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THE MULTI-COMPARTMENT VEHICLE ROUTING PROBLEM IN THE COLLECTION OF RECYCLABLE MUNICIPAL SOLID WASTE

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Abstract

Waste production is an inevitable by-product of today's society activities, and its collection is an essential public service. With an increase in population density and consequently in the production of waste, a growing concern on environmental sustainability came along. European and national legislation imposes material recycling, and in order to ensure the sector's economic viability and offset the strong market regulation, companies seek to find more efficient alternatives.

In a waste collection system, transportation costs represent approximately 70% of the total cost, meaning that routing decisions have a great impact on the financial sustainability of the companies in this sector. This mind-set led to the study of the operation of Valorsul, the company responsible for the collection of recyclable municipal solid waste in the western region of Portugal.

This work intends to assess the impact on the distance travelled by using multi-compartment vehicles, collecting Paper and/Cardboard and Plastic and/Metal simultaneously, in comparison to the use of single compartmented vehicles, where only one material is collected at a time. To do so, a hybrid model was developed that firstly selects which collection points from the existing network are worth visit with multi-compartment vehicles, and then implements a heuristic to cluster and route those collection points.

The proposed model was applied to a specific region of Valorsul system, and the results obtained suggest that the use of vehicles with multi-comparts is more beneficial than the use of vehicles with only one, reducing the total distance travelled.

Keywords: waste management; transportation management; vehicle routing; multi-compartment vehicles

JEL Classification System:

C61 – Optimization Techniques; Programming Models; Dynamic Analysis

R410 – Transportation: Demand, Supply and Congestion; Travel Time; Safety and Accidents; Transportation Noise

Resumo

A produção de resíduos é um subproduto inevitável da atividade da sociedade atual, sendo a sua recolha um serviço público essencial. A acompanhar o aumento da densidade populacional, e consequentemente a produção de resíduos, existe uma crescente preocupação com a sustentabilidade ambiental. A legislação europeia e nacional impõe a reciclagem de materiais e, para garantir a viabilidade económica do setor e compensar a forte regulação do mercado, as empresas procuram alternativas mais eficientes.

Num sistema de recolha de resíduos, o seu transporte representa cerca de 70% do custo total, o que significa que a definição de rotas tem um grande impacto na sustentabilidade financeira das empresas deste setor. O caso de estudo desta dissertação baseia-se na operação da Valorsul, empresa responsável por um sistema de recolha de resíduos recicláveis.

Este trabalho pretende avaliar o impacto na distância percorrida comparando a utilização de veículos com múltiplos compartimentos, recolhendo os contentores de Papel e Plástico em simultâneo, e a utilização de veículos com um único compartimento, recolhendo um material de cada vez. Desta forma, foi desenvolvido um modelo híbrido que, numa primeira fase, seleciona os ecopontos que devem ser visitados por veículos com múltiplos compartimentos. Através do desenvolvimento de uma heurística, são definidas as rotas para recolher esses ecopontos.

O modelo proposto foi aplicado a uma região específica do sistema da Valorsul, e os resultados obtidos sugerem que o uso de veículos com múltiplos compartimentos é mais benéfico (em termos de distância percorrida) do que o uso de veículos com apenas um.

Palavras-chave: gestão de resíduos; gestão de transportes; rotas de veículos; veículos com múltiplos compartimentos

JEL Classification System:

C61 – Optimization Techniques; Programming Models; Dynamic Analysis

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1. Introduction

1.1. Theme

In order to ensure their economic and financial sustainability, companies today are looking for and developing new business models. Legislation, governance, the environment itself, infrastructure or consumer behaviour are some of the aspects that have direct influence on companies. Academic research can be very useful and a great support for companies since it promotes the study and development of innovative alternatives to current enterprise practices.

The study carried out in this dissertation is based on Valorsul, a Portuguese private company that operates a recyclable waste collection system in the western region of Portugal. This work aims to assess the impact on the distance travelled to visit the collection points under the responsibility of Valorsul, by using vehicles with multiple compartments, instead of using single compartmented ones. To fully comprehend the importance of studying the collection routes of such company, it is important to understand its context.

Utilities and sanitation services are under public jurisdiction and their maintenance are essential to guarantee good quality of life of citizens, as United Nations has once declared (Rosa et al., 2015). To ensure the sector's economic viability and offset the strong market regulation and industry variables, the entities responsible for their management are forced to find new solutions.

Waste production is an inevitable by-product of any economic activity and growth, and its disposal and treatment is a global environmental issue. Especially since the late 90s, there has been a growing concern with the collection and treatment of municipal solid waste (MSW). The European Union (EU) imposes material recycling and very ambitious targets concerning waste management – as established, for example, in the Waste Framework Directive –, which leads to extra logistics challenges for companies in all member states.

In order to implement this directive, Portugal has its own National Waste Management Plan (PNGR) that promotes waste prevention and management and aims to ensure greater efficiency in the use of natural resources. PERSU 2020, the current Strategic Plan for MSW, is under its scope. One of its priorities is to promote the optimization of MSW collection systems and evaluate possible solutions (APA, 2016).

Rosa et al. (2015) stated that the Portuguese Waste sector shows a clear tendency to improve the efficiency of technical and technological solutions that are responsible to ensure that the service provision is sustainable and affordable to its users. However, there are a few challenges that companies have to face.

Although recycling aims for a better overall management of environmental resources (raw materials, land, soil quality and water, among others), its supply chain is quite complex and involves large investments in equipment and infrastructure (Cruz et al., 2014). Compared to a non-recyclable MSW collection system, the economic viability of collecting recyclable MSW is much more reduced (Lima et al., 2015) and, despite the enormous advantages of recycling, it is evident that this process has direct costs for companies (public or private).

With an increase in population density, came along an increase in production of MSW and the need to create value for these materials. According to ERSAR – the national Regulatory Authority for Water and Waste Services – in Portugal, in 2014, were produced a total of 4,3 million tons of MSW, with 10% subject to recycling (Rosa et al., 2014). Figure 1.1 shows the evolution of the amount of recyclable MSW collected in Portugal between 1998 and 2015. For all types of waste, the trend is positive and the amount of MSW collected for recycling purposes has been increasing.

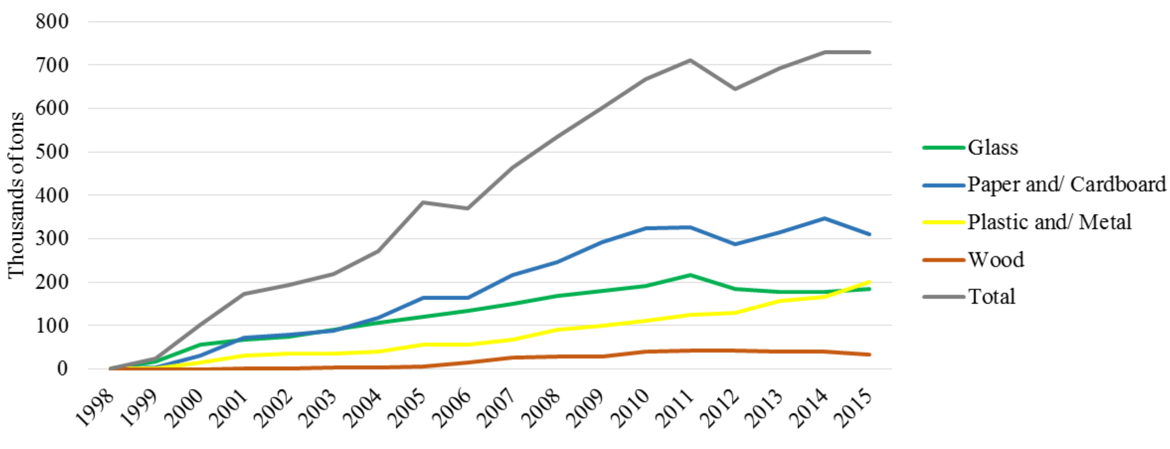


Figure 1.1 - Evolution of the amount collected of recyclable MSW in Portugal, between 1998 and 2015 (SPV, 2016)

The number of collection points scattered throughout urban areas is very high and route management has a great impact on companies' performance and efficiency. Due to the long distances that collection vehicles have to travel in their routes, companies have to be aware of the cost of fuel. Although oil prices have declined sharply since June 2014 (Baffes et al., 2015), since the early 2000s the trend aims for an increase in fuel prices – see Figure 1.2 for the evolution of the cost of fuels sold in Portugal.

