi echelon and multi-level production/distribution system. In their work the authors described a new and effective approach to integrating management decisions taken in configuring and managing a logistic network that involves deciding the number and locations of facilities, the allocation of the generic demand to the available suppliers, the modes of transportation chosen, and the optimization of trips and vehicles/containers loading across roads, railways, and other transportation infrastructures available.

## ***<u>Reverse Supply Chain Models</u>***

All the articles previously referred are related to the FSC, but literature presents also several examples of studies dealing with the RSC. The reverse logistics focuses on the backward flow of materials from customer to supplier (or alternate disposition) with the goals of maximizing the value from the returned item and/or assuring its proper disposal. This may include product returns, source reduction, recycling, materials substitution, reuse of materials, waste disposal, refurbishing, repair, and remanufacturing (Autry, 2005).

An interesting review of the issues arising in the context of reverse logistics was reported in Fleischmann et al. (1997). The authors defined:

- The reuse motivation: which can be *economical* and *ecological*. The economical motivations are related to the growing attention for waste reduction, that has drawn, from one hand, several countries to enforce environmental legislation, charging producers with responsibility for the whole product life cycle, and on the other hand, has increased the customer expectations imposing strong pressure on companies. There is in fact an increasing awareness that the 'green' image has become an important marketing element. The economical motivation regards the possibility of regaining the value still incorporated in a used product. Overhauled products may be used as spares or sold on secondary markets while requiring only a small fraction of the original production costs for repair.
- The type of recovered items: which can be *packages* (e.g. pallets, bottles), *rotable spare parts* (e.g. machine parts, TV-tubes), or *consumer goods* (e.g. copiers, refrigerators).
- The form of reuse: that distinguishes *direct reuse, repair, recycling* and *remanufacturing* as main options, where recycling denotes material recovery without conserving any product structures, while remanufacturing conserves the product identity and seeks to bring the product back into an 'as new' condition by carrying out the necessary disassembly, overhaul, and replacement operations.
- The involved actors and their respective functions: including *collection, testing* and *reprocessing*.

The paper continues by proposing a division of the articles analysed in three areas of interest namely distribution planning, inventory control, and production planning.

- The distribution planning is related to the reverse distribution activity, i.e. the collection and transportation of used products and packages. These planning decisions are focalized on the design of the reverse distribution network. The authors highlight that in literature it is possible to distinguished models in which the reverse distribution take place through the original forward channel, from model wherein it is used a separate reverse channel, or a combinations of the forward and the reverse channel.

- The inventory control deals with the inventory management and requires appropriate control mechanisms to integrate the return flow of used products into the producers' materials planning. The effects of the return flow are twofold. On the one hand it may be cheaper to overhaul an old product than to produce a new one. On the other hand reliable planning becomes more difficult due to increased uncertainty which may lead to higher safety stock levels. In fact, differently from the classical forward supply chain, in case of return products companies have to consider three relevant aspect. First, as a consequence of the return flow the inventory level among new component replenishments is no longer necessarily decreasing but may also increase. Second, external orders and recovery have to be coordinated. This can be compared with a two supply mode inventory system with the special property that supply of one mode cannot fully be controlled. Third, a two-echelon inventory system is required. Thus, investigations on adequate echelon stock control strategies, such as PUSH versus PULL policies are relevant. In this situation the authors classified the models analysed dividing deterministic inventory models, which assume to know with certainty the information on all the components, versus stochastic models, that treat demands and returns as uncertainty processes.

- The production planning the problem arising in this decision phase depends on a large extent on the specific form of reuse considered. In the case of direct reuse where returned products can be reused 'as is' no additional production process has to be taken into account. On the contrary, the most complex situation is found in case of remanufacturing. Where, individual repair requirements for every product returned, and coordination of several interdependent activities makes production planning a highly sophisticated task in this environment.

In Fleischmann et al. (2000), the authors presented a detailed review of the reverse logistic literature, and then, identified general characteristics of product recovery networks and compared them with traditional logistic structures. They pointed out that product recovery networks have in common a set of activity, which are:

- <u>Collection,</u> it refers to all the activities that allow to move the used products to some points where further treatment is taken care of. In general, collection may encompass purchasing, transportation, and storage activities.
- <u>Inspection/Separation,</u> it denotes all operations determining whether a given product is in fact re-usable and in which way. Inspection and separation may include disassembly, shredding, testing, sorting, and storage steps.
- <u>Re-processing,</u> it refers to transformation of a used product into a usable product again by recycling, repair, and remanufacturing. These processes may involve additional activities such as cleaning, replacement, and re-assembly.
- <u>Disposal,</u> it is required for products that cannot be reused for technical or economical reasons.
- <u>Re-distribution,</u> it means supply re-usable products to a potential market and move them to future users. This may encompass sales transportation, and storage activities

The authors pointed out that even if they have identified a number of general characteristics of product recovery networks, the manifold studies presented in literature can be classified considering some discriminating factors.

Likewise the forward supply chain study, the classification of the products recovery network may be based on different aspects. Sasikumar and Kannan (2009) mapped the tools and techniques for a detailed literature classification on the basis of content related issues in reverse supply chain. These issues are summarized in figure 2.2.

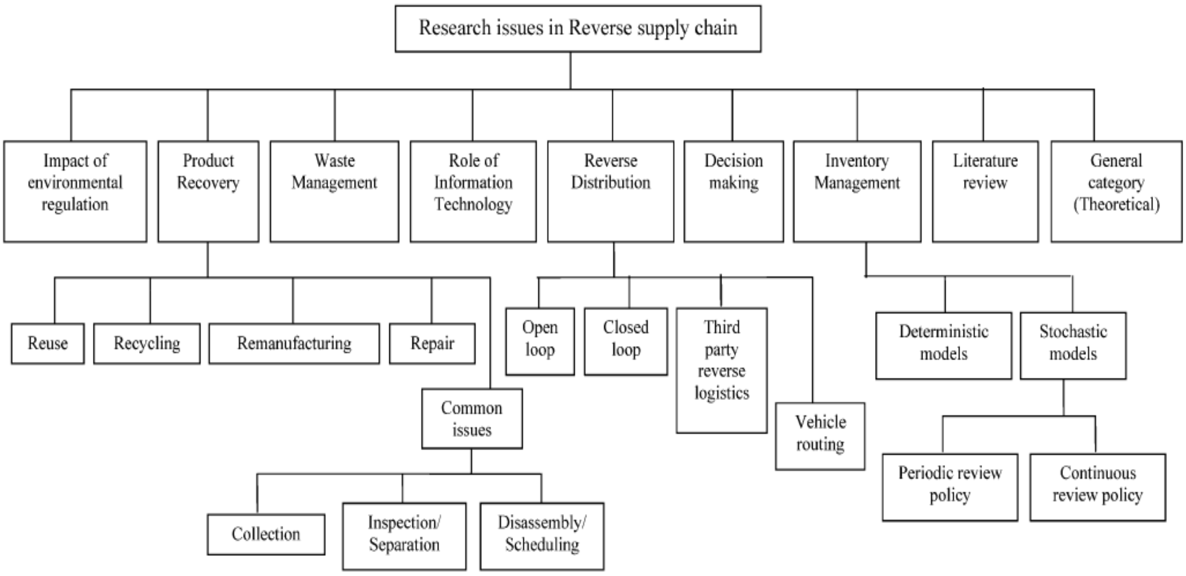



*Figure 2.2: Classification scheme based on content related issues (Sasikumar and Kannan, 2009)*

Several studies have developed models for the managing of the reverse logistic, showing the relevance of this aspect in the supply chain decision. Below are mentioned some interesting examples.

Jayaraman et al. (2003) developed a model whose aim is to find an efficient strategy for the return of products. The supply chain flow depart from the points in which customers bring their products to return , that can be shops or retailers. Then, the used products are sent to collection centers, and subsequently to the refurbishing facilities site, which can be: refurbish site, i.e. systems where the goods returned are reprocessed or disposed of; recycling site; decontamination facilities; or factories. The flow of material consideres products that can be dangerous, damaged, to recycle or dispose of. The article proposed an innovative solution heuristics that may be very useful, since the proposed problem is generic and can be adapted to a wide variety of situations.

Other examples were described in Gou et al. (2008), Mutha and Pokharel (2009) and in Lee et al. (2009). The purpose of the first study was to find the optimal economic delivery batch size as well as the optimal handling batch size in order to minimize the open-loop RSC cost. Mutha and Pokharel (2009) proposed mathematical models for the design of a RL network. It is assumed that the returned products need to be consolidated in the warehouse before they are sent to reprocessing centres for inspection and dismantling. Dismantled parts are sent for remanufacturing or to the secondary market as spare parts.

While Lee et al. (2009) formulated a mathematical model aimed to minimize the total cost of opening disassembly and processing centres and of reverse logistics shipping.

## ***Closed Loop Supply Chain Models***

Many papers considered simultaneously forward and reverse flows and analysed practical cases: Kroon and Vrijens (1995) considered the reuse of secondary packaging material, while Alshamrania et al. (2007) presented a study on reverse logistics motivated by blood distribution of the American Red Cross. Jayaraman et al. (2010) discussed a case study based on a product recovery problem faced by an electronics company and Kannan et al. (2010) proposed a genetic algorithm approach for solving a CLSC model for a case of battery recycling. Fuente et al. (2008) examined supply chain management as implemented in companies which deal simultaneously with forward and reverse logistics and considered the strategic and operational alignments, system interoperability, information share and coordination of activities in a metal-mechanic company.

Akçalı et al. (2009) presented an annotated bibliography of models and solution approaches organised into two main sections that focus on RSC network design, which regards only the reverse channel, i.e., the reverse activities and reverse flows. and CLSC network design, which considers the forward channel, i.e., forward activities and forward flows, along with the reverse channel.

Marin and Pelegrin (1998) proposed a solution for the so-called return plant location problem. They considered both the forward and the revers flows, assuming that the amount of returned products is in proportion with the products supply to satisfy the customers demand. The purpose of the study was to determinate the plants to be opened, the amount of primary product required by each customer that has to be supplied from each plant, and the amount of the secondary product that is returned from each customer to each open plant, so that the total cost of plant opening, supply and return is minimized. Also, Lu and Bostel (2007) studied this problem and demonstrated that reverse flows influences the decisions about location and allocation. While Fleischmann et al. (2001) presented a generic facility location model for a CLSC and discussed the differences with traditional logistic settings. The authors proceeded analysing the impact of product return flows on logistic networks and showed that the influence of product recovery is very much context dependent. The model proposed in Fleischmann et al. (2001) was generalised in

Salema et al. (2007), where a capacitated multi-product reverse logistic network model with uncertainty was developed.

In CLSC, like in FSC, some authors do not consider the location problem exclusively, e.g. Krikke et al. (2003) developed a quantitative modelling to support decision-making, concerning both the design structure of a product and the design structure of the logistic network. Fleischmann and Kuik (2003) considered a stochastic inventory model encompassing random item returns, where returns are independent of past demand and might be directly reused. The uncertainty was also considered in the extended facility location MILP model proposed in Lieckens and Vandaele (2007). Others studies considered a dynamic planning horizon like Ko and Evans (2007), El-Sayed et al. (2008) or, an integration of strategic and tactical decisions, by considering two interconnected time scales: a macro and a micro time, as in Salema et al. (2009) and Salema et al. (2010)

A relevant part of the articles dedicated to the RSC and to the CLSC explains important environmental consideration, but they did not propose any supply chain mathematical model optimization. Autry (2005) examined the relationships between formalization (the degree to which control mechanisms such as rules, processes, or procedures guide the supply chain operations), liberal return policies, and related capabilities and the overall effectiveness of reverse logistics programs. Sarmento et al. (2005) evaluated the industry's behaviour regarding the environment and explained the correlation between financial accounting harmonization and environmental pollution. Nakamura and Kondo (2006) defined life-cycle costing (LCC) as a tool to assess the cost of a product over its entire life cycle and present a hybrid LCC methodology. While Ciliberti et al. (2008) and Kammerer (2009) proposed a study on Logistics Social Responsibility (LSR), for developing a taxonomy of the LSR practices adopted by firms, and an analysis about the influence of customer benefit and regulation on environmental product innovation. Liu et al. (2009), presented an economic evaluation of three typical recycling processes for the five main types of waste electronic home appliances (EHA), classified optional recycling processes for the targeted waste EHA, and evaluated their economic feasibilities.

Other well-known studies proposed mathematical models for the impact of environmental issues on long-term behaviour of a single product supply chain with product recovery. Hammond and Beullens (2007) presented a variation inequality approach to strategic modelling of oligopolistic closed-loop supply chains under legislation. Georgiadis and Vlachos (2004) examined the firm's 'green image' effect on customer demand, the obligation to 'take back' imposed by legislation, and the state campaigns for proper disposal of used products. Also, Wang and Hsu (2010), Sheu et al. (2005) and Ortolani et al. (2009) proposed studies concerning the integration of logistics operations and green supply chain design and management. Sheu (2007) introduced a conceptual framework that describes the process of multi-source hazardous-waste return flows in proposed coordinated reverse logistics (CRL) system, formulated as a multi-objective optimization problem. Where, in addition to inter-organizational logistics operating factors, environmental concerns are considered and formulated as corresponding risk-related constraints. The consequent objectives was to minimize both the total reverse logistics operating costs and corresponding risks. Bojarski et al. (2009) addresses the optimization of SC planning and designs considering economical and environmental issues, while, Cruz and Wakolbinger (2008) developed a framework for the analysis of optimal levels of corporate and social responsibility (CSR) in a multi-period supply chain network.

This preliminary literature analysis shows that many approaches have been taken to design and optimize SCM, managing both inventory control and facility location, but is evident that recent research about SC has not yet focused on the CLSC, a critical issue that needs more investigation. Only a few authors analyze the CLSC related to economical and environmental sustainability, focusing more on the environmental consideration than on costs and benefits inside the SC. Moreover, most authors do not consider these aspects in their mathematical design model of the SC.

The new and significant contribution of this study is firstly to introduce a linear programming model that aims to minimize the total SC costs, then, to compare the proposed CLSC structure, where all the products at their end-of-life are returned and reprocessed at the production plant, with the Forward Supply Chain (FWSC) structure. This comparison was made from 2 different standpoints: the case of a 'social responsibility company perspective', whereby the disposal costs are considered inside the SC, and the case of a 'traditional company perspective', where the SC ends at the customers, and the disposal costs are not considered in the SC, as normally happens with companies. This second part of the study aims to:

- Define the function of the two analysed perspectives, in terms of which and how factors combine impacts on SC costs in case of CLSC and FWSC structure.
- Define, using a parametrical analysis, a decision making tool that, for a given product and network with certain specific characteristics, allows a decision on whether it is possible to modify the classical forward SC structure to a ‘Green Closed Loop SC’.
- Study which elements influence the choice of SC structure and details of in what way and how these factors influence each level of the CLSC, in terms of number and location of elements.

## 2.3 MAIN RELEVANT COSTS

In this paragraph are described the relevant costs that impact on the supply chain networks and influence the design decisions. Among them, it is possible to distinguish more the traditional costs and the environmental ones. Moreover, in this session, are discussed the guidelines to design products and processes with the aim of reducing the environmental impact. A particular attention is given to the transport tasks, because they are a major cause of pollution.

### ***Traditional Costs***

*Facilities installation costs*

The costs of opening new facilities include the investment costs for the purchase of land, of the building structures, including the equipment for the functionality of the building and safety. These costs are influenced by the location chosen. Since the costs of land and rent structures vary from country to country, they can even have different prices within the same country, from region to region and from area to area.

*Production costs*

This cost depends on the volume of products and includes costs of raw materials and components, and costs of utilities (electricity and gas). The costs of labour and energy are influenced by the  plant site selection. The salary of the employees, for example, can vary significantly from region to region. On the other hand, in considering where to locate the facility, it is important to take into account also the productivity of labour. In fact, choosing an area with lower production costs but lower productivity may be disadvantageous, especially if the choice of this location leads to increased other costs. Other cost factors that influence the choice of location are related to:

- The tax legislation and local taxes;
- The possible incentives for investment;
- The possible restrictions on movements of capital;
- The local language;
- The availability of services and infrastructure (banks, highways, schools, etc.);
- The possible restrictions of environmental regulations

*Handling costs*

The handling cost includes costs of manpower and tools, necessary to move the products through the facility and from plant to trucks, from truck to intermediate warehouse and from warehouse to trucks again. Also these costs, as well as the facilities installation and the production costs, depend on the choice of the facility location. Handling costs due to the transit of products through the facility is often a direct function of the volume moved and depends on the characteristics of the product's family.

*Inventory costs*

These costs are due to the warehousing and storage activities, and, as the previous costs, they depend on the warehouse site selection. According to Battini et al. (2007) the inventory costs include:

- capital costs, or opportunity costs, which is the return a company could make on the money tied up in inventory;
- inventory service costs, which includes insurance and taxes on inventory;
- storage space costs, which include those warehousing space-related costs relative to level of inventory;

- inventory risk costs, including obsolescence, pilferage, movement within the inventory system and damage.

In addition each company needs to determine the appropriate safety stock, which needs to be adequate to fulfil the surplus of expected demand and it is usually determined by the manager. This said, it is obvious that inventory costs are the sum of the cost of average stock and the cost of the safety stock.

*Transportation costs*

The transportation cost represents an important component of the total cost, so the decision of the modes of transportation (by train, road, plane, rail, boat) is very important. The main factors that influence the selection are transportation cost, time, reliability and products safety. The costs depend several variables, such as:

- *The characteristics of the goods,* such as the density of the product, if it is perishable or hazardous, the state (solid, liquid, gas), the value and the type of packaging.
- *The service level required*, like the rapidity of delivery, the punctuality, reliability, regularity of service, traceability, security and control.
- *The characteristics of the load / shipment*, it refers to the quantity shipped and the frequency of delivery.
- *The distances and characteristics of the relations "origin-destination",* we distinguish between "primary transport" and "secondary transport». The first indicates inbound traffic on long routes, it considers  to travel at full load and travel times are relevant to the fixed times of load/unload, controls, expectations, while "secondary transport», indicates the phase of the local distribution (outbound) in limited geographical areas.

*Reverse logistic costs*

This cost includes costs of transportation, inventory and management of the reverse flow of products and packaging.  Reverse logistic flow can be divided into process of restoration, re-engineering, recovering and reusing, and waste disposal.

## ***Environmental Costs***

These are costs that the distribution network imposes on society as consequence of its activity. Every product generated, transported, used and discarded within the SC causes a certain impact on the environment, but they are often intangible or difficult to measure. This impact is a function of the material and energy consumed and of the wastes released in the product's whole life cycle, which in turn depend upon the type of the product and the technology used. Thus, it is important to examine all the procedures related to materials' flows, in order to opine regarding the environmental performance of SC (Tsoulfas and Pappis, 2006).

The researchers have developed several systematic methodologies for the detailed characterization of the environmental impacts of products and processes. Among these methodologies the more relevant is the life cycle assessment (LCA). It is a method for identifying, quantifying, and assessing environmental impacts throughout the life cycle of a product, process, or activity. In this method the energy and material consumption and different types of emissions related to a specific product are being measured, analysed and summoned from "cradle to grave" (i.e., from raw material extraction through manufacturing, transportation, use, and disposal) (Tsoulfas and Pappis, 2006). LCA is based on the premise that products and process have life cycles. Products are made of raw materials, transported, used, and eventually disposed of. Processes also have life cycles. During each stage of the life cycle (extracting and processing raw materials, manufacturing, transportation, and distribution, use/reuse, recycling and waste management), products and processes interact with the environment (substances are extracted, modified, and added; land is used; and substances are emitted).

According to Ortolani et al. (2009) one of the main environmental costs is related to the transportation sector: transport is valued to be one of the most polluting activities in the industrial system. The authors made a detailed study on the environmental costs and observe that they can be divided into different categories, among which the more relevant are linked to:

*The atmospheric pollution*

It causes damages to human health, to buildings and monuments, and to ecosystems. One of the major sources of pollution is the emission from vehicular traffic. As observed by

Janic (2007), air pollution does not only come from fuels burning in road transport, but it is produced by all of the transport modes as a result of their energy usage. If electric energy is used, as it happens in some railways, the generated air pollution is indirect, dependent on the composition of sources from which the electric energy is obtained. Consequently it is possible to distinguished tailpipe emissions and lifecycle emissions. The first are pollutants released directly from vehicle exhaust pipes. Instead, the second include both tailpipe emissions and indirect emissions from fuel extraction and refining, vehicle manufacturing, and construction of facilities for transportation (Litman, 2009). Motor vehicles produce various harmful air emissions. The main relevant are carbon monoxide (CO), nitrogen oxides (NOX) and volatile organic compounds (VOCs) emitted by vehicles in the environment. Table 2.2 summarizes various types of motor vehicle pollution emissions and their impacts.

| Emission | Description | Sources | Harmful Effects | Scale |
|---|---|---|---|---|
| Carbon dioxide ($CO_2$) | A product of combustion. | Fuel production and tailpipes. | Climate change | Global |
| Carbon monoxide (CO) | A toxic gas caused by incomplete combustion. | Tailpipes | Human health, climate change | Very local |
| CFCs and HCFC | A class of durable chemicals. | Air conditioners and industrial activities. | Ozone depletion, climate change | Global |
| Fine particulates ($PM_{10}$; $PM_{2.5}$) | Inhaleable particles. | Tailpipes, brake lining, road dust, etc. | Human health, aesthetics. | Local and Regional |
| Road dust (non-tailpipe particulates) | Dust particles created by vehicle movement. | Vehicle use, brake linings, tire wear. | Human health, aesthetics. | Local |
| Lead | Element used in older fuel additives. | Fuel additives and batteries. | Human health, ecological damages | Local |
| Methane ($CH_4$) | A flammable gas. | Fuel production and tailpipes. | Climate change | Global |
| Nitrogen oxides (NOx) and nitrous oxide ($N_2O$). | Various compounds, some are toxic, all contribute to ozone. | Tailpipes. | Human health, ozone precursor, ecological damage. | Local and Regional |
| Ozone ($O_2$) | Major urban air pollutant caused by NOx and VOCs combined in sunlight. | NOx and VOC | Human health, plants, aesthetics. | Regional |
| Sulfur oxides (SOx) | Lung irritant and acid rain. | Diesel vehicle tailpipes. | Human health and ecological damage | Local and Regional |
| VOC (volatile organic hydrocarbons) | Various *hydrocarbon* (HC) gasses. | Fuel production, storage & tailpipes. | Human health, ozone precursor. | Local and Regional |
| Toxics (e.g. benzene) | Toxic and carcinogenic VOCs. | Fuel production and tailpipes. | Human health risks | Very local |

*Table 2.2 Vehicle pollution emission (Litman, 2009)*

*The climate change impacts*

Climate change becomes a global issue and a common concern to the international community, as well as the most serious global environmental problems facing mankind. Global scientific research shows that climate change is primarily depending on human activities and the tremendous energy use, which causes excessive emissions of carbon dioxide ($CO_2$), methane ($CH_4$) and nitrous oxide ($N_2O$) and other greenhouse gases to the atmosphere (Ma et al., 2010).

Major scientific organizations consider human caused global warming a significant cost (in terms of actual damages) and risk (in terms of future damages). One of the main uncertainty factors in the economic evaluation is the difficulty to evaluate with the present monetary unit of measure the projected effects on the ecosystems that will be experienced by future generations. The concrete risk of not including the impacts on the ecosystem in the economic evaluation is to underestimate sustainability issues in the present decision-making (Ortolani et a., 2009).

Other relevant environmental costs due the transportation sector are related to:

*The noise*

Motor vehicles cause various types of noise, including engine acceleration, tyre/road contact, braking, horns and vehicle antitheft alarms. When these unwanted sounds and vibrations exceed tolerable limits, they cause annoyance and, if they persist, can cause a decline in productivity and can even have adverse health effects.

*The accidents*

They are also called collisions, accidents or incidents. Crash costs include internal costs, which are damages and risks to the individual travelling by a particular vehicle or mode, and external costs, which are uncompensated damages and risks imposed by an individual on other people, i.e. the emergency response services and the medical treatment costs.

*The congestion*

Traffic congestion costs consist of incremental delay, vehicle operating costs (fuel and wear), pollution emissions and stress that result from interference among vehicles in the traffic stream, particularly as traffic volumes approach a road capacity (Litman, 2009).

At this point it is important to highlight that every products and activity in the SC may have an undesired environmental impact. This impact is a function of the consumed material and energy and of the wastes released in the product's whole life cycle (Daniel et al., 1997). Producers and suppliers are nowadays assuming more and more responsibility towards placing their products on the market, mainly motivated by the strong pressure they are subject to, as a result of customer expectations and governmental regulations (Gonzalez-Torre et al., 2004). An important measure among these governmental regulations defines the disposal of waste products. Governments are implementing a concept called Extended Producer Responsibility (EPR) which places the responsibility of disposal on the producer. Financially and/or physically, the producer is legally required to recover the product from the consumer and to dispose of it in an environmentally-responsible manner. The most direct form of EPR implementation is take-back legislation and packaging was the first major implementation of it. The legislation’s goal was to minimize weight and volume of packaging, encourage recycling or reuse, and use environmentally-safe materials (Williams et al., 2000). This is also true for the main subject of this work, the food industry, that is one of the world’s largest industrial sectors and a large user of energy. Moreover, it is worthy of note that the food industry, of all the manufacturing industries, makes the largest demand on packaging, whether it be paper/board (including laminates), plastics, glass or metal. Indeed, the food industry is responsible for around two thirds of the total industrial usage. Food production, preservation and distribution consume a considerable amount of energy, which contributes to total greenhouse gases emission (Roy, 2009). Therefore, how to reduce carbon emissions during food raw material production, processing, packaging, transport and other processes and how to develop low-carbon food are the main challenges of the food industrial sector.

To do that can be applied the Environmentally Conscious Manufacturing and Product Recovery. It is concerned, from one hand, with developing methods for manufacturing new products from conceptual design to final delivery and ultimately to the end-of-life disposal such that the environmental standards and requirements are satisfied. On the other hand, it aims to minimize the amount of waste sent to landfills by recovering materials and parts from old or out dated products by means of recycling and remanufacturing (including reuse of parts and products) (Gungor and Gupta, 1999).

In Tsoulfas and Pappis (2006) the authors defined a set of principles that can be applied in the supply chain design in order to develop environmental friendly processes and products. These principles can be classified into 6 groups corresponding to respective company functions. Considering the food industry, they can be summarized as follows:

*Product design*

In this phase are defined and developed new products and processes. Designers should consider the effects that design has on the energy and the materials required for the production and the use of the product. A detailed analysis of the possible design changes allow to understand that they cannot only reduce the environmental impact but also lead to substantial economic benefits. This principles suggest to produce using minimum energy and materials, and employing eco-friendly energy, reducing water usage and keeping control of pollution sources. Reducing the use of energy and water brings both environmental impact benefits and cost savings allowing the long-term sustainability of the business.

*Packaging*

Packaging design is important for the food industry, since it makes the largest demand of all the manufacturing industries. This is because of the main role of packaging in protecting, distributing and offering information about product in industry, in business and for the consumer (Lillford and Edwards, 1997 and Bovea et. al., 2006). However, it affects environment in many aspects, and so finding ways to reduce the packaging quantity and its subsequent waste is a demanding task. As said previously, packaging and packaging waste are regulated by the take back legislation, which aims to minimize weight and volume of packaging, encourage recycling or reuse, and use environmental-safe materials (Williams et al, 2000). Possible ways to do that are:

- Limit the packaging to the necessary size. Minimizing packaging not only brings benefits in terms of environmental impact, but also in transportation. Moreover, the use of eco-friendly packaging may be used as a marketing argument.

- Design packaging for refilling or recycling and use standardized systems whenever possible.

*Collection and transportation*

The collection and transport of recovered products has some environmental costs. Consequently, for not neutralizing environmental benefits due to the reuse and recycle of these products, is important to minimize these costs.

This concept is on the base of the work described in the presents thesis.

The applicable principles to this stage of the supply chain are to:

- Formulate a policy of product recovery. This policy encourages the maximum utilization of the used products.
- Use existing forward supply chain facilities and transportation system as much as possible for the reverse supply chain. Transportation and the consequent environmental effects can be reduced greatly if the recovery of used products can occur at the same time or in combination with the distribution of new products.
- Classify products used as soon as possible in the chain of recovery in order to make easier the storage planning of these products and to avoid redundancy processes.

*Recycling and disposal*

At the end of its useful life, a used product can be disposed of or recycled. As during the collection and transport, recycling and disposal can contribute significantly to the total environmental gain and achieving the environmental objectives of society. In this contest can be important apply the following principles:

- Close the supply loop recycling effectively and efficiently. The objective is to work in systems of closed continuous production, with zero waste factory, in which each output is returned to nature as a nutrient or becomes an input for manufacturing another product. Recycling is essential, but it becomes unproductive when the energy, materials and pollution for the collection and processing of used products exceed those used to produce goods in the first place.

- Reduce the volume and the amount of materials going to landfill and to consider alternative uses of second hand products or waste. For example reusing the food packaging.
- Support the development of markets for the recovery of components and materials.

*Greening the internal and external business environment*

"Greening the business environment" refers to management practices that aim to make the internal market, as well as the external ones, better for the environment. The supply relationships can be a way for companies to influence the sustainability of their products and services through the improvement of the production system, since that system includes functions such as supplier selection, the choice of materials, outsourcing, negotiation, purchasing, delivery planning, inventory and materials management and, to some extent, involvement in design. The staff of a company is responsible to enforce the policies of the company, so it must be aware of the environmental impacts. Finally, the" green" policies include customers and are designed to raise their level of environmental awareness. To this end the following principles can be applied:

- Impose higher environmental standards for suppliers and have a close relationship with them. The adoption of procurement policies that impose on suppliers to apply techniques that enable sustainable development can help companies to reduce waste and pollution problems later.
- It is important to provide the necessary information concerning the recycling of products and provide adequate safety instructions, as well as to indicate the possibility of re-use and recovery of materials. End-users should be aware of what to do after the product has completed its life cycle. For example a benefit can be given by the description of how to reuse or to properly dispose the packaging of the used products.
- Introduce eco-objectives among the staff and make it environmentally conscious.

## 2.4 SUSTAINABLE SUPPLY CHAIN DESIGN

As previously said, the design of distribution networks is one of the most critical issues in management of supply and, in order to consider both economical and environmental aspect, it is necessary to take into account the whole life of the product (manufacturing, distribution, recovery, recycle, disposal, etc.). Consequently, it is required to encompass the forward SC flows as well as the reverse SC flows in the distribution networks design.

Fleischmann et al. (2001) asked about the reverse supply chain: “How robust are traditional logistics networks when they come to address product recovery activities?” To make a generalization, their conclusion was the following: forward flows dominate the network design. The impact of return flows increases with the economic incentive for product recovery (namely higher production savings, higher penalty costs for refusing to collect end of life products, and higher disposal costs) and with a decrease in the number and uniformity of potential facility locations.

In this contest Faccio et al. (2011) addressed the possibility to apply different SC design approaches, analysing the network structure where the considered flows are forward flow exclusively, or forward and reverse flows, or integral closed loop flows. Furthermore the authors presented an integrated methodology in closed loop network design, based on mixed integer programming. The study pointed out that:

- Only if the quantity of reverse flows is limited and the capacity constrains at the intermediate levels of the SC (DCs, distributors) are relaxed, the structure of a forward SC can be implemented for reverse flows without requiring major changes in existing production-distribution networks. If such conditions are not satisfied, the introduction of a reverse flow drastically alters the SC structure.
- An integral approach in designing SC, where shipping is combined and forward and reverse flows have the same route, incurs in costs that are always lower or equal to those of a sequential design, in which each forward and reverse shipment is dedicated and singularly optimized.
- Many models do not considered disposal costs, but the proposed integral design approach in SC shows that if the production plant has the capabilities to recover and to re-process part of the disposal product, then it is possible to

reduce the total costs in SC, recycling components products, with a reduction of waste and disposal costs.

Starting from these considerations the present thesis proposes a sustainable CLSC in which all end-of-life products return to the plants, where all the reprocessing activities take place. Some parts will be reused as raw materials and components for new products and the other parts will be transported to be disposed properly. As showed in figure 2.3 the proposed model permits to a green supply chain. On one hand, the reuse of end-of-life products reduces the need for raw materials, improving the economical sustainability of the process. On the other hand, it allows a reduction of the quantity of disposable products, by improving their environmental sustainability. Economic and environmental sustainability are also guaranteed by the use of closed loop shipments, in which the collection of end-of-life products occurs at the same time as the delivery of new products.

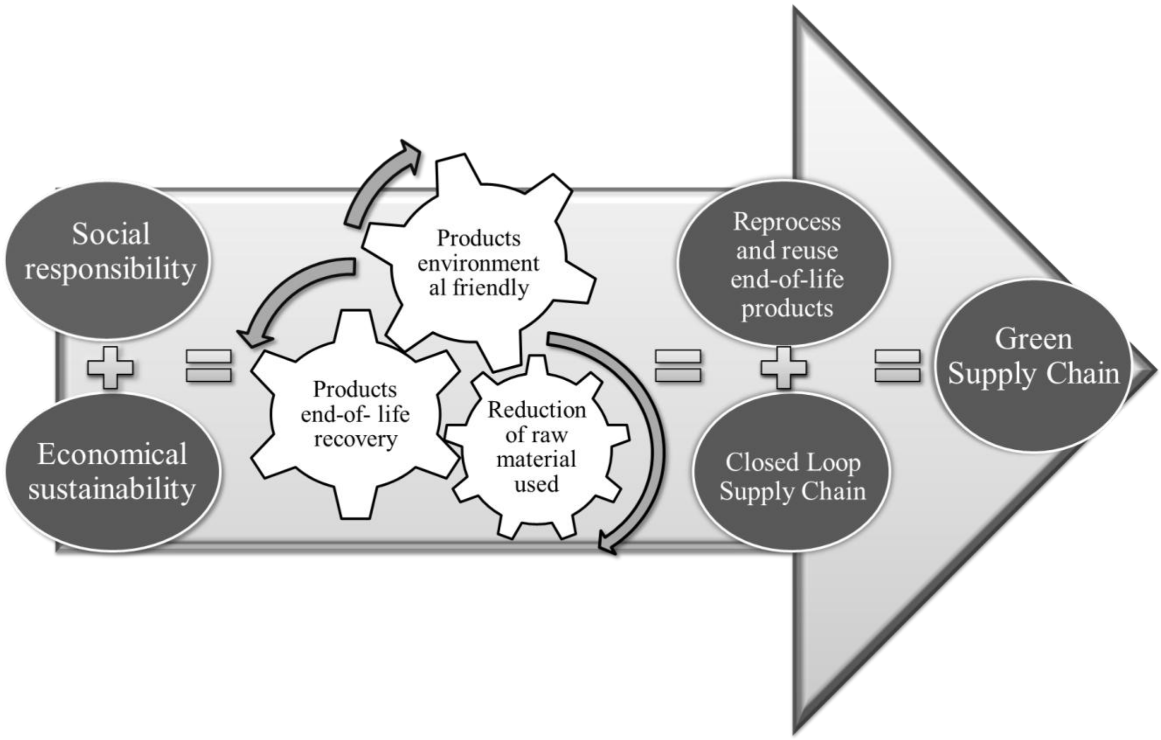



*Figure 2.3: Sustainable CLSC model*

The developed model addresses the closed loop supply chain design from a strategic point of view (long-term planning), considering a multi-echelon, multi-product, multi-production/distribution and multi-transportation system. For that reason the model considers a static planning horizon, where the quantity of forward flows is considered as the average during the period. Figure 2.4 presents a scheme illustrating the structure of this logistic network divided into five levels: Plants, DCs, Distributors, Customers, Disposal facilities.

Moreover, the figure showed that:

- Each level can ship to all the other levels;
- All the end-of-life product are returned to the production plants and a percentage of these is reused, reducing the quantity of raw material necessary for the new products. The remained quantity is shipped to the disposals;

- In the reverse flow the end-of-life products must do the same route as the one in the forward flow, using the same transportation model. For that reason the distance between each couple of SC actors is equal in both directions. In this way it is possible to benefit from the economies of scale when using the same vehicle, optimizing the transportation costs, avoiding empty trips and granting more effective material handling, all without designing a specific reverse logistics. This transportation cost optimization results are highlighted and confirmed in Faccio et al. (2011).

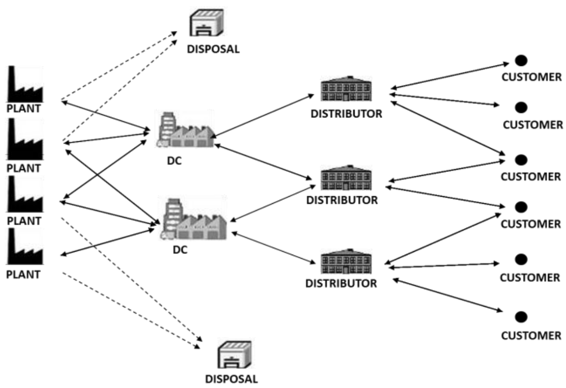



*Figure 2.4 The proposed closed loop supply chain structure*

The mixed integer linear programming model considers all the relevant cost factors, and aims to optimize the SC network design. It is flexible and able to model a closed loop SC and a forward SC just changing some constraints.

The minimization of the total cost function, once are defined the input data, such as possible facility positions in the supply chain, the fixed installation cost for each facility and so on, gives the following SC design outputs:

- The plants, DCs, and distributors open;

- The direct flows, defining the allocation of the customers demand and the quantity of primary product shipped from the plants to the customers through the different DCs and distributors;
- The kind of transportation mode to use.