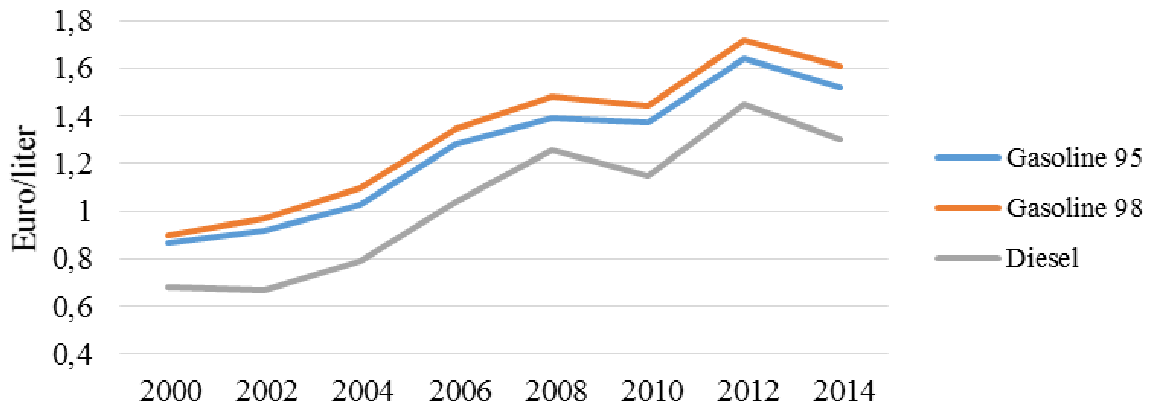


Figure 1.2 - Price change of fuels sold at gas stations in Portugal, between 2000 and 2014 (Pordata, 2015)

Collection costs alone represent about 70% of the total cost for a recyclable waste collection system (Ramos et al., 2014). It is essential that companies responsible for collecting recyclable MSW react and adapt their operations in order to maintain efficiency, simultaneously attending the market needs and demands. In order to make recyclable MSW collection economically viable, companies should aim to travel the minimum distance possible, with the fewest possible vehicles, maximizing productivity. Since most of these costs are not recoverable (Cruz et al., 2014), i.e., sunk costs, this research topic can lead to new models and have great impact on companies' operations efficiency and reduce cost.

1.2. Objectives & Research Questions

Most studies found about route management applied to waste collection systems are based on the traditional methods, where single-material routes are performed to visit collection points, i.e., a single compartment vehicle is used to collect each material individually. However, two or more materials can be collected simultaneously, without being commingled, if vehicles with multiple compartments are used. Real-life applications of Multi-Compartment Vehicle Routing Problems (MCVRP) are seldom studied, although this problem has been getting more attention from the academia in recent years.

This dissertation aims to take this opportunity by analysing the impact of using vehicles with multiple compartments on the real recyclable MSW collection system of Valorsul. To understand the impacts on the distance travelled, a model is developed, which aims to meet the following objectives:

- Identify which materials are worth collecting with vehicles with multiple compartments;
- Identify which collection points are eligible and worth visiting with vehicles with multiple compartment, according to their characteristics – demand and capacity installed –, and which ones are not;
- Develop a heuristic approach to cluster and route collection points, based on the reviewed literature and on the operation of the company in study;
- Compare the obtained solution (MCVRP) with the current method used by company (single-material routes) in order to assess the benefits of the model.

In order to achieve the objectives herein proposed, the following research questions will be answered in this dissertation:

1. Which collection points are eligible to be visited by a multi-compartmented vehicle?
2. What is the impact of the use of vehicles with multiple compartments on the distance travelled of a recyclable MSW collection system, when compared to the traditional method?

1.3. Structure

This dissertation is composed by seven chapters, among which is included this first chapter where the research problem is introduced.

The **second chapter** presents the case study in which this dissertation is based on. It introduces the waste sector and deepens the life cycle of municipal solid waste, exploring the phases of its value chain – from production to disposal. The second part of the second chapter introduces the company in analysis, Valorsul, focusing on its current processes to collect recyclable MSW, and on its own infrastructure to do so (vehicles and collection points).

As for **chapter three**, a literature review is conducted, giving a comprehensive exploration of the subject in question. It starts by introducing the importance of Transportation Management, exploring which drivers, factors and constrains influence logistic systems responsible for the collection of MSW and to be considered when solving routing problems. It also explores Vehicle Routing Problems, presenting the relevant solution methods already developed and published, focusing on its variants (where MCVRP is included).

Subsequently, the methodology is approached in **chapter four**, summarizing the thinking process on how to solve the research problem of this dissertation.

Deriving, **chapter five** explains the model developed to answer the research questions, fulfilling the objectives proposed. It presents a detailed explanation on how collection points are screened and on the cluster and route heuristic developed to solve the MCVRP.

Chapter six is divided in two parts. Firstly, it goes through the analyses performed on the data provided by Valorsul, that support all necessary calculations further on. Lastly, it presents the results obtained by the implementation of the proposed model, and compare them to the current solution of the company – where single-material routes are performed –, in order to assess the impact on the distance travelled.

The **seventh** and last **chapter** is devoted to conclusions and the proposal of future research.

2. Case study

2.1. The Waste Sector

Waste management is acknowledged as a public service and, being of general economic interest, is under Portuguese legislation (Law No. 23/96 of July 26). MSW is defined by the Portuguese law as any household waste, or alike, that comes from the service sector, commercial establishments or healthcare sector, as long as, in any case, the daily production does not exceed 1100 litters per producer (APA, 2016).

Pursuing the first Waste Framework Directive[1] of the EU in 1994, Portugal made a great investment in waste management infrastructure and started to abolish dumps. Several MSW management systems were created and developments in the national legislative framework has led to the licensing of service providers, instigating an increase in recovery and recycling.

Pursuing EU demands, as all member states had to do, Portugal established its own National Waste Management Plan (PNGR) – see Ferrão (2014) –, a macro planning policy that sets strategic guidelines, nationwide, and promotes waste prevention and management. It tends to ensure greater efficiency in the use of natural resources, and is based on two strategic objectives: i) promote the efficient use of natural resources in the economy; ii) prevent or reduce the adverse impacts of production and waste management.

Under the scope of the PNGR there are three specific waste management plans, depending on the material concerned: i) Strategic Plan for Hospital Waste (PERH); ii) Strategic Plan for Industrial Waste Management (PESGRI); iii) Strategic Plan for Municipal Solid Waste (PERSU). For the purpose of this thesis, only the last one is relevant since it is the one specific to MSW.

The first PERSU was established in 1997 and currently is in force PERSU 2020, a goal-setting tool to promote environmental sustainability. It allows each system to develop specific and appropriate solutions to their characteristics, which can and should include the optimization and sharing of infrastructure, the prevention of the generation of municipal waste, the commitment to selective collection, and the adoption of new solutions or the improvement of existing techniques and technologies (Rosa et al., 2015).

[1]Framework designed to emphasise the importance of proper waste management, such as recovery and recycling, to reduce pressure on resources, improve their use and protect human health (European Union, 2016).