### 2.4.1 PRINCIPAL COST FACTORDS

Among the main relevant costs described in section number 2.3 the proposed model considers the following costs factors:

- *The facilities installation costs.* These costs are defined about all kind of facility (production plants, DCs and distributors). They are typically fixed costs function of the location, the theological characteristics and the capacity dimension of the considered facility.
- *Production costs.* These costs are related to the volume of the manufactured products.
- *Handling costs.* The proposed model considers only the variable costs that are a direct function of the volume moved and is dependent on the characteristics of the products. As a consequence, unitary handling costs will be expressed in Euro per cube meter
- *Inventory costs.* They depend on the volume of the average stock and of the safety stock. The unitary inventory costs are calculated as a percentage of the considered product value according to the inventory cost rate.
- *Transportation costs.* The product delivery is made by third part logistics, which guarantee the right fleet. According to Battini et al. (2007) the transportation costs (in direct and reverse flows) include all the costs involved in the movement or transport of a shipment, which are typically defined by third part logistics and vary considerably with the volume and weight of each shipment, distances, transport mode, etc. Four correlated factors make up the transportation costs considered in this model:
    1. delivered goods quantities
    2. physical characteristics of goods delivered

3. transportation mode
4. distance

The developed model is based on an average unitary transportation cost data, obtained by combining the four factors described above and expressed in Euro per km per cube meter of goods. The possibility to obtain economies of scale in transportation is defined in the model both for the forward and the reverse transportation. When only the forward flows are considered it is obtained thanks to the optimization of the customers' demand allocation, while, in case of reverse transportation it is achieved thanks to the combined forward-reverse shipment.

- *Reverse logistic costs.* These costs include costs of transportation, inventory and management of the reverse flow of products and packaging, and, as the previous costs, they are function of the volume of the handled material.
- *Unitary disposal costs.* They are calculated as a percentage of the considered product value.
- *Unitary unsatisfied demand costs.* They are functions of the considered product. These costs are typically very high, taking into account not only the direct cost derived by a lack of turnover, but also the indirect cost related to the company image, the future customer orders, etc.

In case in which the company social responsibility are analysed these classical costs must be increased for considering also the SC environmental impact. How much increase these costs depends on the SC boundary that the study aims to consider.

### 2.4.2 ASSUMPTION

1 The total annual demand for product p from customer l is assumed to include normal distribution. A part of this demand can be unsatisfied, which creates an unsatisfied demand, and the model will optimize the satisfied demand level for each customer/product combination. The annual demand at the other nodes at the other levels of the SC (Plants, DCs, Distributors) is derived by the demands of each served node.

2 A minimum service level has to be imposed at each level of the SC.

3 The inventory and handling costs related the production plants are considered to be included in the production costs, because they are considered negligible, since the finished products are directly shipped.

4 The quantity of products is indicated in cube meters because the model considers facility saturation and carriers-to-volume saturation. In addition, distribution activities (handling, stocking, etc.) are influenced more by the kind of product volume than weight.

5 In forward flows the first level (plants) can ship to all the other levels, the second level (DCs) can ship to the third and fourth level, and so on.

6 The route in the reverse flow is the same as the one in the forward flow, including the same transportation model. For that reason the distance between each couple of SC actors is equal in both directions. In this way it is possible to benefit from the economies of scale when using the same vehicle, optimizing the transportation costs, avoiding empty trips and granting more effective material handling, all without designing a specific reverse logistics. This transportation cost optimization results are highlighted and confirmed in Faccio et al. (2011)

### 2.4.3 MATEMATICAL MODEL

**Indices**

| Indices | Definition | Range |
|---|---|---|
| *i* | Plants | 1,…., I |
| *j* | DCs | 1,…, J |
| *k* | Distributors | 1,…, K |
| *l* | Customers | 1, …, L |
| *d* | Disposals | 1, …, D |
| *p* | Products | 1, …, P |
| *m* | Transportation mode | 1, …, M |

| Indices | Superscript for costs |
|---|---|
| *I* | Installation cost |
| *H* | Handling cost |
| *P* | Production cost |
| *T* | Transportation cost |
| *R* | Reverse cost |
| *D* | Disposal cost |
| *U* | Unsatisfied demand |

*Table 2.3: Indices*

**Input data**

$D_{p,l}$ : Total annual demand for product *p* from customer *l* [m$^3$/year].

$\sigma_{p,l}$ : Standard deviation for product *p* for customer *l* [m$^3$/year].

$d_{s1,s2}$ : Distance between plant *s1* and *s2*, where *(s1, s2)* in *{(i,j); (i,k); (i,l); (i,d); (j,k); (j,l); (k,l); (l,d)}* [Km].

$f_i^I$ , $f_j^I$ , $f_k^I$ : Fixed installation cost of opening a new plant *i,* a new DC *j,* and a new distributor *k* [ €/year].

$c_p^H$ , $c_p^{H*}$ : Unitary handling cost per cube meter of product *p* in the forward and reverse flows [ €/m$^3$].

$c_{m,s1,s2}^T$ :Unitary transportation cost per Km and cube meter of product with transportation mode m, from *s1* to *s2,* where *(s1, s2*) in *{(i,j); (i,k); (i,l); (i,d); (j,k); (j,l); (k,l); (l,d)}* [€/Km*m$^3$].

The unitary transportation cost, considering for example $c_{m,i,j}^T$ , is calculated as (Faccio et al., 2012):

$$c_{m,i,j}^T = \frac{cs_{m,i,j}^T}{d_{i,j} \cdot tl_m \cdot mfl_m} \tag{1}$$

where

$cs^T_{m,i,j}$: specific transportation cost depending on the distance between *i* and *j* and the specific transportation mode *m* typically given by the third part logistics [€/shipments]

$tl_m$: transportation limited capacity with the specific transportation mode *m*[m$^3$/ shipments].

$mfl_m$: maximum load factor or volume saturation level, function of the product category and of the transportation mode *m* [%].

$c_p^U$ : Unitary unsatisfied cost per cube meter of product *p* [€/m$^3$].

$p_p$ : Unit value of product *p* [€/m$^3$].

$cp$ : Percentage of production cost with respect to the product value [%].

$cd$ : Percentage of disposal cost with respect to the product value [%].

$sc$ : Percentage of disposal products with respect to the total return product [%].

$rp$ : Percent of reused product with respect to the total forward flow [%].

*rr :* Ratio between the volume of return products and delivery products [%].

$mp$ : Percentage of raw material cost with respect to the total production cost [%].

$rt$ : Percentage of reverse transportation costs with respect to the forward transportation cost [%].

$h$ : Inventory cost rate [1/year].

$S_{p,i}$ : Maximum production capacity of product *p* in plant *i* [$m^3$/year].

$I_i^{\max}$ : Maximum storage capacity of return product in plant *i* [$m^3$/year].

$I_j^{\max}$ , $I_k^{\max}$ : Maximum storage capacity respectively of DC *j* and distributor *k* [$m^3$/year].

$r_{p,j}$ , $r_{p,k}$ , $r_{p,l}$ : Average rotation index of product *p* respectively in the DC *j*, the distributor *k*, the customer *l* [1/year].

The *r* index defines the number of stock turns over times during the year and evaluates the efficiency with which the inventory is managed. In the proposed model this depends on decision variables, in the sense that it is fixed at the beginning by a decision process made by the managers of the distribution networks in order to obtain the desired level of efficiency. Once fixed at the beginning of the CLSC design process it is considered as a parameter, that pulls the transportation flows with respect to the annual demand required by the customers.

## VARIABLES

$Y_i$ =1 if plant *i* is open, 0 otherwise.

$Y_j$ =1 if DC *j* is open, 0 otherwise.

$Y_k$ =1 if distributor *k* is open, 0 otherwise.

$x_{p,m,i,l}$ , $x_{p,m,j,l}$ , $x_{p,m,k,l}$ : Quantity of product *p* delivered to the customer *l* respectively by plant *i*, DC *j* and distributor *k* and shipped with the model transportation *m* [$m^3$/year].

$x_{p,m,i,j}$ , $x_{p,m,i,k}$ : Quantity of product *p* shipment from *i* respectively to *j* and *k* with the model transportation *m* [$m^3$/year].

$x_{p,m,j,k}$: Quantity of product $p$ shipment from $j$ to $k$ with the model transportation $m$ [m$^3$/year].

$y^R_{p,m,i,j}, y^R_{p,m,i,k}, y^R_{p,m,i,l}$ :Quantity of returned product $p$ from $j$, $k$, $l$ to $i$, with model transportation $m$ [m$^3$/year].

$y^R_{p,m,j,k}, y^R_{p,m,j,l}$ :Quantity of returned product $p$ from $k$ and $l$ to $j$, with model transportation $m$ [m$^3$/year].

$y^R_{p,m,k,l}$ :Quantity of returned product $p$ from $l$ to $k$, with model transportation $m$ [m$^3$/year].

$y^D_{p,i,d}$, $y^D_{p,l,d}$: Quantity of disposal of product $p$ to disposal $d$ from plant $i$, in case of CLSC, and from customer $l$, in case of forward flow [m$^3$/year].

$SS_{p,j}$, $SS_{p,k}$, $SS_{p,l}$: Safety stock of product $p$ in DC $j$, in distributors $k$, in customer $l$ [m$^3$].

Considering for example $SS_{p,j}$ the safety stock. is calculated as (Persona et al., 2007):

$$SS_{p,j} = k_{p,j} \cdot \sigma_{p,j} \cdot \sqrt{LT_{p,j}} \tag{2}$$

where:

$k_{p,j}$ : The factor that indicates the number of standard deviations to be kept as safety stock for the product $p$ in the DC $j$;

$\sigma_{p,j}$ : Standard deviation for the product $p$ in the DC $j$. The standard deviation σ depends on the quantity of product shipment $X$.

$LT_{p,j}$: Supplying Lead Time for product $p$ in the DC $j$.

**EQUATIONS**

The objective function considers the complete product end-of-life reprocessing, reverse flows, disposal cost and product end-of-life recycling and reusing in a multi-echelon, multi-product, multi-transportation and closed-loop supply chain, where the equation is as follows:

$$\text{Minimize } TOTC = IC + PC + HC + INC + TC + UC + TC^* + HC^* + DC \tag{3}$$

Figure 2.5 shows a summary diagram of the proposed sustainable CLSC model.

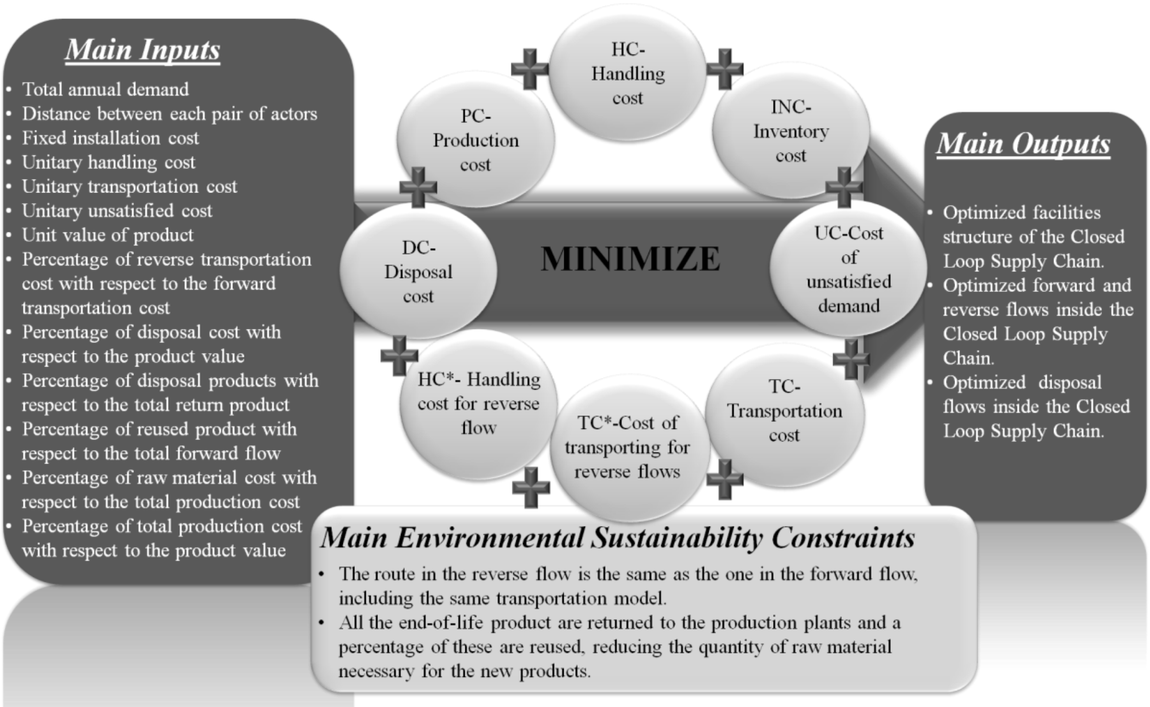



*Figure 2.5: The proposed sustainable CLSC model*

The cost components in the objective function can be calculated by using the following relations:

- <u>IC-Installation cost</u>, of opening new plant, DC, distributor [€/year]

$$IC = Y_i \cdot f_i^I + Y_j \cdot f_j^I + Y_k \cdot f_k^I \tag{4}$$

- <u>PC-Production cost</u>, including reduction due to reuse of returned products [€/year]

$$PC = \sum_p \sum_i \left( \left( cp \cdot p_p - cp \cdot p_p \cdot mp \cdot rp \right) * \left( \sum_m \sum_j x_{p,m,i,j} + \sum_m \sum_k x_{p,m,i,k} + \sum_m \sum_l x_{p,m,i,l} \right) \right) \tag{5}$$

- <u>HC-Handling cost,</u> for forward flow, given by a variable cost function of the quantities handled [€/year]

$$HC = \sum_p \sum_m \sum_i \sum_j \left( c_p^H \cdot x_{p,m,i,j} \right) + \sum_p \sum_m \sum_k \left( c_p^H \cdot \left( \sum_i x_{p,m,i,k} + \sum_j x_{p,m,j,k} \right) \right) \tag{6}$$

- <u>INC-Inventory cost</u>, function of the safety stocks and average levels of operative stocks inside the SC [€/year]

$$INC=\sum_p\sum_m\sum_i\sum_j h\cdot p_p\left(SS_{p,j}+\frac{x_{p,m,i,j}}{(2\cdot r_{p,j})}\right)+$$
$$\sum_p\sum_m\sum_k h\cdot p_p\left(SS_{p,k}+\frac{1}{(2\cdot r_{p,k})}\cdot\left(\sum_i x_{p,m,i,k}+\sum_j x_{p,m,j,k}\right)\right) \tag{7}$$

- <u>TC-Transportation cost</u>, given by a variable cost function of the quantities transported, the distance and the mode of transportation [€/year]

$$TC=\sum_p\sum_m\sum_i\sum_j\left(c^T_{m,i,j}\cdot d_{i,j}\cdot x_{p,m,i,j}\right)+\sum_p\sum_m\sum_i\sum_k\left(c^T_{m,i,k}\cdot d_{i,k}\cdot x_{p,m,i,k}\right)+$$
$$\sum_p\sum_m\sum_i\sum_l\left(c^T_{m,i,l}\cdot d_{i,l}\cdot x_{p,m,i,l}\right)+\sum_p\sum_m\sum_j\sum_k\left(c^T_{m,j,k}\cdot d_{j,k}\cdot x_{p,m,j,k}\right)+$$
$$\sum_p\sum_m\sum_j\sum_l\left(c^T_{m,j,l}\cdot d_{j,l}\cdot x_{p,m,j,l}\right)+\sum_p\sum_m\sum_k\sum_l\left(c^T_{m,k,l}\cdot d_{k,l}\cdot x_{p,m,k,l}\right) \tag{8}$$

- <u>UC-Cost of unsatisfied demand</u> [€/year]

$$UC=\left(\sum_l D_{p,l}-\left(\sum_{m,i}x_{p,m,i,l}+\sum_{m,j}x_{p,m,j,l}+\sum_{m,k}x_{p,m,k,l}\right)\right)\cdot c^U_p,\forall p \tag{9}$$

- <u>TC*-Cost of transporting for reverse flows in case of CSLC</u> [€/year]

$$TC^*=\sum_p\sum_m\sum_i\sum_j\left(c^T_{m,i,j}\cdot rt\cdot d_{i,j}\cdot y^R_{p,m,i,j}\right)+\sum_p\sum_m\sum_i\sum_k\left(c^T_{m,i,k}\cdot rt\cdot d_{i,k}\cdot y^R_{p,m,i,k}\right)+$$
$$\sum_p\sum_m\sum_i\sum_l\left(c^T_{m,i,l}\cdot rt\cdot d_{i,l}\cdot y^R_{p,m,i,l}\right)+\sum_p\sum_m\sum_i\sum_d\left(c^T_{m,i,d}\cdot d_{i,d}\cdot y^D_{p,i,d}\right)+$$
$$\sum_p\sum_m\sum_j\sum_k\left(c^T_{m,j,k}\cdot rt\cdot d_{j,k}\cdot y^R_{p,m,j,k}\right)+\sum_p\sum_m\sum_j\sum_l\left(c^T_{m,j,l}\cdot rt\cdot d_{j,l}\cdot y^R_{p,m,j,l}\right)+$$
$$\sum_p\sum_m\sum_k\sum_l\left(c^T_{m,k,l}\cdot rt\cdot d_{k,l}\cdot y^R_{p,m,k,l}\right) \tag{10}$$

- <u>HC*- Handling cost for reverse flow</u>, given by a variable cost function of the quantities handled [€/year]

$$HC^*=\sum_p\sum_m\sum_k\left[c^{H*}_p\cdot\sum_l y^R_{p,m,k,l}\right]+\sum_p\sum_m\sum_j\left[c^{H*}_p\cdot\left(\sum_k y^R_{p,m,j,k}+\sum_l y^R_{p,m,j,l}\right)\right]+$$
$$\sum_p\sum_m\sum_i\left[c^{H*}_p\cdot\left(\sum_j y^R_{p,m,i,j}+\sum_k y^R_{p,m,i,k}+\sum_l y^R_{p,m,i,l}\right)\right] \tag{11}$$

- <u>DC-Disposal cost</u>, given by a variable cost function of the quantities of disposal product shipped to the disposal [€/year]

$$DC=\sum_p\sum_i cd\cdot p_p\cdot\sum_d y^D_{p,i,d} \tag{12}$$

## CONSTRAINTS

- This constraint ensures that the sum of flow exiting from each plant *i* to all the other member of the SC does not exceed the production capacity $S_{p,i}$, for each product *p*.

$$\sum_m \sum_j x_{p,m,i,j} + \sum_m \sum_k x_{p,m,i,k} + \sum_m \sum_l x_{p,m,i,l} \le Y_i \cdot S_{p,i} \forall p, i \tag{13}$$

- This constraint ensures that the sum of total flows entering each DC *j* does not exceed the DC storage capacity

$$\sum_p \left( SS_{p,j} + \sum_m \sum_i \left( \frac{x_{p,m,i,j}}{r_{p,j}} \right) + \sum_m \sum_k \left( \frac{y^R_{p,m,j,k}}{r_{p,k}} \right) + \sum_m \sum_l \left( \frac{y^R_{p,m,j,l}}{r_{p,l}} \right) \right) \le Y_j \cdot I_j^{\max}, \forall j \tag{14}$$

- This constraint ensures that the sum of flows entering each distributor *k* does not exceed the distributor storage capacity

$$\sum_p \left( SS_{p,k} + \sum_m \sum_i \left( \frac{x_{p,m,i,k}}{r_{p,k}} \right) + \sum_m \sum_j \left( \frac{x_{p,m,j,k}}{r_{p,k}} \right) + \sum_m \sum_l \left( \frac{y^R_{p,m,k,l}}{r_{p,l}} \right) \right) \le Y_k \cdot I_k^{\max}, \forall k \tag{15}$$

- This constraint ensures that the sum of reverse flows entering each plant *i* does not exceed the plant storage capacity

$$\sum_p \sum_m \left( \sum_j \left( \frac{y^R_{p,m,i,j}}{r_{p,j}} \right) + \sum_k \left( \frac{y^R_{p,m,i,k}}{r_{p,k}} \right) + \sum_l \left( \frac{y^R_{p,m,i,l}}{r_{p,l}} \right) \right) \le Y_i \cdot I_i^{\max}, \forall i \tag{16}$$

- This constraint ensures that the sum of flows exiting from each DC *j* to each distributor *k* and customer *l* are equal to the flow entering from all plant *i*

$$\sum_m \sum_k x_{p,m,j,k} + \sum_m \sum_l x_{p,m,j,l} = \sum_m \sum_i x_{p,m,i,j} \forall p, j \tag{17}$$

- This constraint ensures that the flow exiting from each distributor *k* to each customer *l* are equal to the flow entering from all plant *i* and DC *j*

$$\sum_m \sum_l x_{p,m,k,l} = \sum_m \sum_i x_{p,m,i,k} + \sum_m \sum_j x_{p,m,j,k} \forall p, k \tag{18}$$

- These constraints ensure that each return flow is equal to the forward flow, taking into account the different volume of the returned versus delivered products

$$y^R_{p,m,s1,s2} = rr \cdot x_{p,m,s1,s2} \forall p, m \tag{19}$$

with *(s1, s2)* in *{(i,j); (i,k); (i,l); (j,k); (j,l); (k,l)}*

- These constraints ensure that disposal quantity correspond to a percentage of the return product

$$y^{D}_{p,i,d} = sc \cdot \left( \sum_{m}\sum_{j} y^{R}_{m,p,i,j} + \sum_{m}\sum_{k} y^{R}_{m,p,i,k} + \sum_{m}\sum_{l} y^{R}_{m,p,i,l} \right), \forall p, i \tag{20}$$

- This constraint ensures that the sum of the return goods exiting from each customer *l* to all the other member of the SC correspond to a percentage of the total products delivered.

$$\sum_{m}\sum_{k} y^{R}_{p,m,k,l} + \sum_{m}\sum_{j} y^{R}_{p,m,j,l} + \sum_{m}\sum_{i} y^{R}_{p,m,i,l} = rr \cdot \left( \sum_{m}\sum_{k} x_{p,m,k,l} + \sum_{m}\sum_{j} x_{p,m,j,l} + \sum_{m}\sum_{i} x_{p,m,i,l} \right), \forall p, l \tag{21}$$

- This constraint ensures that the sum of the return goods exiting from each distributors *k* to the DC and the plant are equal to the total return products entering from the customers

$$\sum_{m}\sum_{j} y^{D}_{p,m,j,k} + \sum_{m}\sum_{i} y^{D}_{p,m,i,k} = \sum_{l} y^{D}_{p,m,k,l}, \forall p, k \tag{22}$$

- This constraint ensures that the sum of the return goods exiting from each DC *j* to the plant are equal to the return entering goods.

$$\sum_{m}\sum_{i} y^{D}_{p,m,i,j} = \sum_{m}\sum_{l} y^{D}_{p,m,j,l} + \sum_{m}\sum_{k} y^{D}_{p,m,j,k}, \forall p, j \tag{23}$$

This model refers to the CLSC.

**<u>FWSC design model</u>**

In order to analyse the proposed CLSC model versus the classical FWSC, where customers ship the disposal products directly to disposal facilities, without generating reverse flows, the following equations must be changed:

- <u>PC'- Production cost</u>, without reduction due to reused products

$$PC' = \sum_{p}\sum_{i} \left( cp \cdot p_p \cdot \left( \sum_{m}\sum_{j} x_{p,m,i,j} + \sum_{m}\sum_{k} x_{p,m,i,k} + \sum_{m}\sum_{l} x_{p,m,i,l} \right) \right) \tag{5'}$$

- <u>TC*-Cost of transporting the disposal products</u> [€/year]

$$TC^* = \sum_p \sum_m \sum_l \sum_d \left( c^T_{m,l,d} \cdot d_{l,d} \cdot y^D_{p,l,d} \right) \tag{10'}$$

- <u>DC'- Disposal cost</u>, without reduction due to the recovering of returned product

$$DC' = \sum_p \sum_l cd \cdot p_p \cdot \sum_d y^D_{p,l,d} \tag{12'}$$

**<u>FWSC design model Constrains</u>**

$$\sum_p \left( SS_{p,j} + \sum_m \sum_i \left( \frac{x_{p,m,i,j}}{r_{p,j}} \right) \right) \leq Y_j \cdot I_j^{\max}, \forall j \tag{14'}$$

$$\sum_p \left( SS_{p,k} + \sum_m \sum_i \left( \frac{x_{p,m,i,k}}{r_{p,k}} \right) + \sum_m \sum_j \left( \frac{x_{p,m,j,k}}{r_{p,k}} \right) \right) \leq Y_k \cdot I_k^{\max}, \forall k \tag{15'}$$

$$y^D_{p,i,d} = rr \cdot \left( \sum_m \sum_k x_{p,m,k,l} + \sum_m \sum_j x_{p,m,j,l} + \sum_m \sum_i x_{p,m,i,l} \right), \forall p, l \tag{26'}$$

And the equation number 11, 16, 19, 20, 22, 23 have to be disregarded.

### 2.4.4 PARAMETRICAL ANALYSIS

In this section the problem is analyzed in order to investigate the economical sustainability of the proposed CLSC model versus the classical forward supply chain model (FWSC).

The parametrical analysis has been developed analyzing the impact of different parameters, changing the input inside a range of variation in accordance with the literature state of the art (table 2.4).

| Model indices | Parametrical analysis' legend | Percentage of | Respect to | Value |
|---|---|---|---|---|
| *cp* | PC/VAL% | production cost | product value | 35%, 50%, 65% |
| *cd* | DC/VAL% | disposal cost | product value | 10%, 30%, 50% |
| *rp* | REPROC/TOT% | reused products | total forward flow | 80%,60%, 40%, 20%,10%, 0% |
| *mp* | RM/PC% | raw material cost | total production cost | 30%, 40%, 50% |
| *rt* | CT*% | reverse transportation cost | forward transportation cost | 50%, 70%, 90% |
| *Type of SC* | Type of SC | Type of Supply Chain | | CL, FW |
| *Distance* | DISTANCE | Maximun distance in SC | | 600 km, 1200 km |

*TABLE 2.4 – PARAMETERS*

The parameters to study have been chosen according to the environmental principles applicable to SC design as defined by Tsoulfas and Pappis (2006), in order to obtain environmental sustainability. In fact, they stress the importance of the reverse flow and of the reuse of end-of-life products, "... by extending the useful life of equipment items, additional raw materials are not needed to produce new items. Primary raw materials should be used only in cases where there would be no stock of secondary ones." In the parametrical analysis this element is represented with *Reporc/Tot%*, *Pc/Val%* and *Rm/Pc%* parameters. The authors continue "As in the phase of collection and transportation, recycling and disposal may significantly contribute to the total environmental gain and the attainment of the environmental goals of a company". This element is expressed with *Dc/Val%*, *CT%* and *Distance* parameters. In addition, they highlight that "transportation and the consequent environmental effects can be significantly limited if the recovery of used products can occur at the same time or in combination with the distribution of new products. The theoretical minimal average transportation distances can be determined using a tool for allocation." This element is expressed with *Distance* and *Type of SC*, within the CLSC structure. The analysis is developed from two different standpoints: case 1 is from a *"traditional company perspective"*, where the SC ends at the customers, and the disposal costs are not considered, and case 2 is from a *"social responsibility company perspective",* where the disposal costs are considered inside the SC.

**Case 1: "Traditional company perspective"**

From this perspective, the proposed CLSC is compared to the classical FWSC, characterized by no reverse flows and cost of disposal activities is not considered. Companies that do not reprocess products define the SC limits at the customers, who are responsible for the disposal.

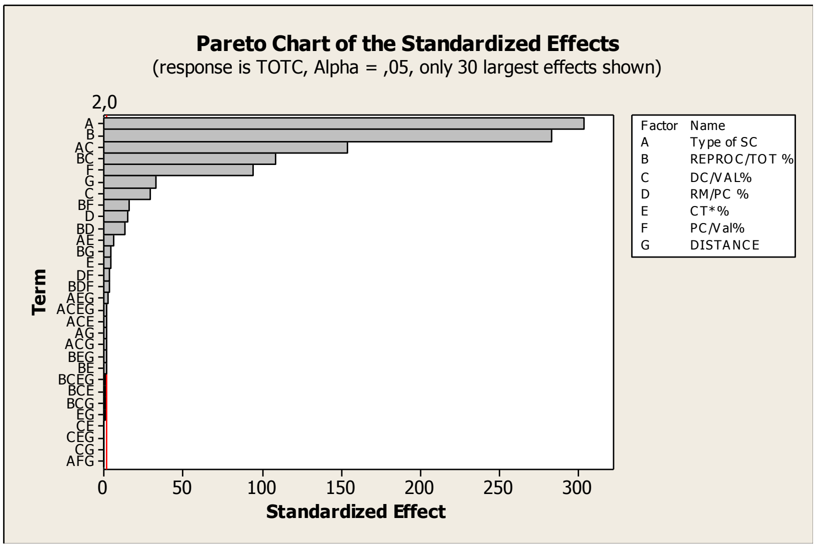



*Figure 2.6 – Case 1, Pareto Chart*

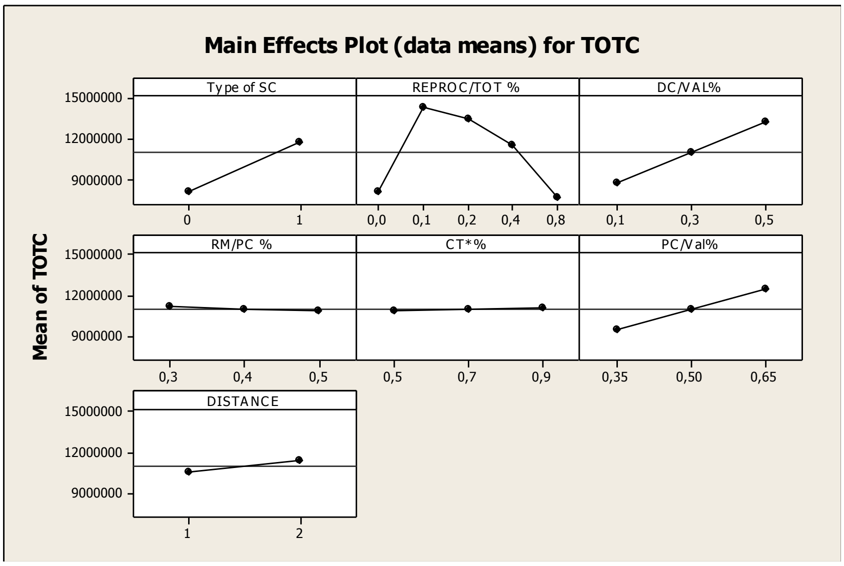



*Figure 2.7 – Case 1, Main effect plot for TOTC*

Thanks to the ANOVA analysis in figure 2.6 and to the main effect plot in figure 2.7, it is fairly easy to identify what factors/correlations influence the system response in term of TOTC (total supply chain costs) and how great is such influence. The ANOVA test is used to determine the impact independent variables have on the dependent variable in a regression analysis. The analysis in fact emphasizes the relevance of two variables:

1. *Type of SC (0=FWSC; 1=CLSC)*
2. *Reporc/Tot%*, (percent of reused products with respect to the total).

For the *Type of SC*, the analysis shows that FWSC structure is much more effective from this perspective than a CLSC and, moreover, the *Type of SC* is the most relevant factor in differencing *TOTCs. Reporc/Tot%* shows that the increment in the percentage of reused products averagely decreases the TOTC, with a more than a linear trend, which means that the benefit of a product end-of-life reuse has a more than linear benefit for the TOTC, stressing the importance for companies of designing and managing products in a modern SC with recycling targets. Figure 2.7 shows that, from this perspective, it is necessary to reuse at least 80% of the products in order to reach a condition of identical performance of the two SC structures, according to many industrial cases with similarity of quantity of recycled material (i.e. automotive for engines and transmission remanufacturing) or product value recycled (i.e. electronic industry with copper recovering). These findings are in accordance with the conclusions proposed by Fleischmann et al. (2001). These authors studied how robust traditional logistics networks are when it comes to addressing product recovery activities, concluding that forward flows dominate the network design until the economic incentive for product recovery and its effect on the reverse flows become significant.

| DISTANCE | TYPE 1 |
|---|---|
| DC/VAL% | 10% |
| PC/Val% | 35% |
| REPROC/TOT % | 80% |

| Somma di TOTC | | Type of SC | | |
|---|---|---|---|---|
| RM/PC % | CT*% | CL | FW | Delta % |
| 30% | 50% | 5,430,349 | 5,873,946 | -8.17% |
| | 70% | 5,676,645 | 5,873,946 | -3.48% |
| | 90% | 5,641,665 | 5,873,946 | -3.95% |
| 40% | 50% | 5,110,759 | 5,873,946 | -12.99% |
| | 70% | 5,357,054 | 5,873,946 | -8.80% |
| | 90% | 5,322,074 | 5,873,946 | -9.40% |
| 50% | 50% | 4,791,168 | 5,873,946 | -18.43% |
| | 70% | 5,037,464 | 5,873,946 | -14.24% |
| | 90% | 5,002,483 | 5,873,946 | -14.84% |

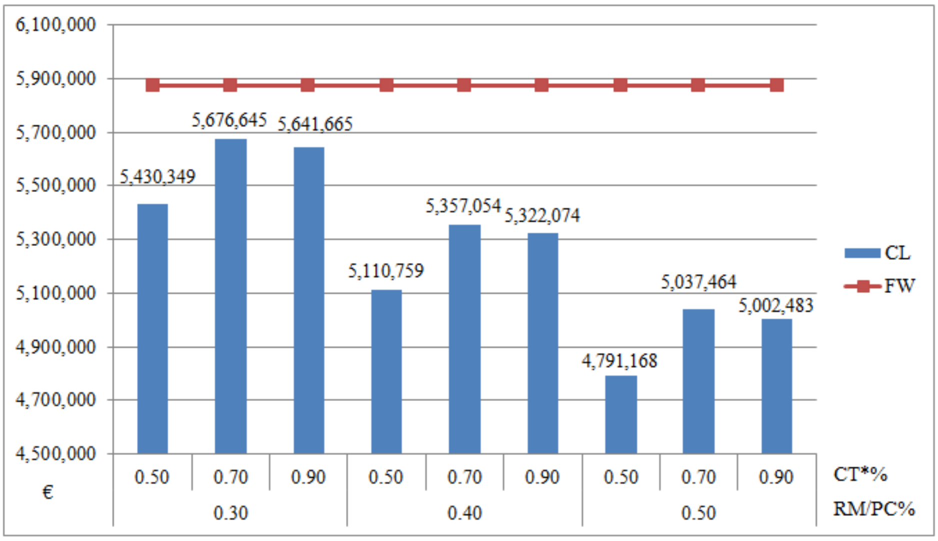



*Figure 2.8 – Case 1, TOTC for CLSC versus FWSC DC/VAL%=10%*

| DISTANCE | TYPE 1 |
|---|---|
| DC/VAL% | 30% |
| PC/Val% | 35% |
| REPROC/TOT % | 80% |

| Somma di TOTC | | Type of SC | | |
|---|---|---|---|---|
| RM/PC % | CT*% | CL | FW | Delta % |
| 30% | 50% | 6,343,465 | 5,873,946 | 7.40% |
| | 70% | 6,589,761 | 5,873,946 | 10.86% |
| | 90% | 6,554,781 | 5,873,946 | 11.59% |
| 40% | 50% | 6,023,875 | 5,873,946 | 2.55% |
| | 70% | 6,270,170 | 5,873,946 | 6.75% |
| | 90% | 6,235,190 | 5,873,946 | 6.15% |
| 50% | 50% | 5,704,284 | 5,873,946 | -2.89% |
| | 70% | 5,950,580 | 5,873,946 | 1.30% |
| | 90% | 5,915,599 | 5,873,946 | 0.71% |

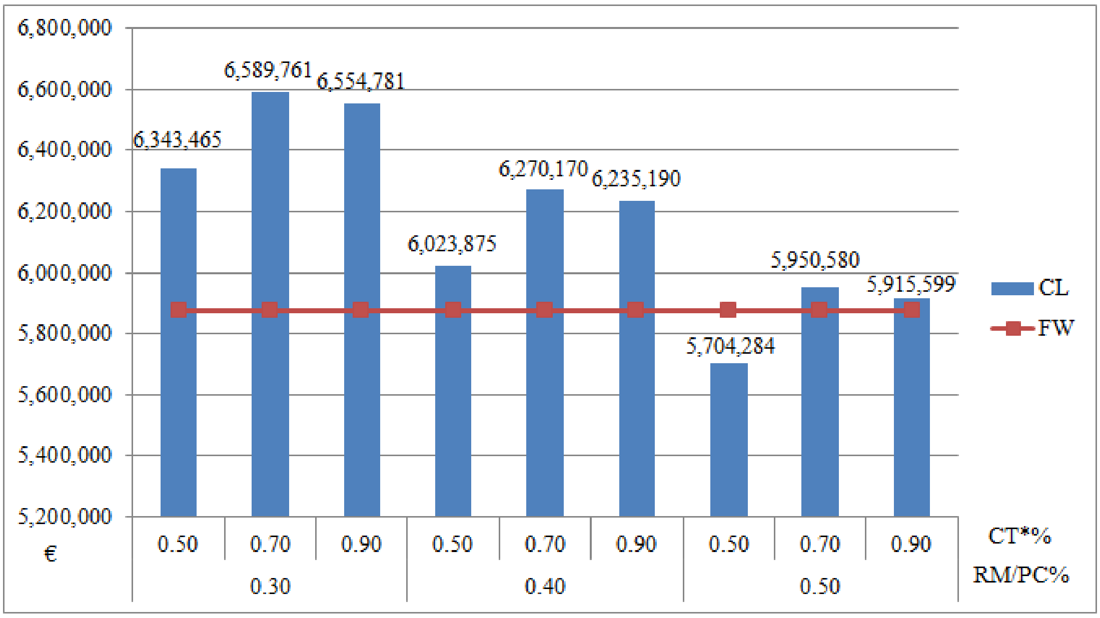



*Figure 2.9 – Case 1, TOTC for CLSC versus FWSC, DC/VAL%=30%*

Delving into the comparison between the two SC structures in this perspective, figure 2.8 shows a part of the parametrical study of C*ase 1*, where, in order to have a convenient CLSC (bold blue istogram) versus FWCL (red line) the *Reproc/Tot%* has to be at least 80%. In case of a lower *Reproc/Tot%*, even when all the other factors are favourable, FWSC will remain a preferable solution.

Comparing figures 2.8 and 2.9 (*Reproc/Tot%* = 80%) it is clear that CLSC does not necessarily have a lower *TOTC* than FWCL. If the disposal costs are not sufficiently low, i.e. 30% (figure 2.9) instead of 10% (figure 2.8) the CLSC is not convenient when compared to the traditional FWSC. These findings confirm that, in a classical perspective of SC, if returned products are not managed efficiently from a reusing and disposal point of view, companies would incur to larger costs than a classical FWSC (Mutha and Pokharel, 2009).

As demonstrated by the results, if the disposal phase is not considered inside the boundary of the company's perspective, the proposed CLSC model with complete reprocessing of end-of-life product is hardly applicable. These results otherwise highlight the importance of an integrated SC design that considers the classical and enviromental sustainability factors together with the supply chain structure.

**<u>Case 2 "Social responsibility company  perspective"</u>**

From this perspective, the proposed CLSC model is compared to a FWSC, with no reverse flows, and the costs of disposal activity are included in the *TOTC* (i.e. customers and the disposals are inside the SC structure from a company costs point of view). Figure 2.10 and figure 2.11 investigate the factors/correlations influencing *TOTC* from this second perspective. The ANOVA analysis demonstrates that the most relevant factors are:

1. *Reporc/Tot%*, (percentage of reused products with respect to the total).
2. *DC/Val%*, (percentage of disposal cost with respect to the product value).
3. The combination of these two factors.

Firstly, the *Type of SC (0=FWSC; 1=CLSC)* involves variable evidence that, from this perspective, CLSC is averagely better than FWCL, but it is no longer one of the relevant factors. The most relevant factor for TOTC is not the network structure, but the percentage of reused products (Reporc/Tot% =0 means FWSC). This point highlights that, from this perspective, for a sustainable SC, not only the closed-loop design is a better choice than the classical SC models. However, the percentage of end-of-life product reuse is a very important factor for a successful sustainable SC. *Reporc/Tot%* shows that increasing the percentage of reused products averagely decreases the TOTC, again with a more than linear trend in the CL structure.

In a different way from Case 1, *Reporc/Tot%* is the most relevant factor in respect of *TOTC*. The second most relevant factor is *DC/Val%*, which shows and high and linear relations compared to *TOTC.* The third factor is the combination of the first two.

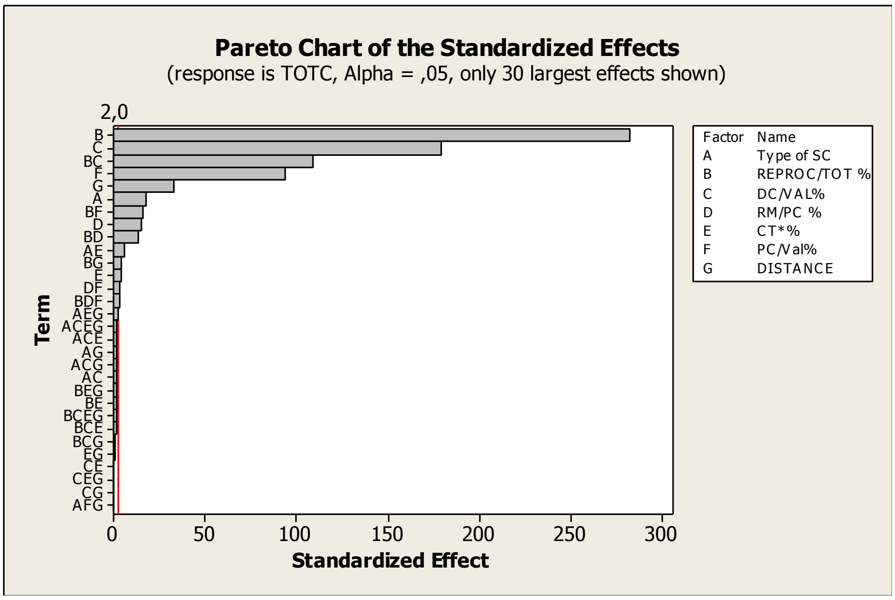



*Figure 2.10 - Case 2, Pareto Chart*

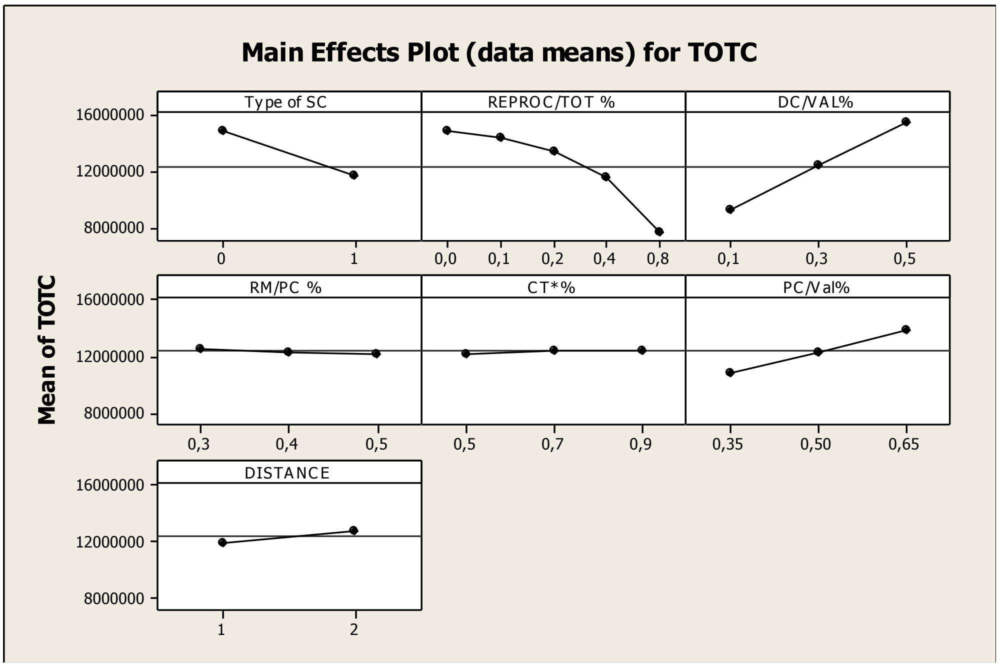



*Figure 2.11 – Case 2, Main effect plot for TOTC*

With the same notations of Figure 2.8 and Figure 2.9, Figures 2.12 and 2.13 analyse the constrains between FWSC and CLSC structure in the social responsibility company perspective. When the *Reporc/Tot%* is greater 20%, all the other factors do not influence the possibility to adopt the introduced CLSC model, this is always convenient when compared to the FWSC model. When the *Reporc/Tot%* =10%, and *DC/Val%* =30% (or higher), CLSC becomes more convenient, independently of all possible variations of the other factors (figure 2.12). On the other hand, with a *DC/Val%* =10%, all the other factors, such as CT% and RM/PC%, influence the results with a trend clearly illustrated in figure 2.13.

| DISTANCE | TYPE 1 |
|---|---|
| DC/VAL% | 30% |
| PC/Val% | 35% |
| REPROC/TOT % | 10% |

| TOTC | | TYPE OF SC | | |
|---|---|---|---|---|
| RM/PC % | CT*% | CL | FW | Delta % |
| 30% | 50% | 12,239,750 | 12,722,320 | -3.94% |
| | 70% | 12,337,260 | 12,722,320 | -3.12% |
| | 90% | 12,440,550 | 12,722,320 | -2.21% |
| 40% | 50% | 12,192,620 | 12,722,320 | -4.16% |
| | 70% | 12,297,320 | 12,722,320 | -3.34% |
| | 90% | 12,400,600 | 12,722,320 | -2.53% |
| 50% | 50% | 12,159,850 | 12,722,320 | -4.42% |
| | 70% | 12,257,370 | 12,722,320 | -3.65% |
| | 90% | 12,360,650 | 12,722,320 | -2.84% |

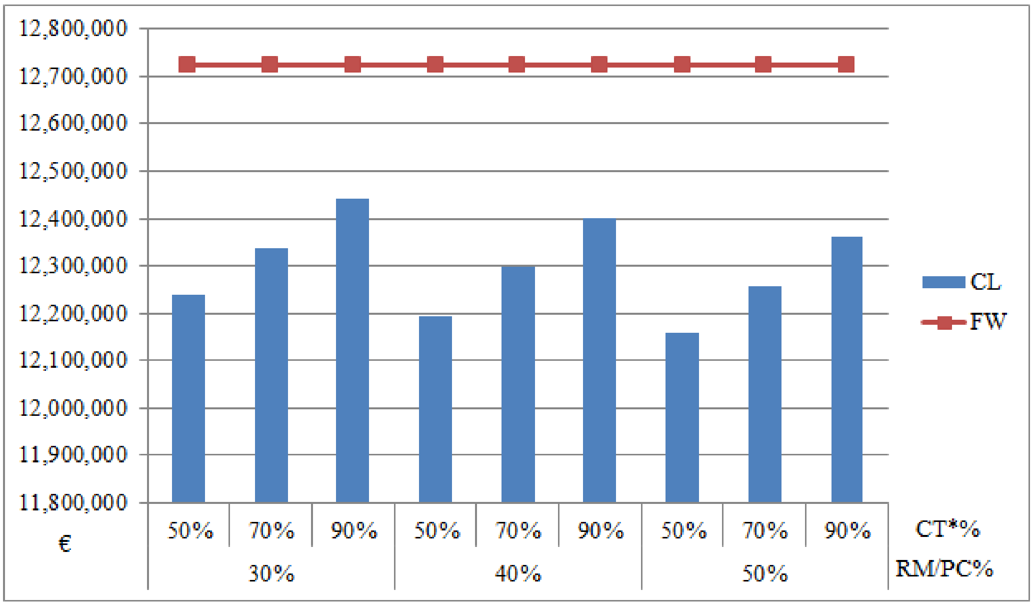



*Figure 2.12 – Case 2, TOTC for CLSC versus FWSC, REPROC/TOT%=10% and DC/VAL%=30%*

| DISTANCE | TYPE 1 |
|---|---|
| DC/VAL% | 10% |
| PC/Val% | 35% |
| REPROC/TOT % | 10% |

| TOTC | | TYPE OF SC | | |
|---|---|---|---|---|
| RM/PC % | CT*% | CL | FW | Delta % |
| 30% | 50% | 8,130,726 | 8,156,736 | -0.32% |
| | 70% | 8,228,242 | 8,156,736 | 0.87% |
| | 90% | 8,331,531 | 8,156,736 | 2.14% |
| 40% | 50% | 8,090,777 | 8,156,736 | -0.81% |
| | 70% | 8,188,294 | 8,156,736 | 0.39% |
| | 90% | 8,291,582 | 8,156,736 | 1.65% |
| 50% | 50% | 8,043,652 | 8,156,736 | -1.39% |
| | 70% | 8,148,345 | 8,156,736 | -0.10% |
| | 90% | 8,251,633 | 8,156,736 | 1.16% |

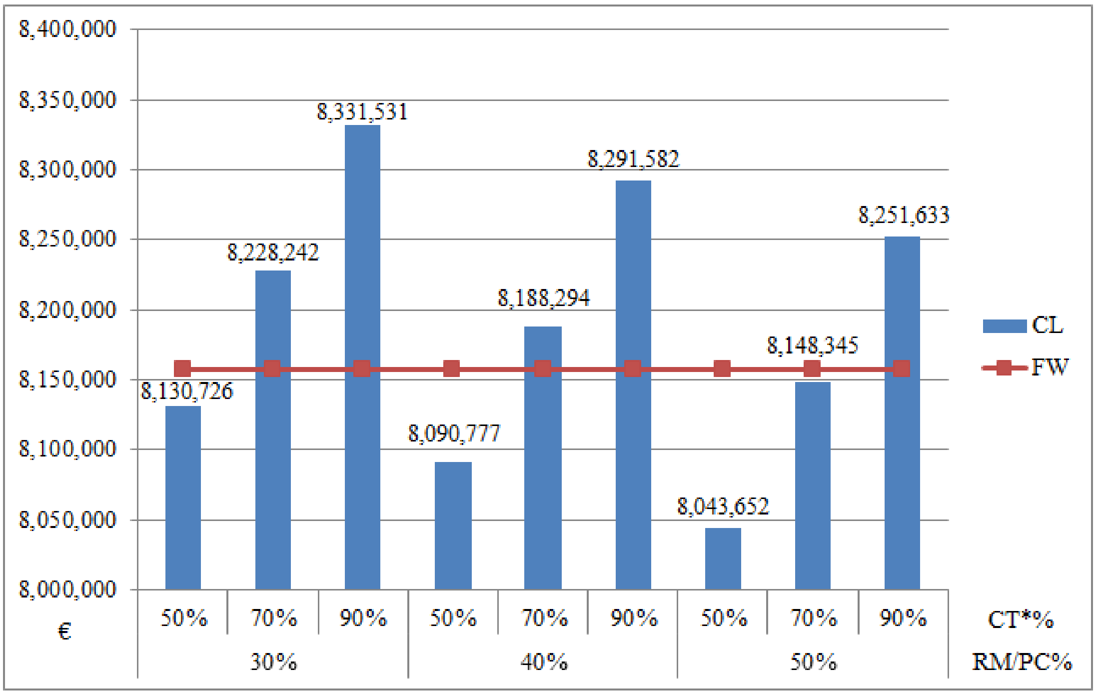



*Figure 2.13 – Case 2, TOTC for CLSC versus FWSC, REPROC/TOT%=10% and DC/VAL%=10%*

**Sustainable CLSC model: network structure analysis**

Finally, it is considered how the classical and sustainability parameters influence the CLSC design approach in terms of TOTC and network structure. Figures 2.14 and 2.15 analysed the main effect plot and the Pareto classification of the parameters, highlighting how this SC design model is widely influenced by the sustainability (reused products, disposal cost), compared to the classical parameters (production cost, distance, etc).

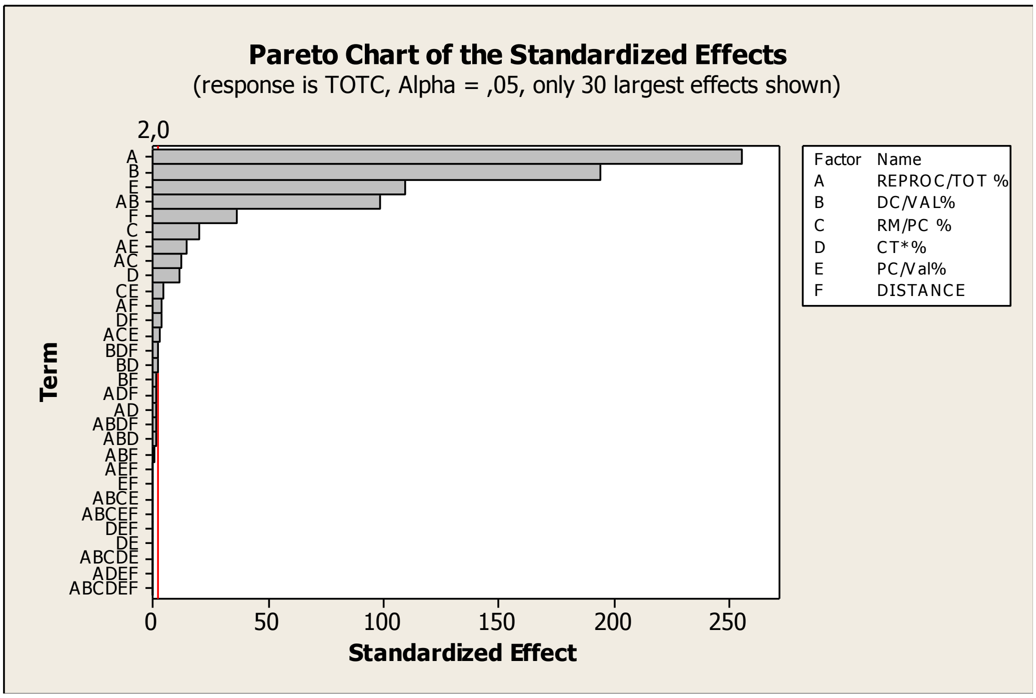



*Figure 2.14 – CLSC model- Pareto Chart*

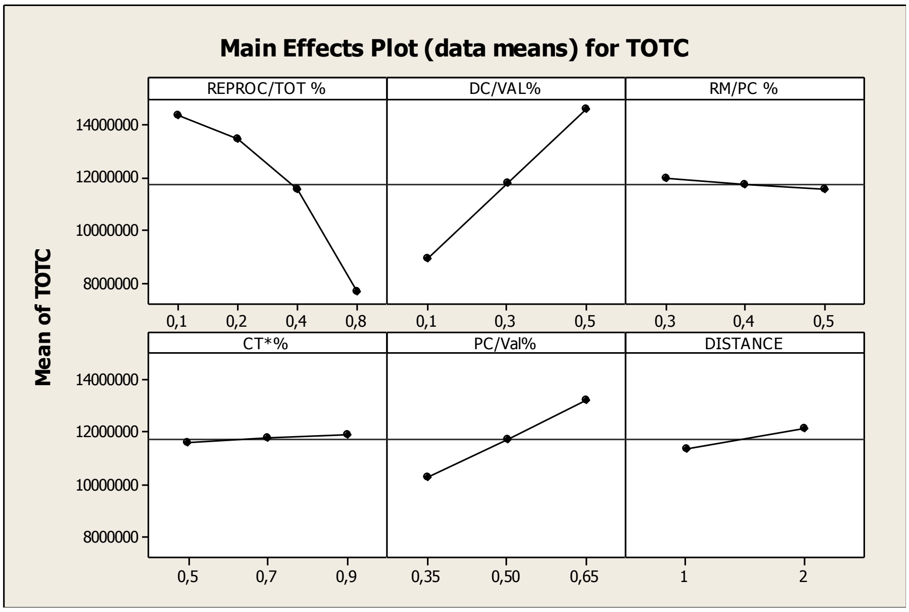



*Figure 2.15 – CLSC model-Main effect plot for TOTC*

Considering the network structure, in terms of number of plants, the number of DCs and the number of distributors, and what facility to open in which location, figure 2.16describes how the *Reporc/Tot%* factor has a substantial impact on the structure.

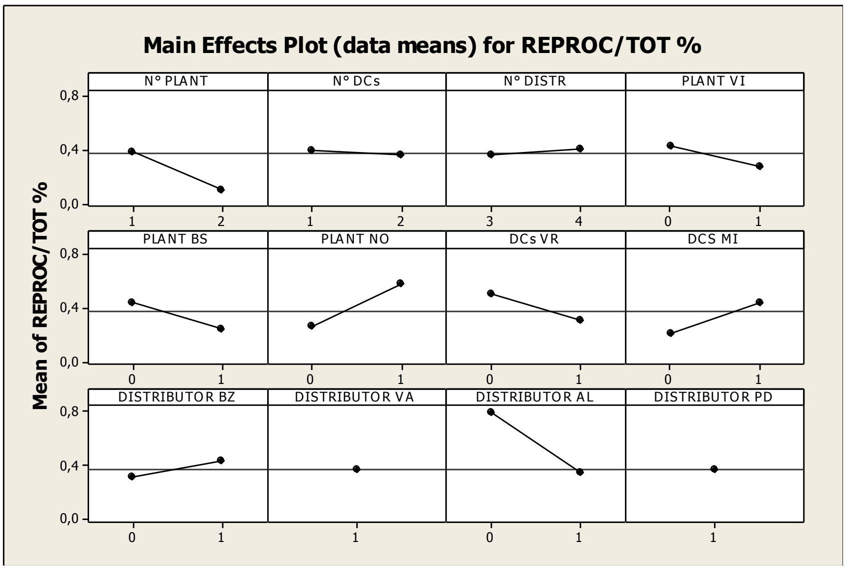



*Figure 2.16 – Main effect plot for reproc/tot%*

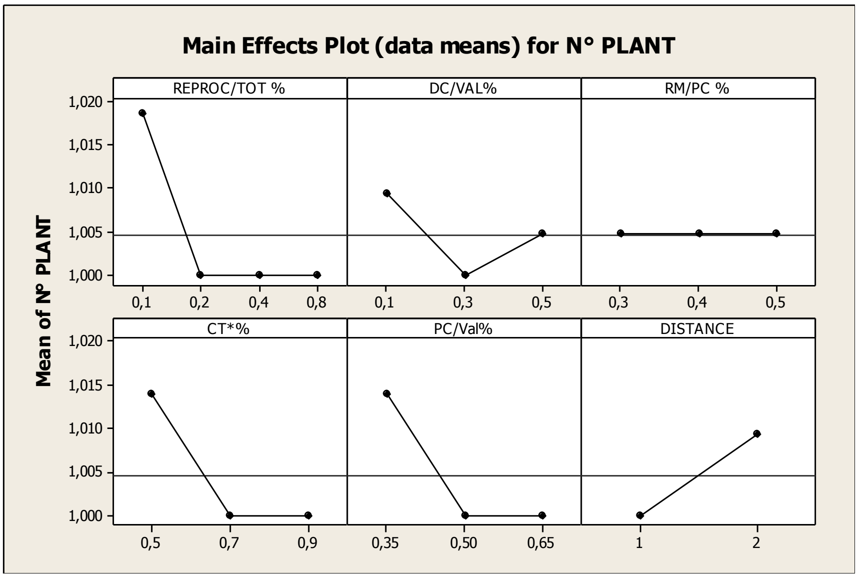



*Figure 2.17 – Main effect plot for n° of plants*

Relatively to the SC structure it is possible to evidence the following global results:

- A number of plants are largely influenced and inversely correlated with the % of reused products (figure 2.17). In fact, as the end-of-life product reuse increases the disposal flow decreases, allowing a centralization of the production plants in the distribution zone, without considering the disposals' location and with lower installation costs.

- The number of DCs is greatly influenced by the reverse transportation costs and the correlation between the % of reused product and the number of DCs at the increasing of the reverse transportation cost (figure 2.18).
- On the contrary the number of Distributors is influenced more by distance and reverse transportation costs, which are a typical design approach for a classical FWSC network (figure 2.19).

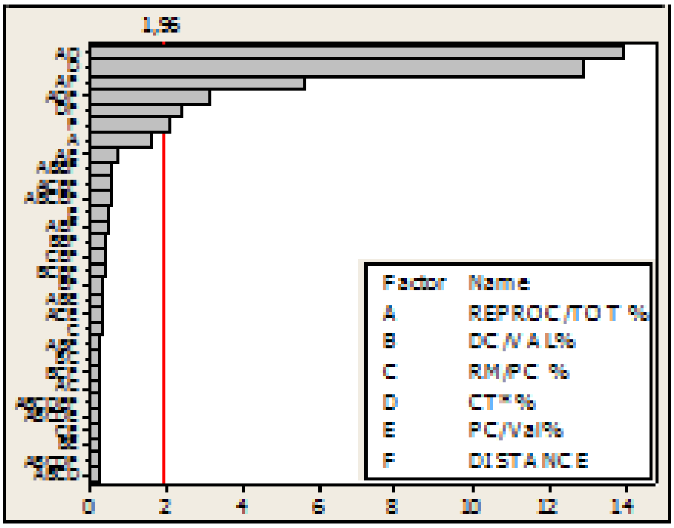



*Figure 2.18 – Pareto chart for number of DCs*

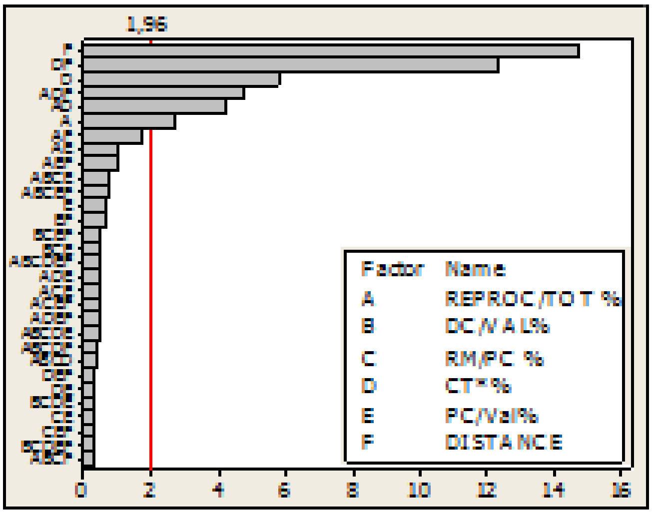



*Figure 2.19 – Pareto chart for number of Distributors*

This analysis gives an important result: the proposed CLSC, could replace for an existing and well designed FWSC, simply by changing the structure of the first and second portions of the SC. The analysis evidences that it is possible to maintain a great portion of the existing downstream SC. In fact, Distributors are mostly influenced by the classical (i.e. FWSC) parameters like distance or transportation costs. On the other hand, if the disposal locations are close to the production plants, it is possible to maintain a large portion of the initial SC (Plants), that are influenced by the flows through disposals.

### 2.4.5 OBSERVATIONS

The study considers an innovative sustainable closed loop SC problem. It first introduces a linear programming model that aims to minimize the total SC costs, whereby the elements of sustainability are the *complete reprocessing of end-of-life product and disposal of unusable parts directly from manufacturers*, with a closed loop transportation system that maximizes transportation efficiency. Secondly, it is considered the problem in a parametrical study, analyzing the economic sustainability of the proposed CLSC model versus the classical forward supply chain model (FWSC) from two perspectives: *Case 1*, the *'traditional company perspective'*, wherein the SC ends at the customers, and the disposal costs are not included in the SC, and *Case* 2, the '*social responsibility company perspective',* where the disposal costs are considered within the SC.

The principal results were:

1. From a '*traditional company perspective'*, where the SC ends at the customers, and the disposal costs are not considered in the SC, the proposed CLSC model is preferable compared to the classical FWSC if few conditions are met, independently from other parameters: a percentage of reused end-of-life products of at least 80%, and optimal reverse transportation costs and disposal costs. This conclusion is confirmed by recent literature (Fleischmann et al., 2001; Mutha and Pokharel, 2009).
2. From a '*social responsibility company perspective'*, where all the disposal costs are considered inside the SC also in the FWSC, the economic and environmental sustainability of the proposed CLSC model, compared to the FWSC, is already realized with 10% of reused end-of-life products.

3. It is important to observe how, in a CLSC structure, the element of % of reused end-of-life products is a critical factor with respect to its influence on the total cost of the SC, and on the other environmental protection (Daniel et al., 2003). An increase of the percentage of reused end-of-life products gives a more than linear reduction on total costs. This focus on the point in the product design enforces the design for reusability concept.

4. From a SC structure point of view, the results demonstrate that 'sustainability factors' such as the percentage of reused end-of-life products and disposal costs influence the CL model, more in the initial portion of the SC (plants) than in the final part (DCs and distributors). Distributors are mostly influenced by the classical parameters of distance or transportation costs. This means that, for an existing, well designed SC, with the classical approach, it is possible to pass to a CLSC structure, maintaining the distributors' facilities. With sufficient economies of scale in the reverse transportation, DCs structure could be also maintained. For the production plants, due to the high flows through the disposal, the structure could be maintained if there is a very high reusing of end-of-life product, or if the disposal facilities are located close to the production plants.

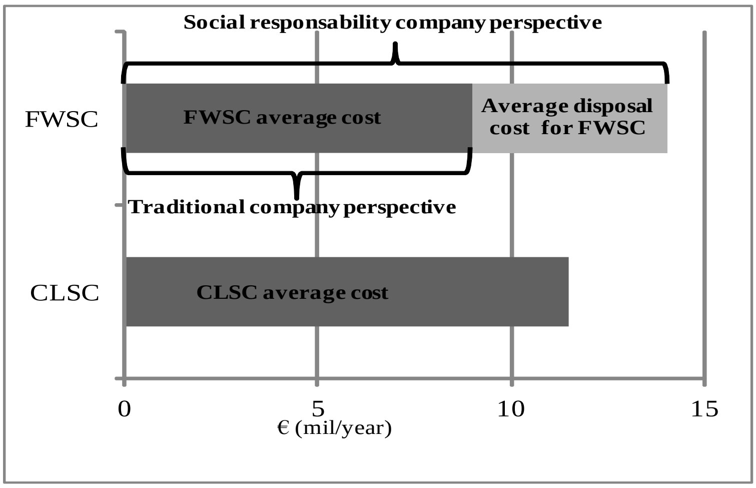



*Figure 2.20 – Average total cost: CLSC versus FWSC in case of traditional-social responsibility company perspective*

As shown in figure 2.20, looking at the average cost situation given by the parametrical analysis, if all the costs of the SC are considered, and the disposal costs in case of FWSC (social responsibility perspective) are included, it is clear that the proposed CLSC gives better results. On the other hand, from a traditional company perspective, looking at the average result, the classical FWSC produces lower costs than the proposed CLSC, and is competitive only in few cases (i.e. few industrial sectors according the parametrical analysis).

The white-gray average disposal costs are mostly paid by society. The results demonstrate that, in the industrial sectors where there is low end-of-life product reusability, the European Union legislation should introduce economic incentives, in order to encourage the manufacturers to take a direct role in the recovery of the end-of-life products. This should facilitate reaching a win-win situation with respect to the traditional end-of-life product management, with a total costs reduction for both companies and society.

The model developed in this thesis has been described in a journal article at present under review: *Faccio M., Persona A. , Sgarbossa F. , Zanin G. (2012) "Sustainable development in a modern supply chain network: closed loop versus forward structure." European Journal of Operational Research*

# 3 SUSTAINABLE SUPPLY CHAIN PLANNING

*This chapter considers the tactical/logical level of the supply chain. Its purposes are to optimize, from both economical and environmental point of view, not only the distribution stage, but also the last part of the food supply chain, i.e. the waste collection.*

*First of all, the chapter introduces an effective and flexible decision making tool to identify the best routing strategy for a given distribution network from an economical perspective. Then the study deals with a new class of routing problems: the sustainable routing problem, where the objective is the CO2 emission minimization. Finally, it is considered the waste collection activity, with the intent of optimizing the solid waste collection, introducing an innovative vehicle routing model integrated with the real time traceability data.*

## 3.1 INTRODUCTION

As said in the previously, this chapter deals with a critical short term decision: the routes construction. The study is divided into three steps:

- Goods daily delivery: economical optimization;
- Goods daily delivery: environmental impact minimization;
- Waste collection: economical optimization and environmental impact minimization;

*Goods daily delivery: economical optimization*

Starting from the analysis of the goods daily delivered it is possible to highlight that when a daily routing optimization strategy is applied, each route can potentially change in a constant way. This implies that each driver daily visits different customers, facing with different delivery areas, different acceptance procedures, different load-unload facilities, different operators to work with. In the study, it is defined the time spent in this kind of activities as “service time” whereas the time for the transportation from a generic point A to a generic point B is defined “travel time”.

Most studies have focused on the “daily routing optimization”, which considers daily re-optimization of delivery routes as a tactic response to randomly fluctuating customer demands. However, daily route optimization may not always be the most efficient choice because of the unstable route assignment to drivers (Haughton, 2002).

A common phenomenon in many practical distribution systems is that the same set of customers has to be visited every day, or there may be a weekly pattern. In these circumstances, some researchers investigated the possibility to apply a “fixed routing strategy”, in which a set of routes are designed to be operated unchanged over a given period of time.

Savelsbergh, & Goetschalckx (1995) and Erera et al. (2009) observed that fixed routes offer numerous advantages, such as to:

- Reduce management costs: it allows to simplify the daily planning process and eliminate the need for route optimization software and (skilled) personnel to effectively use such a software.
- Improve customer service: customers may typically be visited at or around the same time each day, which allows each customer to adjust its processes to accommodate the delivery.
- Enhance drivers’ performance: they familiarize themselves with the routes, schedules, and the delivery area. Moreover, since fixed routes enable the same driver to visit the same customers repeatedly, drivers establish long-term relationships with the customers.
- Increase efficiency at the depot: since standard depot procedures can be developed for loading the vehicles.

These benefits are achieved by reducing flexibility, which may cause an increase in delivery costs and distance compared to daily routing. Specifically, additional travel costs will be associated with travelling to customers who do not need deliveries just because they are on the route. Moreover, since the customer demand is stochastic, a service failure may occur on a planned route, i.e. the vehicle cannot satisfy the demands of the customers at a certain point along the route, forcing the driver to return to the depot, replenish its load and restart its delivery from the next customer on that route. Since insufficient capacity can be costly, minimization of empty trips to the depot and/or multiple loading for insufficient vehicle capacity is extremely important.

Based on these observation, the present PhD thesis takes into account that the service time could be reduced if each driver keeps familiarity with the served territories, for example by making fixed routes. This reduction depends on the level of learning knowledge that each driver has developed during the past visits to the considered customers, whose function is explicable using learning curves. Then it is compared the fixed routing strategy with the daily routing optimization strategy, analysing the benefits derived from the driver familiarity with the surroundings according to the variability of customers' demand, in quantity and frequency, and as a function of the ratio between service time and travel time. This study allows to:

- examine driver learning, i.e. the improvement of the driver's performance due to the implementation of the fixed routing approach and consequently the activity repetition, and its impact on the feasibility of a fixed-routes approach;
- provide a framework to be used by practitioners to decide between the fixed routes approach and daily re-optimizations;

In this part of the work it is applied the drivers' learning effect only on the service activity assuming that it has not influence on the travel time. The analysis carried out demonstrates the importance of the driver learning in the supply chain distribution. Furthermore, it shows that the fixed routing strategy should be applied just in highly or moderately dense distribution networks with a high/medium regularity in frequency and quantity of customers' orders. From these results, it is evident that the fixed routing strategy can be used when the delivery service time has a high impact on the total driver working time, such as deliveries in crowded centers, with a high density of customers and traffic constraints, and generally speaking, any time the driver learning is positively affected by the delivery task repetition.

*Goods daily delivery: environmental impact minimization*

The present study goes beyond the economical optimization and investigating a new class of routing problem: the sustainable routing problem, where the objective is the CO2 emission minimization. This is a consequence of the growing environmental, social, and political pressures to limit the impacts linked to $CO_2$ emissions. As the demand on the world's resources continues to increase, cities, regions, and states find themselves needing to foster economic growth and development while minimizing impacts on the environment (Wygonik and Goodchild, 2011).

The transportation sector produces the largest percentage of emissions from fossil fuel combustion by end use sector, releasing more than 1800 teragrams (Tg) of CO2 equivalents in 2008 and representing nearly one-third of the emissions from fossil fuel combustion (United States. Environmental Protection Agency, 2010).

As well known, these emissions have both direct consequences on human health (i.e. pollution), and indirect ones (i.e. by the depletion of the ozone). An agreement to reduce CO2 emissions from light-duty vehicles (European Parliament, 2009) has been signed in the European Union, limiting CO2 emissions to 130 g/km, with progressive implementation from 2012 to 2015. Even if vehicle manufacturers have been forced to incorporate technological improvements such as weight lightening, engine size reduction, low-rolling-resistance tyres, improved aerodynamics and hybridisation and electrification of vehicles, it is clear that the way of using vehicle plays an important role in the CO2 emission. As far as this last issue is concerned it is possible to say that the technical research in the environmental sustainable vehicles design is still not enough.

It is evident that in order to go from a certain point A to a certain point B, there is a large number of factors that influence the CO2 emission. If the problem is analysed from the driver point of view, these factors could be divided into two sets:

- internal factors, i.e. directly depending on the driver, on the vehicle utilization way such as the driving style, the type of route chosen in order to reach a certain point; the acceleration style (i.e. high/low acceleration at each stop), the average speed (i.e. close/far to the speed limits), the street knowledge, etc.;

- external factors, i.e. not depending on the vehicle utilization way, like the vehicle type, the speed limits, the traffic congestion, etc.

The internal and external factors are obviously connected. For example for a certain chosen route (internal factor), a speed limit is defined for each of its parts, and in function of the day time an expected traffic congestion (external factors) is also derived.

It is important to highlight that among the internal factors it is considered the drivers' familiarity with the delivery area and how this streets knowledge influence positively the routing sustainability. It is possible to said that the driver's learning not only enhance drivers' performance during the service activity, as point out in the first part of the study, but it allows also to improve the travel behaviour.

If the vehicle routing problem is considered, i.e. the determination for a certain vehicle of the specific number and sequence of customers to visit and the determination of the way to drive according to a certain objective, it is clear how the route solution has a large impact in the CO2 emission.

This aspect is supported by the experimental study of De Vlieger et al. (2000) who analyse the relation among fuel consumption and emission, driving behaviour and traffic congestion. According to their study, compared to normal driving, aggressive driving can increase fuel consumption of 40% and emissions up to a factor 8 for the same route covered. Moreover, they highlight how traffic conditions have a large influence on fuel consumption and emissions. The increases in fuel consumption and emissions during rush hours can vary from 10 to 200%.

As highlighted in Figliozzi (2011) although past and current research efforts in the vehicle routing algorithms and scheduling are extensive (Cordeau et al., 2007), most of them have ignored the freight-related environmental and social consequences like CO2 emission level.

Then, after having optimized the good daily delivery from an economical point of view, the research focuses on the sustainable routing problem. Starting from the Fonseca et al. (2011) study, the work intend to propose a simple model for CO2 emission increment estimation as function of the different internal/external factors. The main contributions of this step of the thesis are, not only to introduce an innovative point of view in the routing model optimization, but also to understand the gap with the classical routing approaches.

Moreover, the proposed study tries to analyse the possible situations and condition in which this new approach can be applied in the modern distribution network and to provide some technological and organizational elements to support it.

*Waste collection: economical optimization and environmental impact minimization*

The last part of this thesis related to the short term decision concerns, no longer the daily goods delivery, but deals with the waste collection, last stage of the food supply chain. This study was motivated by the awareness that waste collection is a highly visible municipal service that involves large expenditures and difficult operational problems, plus it is expensive to operate in terms of investment costs (i.e. vehicles fleet), operational costs (i.e. fuel, maintenances) and environmental costs (i.e. emissions, noise and traffic congestions).