Considering the waste sector itself, it works as a legal monopoly (Rosa et al., 2015): for each region, there is only one service provider; thus, consumers do not have the possibility to choose between operators and regulation has a major impact on service quality and cost. Unlike most EU countries, Portugal has a regulator for the waste sector (Cruz et al., 2014): *Entidade Reguladora dos Serviços de Águas e Resíduos* (ERSAR) – it stands for The Regulatory Authority for Water and Waste Services. It main responsibilities are to regulate the public water supply services, urban wastewater management and MSW services, and to ensure the structural adjustment of the sector. APA, the Portuguese Environment Agency (*Agência Portuguesa do Ambiente*), develops and monitors the implementation of public policies for the environment and waste management strategies (APA, 2016). This entity is also responsible for licensing waste management operations and entities that manage specific waste streams, such as *Sociedade Ponto Verde* (SPV). SPV is responsible for the collection and recycling of household, commercial and industrial packaging MSW, regulating over 500 operators nationwide; it coordinates the Green Dot System (see PRO EUROPE, 2016) in Portugal, which has as mission to promote the selective collection, recovery and recycling of packaging waste (SPV, 2016).

Nowadays, there are thirty-two recyclable MSW collection systems operating in Portugal, that ensure that 100% of households are served with public collection and treatment of MSW (SPV, 2016), one of them being Valorsul. These entities, so called SMAUTs, can be of state, municipal or inter-municipal owned systems, and operate in one of the following management models (Rosa et al., 2015): i) concession; ii) delegation; iii) direct management.

As for waste management services, there are two different categories to classify them, depending on the activities performed (Decree-Law No. 379/93 of November 5): “low” or “high” activities. The first one covers collection and transportation (until one depot) of MSW. The “high” system, in turn, includes storage, sorting, transport, recovery and disposal (in a landfill, for example) of MSW. Municipal systems are mainly responsible for the “low” activities, which corresponds to the retail activities of the sector (focusing on the interaction with the end-user), and inter-municipal systems are normally responsible for the high activities (like wholesalers). This industry structure has led to advantages in terms of economies of scale (Rosa et al., 2015). The integration of several municipalities into a single MSW management system, operated by single entities, allows monetizing investments in the sector and contributes to greater structural efficiency in service delivery.

2.1.1. The Life Cycle of Municipal Solid Waste

In short, a MSW collection system refers to a set of units (containers) distributed geographically that have to be visited in a regular basis (Oliveira, 2008). However, the complexity of this sector requires large investments, with a long-term capital recovery (Lima et al., 2015), and is based on a complex technological system comprising the following steps (Rosa et al., 2015): i) collection; ii) transport; iii) sorting; iv) recovery; v) disposal. This study will focus on the first two steps.

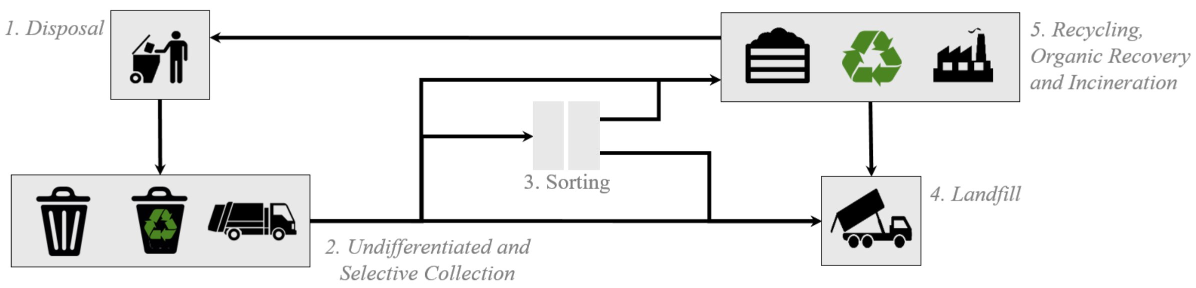


Figure 2.1 - Waste Value Chain illustration (adapted from Rosa et al., 2015)

The life cycle of MSW – illustrated in Figure 2.1 – starts with its production from domestic, industrial or commercial activities. This waste can be disposed selectively, or undifferentiated.

Undifferentiated waste, commonly referred to as "trash", is treated like this from the moment consumers place their MSW in the same disposal container (typically of grey colour), regardless its type. On the other hand, consumers can selectively separate their waste, such as organic matter, home appliances, batteries and packaging materials (the only type of MSW to be considered in this study).

In Portugal, after separated and deposited by the population, MSW can be collected in one of both ways (Bing et al., 2016): in drop-off containers or by curbside (door-to-door). The first system is the most common and consumers have to take their waste to drop-off containers – there are approximately 40000 nationwide (SPV, 2016); as for the second one, the recyclable containers are inside citizens' home buildings, and waste is collected at a known specific day. Some types of MSW cannot be collected in such places due to their dimensions, type of material or weight; therefore, they have to be delivered by consumers in specific places (stores or *ecocentros*).

As for packaging materials, there are three types of drop-off containers and normally they coexist together in every site: green ones are for Glass (G), yellow ones for Plastic and/Metal (PM), and blue ones for Paper and/Cardboard (PC). These type of containers can be placed on the surface (establishing a recycling centre, from now on referred to as "ecoponto" or collection point, and illustrated in Figure 2.2), or underground (a set of underground drop-off containers known as *ilhas ecológicas*).

Figure 2.2 - *Ecoponto* placed in the municipality and parish of Alcobaça (photo taken by the author)

Collection of MSW also includes the transportation of the materials collected to a location where vehicles are unloaded, such as a sorting facility, a transfer station or a landfill site. In these locations, MSW is treated and valued according to its composition.

Bing et al. (2016) stated that the main issues at the collection planning level are (i) the types of waste to be collected, (ii) the organization of collection and (iii) the type of vehicle used. In Portugal, the vehicles used to collect undifferentiated waste are typically rear-loaded trucks, while top loaded single compartmented trucks are mainly used to collect selective MSW. Since there are three different containers for packaging materials, each site has to be visited three different times to collect each one (single-material routes). One alternative with great impact on route planning is the use of vehicles with more than one compartment, collecting at least two types of material simultaneously, which is in fact the topic of this thesis.

Nonetheless, even the single compartmented trucks have some upgrades that make collection more efficient, such as pressing function. According to Bing et al. (2016), the vehicle capacity increases from 150% to 200%, when compared to a vehicle without this function. Such trucks are used in the Netherlands, UK, Germany, and Portugal (Valorsul included).

2.2. Valorsul

This study was motivated by the recyclable MSW collection system of Valorsul – *Valorização e Tratamento de Resíduos Sólidos das Regiões de Lisboa e do Oeste, S.A.*, a Portuguese company that has as mission to take the highest value from waste and packages not used, converting waste in valuable goods for society (Valorsul, 2016).

Valorsul is an inter-municipal SMAUT, responsible for the treatment and recovery of MSW. The company was founded in 1994, and today is a company of the holding EGF (*Empresa Geral do Fomento*, S.A.), recently privatized and handed over to SUMA and Mota Engil. Besides EGF – that owns 52,93% of the company –, Valorsul has more 6 shareholders that represent all 19 municipalities where Valorsul operates; five of them have an individually share – Lisbon (20%), Loures (11,51%), Amadora (5,16%), Vila Franca de Xira (4,61%) and Odivelas (0,54%) –, and the other 14[2] are represented by *Associação de Fins Específicos AMO MAIS* with a share of 5,25%.

Although the service area of Valorsul is around only 4% of the Portuguese territory, the company is responsible for collecting over one fifth of all MSW produced in Portugal. The company provides this service to 1,6 million inhabitants, that produce 1,3 kg/capita/day of MSW, which totals 472 kg/capita/year.

Valorsul also provides its services to private companies – collecting MSW that cannot be disposed on the typical street containers –, and receives MSW collected from other companies (Tratolixo, for example). In 2015, Valorsul directly collected approximately 83% of the 912371 tons of waste received in its facilities – see Table 2.1. To comply with PERSU 2020, there is a limit of MSW produced in the service area of Valorsul of 687614 tons for 2020.

Table 2.1 - Records on the amount of MSW received in Valorsul facilities in 2013, 2014 and 2015 (Valorsul, 2016)

Year	MSW produced in the service area of Valorsul (tons)		MSWproduced in other origins (tons)		Total recevied in Valorsul facilities (tons)
2013	739 447	80,50%	179 120	19,50%	918 567
2014	751 433	84,06%	142 481	15,94%	893 914
2015	753 571	82,59%	158 800	17,41%	912 371

[2] Alcobaça, Alenquer, Arruda dos Vinhos, Bombarral, Cadaval, Caldas da Rainha, Lourinhã, Nazaré, Óbidos, Peniche, Sobral de Monte Agraço, Torres Vedras, Azambuja and Rio Maior.

Valorsul also has the responsibility to recover all MSW received: 67% has as destiny incineration and/or energy recovery, 19% goes to a landfill, 8% is sorted, and 7% is recovered into organic matter (Valorsul, 2016).

In 2015, the company had 349 employees and finished the year with a turnover of 59 million euros. This result came from three main revenue sources: i) sales of recyclable MSW to SPV; ii) fees charged to Valorsul system users; iii) electricity sale to EDP (a Portuguese Energy Company), produced from the waste recovery in its facilities.

Valorsul manages the life cycle of MSW and covers different types of collection for the MSW produced in its service area: undifferentiated, of selective recyclable materials (the ones in study) and of organic matter (waste food and alike). The area where Valorsul operates is asymmetric and has two different geographical realities: the region of Lisbon (marked in grey in Figure 2.3) is an urban area, densely populated and with a wide variety and high prevalence of services; on the other hand, the western region (marked in green) is more rural and the populated areas are more dispersed. Valorsul is only responsible for selective collection in the 14 municipalities of the western region. The municipalities of Amadora, Lisbon, Loures, Odivelas and Vila Franca de Xira are responsible for their own collection of recyclable MSW; therefore, they are not to be considered.

Throughout the municipalities where the company operates, there is a vast network of facilities for treatment, recovery and disposal of the different types of MSW collected, based on their nature – see Figure 2.3.

Icon	Number	Type of Infrastructure	Short description
	2	Sorting facility	Sorting center where recyclabe MSW are received, separated, treated and then sent to recycling companies
	1	Recovery and Treatment of Organic Matter facility	Site where organic matter is processed and valued (to yield organic fertilizer, biogas and produce electricity)
	1	Central Energy Recovery	Undifferentiated MSW is burnt in this type of facilities to produce electricity
	1	Recovery and Treatment of Slag facility	This facility receives slags (materials generated from waste incineration), and separates ferrous metal, non-ferrous and inert
	2	Landfill	Site mainly used for the disposal of waste by burial
	6	Transfer station	Site used for temporary deposition of waste, aiming to optimize the cost/distance travelled; its function is similar to a cross-docking operation or a temporary warehouse
	8	Ecocentro	Public facility to dispose recyclable MSW, free of charge, that cannot be placed in typical containers due to their dimensions, volume or weight

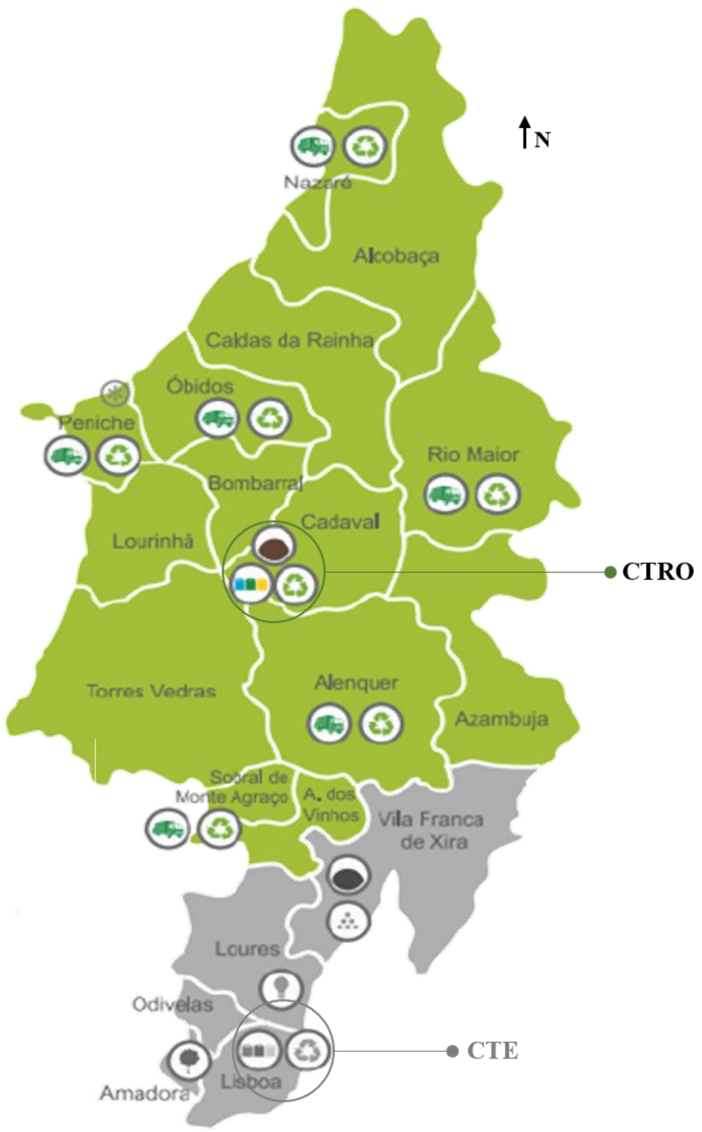


Figure 2.3 - Network of facilities for treatment, recovery and disposal of Valorsul for the different types of MSW collected (Valorsul, 2016)

2.2.1. Selective Collection

Valorsul is responsible for the selective collection of packaging materials (Paper and/ Cardboard, Glass, and Plastic and/Metal) in 14 municipalities of the western region, which includes 138 parishes. Table 2.2 shows the amount of recyclable MSW received between 2013 and 2015 in the sorting facility of the western region (CTRO – see its location in Figure 2.3), in number and in percentage of the total (i) received – which is the sum of the amount that entered in the CTRO and CTE.

Table 2.2 - Amount of recyclable MSW received in CTRO and CTE (Valorsul, 2016)

	2013			2014			2015			Δ CTRO
MSW received (tons)	CTRO		Total[i]	CTRO		Total[i]	CTRO		Total[i]	(2015/2014)
Paper and/Cardboard	4 601	16,3%	28 143	4 675	16,4%	28 524	4 770	16,7%	28 638	2%
Glass	5 220	22,7%	22 957	5 007	21,8%	22 946	4 950	21,0%	23 535	-1%
Plastic and/Metal	3 348	19,8%	16 894	3 383	19,3%	17 539	3 320	18,7%	17 765	-2%
Total	13 169	19,4%	67 994	13 065	18,9%	69 009	13 040	18,6%	69 938	-0,2%

When comparing 2015 with 2014, the only type of material that faced an increased in the amount received was Paper and/Cardboard (2%); Glass and Plastic and/Metal had a decrease in the amount received (of 1% and 2%, respectively). From all MSW received in CTRO in 2015 (13040 tons), 85% was directly collected by Valorsul (Valorsul, 2016).

2.2.1.1. Vehicle Fleet

In 2013, Valorsul operated a heterogeneous fleet of 14 vehicles, described in Table 2.3, all based in CTRO – the only existing depot to serve the 14 municipalities.