Specialty vehicles, with self-compactors, are usually designated to collect urban solid waste, with considerable operating expenses, hence designing efficient collection strategies is vital not only to reduce operating costs and vehicle emissions, but also to maximize the amount of re-cycling, while minimizing traffic congestion associated with refuse collection vehicles (RCV) operations (McLeod and Cherrett, 2008).

While loading and unloading bins, trucks have to keep their engines running, producing constant exhaust emissions, but also causing noise and traffic congestion. The portion of time spent loading and unloading typically depends on different factors (the technology employed, the size and location of the collection operation, etc.), but in case of urban waste in cities with high population density and high traffic congestion, the non-transportation time, which includes time spent for load-unload operations and other idle times can reach 50% of the total time. This consideration highlights the importance not only to optimize the vehicle route, in order to reduce the transportation time, but also to reduce the number of load-unload stops.

The cost of collection of municipal solid waste is typically measured in terms of cost per ton, with an inverse relationship between the costs of collecting solid waste and the amount of materials collected, as a consequence moving bins that are only partially full seems an unnecessary misuse of resources, and an avoidable production of polluting emissions.

Waste collection business is divided into three major areas: commercial, residential and roll-on-roll-off. Each area includes municipal solid waste and recycling material, and each one is very different from the others. Residential waste collection generally involves servicing private homes, while the commercial waste collection involves servicing customers such as strip malls, restaurants and small office buildings. The difference between roll-on-roll-off collection and commercial collection is the size of the container. This study considers a particular type of residential waste collection, largely diffused in Italy, in which waste is located in bins along the streets of a defined road network. Nuortio et al. (2006) observed that the amount of municipal solid waste for each garbage bin is variable and the accumulation of waste depends on several factors such as the number of inhabitants, lifestyle, time of the year, etc., therefore, the considered waste collection problem is stochastic by nature.

This research aims to present a new multi objective routing model with real time data interchange for the residential waste collection, based on the integration of new technological traceability systems with a new heuristic routing model. The basic idea is that, if the real time position and replenishment level of each vehicle are known, as well as the real time waste level at each bin and which bins have been visited, it is possible to decide which bins should be emptied and which can be avoided at a certain time. This allows an optimization of the route plan and to minimize covered distance and number of vehicles needed, which, as a consequence, would minimize travel time, number of load-unload stops, exhaust emissions, noise and traffic congestion. Today, modern traceability devices, like volumetric sensors, identification RFID (Radio Frequency Identification), GPRS (General Packet Radio Service) and GPS (Global Positioning System) technology, can be used to obtain all the data defined before.

The potential benefits of this new approach are both economic and environmental:

- Reduction in investment costs for vehicles fleet, thanks to the ability to schedule on-demand pick-ups according to the effective need, with a consequent reduction in the number of vehicles.
- Reduction in operational costs (fuel, maintenance, etc), thanks to the reduction of vehicles, covered distance and stationary load and unload times.

- The elimination of unnecessary stops, which means a reduction of engine emissions, produced both by sanitation vehicles and traffic congestion.
- The reduction of noise especially in urban areas.

As well as for the study of the SC design the research has been developed starting from the analysis of the state of the art. In this case the literature permits to identify the more relevant routing problems and the solution approaches. Then, paragraph 3 describes the different routing models used in the daily routing optimization strategy and in the fixed routing strategy, and shows and compares the results of the simulation analysis. Moreover, it reports a framework about the learning curves and their use in choosing a routing strategy. Paragraph 4 depicts the $CO_2$ estimation model and sustainable routing problem formulation. Afterword, it is presents a case study, and besides, the parametrical analysis and the sustainable routing problem benchmarking versus the classical routing approaches. Finally, paragraph 5 introduces a framework about the traceability technology available to waste collection and shows an application in the case study. It also presents the software application developed in order to obtain and manage real time data used as inputs for the proposed routing model. Later in the paragraph, it is introduced the heuristics model for waste collection, which is validated simulating the results and comparing the new approach with other classical routing models in function of different patterns of waste generation. The simulative study is concluded analysing the optimization of a set of parameters necessary for the proposed routing model, such as the optimal bin replenishment level, which is the parameter that defines if a bin has to be emptied or not. Beyond that it is analysed the economical feasibility of the real time traceability routing model in terms of costs/benefits versus the classical waste collection model, considering different scenario.

## 3.2 STATE OF THE ART

The vehicle routing problem (VRP) is a significant issue in the Supply Chain Management and it has been widely studied by the researchers (Benton and Rossetti, 1992). The basic version of the problem considers a single depot, from where all the tours start and end, and a fleet of vehicles, which has to serve a set of customers on a given network under side constraints (Sivakumar et al., 2012). It can be defined using a graph $G = (V, A)$, where $V = \{0, . . . . , n\}$ is a set of vertices and $A$ is the set of arcs. Vertices 0 is the depot, whereas the remaining vertices represent the customers. A non-negative cost $c_{ij}$ is associated with each arc $(i, j) \in A$. In some contexts, $c_{ij}$ can be interpreted as a travel cost or as a travel time. If $G$ is a directed graph the cost matrix $c$ is asymmetric, otherwise it is possible to use $c_{ij}$ and $c_{ji}$ interchangeably. The VRP consists of designing m vehicle routes, each starting and ending at the depot. In some versions of the problem, m is fixed a priori, while, in others, it is a decision variable, in this second case it often makes sense to associate a fixed cost $f$ on the use of a vehicle. The traditional objectives of the VRP include the minimization of the total distance or time travelled by all vehicles, or the minimization of the overall travel cost Bektas and Laporte (2011).

In literature several versions of the problem have been proposed. According with Toth and Vigo (2002) and Daneshzand (2011) the most common variants are:

- The Capacitated VRP (CVRP), where each vertex of V\{0} is associated to a non-negative demand $q_i$ and each vehicle has a limited capacity, both of them are known in advance. So for each route the sum of the demand of the vertex visited may not exceed the vehicle’s capacity. It assumes that the vehicles are identical and based at a single depot.
- The VRP with Time Windows (VRPTW), where for each customer it is considered a time interval, called time window, given by an earliest arrival time and a latest arrival time and the customers must be visited within this predefined time slots. This version of the VRP was considered in many studies that analysed different application. For example some studies, like Hsu et al. (2007), Osvald and Stirn (2008) and Chena et al. (2009), introduced different model to solve the VRPTW in case of perishable food distribution. Examples of other application have been described in Solomon (1987), Hashimoto et al. (2006, 2008) and Qureshi (2009). Solomon (1987) proposed an interesting analysis of algorithms for vehicle routing and scheduling problems with time windows constraints, after describing a variety of heuristics, and conducting an extensive computational study of their performance.

- The VRP with Backhauls where the customers are partitioned into two subsets: line-haul and back-haul customers. Each line-haul customer requires a given quantity to be delivered while a given quantity of products must be picked up from back-haul customers. This problem assumes that the sum of demands of the line-haul and back-haul vertices visited by a route does not exceed separately the vehicle capacity and in each route, the line-haul vertices precede the back-haul vertices, if any.
- The VRP with Pickup and Delivery where the vehicles are not only required to deliver goods to customers, but also to pick some goods up at customer's locations (Nagy and Salhi, 2005). This means that a heterogeneous vehicle fleet must satisfy a set of transportation requests. Each request is defined by a pickup point, a corresponding delivery point, and a demand to be transported between these locations. Example of this problem are studied in Mitrović-Minić et al. (2004) which considered the time windows constraint for pickup and delivery, analysing how the distribution of such waiting time may affect the overall solution quality. In a different article Mitrović-Minić and Laporte (2004) introduced the concept of double-horizon based heuristics for dynamic pickup and delivery problem with time windows.

A wide variety of study was proposed to deal with these problems, and most of them are deterministic, this means that they assumed to know in advance with certainty the input data. Nevertheless some articles consider stochastic data, like Li et al. (2010) which studied a version of vehicle routing problems in which travel and service times were stochastic, and time windows constraints are associated with each customer.

Since the very beginning of the vehicle routing problem (VRP), literature has become quite disjointed and disparate. As a consequence, a wide variety of exact and approximate algorithms have been proposed. Generally, the VRP is computationally very hard, and cannot be solved by exact methods; therefore, the literature proposes many heuristics. Laporte and Semet, (2002) proposed a classification of the solution approaches divided two families: the classical and the modern heuristic. This classification was re-proposed in many studies including Cordeau et al. (2007) which distinguished among the classical heuristics:

- The route construction methods. These algorithms typically start from an empty solution and iteratively build routes by inserting one or more customers at each iteration, until all customers are routed.
- The two-phase methods. These methods are based on the decomposition of the VRP solution process into the two separate subproblems:

  (1) clustering: determine a partition of the customers into subsets, each corresponding to a route, and

  (2) routing: determine the sequence of customers on each route.
- The route improvement methods. Starting from a given solution, generated by other heuristics, these methods apply local search approach with simple modifications, such as arc exchanges or customer movements, to obtain neighbour solutions of possiblye better cost. If an improving solution is found, it then becomes the current solution and the process iterates; otherwise a local minimum has been identified.

Whereas, the authors, broadly divided the metaheuristics into three classes:

- Local search methods. These algorithms explore the solution space by iteratively moving from a solution $x_t$ at iteration $t$ to a solution $x_{t+1}$ in the neighborhood $N(x_t)$ of $x_t$ until a stopping criterion is satisfied. If f(x) denotes the cost of solution x, then $f(x_{t+1})$ is not necessarily smaller than $f(x_t)$. As a result, someone mechanisms must be implemented to avoid cycling. These methods include simulated annealing, deterministic annealing and tabu search;
- Population search. In the case of genetic algorithms, at each iteration it is considered a population of solutions: each population is derived from the previous through the combination of the best solutions and the elimination of the worst. These models include genetic search and adaptive memory procedures;
- The learning mechanisms. They include neural networks mechanisms which are able to self-regulate a set of internal factors, progressing towards better solutions.

*Route construction methods*

These algorithms typically start from an empty solution and, after an initialization, they apply iteratively a selection criterion, specifying which customers are chosen for insertion and an insertion criterion to decide where to locate the chosen customers into the current routes. Construction algorithms are subdivided into sequential and parallel, depending on the number of eligible routes for the insertion of a customer. Sequential procedures expand only one route at a time until all customers are scheduled, whereas parallel procedures are characterized by the construction of more than one route simultaneously.

The two main techniques used for constructing VRP solutions are: the *savings criterion* and the*sequential improvements method*.

The Clarke and Wright (1964) savings algorithm is perhaps the most widely known heuristic for the VRP. It starts with a solution in which each customer appears separately in a route and is based on the concept of saving, that considers the possibility of a cost reduction by serving two customers sequentially in the same route, rather than in two separate ones. If $i$ is the last customer of a route and$j$ is the first customer of another route, the associated saving is defined as $s_{ij} = c_{i0} + c_{0j} - c_{ij}$. If$s_{ij}$ is positive, then serving $i$ and $j$ consecutively in a route is profitable.

Of this method are available both parallel and sequential version. The parallel approach is applied if more than one route is active at any time. On the contrary, the sequential version considers each route$\{0, i, \ldots, j, 0\}$ and determinates the first saving $s_{ki}$ or $s_{il}$ that can feasibly be used to merge the current route with another route ending with $(k, 0)$ or starting with $(0, l)$. It implement the merge and repeat this operation to the current route. If no feasible merge exists, it is considered the next route and reapply the same operations. The method stops when no route merge is feasible.

Among the sequential insertion algorithm the two main representative methods are due to Mole

and Jameson (1976) and Christofides et al. (1979). The first algorithm uses as selection and insertion criterion the evaluation of the extra distance resulting from the insertion of an unrouted customer$k$ between two consecutive customers $i$ and $j$ of the current route, namely $\alpha(i, k, j) = c_{ik} + c_{kj} - \lambda c_{ij}$, where $\lambda$ is a user-controlled parameter. Instead, Christofides et al. (1979) proposed a more general and effective two-step insertion heuristic. In the first step, a sequential insertion algorithm is used to determine a set of feasible routes. The second step is a parallel insertion approach. For each route determined in the first step, a representative customer is selected and a set of single-customer routes is initialized with these customers. The remaining unrouted customers are then inserted by using a regret criterion, where the difference between the best and the second-best insertion cost is taken into account.

*Two-phase methods*

These method distinguish cluster-first-route-second and route-first-cluster-second approach. In a cluster-first-route-second method, customers are first grouped into clusters and the routes are then determined by suitably sequencing the customers within each cluster. Different techniques have been proposed for the clustering phase, while the routing phase amounts to solving a TSP.

Among the clustering method a well known approach is the sweep algorithm, within a feasible clusters are initially formed by rotating a ray centered at the depot. As soon as the current customer cannot be feasibly assigned to the current vehicle, a new route is initialized with it. Once all customers are assigned to vehicles for each cluster are obtained the route by solving a TSP. A natural extension of the sweep algorithm is the so-called petal algorithms, which generate several routes, called petals, and make a final selection

A different family of two-phase methods is the class of by solving a set partitioning model.

*Route improvement methods*

A large variety of these methods are available. They may operate on a single route at a time or on several routes simultaneously. The most common of these procedures is the $\lambda$-opt heuristic of Lin (1965). Where, $\lambda$ edges are removed from the tour and replaced by $\lambda$ others. If any profitable reconnection is identified, it is implemented. The procedure stops at a local minimum when no further improvements can be obtained. The computing time required to examine all the possible solution is proportional to $n^{\lambda}$. Thus, only $\lambda = 2$ or 3 are used in practice.

*Local search methods*

These algorithms explore the solution space by iteratively moving from a solution $x_t$ at iteration $t$ to a solution $x_{t+1}$ in the neighborhood $N(x_t)$ of $x_t$ until a stopping criterion is satisfied. If it is applied a simulated annealing approach then a solution x is drawn randomly from $N(x_t)$. Defined as f(x) the cost of solution x, if $f(x) \leq f(x_t)$ then $x_{t+1}: = x$. Otherwise,

$$x_{t+1} \coloneqq \begin{cases} \text{x with probability } p_t \\ x_t \text{ with probability } 1 - p_t \end{cases}$$

where $p_t$ is a decreasing function of t and $f(x) - f(x_t)$. This probability is often equal to

$$p_t = exp\left(-\frac{f(x) - f(x_t)}{\theta_t}\right)$$

where $\theta_t$ is the *temperature* at iteration *t*, which usually is a decreasing step function of t (Toth and Vigo, 2002). The Deterministic annealing is similar to the simulated annealing approach, but in this case a deterministic rule is used for the acceptance of a move. To these class of method belong also the tabu search heuristics which have proved to be the most successful metaheuristic approach. As well as the previous methods, it examines sequence of solution, but in order to avoid cycling, the solutions that were recently examined are forbidden, or tabu, for a number of iterations.

*Population search*

These models include genetic algorithms which solve problems by imitating processes observed during natural evolution. The basic idea is to evolve a population of bitstrings, called chromosomes, representing the binary encoding of a solution to the problem in a particular instance. The evolution of the population is obtained by applying the operators that simulate the most relevant natural phenomena, like reproduction and mutation.

*The learning mechanisms*

A limited number of heuristics based on learning mechanisms have been proposed for the VRP. They include neural networks mechanisms which are computational models whose structure provides for the interconnection of several elements that are interconnected through weighted connectors. These elements may represents the neurons of the human nervous system, while their connections are the synapses. In artificial networks, each link is associated with its own numerical weight, the value of which varies dynamically over time in response to experience in computing. Thanks to the weights associated with the connections, neural networks have the capability to learn from the experience and induce general concept from specific examples through an incremental adjustment of their weights.

Other interesting classification of the VRP and its variant were described in literature.  In Eksioglu et al. (2009) the authors firstly illustrated a review of the classifications precedent to their work, then they presented a taxonomic framework to define and integrate the domain of the existing VRP literature.

As previously said the VRP has been widely studied by the researchers and since the very beginning literature has become quite disjointed and it has been applied in many real-world cases. Some applications are solid waste collection, street cleaning, school bus routing, routing of salespeople and maintenance units, transportation of handicapped people, and so forth (Daneshzand, 2011). In order to deal with the object of this thesis the remain of the literature review focalises on two particular version of the problem, the fixed VRP and the sustainable VRP, and on studies that illustrate applicative case based on waste collection.

## ***The fixed vehicle routing problem***

In Beasley (1984) was illustrate a classification where it was consider that, even if the routing optimization is a short term decision, it is possible to define daily deliveries, regular non-daily deliveries (i.e. once a week) and irregular deliveries, in function the demand pattern of each customer. Consequently the author distinguished:

- The daily routing problem, where a set of vehicle routes need to be developed for each day's deliveries;
- The period routing problem, where a set of vehicle routes are developed for a certain period to meet customer service requirements (not all customers requiring a delivery every day in the period);
- The fixed routing problem: where a set of vehicle routes are developed so that they can be operated without any changes for a given period of time. Due to variability

in demand, it is possible that a vehicle cannot satisfy the demand of a customer, creating a route failure that needs to be dealt with on an as-needed basis.

The major difficulty in the design of fixed routes is the need to deal with demand fluctuations. In the literature there are many studies that show alternative approaches for modelling the VSP with uncertain customer demands. In particular, Benton and Rossetti (1992) consider three alternative ways to adapt the standard vehicle routing algorithm to deal with the daily version of the fixed VRP:

- Fixed routes alternative: keep permanent routes and schedules fixed while visiting each location. Stop only if the demand is positive.
- Modified-fixed routes alternative: keep permanent routes but omit customer locations with zero demand from the routes.
- Variable routes alternative: eliminate permanent routes and reschedule all routes efficiently in each period.

To solve the fixed VRP many studies proposed a two-stage stochastic optimization strategy, like Savelsbergh & Goetschalckx (1995) and Erera et al. (2009). They described a recourse strategy based on the key ideas that the customer base placing orders on each weekday is partitioned into two subsets, regular customers, who place orders frequently on that day and thus are included on planned routes, and irregular customers, who are served infrequently and therefore are only added to operational routes dynamically as necessary. In the two-phase approach, the primary routes are constructed first and once a set of primary routes is given, a set of backup routes is constructed. Gendreau et al. (1995) and Jaillet (1998) proposed a two-stage strategy to solve the probabilistic travelling salesman problems (PTSP), where customers have independent probabilities of requiring service. In the first stage, planned collection routes are designed, and only when the set of present customers is known, these routes are followed as planned by skipping the absent customers, in stage two.

Groër et al. (2009) considered a variant of the periodic VRP, that they called the consistent VRP. For given D days, the problem combines the traditional constraints on vehicle capacity and route length with two additional constraints to improve customer service quality: each customer must always be visited by the same driver; each customer must receive service at roughly the same time each day. In the first stage of the proposed heuristic, a set of template routes is generated, considering only customers that require service on multiple days. In the second stage the routes for all days can be constructed from the template using a removal and insertion procedure.

In addition to these considerations, it's important to highlight that several articles discussed the importance of assigning a fixed driver to a set of customers so that the drivers can familiarize with the routes, schedules, and the delivery area, increasing performance. In this perspective, the driver learning becomes relevant and needs to be directly linked to the problem of choosing the best routing strategy. For example, Wong and Beasley (1984) generalized the fixed routing problem proposing a heuristic algorithm to divide the depot area into subarea, where a single vehicle is assigned to each subarea and the daily routes are designed considering only the customers who require delivery on that day. Haughton (2007) proposed a rule to guide the daily assignment of delivery routes to drivers, based on the idea that increasing a driver's familiarity with the specifics of a given customer, not only improves the efficiency with which the driver can serve the customer, but is also a sign of praiseworthy customer service. Zhengbing et al. (2009) observed that the individual day-to-day travel choice is an adaptive process to various environment factors (such as on-road time and fee, road conditions, weather, land use, and so on), not a one-time activity, and that the process also can be regarded as a feedback learning process in which the traveller makes the conclusion and evaluation of the travel experience, continuously learns and modifies the travel behaviour. The ability to acquire knowledge and skills from experience is called learning ability.

According to Anzanello and Fogliatto (2011) several factors may impact the workers' learning process; namely: (i) structure of training programs; (ii) workers' motivations in performing the tasks; (iii) prior experience; and (iv) task complexity. The way such factors impact workers' learning process can be analysed by mathematical models named Learning Curves (LCs), which graphically represent the relation between the time necessary to complete a task and cumulative number of times to perform it, in function of the learning rate. Wright (1936) was the first to report the learning curves phenomenon and since then many studies have widely analysed it. Wright observed that, as the number of assembled airplanes doubled, the number of direct labour hours required to produce an individual unit were reduced on average 20%, this meant that the average labour requirement was about 80% of what it had been before. This observation originated a rule-of-thumb named “80% learning curve”. LCs have been widely used in several segments to estimate lot conclusion time, to evaluate production cost reduction, to optimize the allocation of tasks-to-workers based on their learning profile, and to mitigate production losses after task interruption. Given the wide variety of applications of the LCs and the increasing number of publications on the subject, extensive literature reviews were proposed by Yelle (1979), Badiru (1992) and Anzanello and Fogliatto (2011). They observed that many modifications of the Wright’s model were proposed by different authors in order to adapt the equation to specific applications, and they reduced them to few relevant models, (Yelle, 1979):

1. The log-linear model or Wright model.
2. The plateau model.
3. The Stanford-B model.
4. The DeJong model.
5. The S-model

The log-linear model was proposed by Wright and is often referred to as the conventional learning curve model. Figure 3.1 shows comparative plots of these models on a log-scale. It is important to observe that when a linear graph paper is used, the log-linear learning curve is a hyperbola (Badiru, 1992).

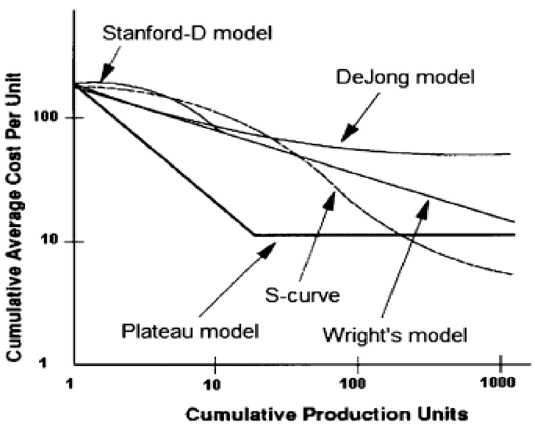



*Figure 3.1: Comparison of learning curve models on a log scale (from: Badiru, 1992)*

Zhong et al. (2007) investigated the construction of routes for local delivery of packages in the presence of driver learning, taking into account tradeoffs between the objective of increasing driver familiarity, which tends to make routes or service territories fixed, and optimizing vehicle dispatching when customer locations and demands vary from day to day, which implies that vehicles/drivers and service territories are re-assigned each day.

Compared to the classical VRP, the fixed vehicle routing problem has not received the same attention from the researchers. It seems that no study has been published to compare the daily routing optimization strategy with the fixed routing strategy considering the benefits of the drivers learning. Moreover, even if many articles recognize the importance of the driver familiarity with routes, schedules, and delivery area, only few of them applied the LCs to the drivers' performance. Therefore, the aim of the first part of the work is to compare the fixed routing strategy with the daily routing optimization strategy according to variation in three key dimensions:

1) customers' orders variability, i.e. variability in quantity of the customer demand.

2) customers' orders frequency, i.e. variability in frequency of customer demand.

3) the ratio between the delivery service time and the delivery travel time; i.e. the ratio between time spent in each point of the network by the drivers for the service operations (load/unload zone finding and positioning, identification and registration activities, documents filling, load/unload activities, etc.) and the time spent in travelling between different points of network.

The present study highlights the importance of the learning curves in predicting the driver performance in the routing management decision.

## ***The sustainable vehicle routing problem***

Due to the growing pressure to limit the Greenhouse Gas (GHG) emissions and the awareness that the transportation field produces the largest percentage of emissions from fossil fuel combustion, a wide range of models, mainly based on simulation, have been proposed to predict fuel consumption and emission rates (Bektas and Laporte, 2011). For this reason, the Green Supply Chain is becoming an important research field in the Supply Chain Management, also distinguished into specific country characteristics (Kim et al., 2011).

The amount of pollution emitted by a vehicle depends on several factors, such as vehicle characteristics, inspection and maintenance levels, fuel characteristics etc. Consequently, vehicle manufacturers have been forced to incorporate technological improvements like weight lightening, engine size reduction, low-rolling-resistance tyres, improved aerodynamics and hybridisation and electrification of vehicles (Fonseca et al., 2011). An alternative solution technology that vehicle manufacturers have developed is the “stop/start” system, in which the internal combustion engine is automatically powered off when the car is stopped and restarted upon driver’s demand or when needed. Fonseca et al. (2011) studied the effect of this technology and points out that it allows A significant reduction of $CO_2$emissions in actual urban traffic.

Other relevant factors that influence the emission are the vehicle driving patterns (André and Rapone, 2009), average speed (De Vlieger et al., 2000), the degree of acceleration (Larsson and Ericsson, 2009) and also the type of street (i.e. rural or urban) and the level of traffic congestion (Smit et al., 2008).

A wide number of $CO_2$ emission models are developed to assess these emission factors, like Fontaras et al. (2007), André and Rapone (2009), Larsson and Ericsson (2009). Smit et al. (2008), proposed an exhaustive classification of the existing emission models. The authors examined how, and to what extent, models, which are currently used to predict emissions and fuel consumption from road traffic, include the effects of congestion. This is because congestion can be associated with a number of interrelated and observable effects that include increased traffic density, increased travel times on the same route (hence lower average speeds), increased deviation from free-flow speeds (hence increased speed fluctuation and delays) and increased queuing (hence increased number of stops). It is not possible to take account of unexpected events that may cause congestion, like an accident, but regular congestion related to the time of the day of travel can be predicted from historical data. Woensel et al. (2001) point out that the use of constant speed, like in most emission models, will lead to an underestimation of the effective emissions. Thereby they used queuing theory to model the impact of traffic congestion on emissions and recommended that private and public decision makers should take into account the high impact of congestion on emissions. Maden et al. (2010) analyse a vehicle routing and scheduling problem with time windows considering the speed variability due to the time of travel, and the relative level of congestion. The authors describe a heuristic algorithm to solve the problem and present a case study of a fleet of delivery vehicles in the United Kingdom. They report up to 7% savings in CO2 emissions when compared with a planning method using constant speed, even if the algorithm does not plan routes that directly minimize the emission.

Although an extensive number of studies propose a CO2 emission model, few researchers have developed routing tools that optimize emission (Wygonik and Goodchils, 2011).

Bektaş and Laporte (2011) present the Pollution-Routing Problem, an extension of the classical Vehicle Routing Problem with a broader and more comprehensive objective function that accounts not only the travel distance, but also the amount of greenhouse emissions, fuel, travel times and their costs. The authors point out the trade-offs between various parameters such as vehicle load, speed and total cost, and offer insights on economies of environmental-friendly vehicle routing. Dessouky et al. (2003), present a methodology for the joint optimization of cost, service, and life-cycle environmental consequences in vehicle routing and scheduling. This research looks at a number of measures of environmental performance and considers the life-cycle environmental impacts of each solution anyway, it does not focus on or minimize the CO2 emissions associated with routing.

Figliozzi (2010) formulated the emissions vehicle routing problem (EVRP) with time-dependent travel times, hard time windows, and capacity constraints. The author showed that a routing formulation and solution algorithm that takes into account co ngestion and aims to minimize CO2 emissions can produce significant reductions in emission levels with relatively small increases in the distance travelled or fleet size.

Nevertheless the formulation proposed includes speed and departure time as decision variables, which are not always possible in real condition.

As conclusion of this part of literature review, it is possible to highlight that there are many contributes on the vehicles CO2 emission analysis, but few study have developed routing tools that minimize the emission. For this reason the aim of this work is to contribute in this important research area:

- Showing the effect on the amount of $CO_2$ emitted by a vehicle due to several factors, "internal", depending on the driver (i.e. driving style, acceleration, average speed, route knowledge, etc.), and "external" (i.e. traffic congestion, speed limits, vehicle type, etc.) starting from the current state of the art in the vehicle $CO_2$ emission estimation models.

- Introducing a new sustainable routing model that gives as result sustainable routes, i.e. a specific sequence of customers to visit and A way to drive that minimizes the $CO_2$ emission in function of these different internal/external factors, proposing as results sustainable routes.
- Highlighting how this sustainable routes are generally not equal to those obtained by the classical routing problem solution using objectives function like distance/time minimization, especially for particular values of internal/external factors like traffic congestion level or driving style.
- Pointing out how, where it is not possible to have instant information on the traffic congestion, the driver familiarity with the territory results in an important element to support this new approach.

## ***Study applied to the waste collection***

VRP has many applications in real-world cases. Some applications are solid waste collection, street cleaning, school bus routing, routing of salespeople and maintenance units, transportation of handicapped people, and so forth (Daneshzand, 2011). Example of these applications were presented in Kim et al. (2006), Benjamin and Beasley (2010) and Nuortio et al. (2006). The first addressed a real life waste collection vehicle routing problem with time windows (VRPTW) assuming multiple disposal trips and drivers' lunch breaks. They assumed a weekly predetermined schedule and presented a route construction algorithm that was an extension of Solomon's insertion algorithm (Solomon, 1987). Instead, Benjamin and Beasley (2010) considered exactly the same waste collection problem as in Kim et al. (2006) involving multiple disposal facilities, drivers rest period and customer/depot/disposal facility time windows. The authors presented a number of meta-heuristic approaches which provide better solutions than previous work existing in the literature. Nuortio et al. (2006) described the optimization of vehicle routes and schedules for collecting municipal solid waste. The authors demonstrated, through experimental results, that significant savings, can be obtained using the proposed heuristic solution method based on the guided variable neighborhood thresholding, compared to the current practice. Nuortio et al. observed that the amount of municipal solid waste is highly variable and the accumulation of waste depends on several factors, as a consequence, in their study the average accumulation rate of waste in each container type is estimated separately using the historical weight and route.

This literature review analysis point out that:

- The vehicle routing problem (VRP), especially with time windows (VPRTW) is computationally very hard, and cannot be solved by exact methods and heuristics are used for this purpose (Nuortio et al., 2006).
- Only few authors considered the waste collection problem and its unique characteristics in the routing problem.
- Many studies in VRP use deterministic input data, and consider the waste collection problem, where the quantity of waste inside the bins is a stochastic variable which invalidates this assumption.
- Only few studies considered real time input data for the routing optimization and no one focuses on the waste collection problem.
- Many models in literature are mono-objective, instead, modern distribution and collection networks aim to be multi-objectives (minimize the total cost, minimize the total distance, minimize the total time, minimize the number of used vehicles, etc).

Moreover, his preliminary literature analysis evidences how a real time traceability data integrated with a multi objective routing model in residential waste collection, represents an important contribution in the management of the last phase of the life cycle of food and its packaging material. Not only the integration of real time data with the multi-object vehicle routing model allows to reduce the number of visited and emptied bins, but as direct effects environmental impacts like emissions, noise and traffic congestion are reduced.

## 3.3 GOODS DAILY DELIVERY: economical optimization

This paragraph deals with routing problem optimization from an economical point of view. It firstly describes and compares the routing models used in the fixed routing strategy and in the daily routing optimization strategy, then it reports a parametrical analysis, which is use to developed a methodological framework. Particular attention are given to the learning effect and it influence on the delivery service. As conclusion of this paragraph it is illustrate a case study which considers a company (named here Company A) that distributes fresh food products for a worldwide chain of well-known restaurants.

Part of this work has been described in a journal article at present under review: *Battini, D., Faccio, M., Persona, A., Røpke, S., Zanin, G. (2012) "Routing strategy in a distribution network: fixed route with driver learning versus variable daily optimized route." International Journal of Physical Distribution & Logistics Management*.

### 3.3.1 ROUTING MODELS

Both the fixed and the daily routing optimization strategy considers:

- A single depot where all the routes start and finish;
- A homogeneous vehicles fleet, with limited capacity, located at the depot;
- A set of customers, for which the location and time window are known;

It is supposed that the position of the depot is in the middle point of the delivery area and the customers have a uniform distribution on that area.

Given a period *D* of 30 days each model has the following inputs:

| Notation | |
|---|---|
| $0$ | Depot |
| $C$ | Set of customers |
| $Q$ | Capacity of each vehicle |
| $q_{id}$ | Customer demand *i* for the day *d* |
| $e_i$ | The earliest start time to serve the customer *i* |
| $l_i$ | The latest finish time to serve the customer *i* |
| $ST$ | The service time, considered equal for all customers |
| $TT(i,j)$ | The travel time from the point *i* to the point *j*, with $i, j \in C \cup \{0\}$, and *i* different from *j* |

*Table 3.1: Input definition*

The objective of the models is to minimize the total time, taking into account time window and capacity constraints, therefore, each route needs to be planned so that the vehicle capacity is not exceeded and if a driver arrives at the point $i$ before $e_i$, he must wait until $e_i$ to begin service. On the other hand delays in deliveries are allowed. Let $r = (i_0, i_1, \dots, i_k)$ denote a route with $i_0 = i_k = 0$ being the depot. Given a departure time $t_0$ from node $i_0$ we can calculate the ready times at node $i_j$, for $j > 0$ using the formula

$$t_j = \begin{cases} \max\left\{e_{i_j}, t_{j-1} + TT\left(i_{j-1}, i_j\right)\right\} & \text{if } j = 1 \\ \max\left\{e_{i_j}, t_{j-1} + ST + TT\left(i_{j-1}, i_j\right)\right\} & \text{if } j > 1 \end{cases}. \tag{1}$$

The total duration of the route can then be calculated as $T(r) = t_k - t_0$ where the departure time from the depot $t_0$ is chosen such that the duration is minimized by eliminating superfluous waiting time. The total time for the solution is then

$$\text{Tot-T} = \sum_{r \in R} T(r) \tag{2}$$

Where R is the set of all routes in the solution.

In the routing model used in the daily optimization strategy, the routes are redesigned every day $d$, in order to satisfy the actual demand of each customer $i$ in that day, $q_{id}$. This implies that each driver visits different customers every day, facing different delivery areas, different acceptance procedures, different load-unload facilities, different operators to work with.

For the fixed routing strategy the model proposed is divided into two stages.

In the first stage template routes are designed to satisfy the mean demand of each customer in the period D, $q'_{iD}$; in the second stage template routes are used every day as fixed routes considering the actual demand of each customer $i$ in that day, $q_{id}$. Each driver goes through the same routes every day, visiting the same set of customers and stopping only if the demand is positive. Due to the variability of the customer demand, service failures may occur on any planned route, i.e. the vehicle cannot satisfy the demands of the customers at a certain point along the route, which will prompt the driver to return to the depot, replenish the load and restart his delivery route from the next customer, with a consequent increase in the total time.

It is obvious that generating the fixed routes based on the average demand does not result in fixed routes that fully takes the stochastic nature of the problem into account and that an approach such as the one described by Gendreau et al. (1996) would generate higher quality fixed routes. However, the approach taken is very simple and can easily be carried out with existing vehicle routing software available to practitioners, as highlight in the case study section. Moreover it allows to introduce a new relevant factor in the model formulation, the drivers learning effect, and to evaluate its influence the distribution system. The repetitiveness for the drivers to go the same routes every day, visiting the same set of customers, not only allows him/her to familiarize with served territory and customers, with a reduction of service time, but also creates the chance of establishing personal relationship that can only improve customer service. The drivers can establish long-term relationships with customers increasing their performance at the facility that gets visited at or around the same time each day, allowing adjustments in the work processes to accommodate the delivery.

In present research the individual vehicle routing problems were solved by a modified version of the adaptive large neighbourhood search heuristic described by Pisinger and Ropke (2007). The heuristic was modified in order to minimize route duration.

The following sections show the comparison between the fixed routing strategy and the daily optimization strategy with the pros and cons of the different parameters considered.

### 3.3.2 PARAMETRICAL ANALYSIS

This section reports the parametrical analysis that allows to identify and classify the most relevant factors and then, considering various scenarios, to identify the best routing strategy among the two different models compared:

- the daily optimization strategy;
- the fixed routing strategy.

The numerical analysis has been developed using Matlab SW. The demand $q_{id}$ has been generated using a normal distribution parameter, with mean μ and standard deviation σ. During the simulation the following three parameters have been changed for all the routing models:

- CV: coefficient of variation of the customers demand in quantity, that is the ratio between the standard deviation σ and the mean μ of the customer demand;
- FREQUENCY: that is the regularity of the customer demand, i.e. it is the ratio between the number of days with customer demand different from zero and the number of days in the period D;
- ST/TT: that is the ratio between the service time and the travel time;

Moreover, in case of fixed routing strategy, the drivers' learning effect on the service time has been simulated, changing the parameter ST(L)/ST, that is the ratio between the service time with driver learning and the standard service time. ST(L)/ST=100% indicates that no learning effect is present.

The last parameter, ST(L)/ST, changes only in the fixed routing strategy in which the average service time decreases as the number of visits to a customer by the same driver increases.

In order to compare the results, all the parameters of the analysis are normalized on 100% base. In fact all the parameters are (CV, FREQUENCY, ST/TT, ST(L)/ST) are smaller than 1, and they have been multiplied by 100. Considering the maximum value of Tot-T, called MAX (i.e. *MAX =max {Tot-T})* obtained during the simulation, the Tot-T values have been normalized to 100% with respect to MAX, obtained as *TOT-T/MAX(%)=(Tot-T/MAX)·100.* A low value of *TOT-T/MAX(%)*therefore corresponds to an attractive solution.