Table 2.3 - Fleet of vehicles of Valorsul (Lopes, 2014)

Type	V#	Brand & Model	Function	Compart-ments	Gross weight (tons)	Volume capacity without pressing materials (m³)	Weight capacity (kg)	Type of material
I	V1	MAN 18.284 LK L2000	SC	1	19	20	15 000	G
	V2	MAN 18.284 LK L2000	SC	1	19	20	15 000	G
	V3	MAN 18.284 LK L2000	SC	1	19	20	15 000	G
II	V4	Volvo FM9	SC	1	26	20	13 945	PC; PM
	V5	Volvo FM9	SC	1	26	20	13 945	PM
III	V6	MAN TGM 18.280	SC	1	19	20	5 580	PC; PM
	V7	MAN TGM 18.280	SC	1	19	20	5 580	PC; PM
	V8	MAN TGM 18.280	SC	1	19	20	5 580	PC; PM
	V9	MAN TGM 18.280	SC	1	19	20	5 580	PC; PM
	V10	MAN TGM 18.280	SC	1	19	20	5 580	PC; PM
IV	V11	Volvo FM9	SC	1	19	15	4 465	PC; PM
	V12	Volvo FM9	SC	1	19	15	4 465	PC; PM
V	V13	Nissan Atleon 140-80/3	ME	1	8	unknown	2 800	None
	V14	Toyota Dyna XZU425LD	ME	1	8	unknown	2 520	None

All vehicles have only one compartment (i.e., Valorsul only performs single-material routes), and their fuel consumption varies between 40L/100km and 60L/100km. The two Volvo FM9 have a system called *Ampiroll*, which allows the removal of their load container, and they are the only ones back loaded; all the other 10 vehicles used for collection are top loaded, using a lifting arm or a crane for that purpose.

The only vehicles that do not have pressing function are the ones used for maintenance (ME) and the ones of type I, which only collect glass.

2.2.1.2. *Ecopontos*

Typically, one *ecoponto* has at least one drop-off container for each material (blue for Paper and/ Cardboard, yellow for Plastic and/ Metal, and green for Glass) – see Figure 2.2 (page 9). However, different sites have different demands and one *ecoponto* do not necessarily has exactly one container for each type of material, or even the three types.

By 2013 – the year in study – Valorsul had 6959 drop-off containers for packaging materials, spread out across 2515 locations – see Appendix A. By the end of 2015, Valorsul had more 681 drop-off containers for packing materials (+10%), spread out across 2736 sites (+9%). Torres Vedras and Alcobaça are the municipalities with the highest percentage of *ecopontos* (20% and 14%, respectively). The one with the lowest is Óbidos, due to the existence of many *ilhas ecológicas*.

2.2.1.3. Collection Process

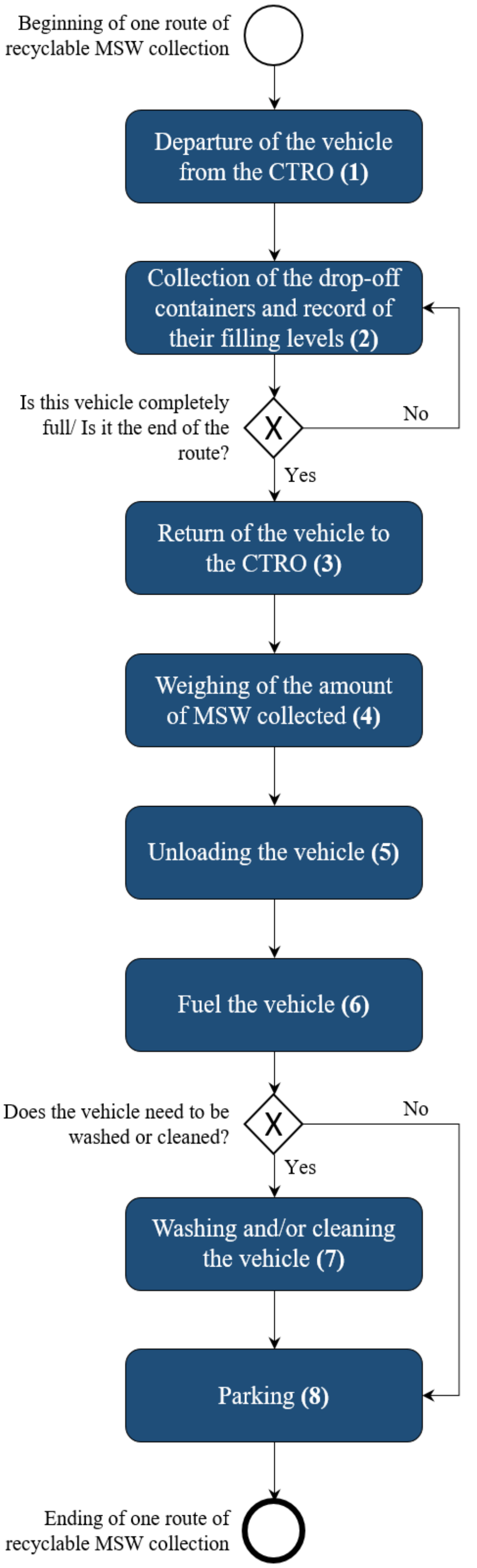


Figure 2.4 - Collection Process of Valorsul for recyclable MSW (adapted from Lopes, 2014)

Any vehicle needs to have a route assigned before leaving the CTRO.

The collection process begins by setting circuits to a vehicle and consequently to the team that will operate it (a driver and an assistant). In order to design the route network, a computer software (GIS – Geographical Information System) analyses the filling level of every container (calculated based on historical and geographical data), estimating the required frequency to visit every collection site. The sum of the quantity to collect in one route cannot surpass the vehicle capacity. Therefore, it is important to consider the type and number of vehicles, as well as the number of workers available during the day (i.e., if they are already assigned to a route or not).

Every circuit begins and ends at the CTRO. They are all static, meaning that the visit sequence of the containers will not change during its course, whatever is the filling level of containers. The routes assigned should ensure that the vehicle returns fully loaded, optimizing costs and/ distance travelled, and that containers are completely collected (each container has to be collected in one single visit). Once a route is assigned, the vehicle leaves the CTRO (1) and goes to the first collection point of the circuit (2). On site, before collecting any material, one of the workers look for the level marks inside the container and then registers the approximate measure in a PDA, out of five possibilities: i) empty (0%); ii) less than half (25%); iii) half (50%); iv) more than half (75%); v) full

(100%) – typically, the filling level is registered by excess. After this part, the container of the material being collected is raised with a crane and dumps its inside to the truck, emptying the container. The driver manoeuvres the crane and the assistant cleans the surrounding of the truck and container, if needed, and activate the compactor, in case the vehicle has pressing function. Then, the vehicle moves to the next collection point. This process is repeated until all containers under that route are collected, or the truck do not have enough capacity to move to any other site, forcing the vehicle to return to the CTRO (3).

After entering the CTRO, the vehicles go to a weighing-machine to register the weight of the amount of MSW collected (4). If the materials collected were Paper and/Cardboard or Plastic and/Metal, the vehicle unloads (5) its cargo at the sorting facility; if it was glass, the vehicle unloads at the glass deposit (this material is not sorted). After unloading, the vehicle moves to a fuel station that exists inside the CTRO (6). Depending on its condition, the vehicle may or may not need to be cleaned or washed (7). Finally, the vehicle is parked (8).

The last step of this process is the transmission of the data registered in the PDA, during the circuit (containers collected, filling levels, and distance and time travelled). This will update the system, influencing the routes over time. A software that estimates the evolution of filling levels uses this data, supporting route design.

2.2.1.4. Statistics about the collection of recyclable MSW

Table 2.4 presents some statistics on the collection of Paper and/Cardboard and Plastic and/Metal between January and June of 2013. All data was provided by Valorsul; Glass is not shown since data was not enough to make any conclusion.

Type of analysis	Indicator	Unit	Paper and/ Cardboard	Plastic and/ Metal
Jan - Jun 2013 (totals)	Number of routes performed	routes	451	518
	Amount collected	kg	1 274 560	1 040 225
	Travelled distance	km	62 442	71 059
	Duration	hours	3 093	3 613
Per route (average)	Amount collected	kg	2 826	2 008
	Travelled distance	km	138	137
	Duration	hours	6,86	6,98
Performance (average)	Amount collected per km travelled	kg	23,2	16,2
	Amount collected per hour travelled	kg	414,6	290,4

Table 2.4 - Statistics on the collection of recyclable MSW by Valorsul, between January and June of 2013

3. Literature Review

3.1. Logistics Management

The Council of Supply Chain Management Professionals (CSCMP) – the largest professional association dedicated to this area – defines Logistics Management (LM) as the “part of supply chain management that plans, implements, and controls the efficient, effective forward and reverses flows, and storage of goods, services and related information between the point of origin and the point of consumption”. LM is an integrating function, which aims to coordinate and optimize all logistics activities, such as inbound and outbound transportation, fleet management, or logistics network design (CSCMP, 2016).

Historically, society has moved from reactive approaches, such as pollution control, to more proactive approaches (Govindan et al., 2015), such as product stewardship and sustainable development across the Supply Chain (SC), evolving the concept of LM. Although its first definition only considered the forward supply chain (from the producer to the end-user), it is today recognized that the product life cycle does not necessarily end with the final customer (Shibao et al., 2010). Stock (1992) was one the first authors to approach this issue, studying the reverse flow with emphasis on managing returns as a problem to be solved. This author related Reverse Logistics (RL) with all logistic activities performed in recycling, reuse and disposal of products and packaging waste.

The relationship between RL and Waste Management has been recurrently addressed in the literature. The latter mainly refers to the processes that manage waste efficiently and effectively through its life cycle, such as waste collection (WC), the topic in study. In turn, RL concentrates on those streams where there is some value to be recovered, with the outcomes entering into a new supply chain (de Brito et al., 2004), which may or may not contribute to environmental sustainability. WC is in charge of taking-back MSW from collection points to an appropriate disposal facility, and is a RL problem, where typically many points need to be collected with only one delivery point, *vs*. deliveries from one point to many destinations in the forward logistics problem (Han et al., 2015). Although RL started to be used to refer the efforts in reducing the environmental impacts of enterprises and supply chains (Carter and Ellram (1998), cited in Carvalho, 2010a), it is today stated that Green Logistics is a more correct designation: forward logistics activities also have a significant environmental impact, not only reverse (de Brito et al., 2004).

A RL system starts from end-users, where products are collected (return products) and has as primary goal to manage end-of-life (EOL) products through different flows and recovery practices: remanufacture, repair, reuse, refurbishing, resale, recycling, scrap or salvage (Govindan et al., 2015). As Fleischmann et al. (1997) stated, a RL network can be motivated by the possibility of reusing products and materials. Their reuse is responsible for creating new flows from the end-user back to producers and suppliers. The same authors identify three main logistics activities related to the stages of transport and transformation of the reuse process: i) planning of reverse distribution; ii) inventory management; iii) production planning. This thesis will focus on the first one, which aims for organizing the collection and transportation of used products from their disposal site (such as drop-off containers).

De Brito et al. (2004) proposed a framework based on the following four questions, which explains the various ways in which RL activities are performed: 1) which products are entering (product-in) the RL network, and which ones are leaving it (product-out)?; 2) how is the main recovery process managed?; 3) who are the actors and which role do they play in the RL network?; 4) why are the products being returned, i.e., which ones are the driving forces and the reasons for initiating a RL network?

In order to answer the first question (1), the authors identified seven categories: i) civil objects (like buildings or bridges); ii) consumer goods; iii) industrial goods; iv) ores, oils and chemicals; v) other materials (such as glass); vi) distribution items; vii) spare parts. As for the recovery process (2), it can be direct (re-sale, re-use or re-distribution), or indirect (repair, refurbishing, remanufacturing, recycling, incineration or disposal). Regarding the third question (3), the authors divided the actors intro four groups: i) forward supply network actors (manufacturers, wholesalers, retailers or service providers); ii) specialized RL actors (recyclers, municipalities or external service providers); iii) governmental entities (such as the EU or national governments); iv) opportunistic players (ONGs). Finally, the drivers that may boost a RL network (4) can be of economic or legislative origin, and of corporate citizenship nature; product returns can be reasoned by manufacturing, distribution or commercial reasons. Summing up, the complexity of waste recycling decisions are determined by external factors (such as EU regulation, change in oil prices, and varying interests of householders, collection companies and municipalities). In order to meet the future demand of sustainability, the output of the decision-making on MSW management has to be a sustainable performance (see Figure 3.1).

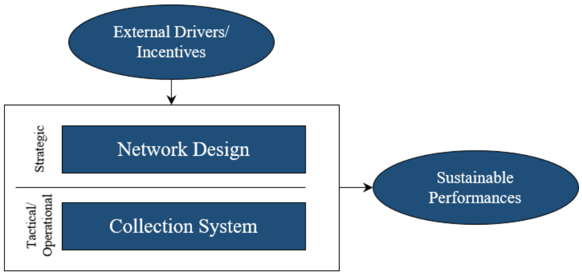


Figure 3.1 - Framework of reverse logistics for household waste recycling (adapted from Bing et al., 2016)

In the context of RL – and therefore in the context of MSW management –, de Brito et al. (2005) stated that companies have to make several strategic, tactical and operational decisions (pursuing the ideas developed by Fleischmann et al., 1997). Lambert et al. (2011) presented a framework based on these three hierarchical levels of planning and execution, dividing them into seven elements: coordination system; gatekeeping; collection; separation; treatment; information system and disposal system. The latter authors applied their framework to three case studies, analysing each of the referred elements in terms of process, cost and performance.

A collection system to operate needs vehicles and must count on infrastructures such as transfer stations, which are significantly costly. Rogers et al. (2012) found that in any RL network is necessary to use mathematical models to make an effective planning and management of its system. There are mainly two subjects regarding the modelling of these type of problems: i) logistics network design (number of facilities, their location, size and area of influence); ii) route planning (places to visit and in which sequence and moment). According to Lambert et al. (2011) the number and the location of facilities can be set as strategic, while its dimension, size and area of influence are tactical decisions. Route planning is related to operational ones.

The work hereby presented will focus on tactical and operational decisions: changing the type of vehicles from single-compartmented to multi-compartmented ones may force to adjust the area of influence of each facility and the route planning of the company in study. Strategic decisions do not arise since changes in the number, location and size of the depots will not be addressed.

3.1.1. Transportation Management

The performance of any SC depends on the efficiency of its logistics system, and transport management is a key activity: it is responsible for absorbing between one to two thirds of the total logistic costs of a company (Ballou et al., 2002). Particularly in those whose points of operation are geographically scattered, companies are highly dependent on transport systems, as well as particularly vulnerable to their weaknesses.

The collection (or distribution) of products is a practical and challenging problem of LM. For a company managing a recyclable MSW collection system, as Valorsul, collection (transport) costs represent about 70% of the total (Ramos et al., 2014). Waste must be collected continuously throughout the year, and transport cost does not spot increasing (Abdelli et al., 2016). By using the collected data and the appropriate analytical tools, a company may optimise its daily operations for collection and transportation in terms of quality of service and costs.

Transport-planning decisions result in the definition of routes and the visit sequence of each one, i.e., definition of the routing and scheduling problems. The solution must meet the basic rule of routing problems, which is, "…a vehicle of collection starts its trip with an empty tank and ends it with a full tank along a minimum route and in a minimal possible time (Abdelli et al., 2016)".

Nonetheless, besides the nature of the business, there are many factors and constrains to consider when solving a routing problem, such as (Carvalho, 2010b) – for the purpose of the study only road transport is considered:

i) Features of the road network: i) distance between nodes (variable costs, such as fuel, tires or maintenance, increase in proportion to the distance travelled; fixed costs – such as salaries, equipment and infrastructure maintenance and insurances – do not depend on the distance); ii) road conditions and service area (urban or suburban, symmetric or asymmetric), which have direct influence on travel time;
ii) Characteristics of the fleet (number, capacity, performance and filling speed);
iii) Return on empty (if the vehicle is not completely full, for example, transport costs increase);
iv) Characteristics of the points to visit, i.e., customers: i) location; ii) demand and/or supply; iii) capacity; iv) density of the cargo (the collection/transport cost per tonne decreases with an increase in cargo density); v) volume of the cargo (transport costs per

unit volume decreases with increasing volume as a result of dilution of fixed costs); vi) size of the cargo (very dependent on the delivery/pick-up frequency).