Table 3.2 reports the design of the simulation showing the different values taken by the parameters. Table 3.3 reports an extract of the results obtained in the simulation.

| **Parameters** | **Values (%)** |
|---|---|
| CV | 10, 20, 30 |
| FREQUENCY: | 60, 80, 100 |
| ST/TT | 45, 55, 65, 75,85,100 |
| ST(L)/ST | 50, 60, 70, 80, 90, 100 |

*Table 3.2: Parameters values*

| CV (%) | FREQUENCY (%) | ST/TT (%) | ST(L)/ST (%) | DAILY/FIXED | TOT-T | TOT-T/MAX (%) |
|---|---|---|---|---|---|---|
| 30 | 60 | 100 | 0 | D | 1839.48 | 76.72 |
| 30 | 100 | 75 | 0 | D | 2022.82 | 84.37 |
| 10 | 100 | 45 | 50 | F | 1508.39 | 62.91 |
| 30 | 60 | 100 | 50 | F | 1784.05 | 74.41 |
| 20 | 100 | 45 | 50 | F | 1580.18 | 65.91 |
| 30 | 80 | 45 | 0 | D | 1415.58 | 59.04 |
| 30 | 60 | 45 | 0 | D | 1283.65 | 53.54 |
| 10 | 100 | 45 | 50 | F | 1559.41 | 65.04 |
| 20 | 100 | 45 | 50 | F | 1553.12 | 64.78 |

*Table 3.3: An extract of the simulation results*

Figure 3.2 shows the ANOVA analysis of the different factors (CV, FREQUENCY, ST/TT, ST(L)/ST) versus Tot-T/Max for the main effect plot identification through the Pareto chart of the standardized effect on Tot-T/Max. The ANOVA test is used to determine the impact independent variables have on the dependent variable in a regression analysis. Figure 3.3 reports in the same way the main effect plot of these different factors on Tot-T/Max.

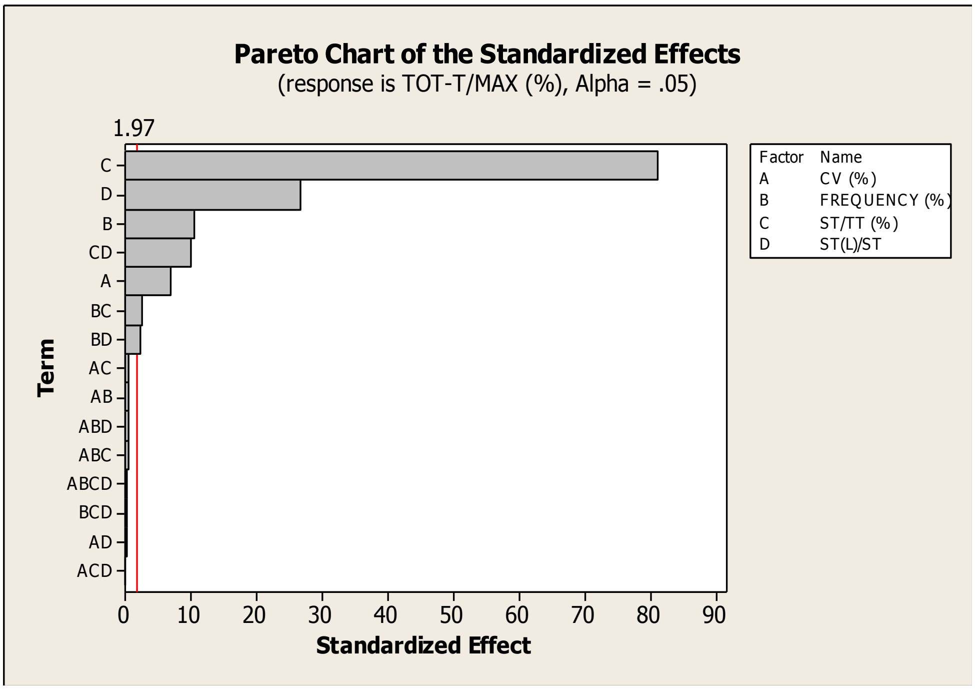



*Figure 3.2: Pareto Chart of the Standardized Effects*

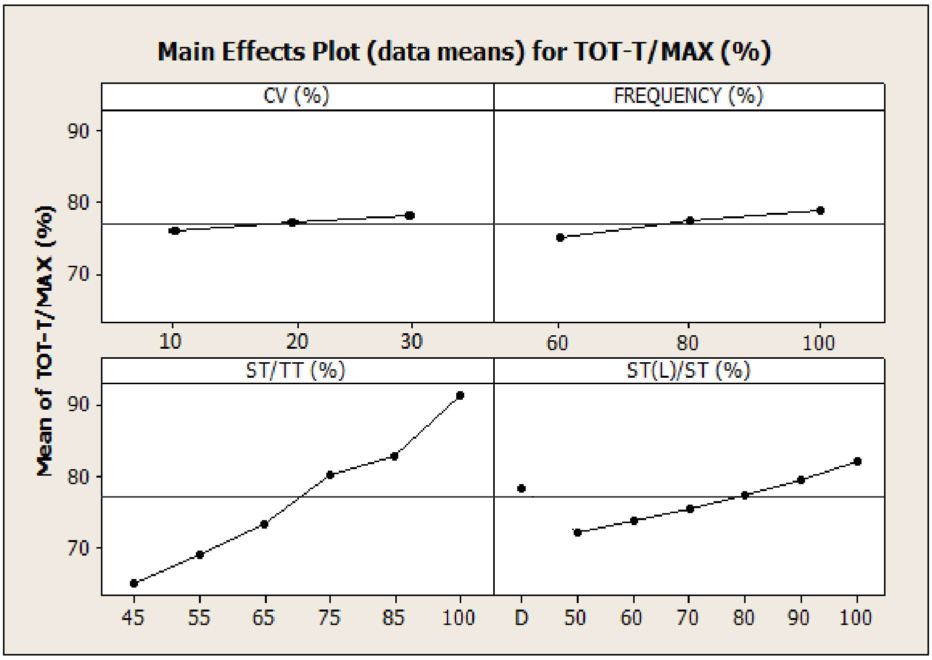



*Figure 3.3: Main Effects Plot of Tot-T/MAX (%)*

As highlighted by figure 3.2 and figure 3.3, CV does not have a relevant impact in the Tot-T/Max respect the other parameters, which means that the system is robust with respect to the quantity variation demand (with a maximum variation of 30% of the average customers demand). On the other hand the influence of the ratio between service time/travel time (ST/TT) on the Tot-T/Max is great. Consequently, the identification of the type of distribution network has a wide effect in the choice of the routing strategy. In fact, as shown below, in networks where the service time has a relevant impact on the total time (i.e. distribution in towns with high density of customers) the fixed strategy can be preferable, while, when the ratio service time-travel time, ST/TT, is low a daily strategy is generally better.

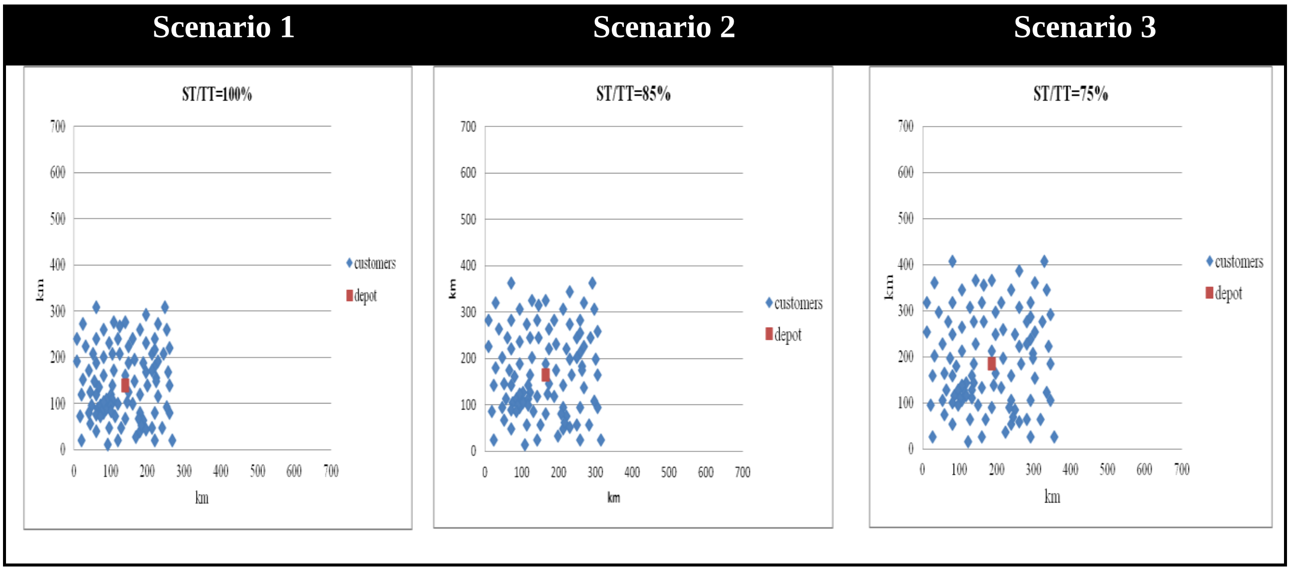
Also, the ratio between the service time with driver learning and the standard service time ST(L)/ST has a great influence on Tot-T/Max, while customers orders frequency (the regularity of the customers demand) has a lower effect that nonetheless needs to be considered. This result is significant and shows that in the routing problem, service time ST is a critical factor, and that once the ST is reduced, thanks to the drivers learning performances, the fixed route strategy can be more suitable. This second result enhances the relevance of the study, looking at the influence of ST(L)/ST (the ratio between service time with driver learning and standard service time), it is possible to see an almost linear correlation between the learning effect on ST and the Tot-T/Max.

Taking into account that the CV parameter is the least influencing factor on Tot-T/Max, its value has been kept fixed to 30% (its maximum value in the simulation), while 6 different scenarios have been considered, just by changing the ST/TT value. The ST/TT values represented in figure 3.4, correspond to six different distribution network with different density of customers for area unit. The tested distribution networks vary from scenario 1 with the maximum customer density possible (100 customers for an area of 300x300 square km) to scenario 6 with the minimum customer density (100 customers for an area of 600x600 square km). The 6 considered scenarios are:

- Scenario n. 1: ST/TT equal to 100% and CV equal to 30%;
- Scenario n. 2: ST/TT equal to 85% and CV equal to 30%;
- Scenario n. 3: ST/TT equal to 75% and CV equal to 30%;
- Scenario n. 4: ST/TT equal to 65% and CV equal to 30%;
- Scenario n. 5: ST/TT equal to 55% and CV equal to 30%;
- Scenario n. 6: ST/TT equal to 45% and CV equal to 30%.

The study considers a service time (ST) that, for a considered travel time (TT) value, gives the ST/TT value as defined in the 6 scenarios.

Assuming that the service time for each of the 100 point to serve is the same, each scenario has a different distribution network representation. Figure 3.4 shows that the scenario with high value of ST/TT corresponds to a distribution network with high customer density. Figure 3.5 reports the comparison between the fixed routing strategy versus the daily optimization strategy for the same 6 scenarios.



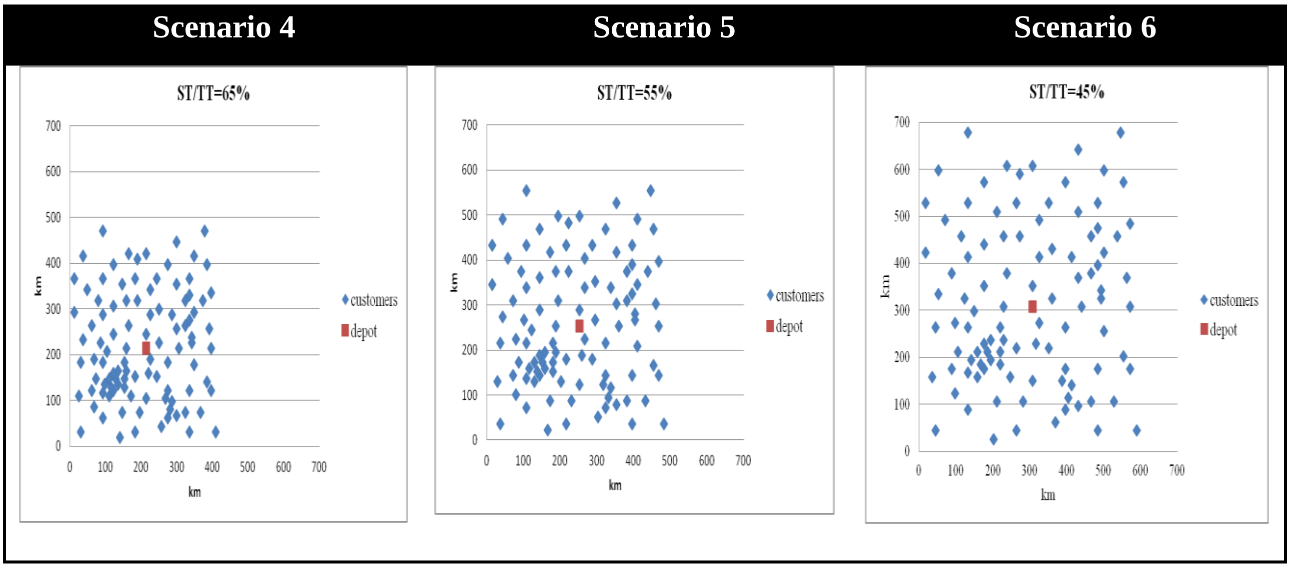



*Figure 3.4: Distribution networks representation: 6 scenarios tested*

- In all the scenarios, the low regularity of the customers demand influences more negatively the fixed routing strategy than the daily routing strategy.
- In case of high values of ST/TT (i.e. scenario n. 1 (figure 3.5-a); scenario 2 (figure 3.5-b)) a little reduction of ST, due to the drivers' learning effect, allows the fixed routing strategy to obtain better results than the daily strategy, even with low regularity of customers demand.
- In case of average values of ST/TT (i.e. scenario n. 3 (figure 3.5-c); scenario 4 (figure 3.5-d)) the fixed routing strategy becomes competitive only in case of an average drivers' learning effect, in presence of high regularity of customers demand (frequency 100%).
- In case of low values of ST/TT (i.e. scenario n. 5 (figure 3.5-e); scenario 6 (figure 3.5-f)) for the fixed routing strategy to be competitive, it is necessary to have a high level of regularity in customers demand (frequency must be very close to100%) and high drivers' learning effect.
- In case of low regularity of the demand (frequency=80% or lower) the fixed routing strategy becomes not competitive when compared to the daily optimization routing strategy whenever the ST/TT values are lower than 65%. In other words, according to figure 3.4, considering a quantity variation minor or equal to 30% of the average demand for each customer, the fixed routing strategy should be applied just in case of a highly or moderately dense distribution networks with an high/medium regularity in customer order frequency.

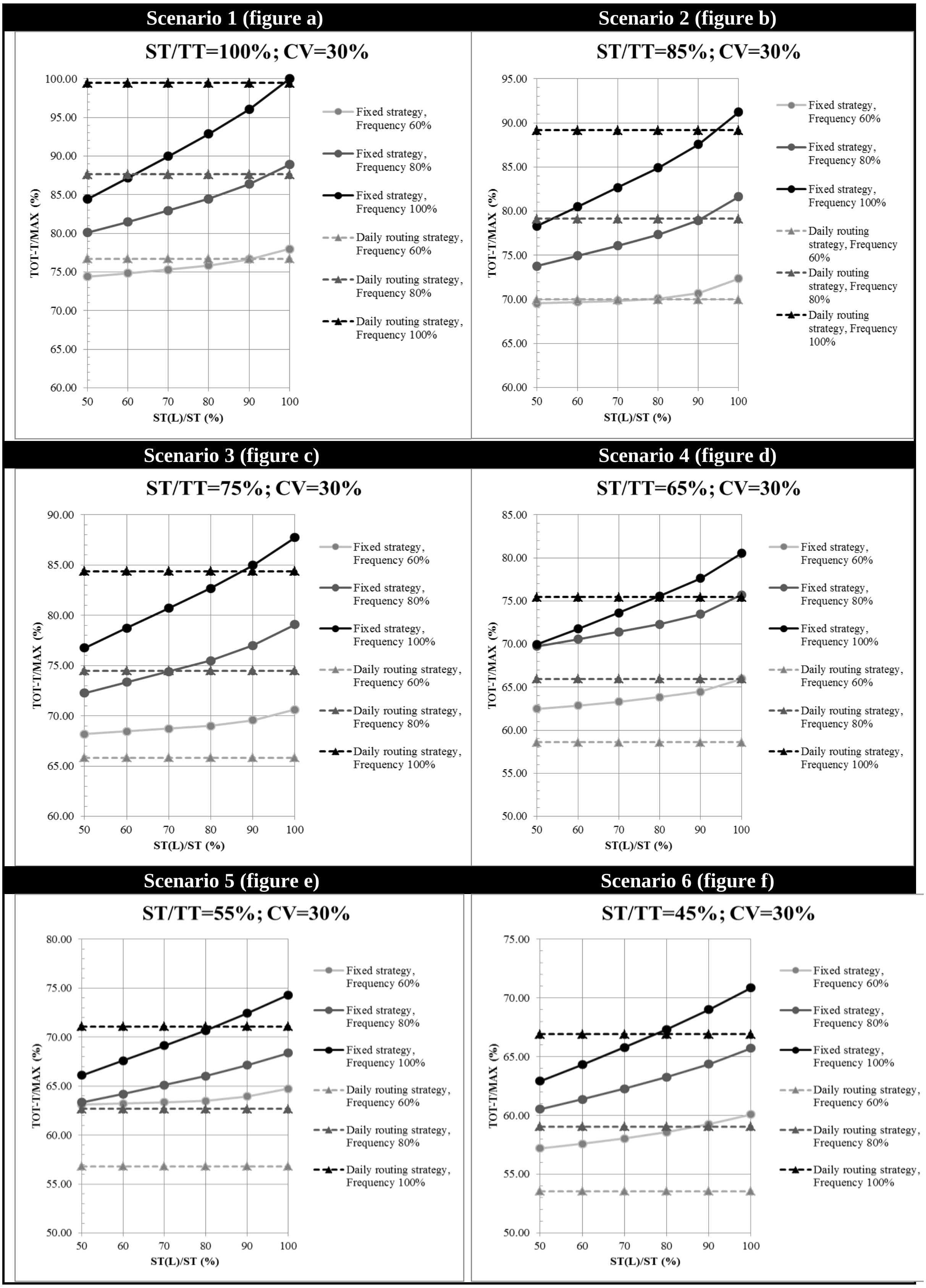



*Figure 3.5: Comparison between the fixed routing strategy versus the daily optimization strategy*

### 3.3.3 LEARNING EFFECT AND LEARNING CURVES

A learning curve is the phenomenon whereby, as a number of cycles increases, the time per cycle or the cost per cycle decreases for a large number of cycles (Hancock and Bayha 1992). The literature on learning effect and learning curves is widely accepted in most manufacturing settings (Hirsch, 1956; Argote and Epple, 1990; Battini et al. 2011).

Learning equations generally take the following expression (Anzanello and Fogliatto; 2011):

$$\mathrm{T_j} = \mathrm{T_1 j^{-l}} \tag{3}$$

Where

- $\boldsymbol{T_j}$ is the average service time on the j[th] consecutive visit;
- $\boldsymbol{T_1}$ is the average service time on the first visit;
- $l$ is the learning slope, which describes the workers' learning rate. Values of $l$ close to 1 denote high learning rate and fast adaptation to task execution.

It is possible to write the equation number (3) as follows:

$$T_j/T_1 = j^{-l} \tag{4}$$

The ratio $T_j/T_1$ corresponds to the ratio ST(L)/ST used in the parametrical analysis. It allows to identify the best routing strategy considering the different scenarios. In fact, it is possible to figure out the ratio between service time with driver learning and standard service time, ST(L)/ST, that made the fixed strategy more desirable than the daily, just by knowing the following points:

- The ratio between the service time and the travel time (ST/TT);
- The customer order variability (CV), and the customer order frequency (FREQUENCY);

As shown earlier, this ratio corresponds to the ratio $T_j/T_{1,}$, hence, knowing the learning slope of the drivers, allows one to apply the equation number 3 and quantify *j*, *equivalent routes number*, which is the number of times a route must be repeated so that the time required to complete that route is equal to the time it would take using the fixed strategy or the daily strategy.

Table 3.4 reports the values of ST(L)/ST, found in the simulation described in the precedent section, which made the fixed strategy equivalent to the daily strategy. In the table below, the values of *j* change as a function of four factors:

- The coefficient of variation of the customers demand in quantity, CV (%)
- The regularity of the customers demand, FREQUENCY (%)
- The ratio between service time and travel time, ST/TT (%);
- The learning ratio, *l* (%).

The values of learning ratio considered are: 1, 5, 10, 15, 20, 25 (%). The symbol "-" indicates when the daily routing strategy is always better than the fixed strategy.

**Scenario n.1**

| *l* | ST/TT =100 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST 90.59% | ST(L)/ST 94.97% | ST(L)/ST 98.60% |
| | *j* | *j* | *j* |
| 0.01 | 19286 | 166 | 5 |
| 0.05 | 8 | 3 | 2 |
| 0.10 | 3 | 2 | 2 |
| 0.15 | 2 | 2 | 2 |
| 0.20 | 2 | 2 | 2 |
| 0.25 | 2 | 2 | 2 |

**Scenario n.2**

| *l* | ST/TT =85 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST 75.62% | ST(L)/ST 90.71% | ST(L)/ST 94.37% |
| | *j* | *j* | *j* |
| 0.01 | 1.323E+12 | 15999 | 317 |
| 0.05 | 267 | 7 | 4 |
| 0.10 | 17 | 3 | 2 |
| 0.15 | 7 | 2 | 2 |
| 0.20 | 5 | 2 | 2 |
| 0.25 | 4 | 2 | 2 |

**Scenario n.3**

| *l* | ST/TT =75 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST - | ST(L)/ST 70.59% | ST(L)/ST 87.41% |
| | *j* | *j* | *j* |
| 0.01 | - | 1.28E+15 | 677922 |
| 0.05 | - | 1056 | 15 |
| 0.10 | - | 33 | 4 |
| 0.15 | - | 11 | 3 |
| 0.20 | - | 6 | 2 |
| 0.25 | - | 5 | 2 |

**Scenario n.4**

| *l* | ST/TT =65 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST - | ST(L)/ST - | ST(L)/ST 79.37% |
| | *j* | *j* | *j* |
| 0.01 | - | - | 1.061E+10 |
| 0.05 | - | - | 102 |
| 0.10 | - | - | 11 |
| 0.15 | - | - | 5 |
| 0.20 | - | - | 4 |
| 0.25 | - | - | 3 |

**Scenario n.5**

| *l* | ST/TT =55 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST - | ST(L)/ST - | ST(L)/ST 82.30% |
| | *j* | *j* | *j* |
| 0.01 | - | - | 308383926 |
| 0.05 | - | - | 50 |
| 0.10 | - | - | 7 |
| 0.15 | - | - | 4 |
| 0.20 | - | - | 3 |
| 0.25 | - | - | 3 |

**Scenario n.6**

| *l* | ST/TT =45 % ; CV =30 % | | |
|---|---|---|---|
| | FREQUENCY | | |
| | 60% | 80% | 100% |
| | ST(L)/ST - | ST(L)/ST - | ST(L)/ST 77.32% |
| | *j* | *j* | *j* |
| 0.01 | - | - | 1.316E+11 |
| 0.05 | - | - | 169 |
| 0.10 | - | - | 14 |
| 0.15 | - | - | 6 |
| 0.20 | - | - | 4 |
| 0.25 | - | - | 3 |

*Table 3.4: Values of ST(L)/ST and the corresponding values of j, number of times that a route must be repeated so that the time required to complete that route is equal using the fixed or the daily strategy*

It is remarkable that if the learning slope is less than 10%, the value of *j* is generally very high. The complexity or changing effect inherent in task performance of the job affects the rate of learning (Hancock and Bayha 1992), hence there is a number of factors that affect the rate at which people learn to do repetitive jobs.

In order to obtain precise values of the driver learning slope *l*, each case should be calculated individually, according to the distribution network under study, and it should be estimated by having a set of drivers, considered a representative sample of the group, to go through a fixed set of routes for a certain period and collect all the service time data. Then it is possible to determine *l* as:

$$l = \frac{log(T_1) - log(T_j)}{\log(j)} \tag{5}$$

Otherwise, if a sample of drivers is not an option, values founded in the literature can be used to calculate *l* from existing parameters. According to Argote and Epple (1990), understanding the reasons why learning slopes varies is a major challenge for the researchers. Through an empirical study in the manufacturing sector Hirsch (1956) found that the learning slopes could vary between 16.5 and 24.8 per cent. Assuming that the learning slope of the drives is within such range, it is possible to observe that the *equivalent routes number, j,* is low. This means that the number of times a route must be repeated so that the time required to complete that route is equal using both the fixed strategy or the daily strategy, is small. Table 3.4 shows that high values of the ratio ST/TT require high ST(L)/ST in order to make the fixed strategy equivalent to the daily strategy. This means that in those cases in which the service time has a high influence on the total time (scenario n. 1, 2, 3), the necessary reduction is not high. On the contrary, if the service time has not a high influence on the total time (scenarios n. 4, 5, 6), the necessary service time reduction is high and in some cases so high that it basically is impossible to make the fixed strategy work as well as the daily strategy. However, this is only true under our assumption that travel time does not decrease as the driver learns the area. Taking this effect into account would make the fixed strategy competitive in even more scenarios.

Due to physical constraints the service time cannot become zero, so it is necessary to consider a learning limit, $T_\infty$. According to Zhong et al. (2007) the equation (3) can be modified as:

$$T_j = max\{T_1 j^{-l}; T_\infty\} \tag{6}$$

so that equation (4) becomes:

$$\frac{T_j}{T_1} = max\left\{j^{-l}; \frac{T_\infty}{T_1}\right\} \tag{7}$$

The value of the drivers learning limit, $T_\infty$, depends on the specific network considered and on the activity the drivers must perform. This learning limit may influence the routing strategy decision, because it is possible that the ratio ST(L)/ST, which would make the fixed strategy preferable to the daily one, needs a service time reduction exceeding the learning limit.

The graphical representation of this equation is the LC illustrated in figure 3.6, which shows that as the number of visits to a customer by the same driver increases, the average time spent to serve him approaches the lower possible limit $T_\infty$.

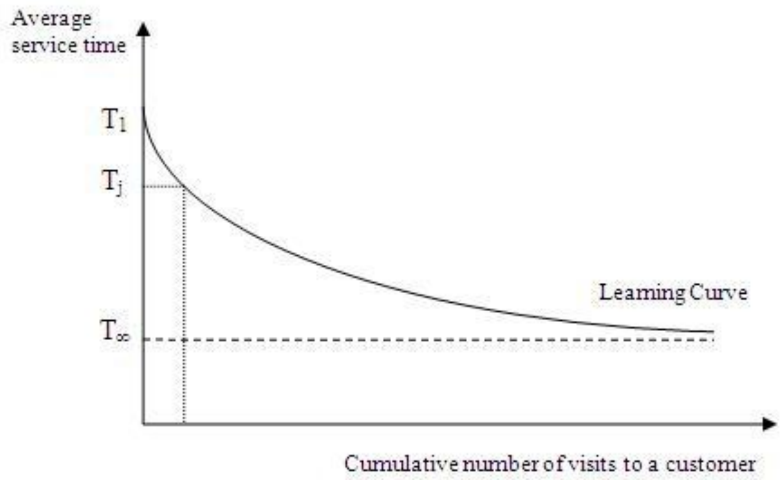



*Figure 3.6: Learning curve*

### 3.3.4 METHODOLOGICAL FRAMEWORK AND NUMERICAL APPLICATIONS

Figure 3.7 shows the methodological framework proposed in this work, to assist managers in the selection of the best routing optimization strategy. The framework consists of a 3-steps-procedure, supported by a set of graphs provided in figure 3.5 and tables 3.4, which ends with the final routing strategy selection. First of all the three decision variables, ST/TT, CV and FREQUENCY are defined, in function of the distribution network considered. As a consequence it is possible to identify the corresponding scenario and, using figure 3.5, to calculate the ST(L)/ST ratio that made the fixed strategy and the daily strategy equivalent, if such ratio exists at all. At this point, according to the identified scenario and to the value of the driver learning slope (either calculated using a sample of drivers and the equation (5) or found in the literature), it is possible to switch to table 3.4 to establish the *equivalent routes number, j*, which is the number of times a route must be repeated so that the time required to complete such route is equal using both the fixed strategy and the daily strategy. Evaluating the value of j managers can choose the fixed routing strategy, or the daily routing strategy according to what is better suited for the company.

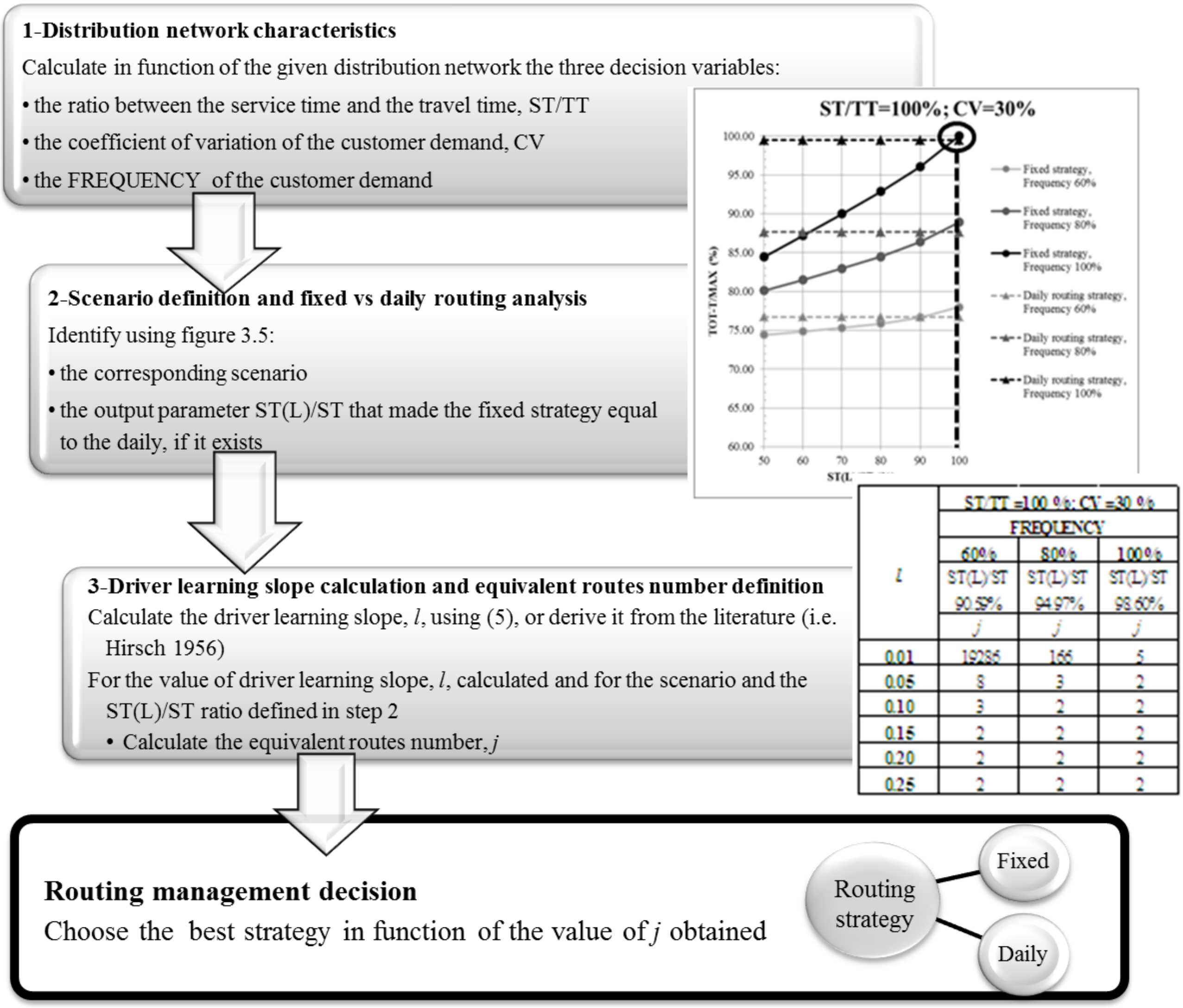



*Figure 3.7: Routing management methodological framework*

The step-by-step methodology proposed is here applied to an Italian distribution networks. The case company (named here Company A) distributes fresh food products for a worldwide chain of well-known restaurants.

The case study will be described in order to show the potential effectiveness of the framework proposed and its potential in drive managers' analysis and decision making.

### 3.3.5 CASE STUDY

Company A is a European service provider which handle all services for 350 restaurants located in all the 20 Italian regions, they receive fresh food ordered from 1 to 5 times per week, depending on daily requests and consumption level. Company A owns a transport fleet of doubles, long and short tractor trailer. In view of the high share of transport costs within the supply chain, transport optimization is a critical factor for the company success and thus for its customers. For this reason, and in order to maximize the exploitation of truck capacity, advanced IT tools are used daily by executives to achieve route optimizations based on individual customer needs through a "daily routing optimization strategy".

In addition to these considerations, an important role is reserved to the drivers learning effect. Company experienced that drivers establishing long-term relationship with the restaurants' personnel and familiarizing with the delivery area (most restaurants are in fact located in crowed city centres) usually reach higher performances. Thus, Company managers express the need to investigate the possibility to apply "fixed routing optimization strategy" instead of the daily one, asking for an easy-to-use methodology able to support their decision making. To solve this question the framework in figure 3.7 is applied step-by-step and the results are illustrated in table 3.5.

| | |
|---|---|
| Input data | |
| Sector | Food fresh products |
| Delivery points | Restaurants |
| N° of delivery points | 350 |
| N° of depots | 2 |
| Distributed volumes/year | 50,148 tons |
| Average route length | 531.5 km |
| Average number of stops per route | 5 |
| Average stop length | 55.2 minutes |
| Average total route service time (ST) | 276 minutes |
| Average total route travel time (TT) | 382.8 minutes |
| Average number of deliveries/customer | 18.8 per month |
| Working day/month | 25 |
| Average customer demand/order | 10.5 load units |
| Customer order standard deviation | 3.1 load units |
| Truck capacity in load units | From 10 to 36 |
| Decision variables | |
| *ST/TT* | *72.2% (276/382.8)* |
| *Frequency* | *75.2% (18.8./25)* |
| *CV* | *28.9% (3.1/10.5)* |
| Output data | |
| *ST(L)/ST (derived from fig. 3.5-c)* | *70%* |

*Table 3.5: Company A numerical input data, decision variables and output data*

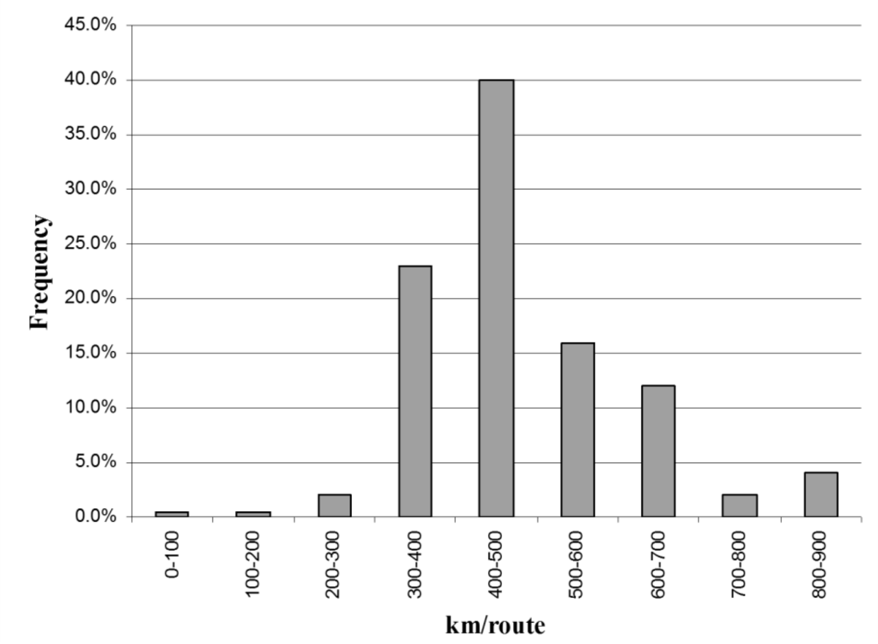



*Figure 3.8: Company A frequency distribution of route lengths*

The histogram illustrated in Figure 3.8 shows the average route length and relative distribution frequency in a one year working period. For the purpose of this research, the study did not focus on the detailed analysis of each route currently performed by the company, but on the average computation of all quantitative input data necessary to conduct the study. The three decision variables necessary to use the graphs provided at the end of parametrical analysis are computed and listed in table 3.5. By entering the three decision variables in graph 3.5-c, it's possible to derive the output parameter ST(L)/ST necessary to drive the strategic decision. The output parameter ST(L)/ST represents the ratio between the service time performed by drivers under a learning effect and the mean service time in case of a traditional daily optimization strategy (that means without a learning effect). The current frequency in this case company is 75%, by entering in table 3.4, with a learning ratio l ranging between 16.5 and 24.8 % (computed in manufacturing environments by Hirsch, 1956) it is clear that with an average frequency of 80% the equivalent routes number is 11 repetitions. On the other hand as reported in figure 3.5-c considering a frequency of 60% the daily optimization routing strategy gives better results independently of the learning effect. As a consequence, the fixed routing strategy in these conditions would not be competitive with the daily optimization routing strategy. Supported both by the methodology results and by company expert opinions, Company A reached the conclusion that a fixed routing strategy is not feasible in the present situation. To take advantage of each drivers learning, it is possible to explore the feasibility of a hybrid solution between the fixed and the daily optimization strategy: a routing optimization based on fixed routing area associated to the same driver, but with daily optimization routes inside each area.

### 3.3.6 OBSERVATIONS

In this paragraph deals with the problem of optimize the delivery distribution. It investigates the possibility to apply a fixed routing strategy instead of a daily routing optimization strategy, analysing the benefits derived from the driver familiarity with customers and surroundings, according to three decision variables:

1. (CV) the customer order variability, i.e. the variability in quantity of customer demand.

2. (FREQUENCY) the customer frequency, i.e. the frequency variability (yes/no) in customer demand.
3. (ST/TT) the ratio between delivery service time and delivery travel time; i.e. the ratio between the time spent in each point of the network by the drivers for the service operations and the time spent in travelling between the different points of the network.

Moreover in case of fixed routing strategy the learning effect on drivers for the service time has been simulated changing the parameter ST(L)/ST, that is the ratio between the service time with driver learning and the standard service time. At the end of the research a methodological framework has been proposed in order to assist managers in the selection of the best routing optimization strategy.

From the results obtained by a simulation study, the authors were able to demonstrate that:

1. In the studied range of variation, the factors that mostly influence the final results are those directly connected to service time: both ST/TT and ST(L)/ST have a relevant influence on the Tot-T/Max, while FREQUENCY has a middle influence and CV affects the Tot-T only slightly.
2. In all the scenarios illustrated, the low regularity of the customers demand influences more negatively the fixed routing strategy than the daily routing strategy.
3. The strategy of fixed routes can often be better than the daily optimized strategy and strongly depends on the parameters investigated in this work. For this reason it is important to identify the correct scenario according Figure 3.5. Generally speaking, the fixed routing strategy should be applied just in highly or moderately dense distribution networks with a high/medium regularity in customers' orders frequency and quantity. From these results it is evident that the fixed routing strategy can be used when the delivery service time has a high impact on the total driver working time, such as deliveries in crowd centers, with a high density of customers and traffic constraints, and generally speaking any time the driver learning is positively affected by the delivery task repetition.

4. The proposed methodological framework, derived by the parametrical analysis of normalized variables, represents, from an applicable research point of view, is a useful tool in routing strategy decision. The case study reported demonstrate the applicability of the proposed decision making tool in the routing strategy selection.

As highlighted in the paragraph, the learning parameters (learning slope, number of repetition) are often critical factors in making the fixed routing strategy competitive. On the other hand, there are only few examples in literature of the possible range of variations of such parameters in the logistics activities, while different results are available in manufacturing. As demonstrated in this paper, the possibility to obtain better performances by repeating many times the same activities is applicable also in logistics activities. Further research, starting from different case studies, should be conducted and should lead to give better explanation of the learning parameters in logistics.

## 3.4 GOODS DAILY DELIVERY: environmental impact minimization

This paragraph investigates the routing problem optimization from the environmental point of view. The research is based on the consideration that factors such as the traffic congestion and the consequently continuous vehicles stop and start influence negatively the $CO_2$ emissions. Then the study highlight how the drivers' familiarity with the served territory permits to choose alternative routes avoiding the traffic zone, reducing the greenhouse gas emission. The purpose is to point out that, in areas with high traffic constraints, the use of fixed route, or the allocation of a definite delivery zone to each driver, allows not only to optimize the daily distribution from an economical point of view, as previously demonstrated, but also from an environmental sustainable point of view. The present paragraph firstly describe the $CO_2$ estimation model and the relative sustainable routing problem formulation, then it illustrates the application of the model to an Italian case study, which aims to optimize the municipal distribution of fresh food products. The work developed in this part of the thesis has led to the publication of a journal article: *Faccio, M., Persona, A. , Zanin, G. (2012) "The Sustainable Routing Problem." International Journal of Operational Research (ACEPTED) (IN PRESS)*

### 3.4.1 CO2 ESTIMATION MODEL AND SUSTAINABLE ROUTING PROBLEM FORMULATION

The sustainable routing problem can be defined as follows.

For a considered geographical area in which the routing problem is set, it is possible to define:

- A series of nodes, i.e. a series of points that can represent customers, depots, or generally other specific locations.
- A series of arcs, i.e. ways to connect two different nodes; each street can be represented by an arc.
- A graph as the union of nodes and arcs that represent the whole geographical area.

So, given the graph $G = (N, A)$, where $N = \{1..n\}$ is the set of nodes and $A = \{(i, j) | i, j \in N, i \neq j\}$ is the set of arcs, each vehicle emits a certain amount of $CO_2$ when travelling over an arc $(i, j)$.

The proposed sustainable routing model is defined in Figure 3.9.

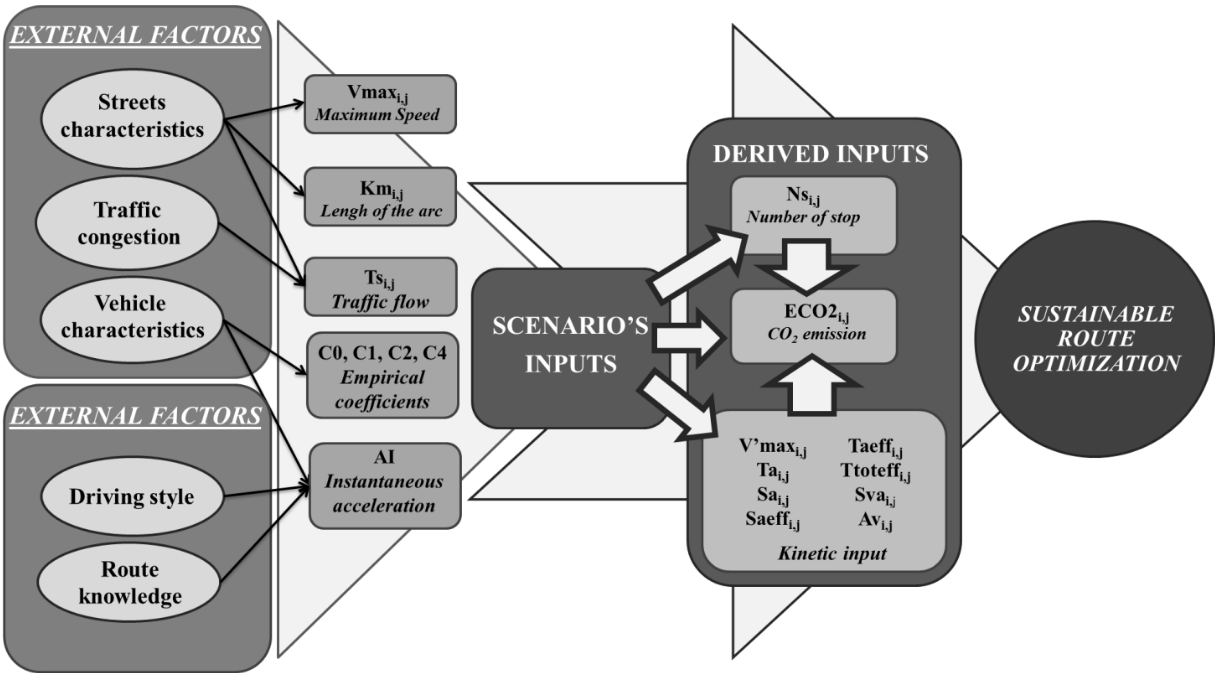



*Figure 3.9: Sustainable routing model*

A set of different factors influence the $CO_2$ emission. They can be divided, from the driver point of view, into:

- *Internal factors:* they depend on the driver, like the driving style and the route knowledge. These factors influence the instantaneous acceleration (i.e. high/low acceleration at each start and stop), and consequently the route average speed;
- *External factors:* i.e. not depending on the driver, like streets/vehicle characteristics, or traffic congestion level.

These factors define the inputs for the proposed model that, in the remainder of paper, are called "Scenario's Inputs". These are all the variables of the problem related to the internal/external factors, and are calculated as function of these factors as explained in the following part of this section. The "Scenario's Inputs" are:

- the length of the arc *(i, j)*, $km_{i,j}$,
- the maximum speed at which a vehicle can travel on the arc *(i, j)*, $Vmax_{i,j}$,
- the expected level of traffic congestion in each arch, $Ts_{i,j}$,
- the instantaneous acceleration, AI, related to the driving style (i.e. aggressive, normal, etc).

This part of the thesis suggests a $CO_2$ estimation model starting from Fonseca et al. (2011) study, which proposed a general mathematical expression to calculate the specific kilometre $CO_2$ emission:

$$e_{vco2} = C_0 + \frac{C_1}{S_{va}} + C_2 * A_v + C_3 * G + \frac{C}{t_s} + C_5 * T_E \tag{9}$$

Where:

- $C_0$, $C_1$, $C_2$, $C_3$, $C_4$ and $C_5$ are coefficients derived by the empirical test of the model. They depend on the vehicle characteristics;
- $S_{va}$ is the average speed, [km/h];
- $A_v$ is the average acceleration, [km/h/s];
- G is the road grade, [%];
- $T_E$ is the engine oil temperature, [°C];

As assumptions in the paper the engine oil temperature, $T_E$, is neglected, because it is assumed that the engine is always in temperature. Also the road grade, *G*, is left out, because Fonseca et al. (2011) study points out that this coefficient has lost more influence on the $CO_2$ emission than the others.

The basic idea of the proposed research is that using the Fonseca formulation for the $CO_2$ emission estimation, it is possible to calculate how $CO_2$ increase/decrease at the variance of the internal/external factors. In this way it will be possible to optimize the routing according the $CO_2$ minimization.

It is important to highlight how the proposed model is dynamical, i.e. at the change of the internal/external factors (i.e. traffic flow, driving style, etc.) it will be possible to re-define the optimum sustainable routing.

The following tables show the step-by-step description of the proposed sustainable routing model, defined using the pseudo code language. Pseudo code is a kind of structured English for describing algorithms that allows to focus on the logic and on the basic idea of the algorithm.

First of all, from the internal/external factors influencing the $CO_2$ emission are derived the scenario's inputs (Table 3.6). Then a point to point sustainable routing problem optimizations are considered. In this case the set of vertex to visit is only 2, *V={A, B}*.The problem aims to define the correct series of arcs to use in order to reach a certain point B starting from a certain point A minimizing the $CO_2$ emission.

| Scenario's Input | Description | Measure unit |
|---|---|---|
| $G$ | Graph: $G=(N,A)$ | |
| $N$ | Vertex set: $N = \{1..n\}$ | |
| $A$ | Arc set: $A = \{(i,j) \mid i,j \in N, i \neq j\}$ | [num.] |
| V | Set of vertexes that must be visited: V= $\{S1, S2, S3\}$ | [num.] |
| $X_{i,j}$ | Binary index equal to 1 if a vehicles can travel on arc *(i, j)* | [num.] |
| $Km_{i,j}$ | Length of the arc *(i, j)* | [km] |
| $Vmax_{i,j}$ | Maximum speed at which a vehicle can travel on the arc *(i, j)* | [km/h] |
| AI | Instantaneous acceleration | [km/h/s] |
| $Ts_{i,j}$ | Index that evaluates the traffic flow. Being 1 for streets with very low traffic flow and 0 for those with very high traffic flow (Fonseca et al., 2011) | [num.] |
| $C_0$, $C_1$, $C_2$, $C_4$ | Empirical coefficients to calculate the $CO_2$ emission (Fonseca et al., 2011) | [num.] |

*Table3.6: Scenario's input*

Starting from values of the “Scenario’s Input” a series of “Derived Inputs” are calculated (Table 3.7):

- Nsi,j, the number of estimated stop on each arc (i, j), related to the traffic flow. According with Smit et al. (2008), congestion can be associated with a number of interrelated and observable effects that include increased traffic density, increased travel times on the same route (hence lower average speeds), increased deviation from free-flow speeds (hence increased speed fluctuation and delays) and increased queuing (hence increased number of stops)

- V’maxi,j, the maximum speed at which a vehicle can travel, also related to the traffic flow. We assume that if the traffic flow is very high (Tsi,j $\leq$ 0.30) the maximum reachable speed is equal to half of the maximum speed allowed in the considered arc. It is in accordance with Smit et al. (2008).

From the “Scenario’s Input” and considering the number of stop for each arc (i, j) are also derived the kinetic values, like:

- the actual distance covered during the acceleration, Sai,j,
- the acceleration and travel time, Taeffi,j and Ttoteffi,j,
- the average speed and average acceleration, Svai,j and Avi,j.

Then, using the kinetic values in the expression proposed in Fonseca et al. (2011), eq. (1), it is calculated the quantity of $CO_2$ emitted in each arc (i, j), $ECO2_{i,j}$.

| **Derived Input** | | |
|---|---|---|
| $Ns_{i,j}$ | Number of stop on the arc *(i, j)* function of $Ts_{i,j}$ | [num.] |
| $V'max_{i,j}$ | Maximum speed at which a vehicle can travel on the arc *(i, j)* | [km/h] |
| $Ta_{i,j}$ | Acceleration time on the arc *(i, j)* | [s] |
| $Sa_{i,j}$ | Distance covered during the acceleration on the arc *(i, j)* | [km] |
| $Saeff_{i,j}$ | Actual distance covered during the acceleration on the arc *(i, j)* in order to consider the number of stop | [km] |
| $Taeff_{i,j}$ | Actual acceleration time on the arc *(i, j)* | [s] |
| $Ttoteff_{i,j}$ | Actual travel time of the arc *(i, j)* | [s] |
| $Sva_{i,j}$ | Average speed on the arc *(i, j)* | [km/h] |
| $Av_{i,j}$ | Average acceleration on the arc *(i, j)* | [km/h] |
| $ECO2_{i,j}$ | $CO_2$ emission on the arc *(i, j)* | [g] |

*Table 3.7: Derived input*

The $CO_2$ emission estimation is derived from the estimation of the number of stops of each arc as function of the traffic congestion level, and from the related estimation of the kinetic variables (Table 3.8).

| **$CO_2$ emission estimation** | |
|---|---|
| for $i$ = 1 to $n$<br>  for $j$ = 1 to $n$<br>    if $Ts_{i,j} \geq 0.9$ then $Ns_{i,j} \leftarrow (0^* Km_{i,j})$ or<br>    if $0.90 \leq Ts_{i,j} \leq 0.75$ then $Ns_{i,j} \leftarrow (1^*Km_{i,j})$ or<br>    if $0.75 \leq Ts_{i,j} \leq 0.60$ then $Ns_{i,j} \leftarrow (4^*Km_{i,j})$ or<br>    if $0.60 \leq Ts_{i,j} \leq 0.45$ then $Ns_{i,j} \leftarrow (8^*Km_{i,j})$ or<br>    if $0.45 \leq Ts_{i,j} \leq 0.30$ then $Ns_{i,j} \leftarrow (15^*Km_{i,j})$ or<br>    if $0.30 \leq Ts_{i,j} \leq 0.00$ then $Ns_{i,j} \leftarrow (20^*Km_{i,j})$<br>  end<br>end | Estimation of the number of stops of each arc *(i, j)* |
| for $i$ = 1 to $n$<br>  for $j$ = 1 to $n$<br>    if $Ts_{i,j} \leq 0.30$<br>      then $V'max_{i,j} \leftarrow (Vmax_{i,j}/2)$<br>      else $V'max_{i,j} \leftarrow (Vmax_{i,j})$<br>    endif<br>    $Ta_{i,j} \leftarrow (V'max_{i,j}/ AI)$;<br>    $Taeff_{i,j} \leftarrow (Ta_{i,j}{}^* Ns_{i,j})$;<br>    $Saeff_{i,j} \leftarrow ((V'max_{i,j}{}^* Ta_{i,j})/(3600^*2))$;<br>    $Ttoteff_{i,j} \leftarrow ((Taeff_{i,j} + ((Km_{i,j} - Saeff_{i,j})^*3600)/ V'max_{i,j})$;<br>    $Sva_{i,j} \leftarrow (Km_{i,j}{}^*3600/ Ttoteff_{i,j})$;<br>    $Av_{i,j} \leftarrow (AI^* Taeff_{i,j} / Ttoteff_{i,j})$;<br>  end<br>end | Estimation of the kinetic variables of each arc *(i, j)*.<br><br>It is presumed that if the traffic flow is very high ($Ts_{i,j} \leq 0.30$) the maximum reachable speed is equal to half of the maximum speed allowed in the considered arc. |
| for $i$ = 1 to $n$<br>  for $j$ = 1 to $n$<br>    $ECO2_{i,j} \leftarrow ((C_0 + (C_1/ Sva_{i,j}) + (C_2{}^* Av_{i,j}) + (C_4/ Ts_{i,j}))^* Km_{i,j})$;<br>  end<br>end | $ECO2_{i,j}$ estimation.<br>Based on the equation proposed in Fonseca et al., 2011 |

*Table 3.8: CO2 emissions estimation*

After that, the first route is generated. It starts from the point A, represented by the vertex 1, and stops on the point B, represented by the vertex *N*. The vertexes considered are random generated, and an arc *(i, j)* is associated to the route only if $X_{i,j}$ is equal to 1. Every time that a vertex is assigned to the route the indicators of $CO_2$ emitted, distance and time travelled are updated. At this point, the indicators of the best route are initialized with the first route's data. Then the other routes, temporary routes, are generated in the same way of the first one. The indicators of each temporary route are compared with the first route's indicators, and if they result better than the best route and its indicators are redefined (Table 3.9) as defined in the sustainable routing model reported in Table 3.10.

The model generates the routes, each one starts from the vertex 1 and stops only when all the vertexes in *V* are visited. It is important to highlight that is not defined the order in which the vertexes must be visited

| **Route's indicators** | | |
|---|---|---|
| count | Counter | [num.] |
| p | Counter | [num.] |
| RouteN | Number of route generated for the comparison | [num.] |
| OK1 | Check, if the vertex S1 is visited OK1 is equal to 1otherwise is equal to zero | [num.] |
| OK2 | Check, if the vertex S2 is visited OK1 is equal to 1otherwise is equal to zero | [num.] |
| OK3 | Check, if the vertex S3 is visited OK1 is equal to 1otherwise is equal to zero | [num.] |
| firsteroute | First route | [vector] |
| ECO2f | Indicator of $CO_2$ emission of the first route | [g] |
| DISTANCEf | Indicator of the distance travelled in the first route | [km] |
| TIMEf | Indicator of time travelled in the first route | [s] |
| routeminco2 | Route with min $CO_2$ emission | [vector] |
| routemindistance | Route with min distance travelled | [vector] |
| routemintime | Route with min time travelled | [vector] |
| minco2 | Indicator of $CO_2$ emission of the route routeminco2 | [g] |
| mindistance | Indicator of distance travelled in the route routemindistance | [km] |
| mintime | Indicator of travelled time in the route routemintime | [s] |
| temproute | Temporary route | [vector] |
| ECO2temp | Indicator of $CO_2$ emission of the temporary route | [g] |
| DISTANCEtemp | Indicator of distance travelled in the temporary route | [km] |
| TIMEtemp | Indicator of travelled time in the temporary route | [s] |

*Table 4: Routes indicators*

| **First route generation** | |
|---|---|
| $i$←1; $j$←1; p ←1; firsteroute(p) ← 1;<br>OK1←0; OK2←0; OK3←0;<br>ECO2f← 0; DISTANCEf← 0; TIMEf← 0; | Variables and indicators initialization. |
| while OK1=0 or OK2=0 or OK3=0<br>    p ← (p+1);<br>    while $X_{i,j}$ = 0 | The route starts from the vertex 1 and the next vertex, *j*, is random generated. |

| | |
|---|---|
| *j*← random number between 1 and n;<br>end<br>firsteroute(p) ← *j*;<br>ECO2f← (ECO2f+ $ECO2_{i,j}$);<br>DISTANCEf← (DISTANCEf + $Km_{i,j}$);<br>TIMEf← (TIMEf+ $Ttoteff_{i,j}$);<br>*i*← *j;*<br>if *i* = S1then OK1←1 or<br>if *i* = S2 then OK2←1 or<br>if *i* = S3 then OK3←1 or<br>end | In order to generate the route it is considered only the arc whit the index $X_{i,j}$ different to zero.<br>The route generation stops when all the vertexes S1, S2, S3 are visited. |
| routeminco2 ← firsteroute; minco2 ← ECO2f;<br>routemindistance ← firsteroute; mindistance ← DISTANCEf;<br>routemintime ← firsteroute; mintime← TIMEf; | Initialization of the indicators for the comparison of the routes |
| **Temporary route generation and comparison** | |
| count = 1;<br>while count < RouteN | Generation of RouteN temporary routes to compare with the first. |
| *i*←1; *j*←1; p ←1; temproute(p) ← 1;<br>OK1←0; OK2←0; OK3←0;<br>ECO2temp← 0; DISTANCEtemp← 0; TIMEtemp← 0; | Variables and indicators initialization. |
| while OK1=0 or OK2=0 or OK3=0<br>p ← (p+1);<br>while $X_{i,j} = 0$<br>*j*← random number between 1 and n;<br>end<br>temproute(p) ← *j*;<br>ECO2temp← (ECO2temp+ $ECO2_{i,j}$);<br>DISTANCEtemp← (DISTANCEtemp + $Km_{i,j}$);<br>TIMEtemp← TIMEtemp+ $Ttoteff_{i,j}$);<br>*i*← *j;*<br>if *i* = S1then OK1←1 or<br>if *i* = S2 then OK2←1 or<br>if *i* = S3 then OK3←1 or<br>end | Each route is created with the same method used for the first route |
| if ECO2temp < minco2<br>routeminco2 ← temproute;<br>minco2 ← ECO2temp;<br>end | For each temporary route is made a comparison between its $CO_2$ emission indicator and the indicator of the route with min |

| | |
|---|---|
| if DISTANCEtemp < mindistance<br>routemindistance ← temproute;<br>mindistance ← DISTANCEtemp;<br>end<br>if TIMEtemp < mintime<br>routemintime ← temproute;<br>mintime← TIMEtemp;<br>end<br>end | $CO_2$ emission. If the indicator of the temporary route results lower than the other the route with min $CO_2$ emission and its indicator are redefined.<br>The same comparison is made for defining the route with minimum distance and minimum travelled time. |

*Table 3.10: Routing Model*

In order to compare the solution of the proposed method with the solution of the classical method, which minimized the minimum time and distance travelled, the model generates the route with minimum $CO_2$ emission, the route with minimum distance travelled and the route with minimum travelled time, and their respective indicators. The comparison is illustrates in the following section, based on an Italian case study.

### 3.4.2 CASE STUDY

In this section the solution model proposed for the sustainable routing problem is applied in the optimization of municipal distribution of fresh food product in the centre of Vicenza, a city in the north east of Italy.

It has been assumed that the vehicle used is the same used in Fonseca et al., 2011, consequently it is possible to keep equal the empirical coefficients. The values of the coefficients C0, C1, C2 and C4 are respectively: 221.4, 1382.4, 46.9, 18.1.

In this applicative case is considered a graph with 20 vertexes. The representation of the graph G is showed in figure 3.10 where are indicated each one of the 20 nodes of the set N, and where the blue links between two nodes represent the possible usable arcs.

The routing problem is related to the distribution of products to 4 customers that lie in point 10, 15, 19 and 20 starting from point 1.

Case study graph

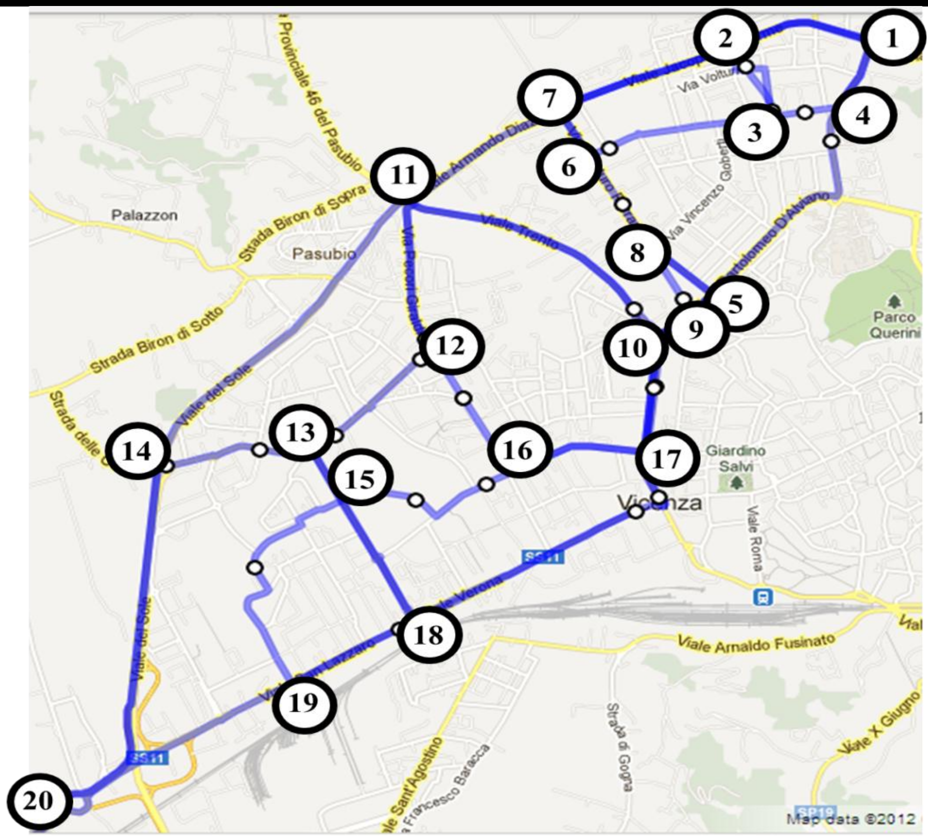



*Figure 3.10: Map of the centre of Vicenza*

Considering this graph the scenario's inputs are indicated in table 3.11, 3.12, 3.13 and 3.14. More in detail, table 3.11 represents Xi,j the Binary index equal to 1 if a vehicles can travel on arc *(i, j)*, table 3.12 shows $km_{i,j}$, the distance from each couple of vertexes of the graph *G* and table 3.13 and 3.14 indicate respectively the maximum speed at which a vehicle can travel on the arc *(i, j)*, $Vmax_{i,j}$, and the expected average level of traffic at each arc, $Ts_{i,j}$. These last data can be variable in function of the day time and it is assumed constant in first part of the analysis.

| $X_{i,j}$ | Binary index equal to 1 if a vehicles can travel on arc (i, j) | | | | | | | | | | | | | | | | | | | [num.] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Table 3.11: Scenario's input: $X_{i,j}$*

| $km_{i,j}$ | Length of the arc (i, j) | | | | | | | | | | | | | | | | | | | [km] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| 1 | 0 | 0.7 | 0 | 0.4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0.7 | 0 | 0.45 | 0 | 0 | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0.45 | 0 | 0 | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0.4 | 0 | 0.25 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 1.1 | 0 | 0 | 0 | 0 | 0.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0.8 | 0 | 0 | 0 | 0.25 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0.8 | 0 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0 | 0.7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0.3 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0.15 | 0 | 0 | 0.35 | 0 | 0.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.15 | 0 | 1.2 | 0 | 0 | 0 | 0 | 0 | 0.55 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0.7 | 0 | 0 | 1.2 | 0 | 0.65 | 0 | 1.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.65 | 0 | 0.7 | 0 | 0 | 0.5 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.7 | 0 | 0.6 | 0.3 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.5 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 | 1.4 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.9 | 0 | 0.65 | 1.2 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0 | 0.9 | 0 | 0.65 | 0 | 0 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.55 | 0 | 0 | 0 | 0 | 0 | 0.65 | 0 | 1.6 | 0 | 0 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.65 | 0 | 1.6 | 0 | 0.55 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.2 | 0 | 0 | 0.55 | 0 | 0.8 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.4 | 0 | 0 | 0 | 0 | 0.9 | 0 |

*Table 3.12: Scenario's input: $km_{i,j}$*

| $Vmax_{i,j}$ | Maximum speed at which a vehicle can travel on the arc (i, j) | [km/h] |
|---|---|---|

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 50 | 0 | 50 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 50 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 50 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 50 | 0 | 0 | 0 | 50 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 50 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 50 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 70 | 0 | 50 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 50 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 50 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 70 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 50 | 0 | 50 | 50 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 0 | 0 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 0 | 50 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 50 | 0 | 50 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 50 | 0 |

*Table 3.13: Scenario's input: $Vmax_{i,j}$*

| $Ts_{i,j}$ | Index that evaluates the traffic flow. Being 1 for streets with very low traffic flow and 0 for those with very high traffic flow (Fonseca et al., 2011) | [num.] |
|---|---|---|

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.6 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0.6 | 0 | 0.3 | 0 | 0 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0.3 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0.45 | 0 | 0.3 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0.3 | 0 | 0 | 0 | 0.3 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0.6 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0.3 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0.45 | 0 | 0 | 0.3 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.45 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0.45 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6 | 0 | 0 | 0.6 | 0 | 0.3 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0.3 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0.3 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.3 | 0 | 0.3 | 0.3 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.45 | 0 | 0 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.45 | 0 | 0.45 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.45 | 0 | 0.45 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.45 | 0 | 0 | 0 | 0 | 0.45 | 0 |

*Table 3.14: Scenario's input: Tsi,j*

Another important Scenario's input is the instant acceleration that depends on the driving style. Typically rapid acceleration results in significant increase in the emission (Larsson and Ericsson, 2009). In order to analyse this influence are considered three types of driving behaviours: calm driving, normal driving and aggressive driving. According to De Vlieger et al.,(2000) and Larsson and Ericsson (2009) these driving styles can be associated respectively to an instant acceleration of 2.4, 3.9 and 5.4 km/h/s. These values have been also used in the thesi.

The results of the case study are reported as follows:

- In order to make the application of the proposed routing model easier to understand, it is first analysed the point to point routing problem where V={1, 20} and the problem solution aims to define the correct series of arcs to use in order to connect the point 1 to the point 20.
- To make the proposed sustainable routing model benefits clearer, the results are compared with the classical routing objectives (distance minimization; time minimization)
- The problem is solved considering different driving styles: calm driving, normal driving and aggressive driving, changing the instant acceleration.
- Finally the same analysis has been developed for the routing problem related to the distribution of fresh food products to 4 customers that lie in point 10, 15, 19 and 20 starting from point 1.

*Point to points routing optimization*

The results for the point to point sustainable routing optimization are showed in table 3.15, where are indicated the total quantity of $CO_2$ emitted, the total distance and time travelled, for each driving behaviour considered and for each criteria used ($CO_2$ minimization, distance minimization and time minimization). Moreover, for each driving style is indicated the solution route given by the different criteria.

| Driving Style | Criteria | CO2 (Kg) | Distance (Km) | Time (sec) | CO2 [g] Increment | Distance [km] Increment | Time [s] Increment | ROUTE | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aggressive | Min CO2 | 2393.9 | 5.1 | 327.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Km | 2393.9 | 5.1 | 327.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Time | 2393.9 | 5.1 | 327.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| Normal | Min CO2 | 2385.2 | 5.1 | 330.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Km | 2385.2 | 5.1 | 330.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Time | 2385.2 | 5.1 | 330.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| Calm | Min CO2 | 2375.2 | 5.1 | 334.5 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Km | 2375.2 | 5.1 | 334.5 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | Min Time | 2375.2 | 5.1 | 334.5 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 |
| | | | | Min CO2 | 0.0% | 0.0% | 0.0% | | | | | | |
| | | | | Min Km | 0.0% | 0.0% | 0.0% | | | | | | |
| | | | | Min Time | 0.0% | 0.0% | 0.0% | | | | | | |

*Table 3.15: point to point routing solution for values of traffic flow as reported in Table 3.14*

From the results reported in table 3.15 it is possible to derive some important points:

- The $CO_2$ emission increases when the driving style is more aggressive
- For the values of traffic flows as in Table 3.14 the optimal sustainable point to point route (min $CO_2$) does not change when the driving style changes.
- In this condition the optimal sustainable point to point route is equal to the optimal route obtained with the criteria of distance minimization and time minimization.

These low relevance of the results is consequence of the simplicity of the problem (point to point routing).

On the other hand it is very interesting to see the influence of the traffic flow on the results.

Table 3.16 reports the results considering a uniform increase of traffic flow of 15%.

When the traffic flow increases ($Ts_{i,j}$ decreases), the sustainable routing solution given by the proposed model can be different from the routing solution obtained by the distance or time minimization.

This point is very interesting because it highlights how sustainable routing does not means distance minimization. From a routing point of view, as demonstrated from case study even in the simple point to point routing optimization, the distance minimization approach can be unable to really minimize the $CO_2$ emissions that are influenced by other important factors as showed also in figure 3.9. For this reason some logistic providers are nowadays developing important projects in managing these factors in order to achieve results in emissions reduction. For example TNT has developed a project, called "Innight Distribution" where TNT Express volumes are shifted from day to night, decreasing day-time congestion and allowing customers more time during the day to focus on core activities (www.tnt.com). But this approach can be often inapplicable in order to match customer requirements and to satisfy different kinds of constrains.

The following table reports the point to point solutions for the increasing of the traffic flow of 15%, i.e. a decreasing of $Ts_{i,j}$ of 15% (Table 3.16)

| Driving Style | Criteria | CO2 (Kg) | Distance (Km) | Time (sec) | CO2 [g] Increment | Distance [km] Increment | Time [s] Increment | ROUTE | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aggressive | Min CO2 | 3176.7 | 5.6 | 570.0 | 0.0% | 8.8% | 57.1% | 1 | 2 | 7 | 11 | 12 | 13 | 14 | 20 | | |
| | Min Km | 3215.6 | 5.1 | 362.7 | 1.2% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| | Min Time | 3215.6 | 5.1 | 362.7 | 1.2% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| Normal | Min CO2 | 3129.6 | 5.8 | 1138.9 | 0.0% | 12.7% | 208.9% | 1 | 4 | 3 | 6 | 7 | 11 | 12 | 13 | 14 | 20 |
| | Min Km | 3186.9 | 5.1 | 368.7 | 1.8% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| | Min Time | 3186.9 | 5.1 | 368.7 | 1.8% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| Calm | Min CO2 | 3154.2 | 5.1 | 375.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| | Min Km | 3154.2 | 5.1 | 375.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| | Min Time | 3154.2 | 5.1 | 375.9 | 0.0% | 0.0% | 0.0% | 1 | 2 | 7 | 11 | 14 | 20 | | | | |
| | | | | Min CO2 | 0.0% | 7.2% | 88.7% | | | | | | | | | | |
| | | | | Min Km | 1.0% | 0.0% | 0.0% | | | | | | | | | | |
| | | | | Min Time | 1.0% | 0.0% | 0.0% | | | | | | | | | | |

*Table 3.16: point to point routing solution for values of traffic flow in Table 3.14 increased of 15%*

Other results not reported in the thesis demonstrate how at the increasing of the traffic flow (also more than 15%) the trend in changing the optimal sustainable route versus the other solution (time or distance minimization) is maintained and the benefits in $CO_2$ emission reduction typically increase, especially in case of aggressive driving style. On the other hand according to other results, not reported in the thesis, that consider a decreasing of traffic flow ($Ts_{i,j}$ increases) the routing solution of the different optimization criteria is the same as Table 3.15.

Finally if traffic flow congestion indexes $Ts_{i,j}$ are casually generated, the optimal sustainable route versus the other solution (time or distance minimization) is completely different, and the possible $CO_2$ saving is typically very high, demonstrating how, in case of variable traffic flow congestion it is important to:

- have familiarity with the territory in order to know the alternative possible way or, otherwise, to Obtain instant traffic flow data using traffic sensors across the streets.

- Develop sustainable routing solutions according to specific routing models as the proposed one.

The point to point routing problem solution, as reported from the case study results, demonstrates that even for simple point to point routing problem:

- The $CO_2$ emission increases when the driving style is more aggressive and when the traffic flow increases.
- The optimum sustainable routing, even for point to point problem, changes in function of the traffic flow and of the driving style.
- When the driving style is calm, the routing solution is maintained the same, as Table 3.14, while changing when the driving style is normal or aggressive.
- The optimal sustainable routing solution can be different from the routing solution given by the classical routing objectives, even for simple routing problems (point to point), especially in function of traffic flow variation. For this reason it is very important to be able to have real time traffic flow data in order to better optimize the sustainable routes.

*N points routing optimization*

The results for the N point sustainable routing optimization are showed in Table 3.17, where are indicated for each driving behaviour considered the total quantity of $CO_2$ emitted, the total distance and time travelled, and the selected route. As reported in Table 3.17, in case of traffic condition defined in table 3.14, the optimal sustainable route is the same for different condition of driving style and it is equal to the solution obtained using as objective function the distance minimization or the time minimization. These results confirm the point to point result in case of traffic condition as Table 3.14.