The more information a company has in advance, the better and more constant is the planning (static routing). If the set of customers to be visited by each vehicle and the visit sequence are established on a daily basis, then the company faces a more dynamic routing.

As for the vehicle itself, there are also some aspects that may be improved to support a more efficient management and positively affect routing (Carvalho, 2010b):

i) Efficient use of vehicles (handling systems, efficient use of space, cooperation in transport and cargo consolidation);
ii) Route optimization (reduction in the number and distances of routes, reduction of transport speed, usage of more IT planning);
iii) Consumption efficiency (driver behaviour - eco driving, fleet management, preventive maintenance);
iv) Technological innovation (usage of efficient fuels and engines, better tires, and more aerodynamics).

MSW collection, the topic in study, can be treated as a Vehicle Routing Problem (VRP). Its classical form, variations, and solution methods will be addressed in more detail in the next sections.

3.2. Vehicle Routing Problem

Routing problems are identified in the literature as one of the main problems companies face when managing their SC; for this reason, they have been widely studied due to the economic importance of developing efficient techniques for optimization in transportation (Cacchiani et al., 2014).

3.2.1. General Definitions and Notation

The Vehicle Routing Problem (VRP) plays a central role in physical logistics and is an important combinatorial optimization problem. It "…consists of designing least cost delivery routes through a set of geographically scattered customers, subject to a number of side constraints" (Laporte et al., 2013).

The components to consider when studying a routing problem are the road network, customers, depots, vehicles and drivers. Toth et al. (2002a) related all of them: the distribution or collection of goods "…concerns the service, in a given time period, of a set of customers by a set of vehicles, which are located in one or more depots, that are operated by a set of crews (drivers), and perform their movements by using an appropriate road network".

VRPs are an extension of the travelling salesman problem (TSP) – the most common practical interpretation of the TSP is that of a salesman (i.e., one vehicle) seeking to travel the minimum distance possible, visiting all cities (customers) once and only once, during one day (Laporte, 1992).

In a VRP (i) more than one vehicle can be traveling around a network; the number of vehicles is either an input value or a decision variable (Cordeau et al., 2005). All (ii) routes begin and end at the same place (a depot node), (iii) after all customers were visited and their known demand satisfied; (iii) each one has to be visited by exactly one vehicle and (iv) cannot be visited more than one time per route, over a given planning horizon (the classical VRP considers only one day) (Reed et al., 2014).

A road network, and therefore a VRP, is described through a complete undirected graph $G = (V, E)$ (Cordeau et al., 2005) – see Figure 3.2 –, where $V = (v_0, v_1, \dots, v_n)$ is the set of nodes (vertices) and $E = \{(v_i, v_j) : v_i, v_j \in V,\ i < j\}$ the set of edges. The node v_0 typically represents a depot, where K homogeneous vehicles of capacity Q are based. The remaining vertices are customer locations, and may be associated with a non-negative demand (D_i), and/or supply (S_i). Each arc (i, j) represent a road section, connecting the nodes, and is associated with a non-negative cost (c_{ij}), distance (d_{ij}) or travel time (t_{ij}); each customer may have a non-negative drop time dt_i, i.e., the time to deliver or collect a product. A VRP aims to find a set of n routes that fulfils one of the following objectives, or any weighted combination of them (Toth et al., 2002a):

- Minimization of the global transportation cost, dependent on the global distance travelled (or on the global travel time) and on the fixed costs associated with the used vehicles (and with the corresponding drivers);
- Minimization of the number of vehicles (or drivers) required to serve all the customers;
- Balancing of the routes, for travel time and vehicle load (decrease variation);
- Minimization of the penalties associated with partial service of the customers;

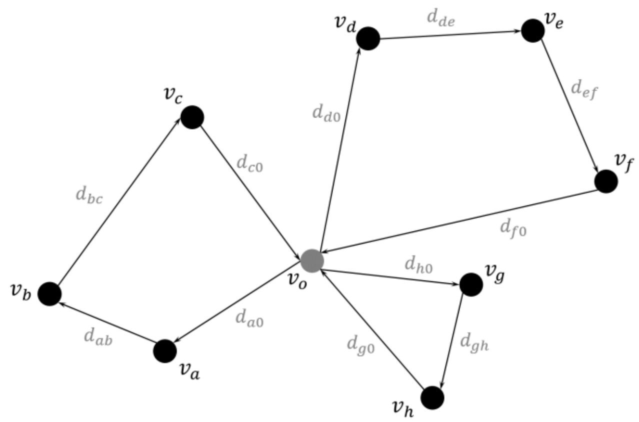


Figure 3.2 – Illustration of a simple directed graph made up by 8 nodes and 1 depot, with 3 defined clusters

The representation of a VRP in a graph can be classified as a Node Routing Problem, which considers distribution/collection of goods point to point, i.e., demand and/or supply is at the nodes. However, there are also Arc Routing Problems, which considers distribution/collection of goods along the edges of a road network, i.e., demand/supply exists along the arcs of the graph. This dissertation will only discuss Node Routing Problems.

3.2.2. Solution Methods

When Dantzig and Ramser first introduced the TSP almost 60 years ago, they formulated a problem with only 12 delivery points and 1 bulk terminal to find the optimum routing of a fleet of gasoline delivery trucks (Dantzig and Ramser, 1959). Today, due to a steady evolution in the design of solution methodologies, vehicle routing is one of the most studied problems in operations research and applies to a wide variety of industries. This approach to reality hinders problem solving, mainly for two reasons: i) complexity and limitations of computation; ii) large number of problem constraints (a closer a problem is to reality, the more constraints have to be considered).

An increased number of clients generate an exponential increase in the number of possible solutions – Lenstra et al. (1981) have classified the VRP as a NP-hard combinatorial problem. For this reason, several solution methods have been proposed for the VRP, which can be broadly classified into three main classes: i) exact algorithms; ii) heuristic algorithms; iii) metaheuristics.

Exact methods guarantee that the optimal solution is achieved, but only if the method is given enough time and space. Their efficiency relies on two variables: problem size and computational time. The time taken by this kind of methods to find an optimum solution to a VRP sometimes is so long that in many cases it is inapplicable (Martí et al., 2011). Exact methods can rarely tackle problems that involve more than 100 nodes; they are mainly used to solve small instances (Laporte et al., 2013). Branch-and-bound or branch-and-cut are two examples of exact algorithms (see Cordeau et al., 2007).

Heuristic methods (or approximate) only attempt to yield a good solution – not optimum – but they are often used to solve real optimization problems when the process speed is as important as the quality of the solution obtained (effectiveness). In addition to the need to find a good solution in a reasonable time, Martí et al. (2011) also highlighted that heuristic methods are more flexible than the exact ones, allowing to add constrains difficult to model. Heuristic methods can be divided into classical – see 3.2.2.1 –, mostly developed between 1960 and 1990 (Toth et al., 2002b) and modern (metaheuristics) – see 3.2.2.2 –, whose development started in the 90s (Laporte et al., 2013).

3.2.2.1. Classical Heuristics

Laporte (2007) explains that the term “classical” refers to the fact that the improvement steps of these heuristics always proceed from one solution to a better one in its neighbourhood, until no further gain can be achieved. They are broadly classified into three categories (Toth et al., 2002b): constructive heuristics, two-phase heuristics or improvement heuristics.

Constructive Heuristics

Constructive heuristics do not contain an improvement phase per se, but they gradually build a feasible solution focused on solution cost (Toth et al., 2002b): they involve building a solution to the problem gradually, from scratch. One of the most popular construction heuristic is the one developed by Clarke and Wright, in 1964, the so-called savings algorithm: there is a cost reduction when two customers can be served in the same route, opposed to deliver or collect goods directly to them from the depot, i.e., when two routes can be merged into a single-one (Carvalho et al., 2010b). This algorithm, illustrated in Figure 3.3, naturally applies to problems for which the number of vehicles is a decision variable.