On the other hand if an increasing of traffic condition is considered, the optimal solution of the three methods are different as reported in table 3.18, in which is considered a traffic flow increasing of 15%.

| Driving Style | Criteria | CO2 (Kg) | Distance (Km) | Time (sec) | CO2 [g] Increment | Distance [km] Increment | Time [s] Increment | ROUTE | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aggressive | Min CO2 | 3589.9 | 5.9 | 514.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Km | 3589.9 | 5.9 | 514.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Time | 3589.9 | 5.9 | 514.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| Normal | Min CO2 | 3564.9 | 5.9 | 522.3 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Km | 3564.9 | 5.9 | 522.3 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Time | 3564.9 | 5.9 | 522.3 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| Calm | Min CO2 | 3536.3 | 5.9 | 531.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Km | 3536.3 | 5.9 | 531.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | Min Time | 3536.3 | 5.9 | 531.6 | 0.0% | 0.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 |
| | | | | Min CO2 | 0.0% | 0.0% | 0.0% | | | | | | | | | | |
| | | | | Min Km | 0.0% | 0.0% | 0.0% | | | | | | | | | | |
| | | | | Min Time | 0.0% | 0.0% | 0.0% | | | | | | | | | | |

*Table 3.17: N points routing solution*

| Driving Style | Criteria | CO2 (Kg) | Distance (Km) | Time (sec) | CO2 [g] Increment | Distance [km] Increment | Time [s] Increment | ROUTE | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aggressive | Min CO2 | 3515.2 | 5.9 | 732.0 | 0.0% | 0.0% | 4.6% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Km | 3515.2 | 5.9 | 732.0 | 0.0% | 0.0% | 4.6% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Time | 5728.8 | 8.2 | 699.9 | 63.0% | 39.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 11 | 14 | 20 | 14 | 13 | 15 |
| Normal | Min CO2 | 3332.4 | 5.9 | 1137.2 | 0.0% | 0.0% | 32.8% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Km | 3332.4 | 5.9 | 1137.2 | 0.0% | 0.0% | 32.8% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Time | 5605.6 | 8.2 | 856.3 | 68.2% | 39.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 11 | 14 | 20 | 14 | 13 | 15 |
| Calm | Min CO2 | 3541.8 | 5.9 | 1969.1 | 0.0% | 0.0% | 68.4% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Km | 3541.8 | 5.9 | 1969.1 | 0.0% | 0.0% | 68.4% | 1 | 4 | 5 | 9 | 10 | 17 | 16 | 15 | 19 | 20 | |
| | Min Time | 5617.2 | 8.2 | 1168.9 | 58.6% | 39.0% | 0.0% | 1 | 4 | 5 | 9 | 10 | 11 | 14 | 20 | 14 | 13 | 15 |
| | | | | Min CO2 | 0.0% | 0.0% | 35.3% | | | | | | | | | | | |
| | | | | Min Km | 0.0% | 0.0% | 35.3% | | | | | | | | | | | |
| | | | | Min Time | 63.3% | 39.0% | 0.0% | | | | | | | | | | | |

*Table 3.18: N points routing solution for values of traffic flow in Table 3.14 increased of 15%*

The results confirm the point to point sustainable routing results in which in case of decrement of traffic flow the results obtained with the three criteria (Min CO2, Min Distance, Min Time) are the same, while the results are different in case of increment of traffic flow. If the increment of traffic flow is high (i.e. 30%) the CO2 emission reduction using the proposed sustainable routing criteria instead of the distance-time minimization criteria is very high. Normally this reduction is higher than the increment of time and distance given due to the use of the sustainable criteria instead of the other two. Table 3.19 reports the summary of the results considering the effect of an increment/decrement of $Ts_{i,j}$ respectively of 15 and 30 per cent compared to the values of the case zero.

| Ts | Criteria | CO2 [g] Increment | Distance [km] Increment | Time [s] Increment |
|---|---|---|---|---|
| +30% | Min CO2 | 0.0% | 0.0% | 0.0% |
| | Min Km | 0.0% | 0.0% | 0.0% |
| | Min Time | 0.0% | 0.0% | 0.0% |
| +15% | Min CO2 | 0.0% | 0.0% | 0.0% |
| | Min Km | 0.0% | 0.0% | 0.0% |
| | Min Time | 0.0% | 0.0% | 0.0% |
| 0% | Min CO2 | 0.0% | 0.0% | 0.0% |
| | Min Km | 0.0% | 0.0% | 0.0% |
| | Min Time | 0.0% | 0.0% | 0.0% |
| -15% | Min CO2 | 0.0% | 0.0% | 35.3% |
| | Min Km | 0.0% | 0.0% | 35.3% |
| | Min Time | 63.3% | 39.0% | 0.0% |
| -30% | Min CO2 | 0.0% | 5.6% | 133.7% |
| | Min Km | 1.6% | 0.0% | 159.3% |
| | Min Time | 67.5% | 103.4% | 0.0% |

*Table 3.19: N points summary results*

The N points routing problem solution, as reported from the case study results, demonstrates the general results of the point to point solution, and moreover:

- The $CO_2$ emission increases when the driving style is more aggressive, the traffic flow grows and in case of N points routing solution. It is possible to have an increment of the $CO_2$ emission saving when the number of points to reach increases (i.e. results comparison -15% $Ts_{i,j}$ point to point/N points).
- The optimum sustainable routing changes in function of the traffic flow and of the driving style, especially in case of complex problem with high number of points to cover.
- The optimal sustainable routing solution can be different from the routing solution given by the classical routing objectives (distance or time minimization). On the other hand the traffic flow is a very influencing factor in the sustainable routing model and the acquisition of real time traffic flow data could make the proposed model very suitable for urban routing problem.

### 3.4.3 OBSERVATIONS

The transportation sector produces the largest percentage of emissions from fossil fuel combustion by end use sector. On the other hand environmental, social, and political pressures to limit the impacts associated with $CO_2$ emissions are mounting rapidly. This part of the research addresses to the solution of a new class of routing problem: the sustainable routing problem, where the objective differently from the classical approaches is the $CO_2$ emission minimization.

A set of different factors influence the $CO_2$ emission. They can be divided, from the driver point of view, into internal/external factors:

- internal factors, which are related to the driver, like driving style and the route knowledge. These factors influence the instantaneous acceleration (i.e. high/low acceleration at each start and stop), and consequently the route average speed;
- external factors, i.e. not depending on the driver, like streets/vehicle characteristics, or traffic congestion level.

The basic idea of the proposed study is that using the Fonseca formulation for the $CO_2$ estimation, it is possible to calculate the $CO_2$ increase/decrease at the variance of the internal/external factors . In this way it will be possible to optimize the routing according the $CO_2$ minimization.

Firstly the research, starting from the of Fonseca et al. (2011) study, proposes an $CO_2$ emission estimation as function of the different internal/external factors. Secondly, it is formalized a sustainable routing model, validating it through a case study and through a parametrical analysis comparing the proposed approach with the classical routing criteria of distance or time minimization.

The main obtained results are:

- Sustainable routing does not mean distance minimization (or distance minimization does not mean $CO_2$ minimization). As demonstrated from case study even in the simple point to point routing optimization, the distance minimization approach can be unable to really minimize the $CO_2$ emissions that are influenced by other important factors (figure 3.6).
- The $CO_2$ emission increases when the driving style is more aggressive and when the traffic flow increases and the optimum sustainable routing changes in function of the traffic flow and of the driving style. These results are valid even for simple routing problem solution (i.e. point to point) and become more evident with complex routing problem (N points).

- The optimal sustainable routing solution can be different from the routing solution given by the classical routing objectives, even for simple routing problems (point to point), especially in function of traffic flow variation. In case of low traffic flow the sustainable routing solution is in accordance with the solutions obtained with the other methodologies, while it is very different when the traffic flow is high. In this situation the possible CO2 saving obtainable with the proposed model is typically very high.
- For this reason the driver familiarity with the territory results in an important element to support this new approach, giving to the driver the knowledge of the street and the level of traffic congestion on different day time, that allow him/her to choose carefully a different route.
- Moreover, it can be helpful the possibility to have real time traffic flow data, using for example traffic sensors along the streets, in order to better optimize the sustainable routes. The proposed sustainable routing model is dynamical, i.e. at the change of the internal/external factors (i.e. traffic flow, driving style, etc.) it will be possible to re-define the optimum sustainable routing.

As conclusion of the research on the distribution optimization it is possible to said that the drivers' familiarity with the served territory allows, not only to reduce the service time at each customers, by the drivers learning, but results also an important element to support the new approach proposed with the aims to reduce the greenhouse emission, since, in case of high traffic congestion, the driver must change the routes based only on his/her knowledge of the streets.

## 3.5 WASTE COLLECTION

The present paragraph deal with the waste collection, since it is a highly visible municipal service that involves large expenditures and difficult operational problems. It is expensive to operate in terms of both:

- investment and operational costs, related to the purchase and maintenance of the vehicles fleet, the fuel consumption and so on, and

- environmental costs, consequents of the greenhouse emission, the vehicle noise and the traffic congestions.

This part of the thesis introduce an efficient and innovative waste collection routing model integrated with modern traceability devices, that permit to obtain data in real time, like volumetric sensors, identification RFID (Radio Frequency Identification) systems, GPRS (General Packet Radio Service) and GPS (Global Positioning System) technology.

The basic idea is that knowing the real time data of each vehicle and the real time replenishment level at each bin makes it possible to decide, in function of the waste generation pattern, what bin should be emptied and what should not, optimizing different aspects like the total covered distance, the necessary number of vehicles and the environmental impact.

First of all, the next section describes a framework about the traceability technology available in the optimization of solid waste collection and shows an application in a case study, which considers an Italian city of about 100,000 inhabitants. It also presents the software application developed in order to obtain and manage real time data used as inputs for the proposed routing model. Later, it is introduce the heuristics model for waste collection, that is validated through the simulation of the results and comparing the new approach with other classical routing models in function of different patterns of waste generation. Moreover, it is identified the optimal set of parameters necessary for the proposed routing model, such as the optimal bin replenishment level, which is the parameter that defines if a bin has to be emptied or not. Finally it is analyzed the economical feasibility of the real time traceability routing model in terms of costs/benefits versus the classical waste collection model, considering different scenario. Also the work developed in this part of the thesis has led to the publication of a journal article: *Faccio, M., Persona, A. , Zanin, G. (2011) "Waste collection multi objective model with real time traceability data." Waste Management, Vol. 31 (12), pp. 2391-2405.*

### 3.5.1 WASTE COLLECTION FRAMEWORK

The present section proposes a framework, that is illustrated in figure 3.11, for the solution of the municipality solid waste collection optimization problem. In this work it is considered a single depot, a fleet of vehicles with variable size and a set of bins that must be emptied if it is necessary. The inputs data can be classified in two main, types static inputs and real time traceability data inputs, which can be described as follows:

- The *static inputs* regard the information about both bins and vehicles types. In addiction for each bin is define its positions, maximum volume capacity and the type of waste stored. On the contrary, for each vehicles is identified its maximum weight capacity.
- The *real time traceability data inputs* are received by the traceability technology devices installed and indicate the effective replenishment of bins and vehicles, the visited bins and the vehicles position.

By processing all these information through the proposed heuristic routing optimization model is possible to obtain the optimal route for each vehicle in order to reduce the number of bin to service, minimize the distance covered by the fleet, the number of vehicles used and the collection time. Every time a vehicle empties a bin the input data are reprocessed at the operations center, both static and real time inputs are updated, defining the new optimal route for each vehicle, and the real time traceability data routing model starts again (figure 3.11).

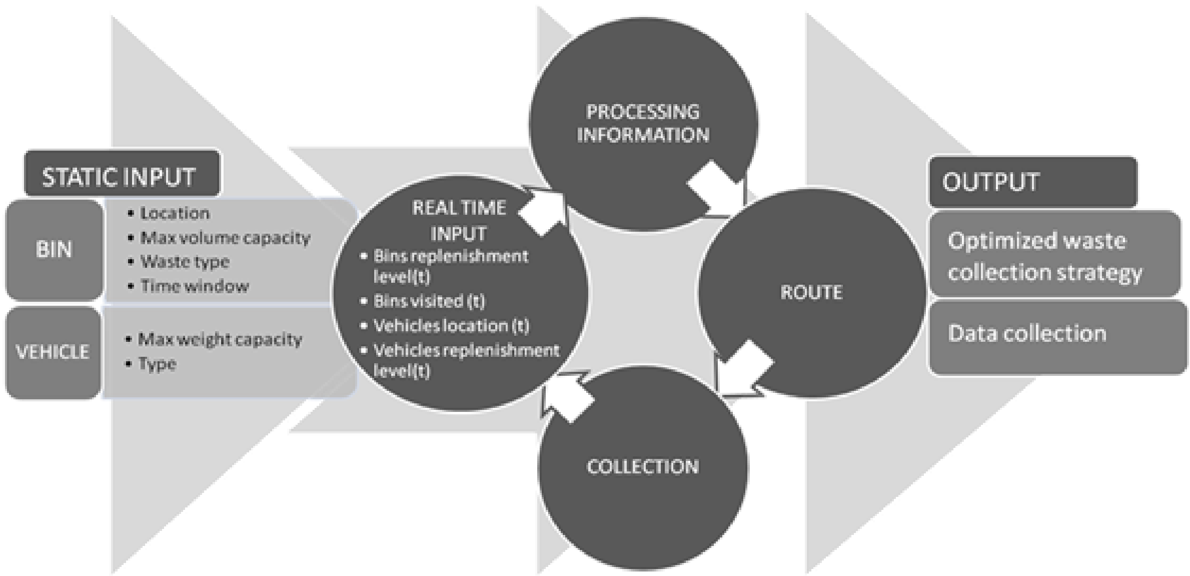



*Figure 3.11: Real time traceability data routing model for waste collection*

The traceability system necessary for real time input is based on three fundamental levels, each one connected to other as indicated in figure 3.12:

- Bins
- Vehicles
- Operations center

The considered vehicle types are self-compactors, and for this reason it is assumed that they saturate their capacity in weight not in volume, while in general, bins saturate their capacity in volume. In the proposed approach bins periodically communicate to the operations center their waste replenishment level in term of volume. Moreover, every time a vehicle empties one bin, the bin communicates to the vehicle its identification number and its waste type. Usually, at bin level, the traceability devices can be fed with solar energy rechargeable battery. As regards vehicles, the operations center know in real time their position, and, at each bin serviced, the vehicle communicates to the operations center the weight of loaded waste, the bin identification and the remaining available weight capacity of itself. The vehicle, subsequently, receives information from the operations center about the next bins to visit according to the proposed routing model.

The real time traceability data inputs need the application of different traceability devices, like volumetric sensors, RFID, GPRS and GPS. If GPS and GPRS technology are nowadays largely available used and diffuse, even in the day by day life (cell phones, satellite navigator, etc), RFID devices are not as popular or as user-friendly. In the past few years, many applications in industrial and logistic environments have been developed using RFID technology (Battini et al., 2009), where is not possible a line of sight with the object, which is required for using the common automatic identification devices, like bar codes, magnetic strips, microprocessor papers and biometric systems. These systems, as convenient as they might seems in some instances, actually present a fairly limited range of possible applications. Analyzing for example the bar codes, it offer a limited amount of data stored, little flexibility of stored data due to the impossibility of re-writing, the incapacity of reading more codes simultaneously, degradation of the identification systems, need for a very precise range reading, and reading difficulties due to dirt and damage to look of the code. RFID technology aims at avoiding these problems by using the electromagnetic field between the tag that is applied to the object and the antenna. This electromagnetic field allows automatic data capture, unique for each object, and, if needed, it allows an automatic insertion of these data into several software and databases, using a middleware system able to compute and filter the identification code and the data stored in the tags. In a nutshell, it allows the automatic acquisition of identification data without a line of sight with the object and the automatic insertion of the data in the tags.

The reliability of this technology is relative to the reliability of the tags themselves and the reader antenna device: in normal conditions the tag reliability is approximately equal to 100%, especially if using passive tags (composed by principally a spire covered by plastic material), while the reader device is protected. According to Battini et al. (2009) to achieve a successful application of the RFID technology, the main variables to keep into account in the preliminary study of RFID project are: project variables (PVs) and project conditions (PCs). PVs represent different aspects of the technology and they are related to the main decisions faced by the project manager during the technical–economic evaluation of the RFID project. PCs take into consideration the different operating aspects where the RFID system will be implemented.

The PVs variables and their definition in this waste collection project are:

- *Tag type*: the tag is used at the bin level for its identification. Due to its use it is recommended a rugged passive tag in order to increase reliability, to reduce the need of energy at the bin level, to survive extreme environmental conditions of humidity and temperature, and in order to overcome difficulties due to dirt and damage.
- *Reader type*: a middle frequency RFID antenna is positioned on the vehicle's container hooking (13,56 MHz), so that the distance between devices is less that 1 meter.
- *Middleware-software* and *system integration*: the RFID system is interfaced with the other devices through systems of data interchange and with the operations center traceability software application.

The PCs variables and their definition in this waste collection project are:

- *Environmental conditions*: in the application, the environmental variables that can influence the results are related to humidity and temperature levels, that can be easily managed using rugged passive tags protected by plastic materials. In this application the interference created by magnetic fields is unusual and the short reading distance between antenna and tag prevents disturbance due to metal objects in the vicinity of the tag.

- *Operating conditions*: the reading range is short and the amount of storing data and concurrent reading is low.

Looking at PVs and PCs variables the proposed RFID solution appears reliable and robust respect the working conditions.

Summarizing the three traceability levels are composed, by (figure 3.12):

*Bin level:*

- A programmable microprocessor (MPU) that is the heart of the system at bin level. It manages the detective measures inside the bin (such as volume, time).
- A volumetric ultrasonic detection sensor connected to the microprocessor for the periodic volume measure.
- A rugged passive RFID tag for the bin identification.
- A GPRS data service technology ensures data exchange with the other levels of the system.

*Vehicle level:*

- A GPS system can determine the real time location of each vehicle.
- A GPRS data service technology ensures data exchange with other levels of the system.
- The vehicle traceability software application, installed in a mobile laptop, allows the driver to know the next bin to service, according to the proposed routing model.
- An RFID antenna positioned on the container hooking rack for the bin identification.
- A weighing system, consisting of two units installed at the ends of the bin lifting arm, allows to weight the loaded waste in order to define the instantaneous available capacity of the vehicle.

*Operations center level:*

- A GPRS data service technology ensures data exchange with the other levels of the system.
- The operations center traceability software application permits to collect and illustrate all real time data from the different levels of the traceability system, and to process them in order to define the optimal routing according to the proposed model.

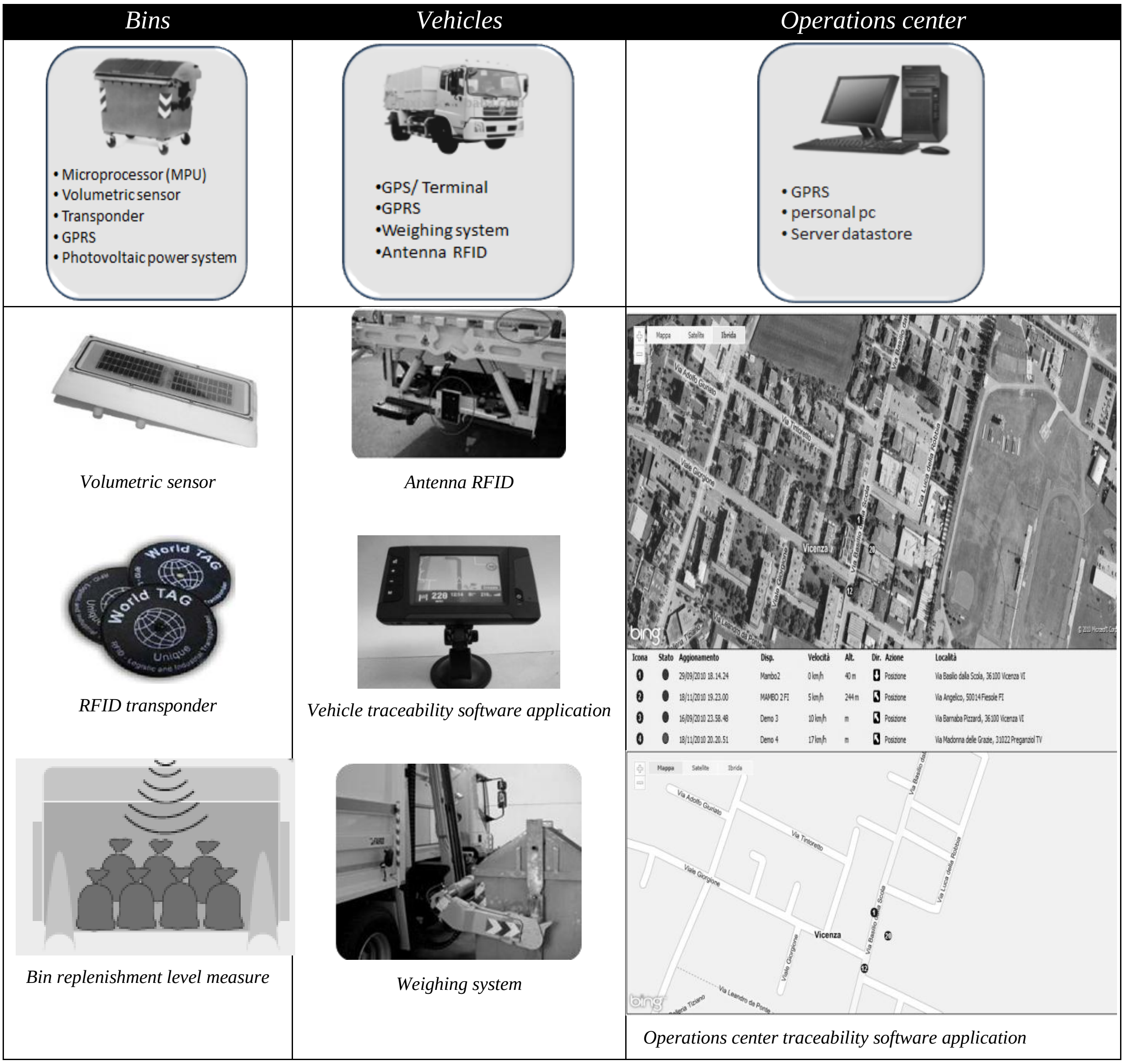



Figure 3.12: Traceability technology framework

### 3.5.2 REAL TIME TRACEABILITY DATA ROUTING MODEL

This section shows the heuristic model for routing optimization. The objectives of the routing model are multiple:

- To minimize number of vehicles per fleet.
- To minimize travel time.
- To minimize total distance covered.

These three objectives are achieved according to the basic idea of the proposed routing model: if it is possible to reduce the number of serviced bins, then it becomes possible to minimize the number of vehicles needed to serve an area, the distance covered and the travel time. As a direct effects it is possible to reduce environmental impact of emissions, noise and traffic congestion.

In order to apply these criteria is important to consider the following data:

- The *static* and *real time traceability data inputs*.
- The *oversize risk parameter, OR [%]*. It indicates is the risk to exceed bin capacity, and it depends, on the number of users, on a management decision about the admitted maximum % of bins that are allowed to exceed their capacity, respect the total number of bins. Obviously the oversize risk needs to be kept low and close to 0 in order to preserve the integrity and safety of the city, but in case of very variable patterns of waste creation, this parameter is an indication that the bin needs to be visited with high frequency. As reported in the simulation analysis section the definition of the oversize risk parameter, OR [%] is a critical aspects related to the pattern of waste creation at the bin.
- The *optimal replenishment level parameter, RL [%]*.It represents the minimum level of filled that the bins must reach before it is eligible to be emptied. This parameter is, like the OR [%] parameter, another management decision, that directly influences the costs of waste collection. As reported in the simulation analysis section the definition of the optimal replenishment level parameter, RL [%], is a critical aspects, related to the decision of the oversize risk parameter, OR [%], and on the pattern of waste creation at the bin. As highlighted in the next section it is possible to optimize the RL [%] in order to minimize the total costs for

waste collection once OR [%] is defined according to the pattern of waste creation at the bin.

The *oversize risk parameter* has to be a fixed parameter, because waste generation at each bin is typically a stochastic variable, and the risk of oversize bin capacity has to be considered.

An important consideration is that the three parameters defined are inter-dependent. The proposed model allows, using stochastic input based on historical data, to analyse the parameters relations and to define the value of oversize risk and optimal replenishment level that allow to achieve the expected benefits and results.

The proposed heuristics consists of two main steps (table 3.21):

1. To define which bins must be serviced. Only the bins that reach the imposed minimum replenishment level are visited. This information depends on the real time traceability data acquired and on the optimal replenishment level parameter.
2. Once defined which bins have to be emptied each vehicle route is optimized according to the real time traceability data (figure 3.11).

Moreover the following main constraints are considered:

Vehicles constraints:

1. The *capacity constraint*: when a vehicle is full, it needs to return to the depot to be emptied. Typically this parameter is fixed in weight. The weight of each unloaded bin is given by the traceability devices installed in the vehicle.
2. The *distance constraint*: each vehicle can, and typically does, make multiple disposal trips per day. When the vehicle reached the maximum daily distance covered, another vehicle will take over. For the waste collection problem this kind of constrain is overcome by the start and finish time constrain.
3. The *time windows constraint*: the vehicles can leave the depot only after the imposed "start time" and they must return to the depot within the set "finish time". In this study, due to the small number of vehicles considered (4- 5 vehicles), it is implied that all the vehicles leave the depot at the same time without queuing

problems. In case of a large number of vehicles the queuing problem at the depot has to be considered and managed (Wilson et al. 2002).

4. The *time constraint*: in terms of average speed and unload time for each bin.

Bins constraints:

5. The *capacity constraint*: a bin has a limited capacity. Typically this parameter is fixed in volume, so the replenishment level of each bin is given by the traceability devices installed in the bin itself. The admitted maximum number of bins that can exceed this limit is given by the OR parameter.

6. The geographical position of each bin, the location of the depot and the distance between each other.

Boundary conditions:

7. The *initial waste level at each bin*: it depends on the waste quantity generation pattern at each bin. If a bin is not serviced in period 0, in the second waste collection mission at period 1 its replenishment level will be the sum of the waste generation at instant 0 and at instant 1. The waste generation quantity at each considered periods depends on the waste generation pattern of the considered bin, an information provided by the real time traceability data device.

8. The *ratio weight/volume for the collected waste*, due the different saturation parameter at bins (volume) and self-compactors vehicles (weight) is directly given by the real time traceability data.

Finally, the model assumes an operational area composed by a set of bins that must be emptied, a single depot, that is also the landfill, and an homogeneous vehicles fleet. Vehicles start and finish each route at the depot.

Table 3.20 introduces the notation used in the model such as temporary variables, inputs, composed by static inputs and real time traceability data inputs, and outputs of the model.

Table 3.21 shows a step-by-step description of the proposed routing model, defined using the pseudocode language. Pseudocode is a kind of structured English for describing algorithms that allows to focus on the logic and on the basic idea of the algorithm.

| Temporary variables | Description | Measure Unit |
|---|---|---|
| ***I*** | ID number. *I*=1,..,*n* identifies the actual bin serviced by the vehicle, while *I*=0 indicate that the vehicle is at the depot | [num.] |
| ***J*** | ID number. *J*=1,..,*n* identifies the possible next bin to be serviced by the vehicle, while *I*=0 indicate that the next possible stop of the vehicle is at the depot | [num.] |
| ***K*** | ID number of the vehicle, *K*=1,..,*n_vehicles* | [num.] |
| ***p*** | Mission. It defines the sequence of trips for a considered vehicle | [num.] |
| ***travel_time(I,J)*** | Travel time from *I* to *J* | [h] |
| ***time*** | Time variable | [h] |
| ***q_vehicle(K)*** | Replenishment level of the vehicle k | [kg] |
| ***qw(J)*** | Weight of waste inside the bin *J* , with *J*=1,..,*n* | [kg] |
| ***qv (I)*** | Volume of waste inside the bin I, with *I*=1,..,*n* | [liters] |
| ***not_visited*** | Counter: number of bins not serviced | [num.] |
| ***exceed_capacity*** | Counter: number of bins that exceed their capacity | [num.] |
| ***ok*** | Cycle Control binary variable (for the while cycle) | |
| **Static inputs** | **Description** | |
| ***n*** | Number of bins | [num.] |
| ***x(I) and y(I)*** | Position of each bin, *I*=1,..,*n* | (x, y) |
| ***x(0) and y(0)*** | Position of the depot | (x, y) |
| ***unload_time*** | Fixed time to unload a bin | [h] |
| ***vehicle_speed*** | Average vehicle speed | [km/h] |
| ***start_time (I)*** | Time windows: start time imposed equal for bin *I* | [h] |
| ***finish_time (I)*** | Time windows: finish time imposed equal for bin *I* | [h] |
| ***OR*** | Oversize risk: maximum number of bins that can exceed their capacity | [%] |
| ***INIT_RL*** | Initial value of the replenishment level of the bin to be serviceable | [%] |
| ***maxd_ vehicle*** | Maximum distance to be traveled per vehicle per day | [km] |
| ***maxq_vehicle*** | Maximum weight capacity of the vehicle | [kg] |
| ***maxq_bin*** | Maximum volume capacity of the bin | [liters] |
| ***distance(I,J)*** | Distance from *I* to *J* | [km] |
| **Real time traceability data inputs** | **Description** | |
| ***qv0(I)*** | Volume of waste generated at period 0 inside the bin *I* | [liters] |
| ***qv1(I)*** | Volume of waste generated at period 1 inside the bin *I* | [liters] |
| ***ratio_weight_ volume*** | Average ratio weight/volume | [kg/ liters] |
| ***ac_time*** | Actual time | [h] |
| ***visited(I)*** | Binary value, it is equal to 1 if the bin I has already been visited, zero otherwise. *I*=1,..,*n* | |
| ***k_vehicle*** | ID number of the vehicle | [num.] |
| ***n_vehicles_in*** | Number of vehicles already in use = max(*K_vehicle*) | [num.] |
| ***posiz*** | ID number of the position of the considered vehicle. It corresponds to the position of the last visited bin by the considered vehicle | [num.] |
| ***q_vet(K)*** | Actual replenishment of the vehicle *K* | [kg] |
| ***L_not(K)*** | Distance already traveled by the vehicle *K* | [km] |
| **Outputs** | **Description** | |
| ***n _vehicles*** | Number of planned vehicles in order to complete the collection in the | [num.] |

| | | |
|---|---|---|
| | considered period | |
| ***L(K)*** | Planned distance traveled by the vehicle *K* | [km] |
| ***rout(K,p)*** | Planned bin to service by the vehicle *K* in the mission *p* | |
| ***bin_not_to_vis(I)*** | List of the planned bin not to be emptied | |
| ***tot_dist*** | Planned total covered distance as sum of the distance covered by each vehicle | [km] |
| ***bin_time(I)*** | Planned collection time for the bin located in *I* | [h] |
| ***Tot_q*** | Total quantity of generated waste | [liters] |
| ***RL*** | Optimal replenishment level parameter | [%] |

*Table 3.20: Notations, inputs and outputs of the routing model*

| Pseudocode | Description |
|---|---|
| **STEP 1:** *Defines which bins must be visited.* | |
| RL= INIT_RL; travel_time (I,J)=distance(I,J)/vehicle_speed; ok=0; tot_dist=0; not_visited=0; exceed_capacity=0; | *Bin variables initialization* |
| ***while*** ok =0 | |
| ***for* I=1 to n** | *For each bin* |
| ***if*** qv0(I) > (maxq_bin * RL ) | *Verify if the bin reach RL* |
| qv0(I)=0; | *If so, the bin is emptied* |
| ***end if*** | |
| qv(I)= qv0(I)+qv1(I); | *Acquisition of the initial waste level at each bin* |
| ***if*** qv(I) < (maxq_bin *RL) | *Verify if the bin does not reach RL* |
| not_visited= not_visited+1; bin_not_to_vis(I)=1; | *If so, the bin is identified and the relative counter is increased* |
| ***else if*** qv(I)> maxq_bin | *Verify if the bin overtakes its capacity* |
| exceed_capacity=exceed_capacity+1; | *If so, is the counter of the bins that exceed their capacity is increased* |
| ***end if***<br>***end for*** | |
| ***if*** exceed_capacity > OR*n | *Verify if the counter of the bins that exceed their capacity does not respect the OR parameter* |
| RL = RL - (0.01); | *If so, RL is decreased of 1%* |
| ***else*** | |
| ok=1 ; | *Else the cycle can finish* |
| ***end if***<br>***end while*** | |
| **STEP 2:** *Vehicle routing optimization.* | |
| I = posiz; n_vehicles=0; K=0; Tot_q=0 | *Vehicle variables initialization* |
| ***if*** I = 0 | *Verify if the considered position is the depot* |
| n_vehicles= n_vehicles+1; K=K+1; time=start_time; L(K)=0; q_vehicle(K)=0; p=1; | *Is so, the vehicle variables is update* |
| ***else*** | |
| Time= ac_time; K= k_vehicle; L(K) = L_not(K) ; n_vehicles= n_vehicles_in ; q_vehicle(K)=q_vet(K); p=1; | *Else the vehicle variables are acquired using the real time traceability input data* |
| ***end if*** | |
| rout (K,p)=I | *Route annotation* |
| ***for I=1:n*** | |
| qw(I)=qv(I)* ratio_ weight_ volume;<br>Tot_q=Tot_q+qv(I); | *Vehicle acquisition of the waste weight at the bin I.*<br>*Total quantity of generated waste acquisition.* |
| ***end for*** | |
| ***while* all(visited(I)+ bin_not_to_vis(I)) < > 1** | |
| J= ID number of the bin with less distance from I | *Found of the nearest neighbor* |

| | |
|---|---|
| ***if*** (L(K)+distance(I,J)+distance(J,0)> maxd_ vehicle) *or* (time + travel_time(I,J) + unload_time +travel_time (J,0)>finish_time) | *Verify if the distance and time windows constraints not respected* |
| ***if*** I < >0 | *If so, verify if the actual position is different from the depot* |
| L(K) = L(K) + distance(I,0); Time= time+ travel_time(I,0); I = 0; p=p+1; rout (K,p)=I | *If so, vehicle K must returns to the depot and the variables are updated* |
| ***end if*** | |
| tot_dist=tot_dist+L(K); return to the vehicle initialization; | *Total distance annotation* |
| ***else*** | |
| ***if*** q_vehicle(K) + qw(J) <= maxq_vehicle | *Verify if the vehicle capacity constraint is respected* |
| p=p+1; L(K) =L(K) + distance(I, J); q_vehicle(K)= q_vehicle(K) + qw(J) time= time+ travel_time(I, J)+ unload_time; I =J; visited(I) = 1; rout(K,p)=I; bin_time(I)= time; | *If so, vehicle K must goes to visit the bin J and the variables are updated* |
| ***else*** | |
| L(K) = L(K) + distance(I,0); time= time+ travel_time(I,0); p=p+1; I =0; rout(K,p)=I ; q_vehicle(K)=0 | *Else the vehicle K must return to the depot and the variables are updated* |
| ***end if*** ***end if*** ***end while*** | |
| ***if*** I < > 0 | *Verify if the vehicle is not at the depot* |
| L(K) = L(K) + distance(I,0); time= time+ travel_time(I,0); I =0; p=p+1; rout(K,p)=I ; | *If so, the vehicle K must return to the depot and the variables are updated* |
| ***end if*** | |

*Table 3.21: Heuristic waste collection routing model with real time traceability data*

### 3.5.3 SIMULATIVE ANALYSIS

This section presents a simulative analysis. The waste generation input data, given by the real time traceability devices is a stochastic variable. From the historical data obtained in an applicative case in north eastern Italy the normal distribution optimally fits the quantity of waste generated at each bin. So these results are validated in case of normal distribution, in other cases the results could be altered.

The two parameters of the normal distribution for waste generation at each bin are:

- *WAL, waste average level*, as the % of the replenishment level of the bin [%]
- *SD/WAL*, as the ratio between the standard deviation and the average level waste inside the bin [%]

They have been changed from an initial average value obtained by the historical data with the objective of:

1. To compare the classical vehicle routing models versus the propose heuristics in function of the oversize risk parameter, OR [%], in order to validate the proposed approach.
2. To define the optimal replenishment level parameter, RL [%], i.e. the minimum bin replenishment level for waste collection. Parameter that defines if a bin has to be emptied or not, in function of the oversize risk OR and of the pattern of waste generation with a normal distribution with average value WAL and standard deviation SD.

The fixed input data are derived from an applicative case relative to a city, in north eastern Italy, with more than 100,000 inhabitants with a twice/ weekly waste collection as illustrated in table 3.22.

| **Bins characteristics** | | |
|---|---|---|
| ***n*** | Number of bins [num.] | 200 |
| ***x(I) and y(I)*** | Geographical coordinates of each bin | (x; y) |
| ***maxq_bin*** | Max volume capacity of the bin [liters] | 1100 |
| Vehicles characteristics | | |
| ***maxd_ vehicle*** | Maximum distance that can be traveled per vehicle per day [km] | 400 |
| ***maxq_vehicle*** | Maximum weight capacity of the vehicle [kg] | 12625 |
| ***unload_time*** | Duration of bin unload [h] | 0.05 |
| ***vehicle_speed*** | Average vehicle speed [km/h] | 40 |
| ***INIT_RL*** | Initial value bins replenishment level for waste collection [%] | 100% |
| ***start_time*** | Start time imposed [time] | 5 a.m. |
| ***finish_time*** | Finish time imposed [time] | 8 a.m. |
| Network characteristics | | |
| ***x(0) and y(0)*** | Position of the depot | (x; y) |
| ***distance(I,J)*** | Min. distance between two location [km] | 0.04 |
| ***distance(I,J)*** | Max. distance between two location [km] | 12.56 |
| ***ratio_weight_ volume*** | Average ratio weight/volume [kg/liters] | 0.8 |

*Table 3.22: Fixed inputs, waste collection problem characteristics*

*Routing models benchmark and proposed approach validation*

The objective of this section is to validate the proposed approach for waste collection, through a simulation and a routing model benchmark. The simulation is made using Matlab software package (www.mathworks.com). Table 3.23 summarizes the range of variation for the input data in the simulation (WAL, SD/WAL, OR, RL) considering the waste generation at each bin as stochastic variable with average value WAL and standard deviation SD. The range of variation has been fixed looking at historical data of the applicative case.

| Variable inputs | Percent values | Values |
|---|---|---|
| **OR [%]** | 5-10-15% | 10-20-30 [num. bins] |
| **WAL [%]** | 40-55-70% | 440-605-770 [liters] |
| **SD/WAL [%]** | 20% | 88-121-154 [liters] |

*Table 3.23: Range of variation of the inputs for routing models benchmark*

The analysis compares different models and whether to adopt or not real time traceability data as inputs and whether or not they respect the collection rules. The considered routing models in the analysis are:

1. *Model A*: it is the classic vehicle routing model for waste collection, where all the location are visited at each trip
    - The collection rule is the nearest neighbor.
    - Real time traceability data inputs are not necessary.
    - All bins are visited.

B1) *Model B1*: it is a real time traceability data routing model where

- The collection rule is the maximum ratio quantity of waste/distance.
- Real time traceability data are necessary.
- Only bins that exceed the optimal replenishment level parameter RL are visited according the collection rule. RL is optimized as a function of the waste generation pattern and of the OR [%].

B2) *Model B2*: it is a real time traceability data routing model where

- The collection rule is the maximum ratio of waste/distance$^2$
- Real time traceability data are necessary.
- Only bins that exceed the optimal replenishment level parameter RL are visited according the collection rule. RL is optimized as a function of the waste generation pattern and of the OR [%].

B3) *Model B3*: it is a real time traceability data routing model where

- The collection rule is the maximum ratio quantity of waste/distance$^3$.
- Real time traceability data are necessary. Only bins that exceed the optimal replenishment level parameter RL are visited according the collection rule. RL is optimized as function of the waste generation pattern and of the OR[%].

C) *Model C*: it corresponds to the real time traceability data routing model proposed in this work, showed in the previous section, where

- The collection rule is the nearest neighbor.
- Real time traceability data are necessary.
- Only bins that exceed the optimal replenishment level parameter RL are visited according the collection rule. RL is optimized as a function of the waste generation pattern and of the OR[%].

Figure 3.13 shows the results in terms of number of necessary vehicles and total covered distance in function of the total amount of generated waste with 5% of OR, figure 3.14 and 3.15 show the same but with respectively 10% of OR and 15% of OR. As reported in table 3.23, RD/WAL=20% for all the considered cases.

Analyzing figure 3.13 and looking at the first case with WAL= 40%, it is clear how the real time traceability routing models (models B and C) produce benefits compared to the classical routing model (model A) in term of the reduction of number of vehicles necessary and total distance covered in function of the total generated waste. As predictable, these benefits are directly related to the average level of waste for bin WAL, because of the number of bins to service when available real time data decrease. Another consequence is the identification of the best collection rule in case of real time traceability data utilization, showing how model C gives better overall results than models B, when the average level of waste for bin WAL grows. This result defines that critical factors to consider in the collection rule are distance, in terms of covered distance and vehicles utilization as you go from routing model B1 to routing model B3, where the distance weight is growing in respect to the quantity of waste in the bin.

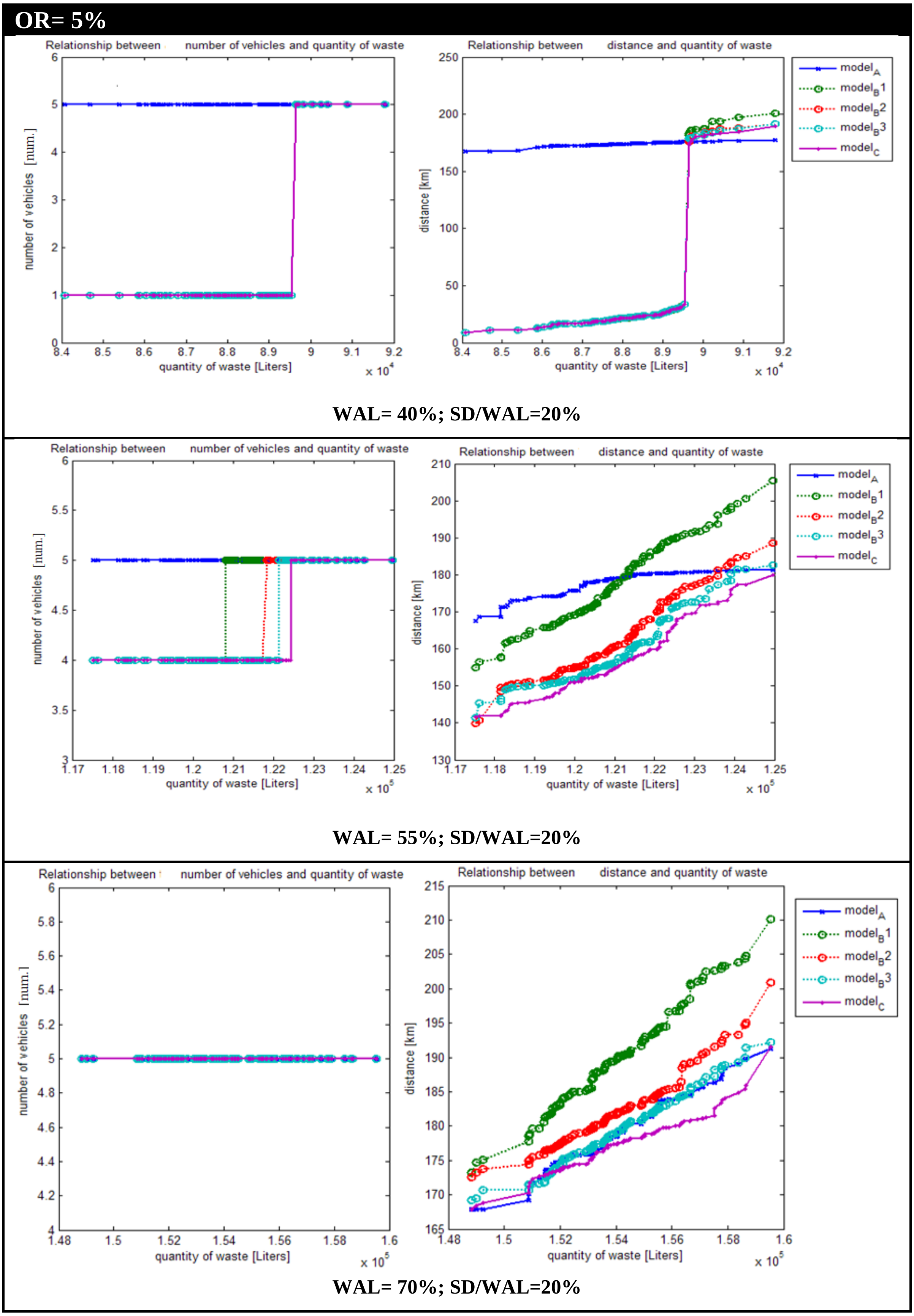



*Figure 3.13: OR=5%, Routing models benchmark*

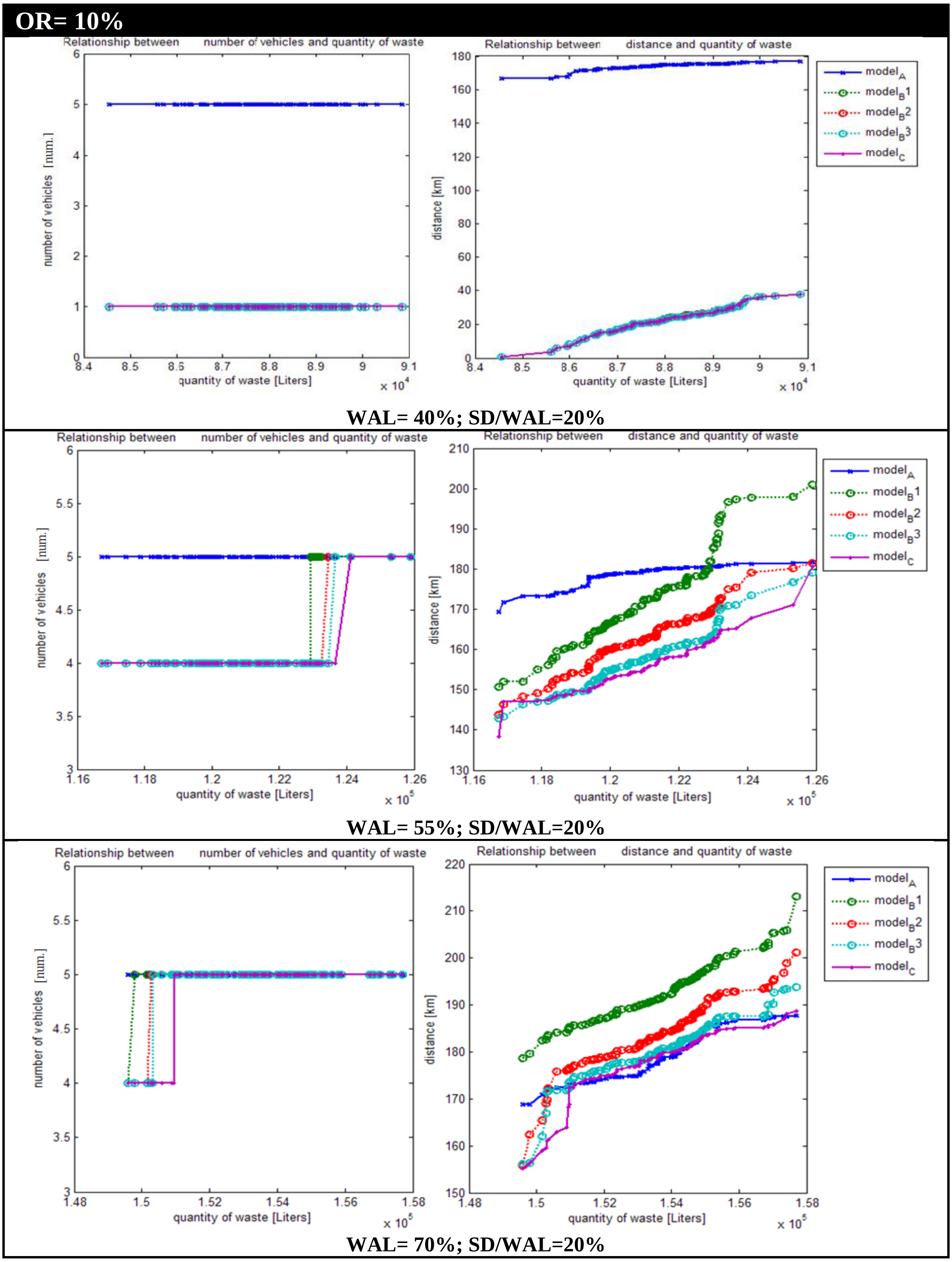



*Figure 3.14: OR=10%, Routing models benchmark*

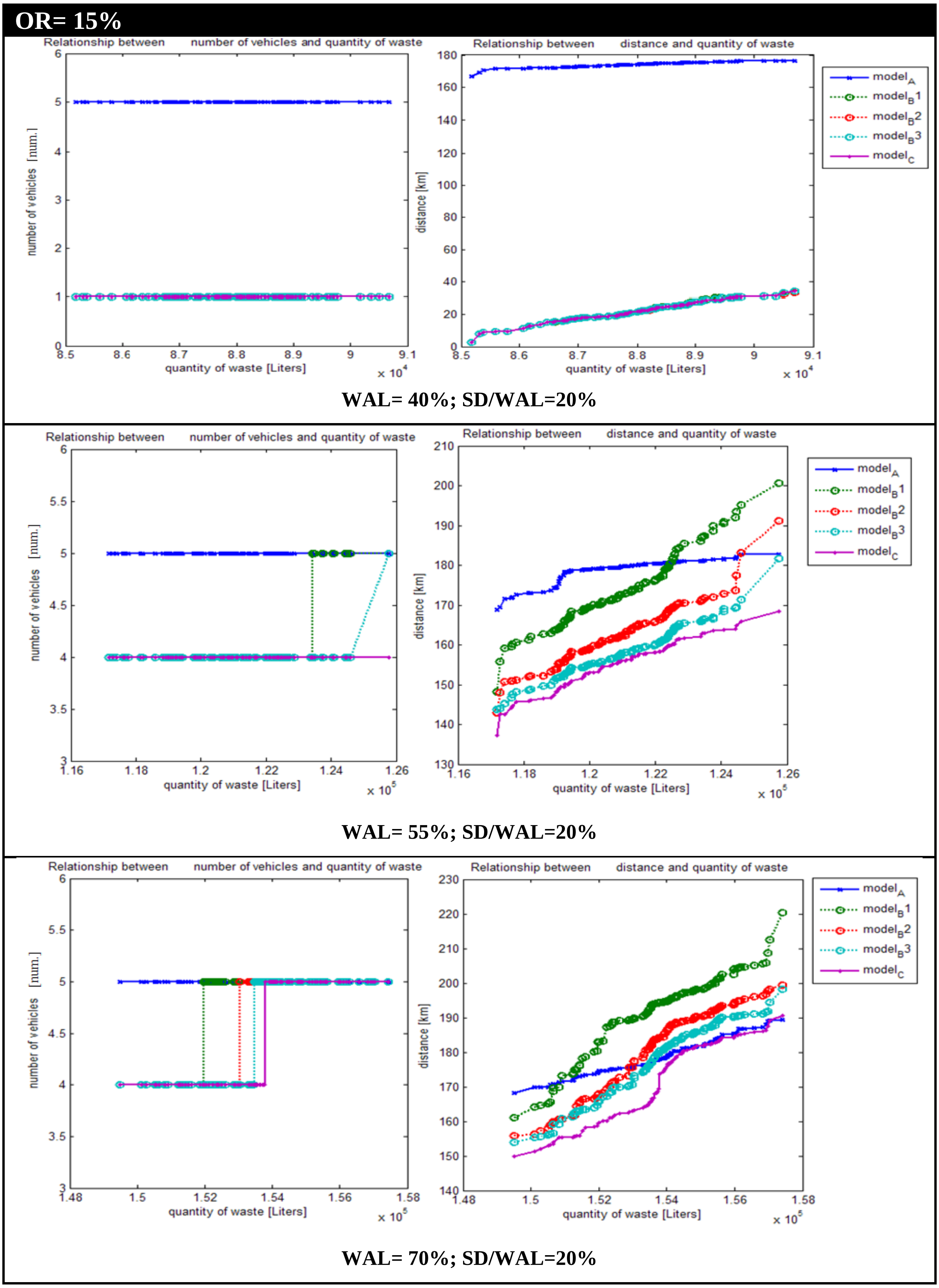



*Figure 3.15: OR=15%, Routing models benchmark*

Looking at figure 3.13, 3.14 and 3.15, where the oversize risk OR changes from 5% to 10% and to 15%, the benchmark between model A (the classical waste collection routing model) versus model C (the proposed routing model for waste collection) shows an increment of benefits with OR risk growth, for a fixed value of WAL parameter. This point is very clear comparing OR=5% with OR=15% for fixed WAL=70%. The final results of the routing models benchmarking are:

- The proposed routing model (model C) that considers real time traceability data as input, with optimal replenishment level parameter RL as a fixed function of the waste generation pattern and of the OR[%] in order to define what bin has to be serviced, and uses the nearest neighbor as collection rule, results to be always the best method in terms of used vehicles and total covered distance reduction.
- The proposed routing model (model C) with respect to the classical routing model used for waste collection (model A) gives better results when the oversize risk parameter OR increases and when the average waste level at bin, WAL, decreases.
- Looking for example at the case of OR=5% and WAL=55% comparing model C versus model A, for an average total generated waste of 122 $m^3$ the reduction of vehicles necessary is about 20% (from 5 to 4) and the total distance covered by all the vehicles in a waste collection is reduced of 12% (from 179 to 158 km)

*Optimal bin's replenishment level parameter analysis*

The objective of this section is to define, for a given waste generation pattern at bin level and for an assumed oversize risk OR[%], what is the optimal replenishment level parameter, RL[%], that would define which bin has to be serviced and which does not. This analysis gives a valid decision making tool in using the proposed real time traceability data routing model. This analysis has been explained in the section dedicated to the model description. The waste generation pattern, verified using data derived by the applicative case, is a normal distribution, with average value WAL and standard deviation SD. In this analysis, like previously explained, these parameters are related to the bin capacity in term of percentage for WAL[%], and standard deviation is related to the average value considering SD/WAL [%]. The range of variation for this analysis is reported in table 3.24 and the results of this analysis it is reported in figure 3.16.

| Variable inputs | Values |
|---|---|
| **OR [%]** | 5-10-15 |
| **WAL [%]** | 35-40-45-50-55-60-65-70 |
| **SD/WAL [%]** | 20-35-50 |

*Table 3.24: Range of variation of the inputs for optimal bin's replenishment level parameter analysis*

In case the optimal replenishment level parameter RL[%] is equal to 0, the number of bins that need to be serviced corresponds to all, and the proposed routing model (model C) is equal to the classical routing model for waste collection (model A). As reported in figure 3.16 it is possible to obtain different curves in function of the oversize risk OR[%] chosen. Such curves give the optimal replenishment level parameter RL[%] output in function of the waste average WAL[%] and of the standard deviation percentage SD/WAL[%].

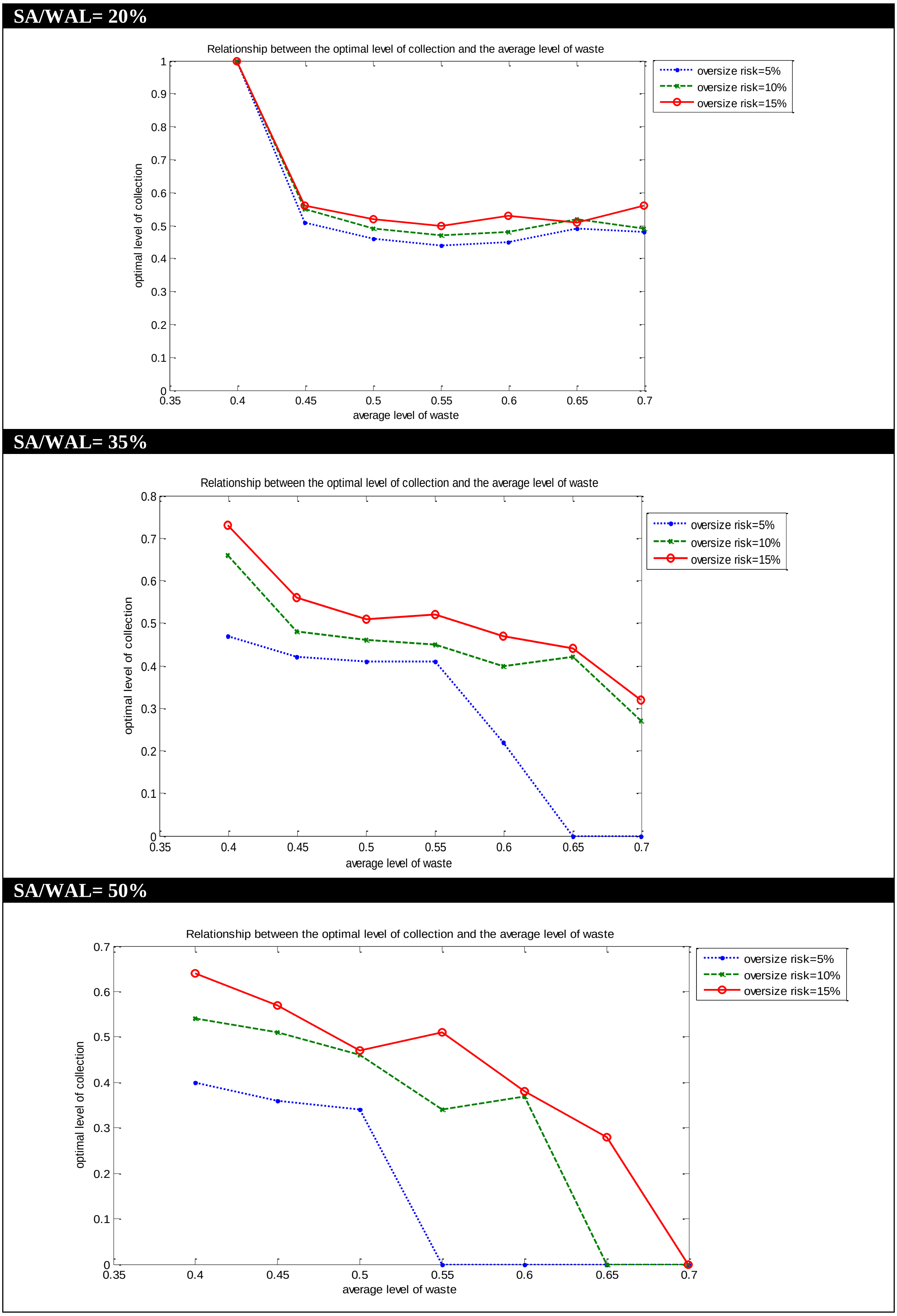



*Figure 3.16: Optimal bin's replenishment level parameter analysis*

The main results of the optimal bin's replenishment level parameter analysis are:

- When the optimal replenishment level parameter RL[%] decreases, a major number of bins has to be serviced. That means that the benefits of the proposed model in term of necessary vehicles and total covered distance reduction are limited.
- The presented curves allow to choose the optimal replenishment level in function of the waste generation pattern and in function of the oversize risk OR[%] chosen, which turns out to be an optimal decision making tool for engineers who decide to adopt the proposed routing model.
- The optimal replenishment level parameter RL[%]decreases when
  - OR[%] decreases
  - WAL increases
  - SD/WAL increases
- In case of SD/WAL=20% the proposed routing model (model C) is always (in the considered range of WAL) better than the classic (model A) in terms of number of bins to service, of vehicles necessary and total distance covered.
- When SD/WAL=35% for OR=5% with WAL≥65% all the bins have to be emptied.
- When SD/WAL=50% for OR=5% with WAL≥55% all the bins have to be emptied.

### 3.5.4 ECONOMICAL FEASIBILITY ANALYSIS

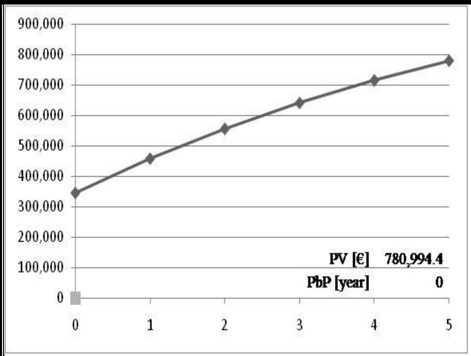
The implementation of the proposed routing model for waste collection imposes to install traceability devices at different levels of the system to be able to communicate real time data, a fundamental input for the model which is an expense outweighed by a reduction of vehicles necessary and total distance covered. Objective of this section is to analyze, from an economic feasibility point of view, the return of the investment in using traceability devices and applying the proposed routing model (model C) versus the classical routing model for waste collection (model A). The analysis, as reported in table 3.25, defines installation costs and operative annual costs but does not consider costs that are necessary in both models. The analysis uses the classical indicators for economic feasibility studies like Present Value (PV), that defines the final value of the investment return, and Pay Back Period (PbP), which defines how long is the period to regain the initial investment. The scenarios differ in function of OR[%] and WAL[%] parameters, given that SD/WAL[%] is fixed at 20%. The considered conditions are the same as those in the case study analyzed (table 3.22) for a urban environment of 100,000 inhabitants, where waste collection happens twice weekly. Table 3.25 shows the specific costs considered and the results in terms of PV and PbP of the analysis. For the purpose of our study, the duration of the investment has been fixed to 5 years, even if it could be considered longer.

| **Installation costs** | |
|---|---|
| **Vehicles purchase cost** | It includes initial cost for the purchase of vehicles. |
| **Traceability equipment cost per vehicle** | It includes purchase of traceability equipment per vehicle. |
| **Traceability equipment cost per bin** | It includes purchase of traceability equipment per bin. |
| **Traceability operations center cost** | It includes purchase of traceability equipment for operations center. |
| **Annual costs** | |
| **Fuel and oil consumption** | It includes cost for fuel and oil consumption depending on the number of kilometers/year. |
| **Drivers cost** | It includes cost for drivers/operators and depends on number of vehicles. |

*Table 3.25: installation costs and annual costs*

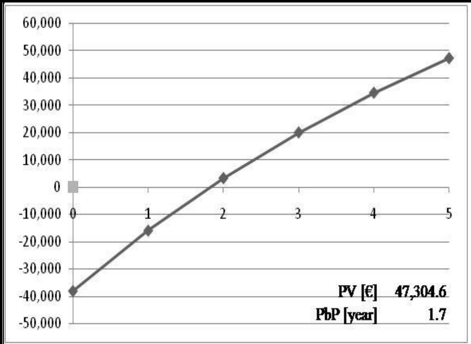
## Scenario 1

| Oversize risk 10%<br>Average level of waste 40% for each bin | Specific Cost [€] | num. | A) Classic waste collection model [€] | num. | B) Real time data traceability model [€] | Delta A-B |
|---|---|---|---|---|---|---|
| **Installation costs** | | | **600,000** | | **254,000** | **346,000** |
| Vehicles purchase cost [€] | 120,000 | 5 | 600,000 | 1.0 | 120,000 | 480,000 |
| Traceability equipment cost per vehicle [€/vehicle] | 1,000 | 0 | 0 | 4 | 4,000 | -4,000 |
| Traceability equipment cost per bin [€/bin] | 500 | 0 | 0 | 200 | 100,000 | -100,000 |
| Traceability operation center cost [€] | 30,000 | 0 | 0 | 1 | 30,000 | -30,000 |
| | | | | | | |
| **Annual costs** | | | **161,170** | | **31,404** | **129,766** |
| | | Km/year | | Km/year | | |
| Fuel-Oil consumption cost per km/ vehicle [€/km] | 0.6 | 18,616 | 11,170 | 2,340 | 1,404 | 9,766 |
| | | num. | | num. | | |
| Drivers annual cost [€/anno] | 30,000 | 5 | 150,000 | 1.0 | 30,000 | 120,000 |



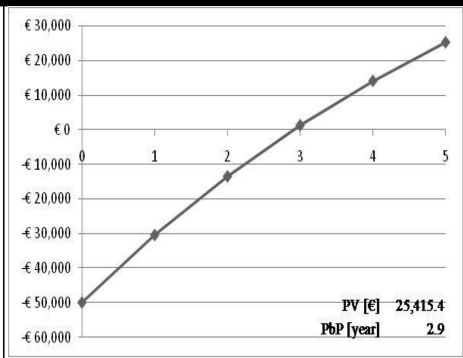

## Scenario 2

| Oversize risk 10%<br>Average level of waste 55% for each bin | Specific Cost [€] | num. | A) Classic waste collection model [€] | num. | B) Real time data traceability model [€] | Delta A-B |
|---|---|---|---|---|---|---|
| **Installation costs** | | | **600,000** | | **638,000** | **-38,000** |
| Vehicles purchase cost [€] | 120,000 | 5 | 600,000 | 4.2 | 504,000 | 96,000 |
| Traceability equipment cost per vehicle [€/vehicle] | 1,000 | 0 | 0 | 4 | 4,000 | -4,000 |
| Traceability equipment cost per bin [€/bin] | 500 | 0 | 0 | 200 | 100,000 | -100,000 |
| Traceability operation center cost [€] | 30,000 | 0 | 0 | 1 | 30,000 | -30,000 |
| | | | | | | |
| **Annual costs** | | | **161,170** | | **135,722** | **25,448** |
| | | Km/year | | Km/year | | |
| Fuel-Oil consumption cost per km/ vehicle [€/km] | 0.6 | 18,616 | 11,170 | 16,203 | 9,722 | 1,448 |
| | | num. | | num. | | |
| Drivers annual cost [€/anno] | 30,000 | 5 | 150,000 | 4.2 | 126,000 | 24,000 |




## Scenario 3

| Oversize risk 5%<br>Average level of waste 55% for each bin | Specific Cost [€] | num. | A) Classic waste collection model [€] | num. | B) Real time data traceability model [€] | Delta A-B |
|---|---|---|---|---|---|---|
| **Installation costs** | | | **600,000** | | **650,000** | **-50,000** |
| Vehicles purchase cost [€] | 120,000 | 5 | 600,000 | 4.3 | 516,000 | 84,000 |
| Traceability equipment cost per vehicle [€/vehicle] | 1,000 | 0 | 0 | 4 | 4,000 | -4,000 |
| Traceability equipment cost per bin [€/bin] | 500 | 0 | 0 | 200 | 100,000 | -100,000 |
| Traceability operation center cost [€] | 30,000 | 0 | 0 | 1 | 30,000 | -30,000 |
| | | | | | | |
| **Annual costs** | | | **161,170** | | **138,672** | **22,498** |
| | | Km/year | | Km/year | | |
| Fuel-Oil consumption cost per km/ vehicle [€/km] | 0.6 | 18,616 | 11,170 | 16,120 | 9,672 | 1,498 |
| | | num. | | num. | | |
| Drivers annual cost [€/anno] | 30,000 | 5 | 150,000 | 4.3 | 129,000 | 21,000 |




## Scenario 4

| Oversize risk 10%<br>Average level of waste 70% for each bin | Specific Cost [€] | num. | A) Classic waste collection model [€] | num. | B) Real time data traceability model [€] | Delta A-B |
|---|---|---|---|---|---|---|
| **Installation costs** | | | **600,000** | | **734,000** | **-134,000** |
| Vehicles purchase cost [€] | 120,000 | 5 | 600,000 | 5.0 | 600,000 | 0 |
| Traceability equipment cost per vehicle [€/vehicle] | 1,000 | 0 | 0 | 4 | 4,000 | -4,000 |
| Traceability equipment cost per bin [€/bin] | 500 | 0 | 0 | 200 | 100,000 | -100,000 |
| Traceability operation center cost [€] | 30,000 | 0 | 0 | 1 | 30,000 | -30,000 |
| | | | | | | |
| **Annual costs** | | | **161,170** | | **161,045** | **125** |
| | | Km/year | | Km/year | | |
| Fuel-Oil consumption cost per km/ vehicle [€/km] | 0.6 | 18,616 | 11,170 | 18,408 | 11,045 | 125 |
| | | num. | | num. | | |
| Drivers annual cost [€/anno] | 30,000 | 5 | 150,000 | 5.0 | 150,000 | 0 |

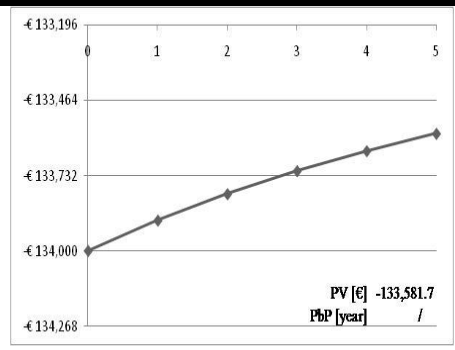



*Figure 3.17: Economic feasibility analysis*

As highlighted in the figure 3.17 the proposed real time traceability data routing model gives, even from an economic point of view, optimal results in the average condition of waste collection management, with an average replenishment level per bin WAL=55% (scenario 2 and scenario 3) if compared with the classical waste collection routing model. The PbP is less than 3 years and the PV is almost equal to 50,000 € in 5 years. Only if the condition are very extreme (scenario 4 WAL=70%) the initial investment in traceability systems is not regained in the first 5 years.

### 3.5.5 OBSERVATIONS

Waste collection is an important, but expensive municipal service, especially in terms of investment costs, operational costs and environmental impact. Modern traceability devices, like volumetric sensors, identification RFID systems, GPRS and GPS technology, allow to obtain real time data which are fundamental to the implementation of an efficient and innovative waste collection routing model. This research introduces a multi-objective routing model for waste collection that aims to minimize the number of vehicles necessary and travel time and increase total covered distance, without mentioning the direct effect of reducing environmental impact like emissions, noise and traffic congestion. The main innovative aspects introduced are a framework to implement the modern traceability devices in waste collection, the integration of real time traceability data inputs with static inputs in an effective and innovative routing model, and the optimization of some critical parameters used in the routing model in function of utilization conditions like, for instance, waste generation patterns.

The main results can be summarized as follows:

- The use of the modern traceability technology in waste collection allows to produce real time input (like real time replenishment level of each bin, real time vehicle position, etc.) which are fundamental in the proposed routing model.
- The integration of static inputs with real time traceability data inputs in an effective routing model, where the collection rule is the nearest neighbor and only bins that exceed the optimal replenishment level parameter RL are serviced, as described in the section that illustrates the model, allows to achieve the different objectives described before. If this model is compared with the classical routing

model used in waste collection, where the collection rule is the nearest neighbor, real time traceability data inputs are not used and all bins are services all the times, the results reported in the section dedicated to the simulating analysis and validate the potential benefit in using the proposed routing approach.

- A set of important parameters are introduced in the proposed routing model:
  - The oversize risk parameter, OR [%], i.e. the risk of oversize bin capacity, that define the maximum % of risk and depends on a waste collection management decision.
  - The optimal replenishment level parameter, RL [%], i.e. the minimum bin replenishment level for waste collection, that defines the % of replenishment that make a bin serviceable or not.

  These parameters are interdependent with the waste generation pattern at bin level. In this thesis is also analyzed this interdependency, assuming a normal distribution (as highlighted by the experimental results) for waste generation pattern, and outputs a valid decision making tool in setting these parameters for the proposed routing model as functions of the utilization conditions.

- The economical feasibility analysis, developed in the last section, demonstrates that the benefits of using the proposed routing approach are averagely wider than the costs for the implementation of the traceability technology. This result validates not only from a technical point of view, but also from an economical point of view, the proposed routing model for waste collection.

This study represents an important contribution in the management of the last phase of the life cycle of food and its packaging material. However this kind of approach in the routing optimization it is potentially applicable in other fields of the food industry. For example, according with Jedermann et al. (2009) perishable food products are at risk of suffering various damages along the cold chain. The parties involved should control and monitor the conditions of goods in order to ensure their quality for consumers and to comply with all legal requirements. Consequently an important research area appears the development of effective distribution routing models in very critical contexts in term of perishable food, integrating the presented real time traceability data with the physical conditions of the transported items (temperature, humidity, etc).

# 4 CONCLUSION

*This chapter reports the conclusion of the present work summarizing the most important results of the study and the consequently recommendation in order to design and manage eco-compatible food supply chain.*

In the recent decades climate change becomes a global issue and a common concern to the international community, as well as the most serious global environmental problem facing mankind. As the global scientific research demonstrated the climate change is primarily depending on human activities and the tremendous energy use. Considering the food industry, which is one of the world largest industrial sectors, studies clearly demonstrate that it is one of the most prolific energy users, and thus a significant contributor to global warming potential. One of the consequences is that recent legislation, social responsibility, corporate imaging and customer awareness are forcing manufacturers to provide more environmentally friendly products. This imposes to apply the green supply chain management concept, that allows to reduce the greenhouse emissions and the consequent impact on the environment and the human health.

In this circumstance the present PhD thesis is focalized on the sustainable supply chain. The research was organized in two consecutive and correlate phases:

- The first is related to the strategic decision and analyzed the model for the supply chain design. This phase highlights that it is necessary to study the network structure considering the direct and the reverse flow simultaneously. For this reason it was introduced a linear programming model that aims to minimize the total SC costs assuring the environmental sustainability by means of the complete reprocessing of end-of-life product and the disposal of unusable parts directly from manufacturers, with a closed loop transportation system that maximizes the transportation efficiency. The proposed CLSC model has been compared with the classical forward supply chain model (FWSC) through a parametrical study from two different perspectives: *Case 1,* the *'traditional company perspective'*, wherein the SC ends at the customers, and the disposal costs are not included in the SC, and *Case* 2, the '*social responsibility company perspective',* where the disposal costs are considered within the SC. As regard as the second one, the study demonstrated that the economic and environmental sustainability of the proposed CLSC model, compared to the FWSC, is already realized with 10% of reused end-of-life products. Furthermore, the analysis made shows that an increase of the percentage of reused end-of-life products gives a more than linear reduction on total costs. This confirmed the observation of Daniel et al. (2003) which point out that the element of % of reused end-of-life products is a critical factor with respect to its influence on the total cost of the SC, and on the other environmental protection, stressing the importance of taking into account the reusability concept during the design of the products.

- The second phase is related to the tactical decision and proposed new models for the supply chain planning. It starts introducing the learning effect in the routing optimization, motivated by the advantages given by the drivers' familiarity with the customers supplied, that allows to reduce the service time and, at the same time, to improves the service level. The first part of this study compares, through a parametrical analysis, the fixed routing strategy with the daily routing optimization strategy. It points out that the strategy of fixed routes can often be better than the daily optimized one and this strongly depends on the parameters investigated in work. From the results it is possible to say that the fixed routing strategy can be used when the delivery service time has a high impact on the total driver working time, such as deliveries in crowded centers, with a high density of customers and traffic constraints, and generally speaking any time the driver learning is positively affected by the delivery task repetition. An additional output of this study is the proposed methodological framework, which is a useful tool in routing strategy decision. The study continues from the consideration that the drivers' familiarity with the served territory is also a relevant aspect in the reduction of the transportation environmental impact. This derived from the observation that factors such as the traffic congestion and the consequently continuous vehicles stop and start influence negatively the CO2 emissions. Then this research highlights how the drivers' familiarity with the served territory permits to choose alternative routes avoiding the traffic zone, reducing the greenhouse gas emission. More in detail this part of the work describes the $CO_2$ estimation model and the relative sustainable routing problem formulation. Starting from the idea that different factors influence the $CO_2$ emission and that from the driver point of view they can be divided into internal/external factors, the study formalized a sustainable routing model, validating it through a case study and through a parametrical analysis comparing the proposed approach with the classical routing criteria of distance or time minimization. The analysis confirm that the $CO_2$ emission increases when the traffic flow increases and the driving style is more aggressive. Then optimum sustainable routing changes in function of these factors. As a consequence, in case of in case of high traffic flow, a routing model which consider these factors, as the one proposed in this thesis, may allow relevant $CO_2$ saving if compared with a classical model. As conclusion of the research on the distribution optimization it is possible to said that the drivers' familiarity with the served territory allows, not only to reduce the service time at each customers, by the drivers learning, but results also an important element to support the new approach proposed with the aims to reduce the greenhouse emission. As conclusion of the present work it is considered the possibility of apply real time traceability data in the routing optimization. The study deals with the municipally waste collection and introduce an innovative dynamic model. The basic idea is that knowing the real time data of each vehicle and the real time replenishment level at each bin makes it possible to decide, in function of the waste generation pattern, what bin should be emptied and what should not, optimizing different aspects like the total covered distance, the necessary number of vehicles and the environmental impact. The main innovative aspects introduced in this study are a framework to implement the modern traceability devices in waste collection, the integration of real time traceability data inputs with static inputs in an effective and innovative routing model, and the optimization of some critical parameters used in the routing model in function of utilization conditions like, for instance, waste generation patterns. In the research it was compared the proposed model with a classical one, showing the advantages given by the integration of real time data with static data in order to guarantee both economical and environmental sustainability. This study represents an important contribution in the management of the last phase of the life cycle of food and its packaging material. However, this kind of approach in the routing optimization it is potentially applicable in other fields of the food industry.

As general conclusion it is possible to say that for reduce the transportation environmental impact it is necessary to implement supply chain design and planning models developed ad hoc for guarantee the sustainability. Moreover, if it is considered the economical impact of some environmental factors, the sustainable models may also reduce the total costs respect to the classical model.

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