The savings achieved by travelling from customer i to customer j before returning to the depot (origin) v_o is given by $S_{ij} = 2\left(d_{i0} + d_{j0}\right) - \left(d_{i0} + d_{ij} + d_{j0}\right) = d_{i0} + d_{j0} - d_{ij}$, where d_{i0} is the distance from the customer i to the depot v_0; d_{j0} is the distance from customer j to the depot; and d_{ii} is the distance between both customers i and j. The algorithm is as follows: i) calculate the savings for every pair (i, j); ii) rank the savings and list them in descending order of magnitude; iii) for each saving, include link (i, j) in a route, if no problem constrain is violated; iv) if the savings list has not been exhausted, repeat step (iii) until all customers are included in a route.

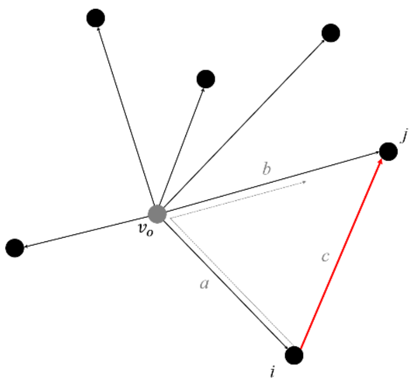


Figure 3.3 - Illustration of the Savings Algorithm

While this algorithm is not the best available in terms of accuracy, it is rather fast and simple to implement (Laporte, 2007). The biggest disadvantage of this method relates to the fact that the inclusion of the best saving in a given step can prevent a new connection to generate greater savings (Carvalho et al., 2010b). There are extensions to the savings heuristic in the literature, as well as other classical route construction heuristic, such as the sequential insertion algorithms (see Toth et al., 2002b; Laporte, 2007; Martí et. al., 2011).

Two-phase Heuristics

The two-phase heuristics decomposed the VRP solution process into two separate issues: (i) clustering and (ii) routing. The first aims to determine a partition of the customers into subsets, each corresponding to a route, while the second aims to determine the sequence of customers to visit on each route (Cordeau et al., 2007).

In a cluster first – route second method customers are first grouped into clusters and only then it is determined a vehicle route for each cluster. In 1974, Gillet and Miller developed the sweep heuristic based on the mention method, which is illustrated in Figure 3.4. The algorithm starts by (Cordeau et al., 2007) (i) choosing a random customer, and then, (ii) sequentially assigning the remaining customers to the current vehicle (route), considering them in order of increasing polar angle with respect to the depot and the initial customer. When the (iii) vehicle capacity is at its maximum and no more customers can be assigned to the current route, a new one is initiated. After assigning all vehicles, (iv) each vehicle route has to be optimized separately by solving the corresponding TSP, i.e., by visiting each customer only once and making the vehicle travel the minimum distance possible.

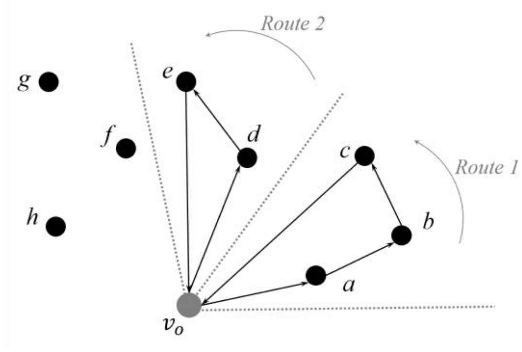


Figure 3.4 - Illustration of the Sweep Algorithm

Fisher and Jaikumar (1981) – see Sethanan et al. (2016) – proposed another type of heuristic based on a two-phase decomposition procedure; the algorithm developed by the authors solves the clustering step through the solution of a Generalized Assignment Problem (GAP), instead of using a geometric method like the sweep algorithm. Each vehicle is assigned a representative customer (a seed) and the assignment cost of a customer to a vehicle is equal to its distance to the seed. Routes are determined by solving a TSP for each cluster (Cordeau et al., 2007). The authors do not specify how to handle distance restrictions – see extensions to their heuristic and others based on a cluster first – route second approach in Toth et al, 2002b.

Moreover, there is also route first – cluster second methods, where a giant TSP tour over all customers is built, and then split into feasible routes (Cordeau et al., 2007). The savings algorithm (explained in the previous page) can be considered a route first – cluster second heuristic. More examples of such algorithms are given in Toth et al., 2002b.

Route improvement heuristics

Route improvement heuristics for the VRP are often used to improve initial solutions generated by other heuristics, using local search algorithms – starting from a given solution, this method applies simple modifications, such as arc exchanges or customer movements, in order to achieve a better solution and reduce cost (Cordeau et. al, 2007). Such heuristics can be performed on each vehicle route separately (intra-route movements) or on several routes at a time (inter-route movements) (Toth et al., 2002b).

Lin (1965) proposed the λ-opt heuristic, where λ edges are removed and then replaced by other λ, from the given solution – typically λ assumes the values of 2 or 3 in practice (Cordeau et al., 2007). Other local search algorithms are (Groër et al., 2010): i) the one-point move, where an existing node is relocated into a new position; ii) the two-point move, that consists in swapping the position of two nodes; iii) the three-point move, where the position of a pair of adjacent nodes swap with the position of a third node.

3.2.2.2. Metaheuristics

Metaheuristics perform a more thorough search of the solution space and are less likely to end with a local optimum (as opposed to classical heuristics). Although they embed procedures from classical construction and improvement heuristics, they outperform classical methods in terms of solution quality, and sometimes in terms of computing time. Cordeau et al. (2007) presented three classes for metaheuristics, all applied to the VRP (see Toth et al., 2002c): i) local search (LS); ii) population search (PS); iii) learning mechanisms (LM).

LS methods (i) start with some feasible solutions to a problem and progressively improves them (Martí et al., 2011). These kind of algorithms explore the solution space by iteratively moving an initial (current or random) solution s_0, moving at each interaction t from the solution of value $f(s_t)$ to another solution located in the neighbourhood $N(s_t)$ of s_t. This neighbourhood represents all the solutions that can be reached from s_t by applying some transformation to the system, such as relocating a node from one route to another. The LS goes on until a stopping criterion is satisfied, such as a pre-set number of consecutive iterations without any improvement (Cordeau et al., 2007). Since each global iteration produces a solution (a local optimum), the best overall is the output of the algorithm (Martí et al., 2013). LS procedures include, for example, Simulated Annealing (SA), Deterministic Annealing (DA), and Tabu Search (TS).

The SA method is a probabilistic metaheuristic technique that provides a set of near optimal solutions instead of an optimal one (approximation algorithm). Inspired by the process of annealing in metallurgy, SA interprets slow cooling as a slow decrease in the probability of accepting worse solutions as it explores the solution space, all influenced by a temperature parameter T (see Tavakoli et al., 2016). Van Breedam (1995) presented an application of SA to the VRP. DA is the deterministic variant of SA (see Yasuda, 2009).

Proposed by Fred W. Glover, in 1986 – see Toth et al., 2002c – the TS begins with a local search around an initial solution, with the next move being made to the best neighbour of the current solution s_t. In order to avoid loops, the movement that found the new solution is registered in a list – the tabu list (this movement is forbidden, or tabu, for a number of iterations). Cordeau et al. (2007) stated that this is the metaheuristic that better suits VRPs.

PS (ii) methods include genetic search algorithm (GA) and adaptive memory procedures (AMP). GA simulates the way natural selection is carried out; such algorithms apply operators to a population of solutions, in order to improve the new generation – see "Flow Chart of solution of VRP using GA" in Masum et al. (2011). As for AMP, they work as a pool of good solutions, which is updated by replacing its wort elements with better ones. The concept of AMP is similar to GA, but the solution method is different and has TS included in its final step (Cordeau et al., 2007).

Finally, there is LM (iii), which include neural networks (NN) and ant colony systems (ACS). NN are inspired by the neurons in the brain and gradually adjust a set of link weights until an acceptable solution is reached; the elastic net and the self-organizing map are examples of models used in VRP to generate a feasible solution (Cordeau et al., 2007). On the other hand, ACS are based on ants' behaviour in search of food. Yu et al. (2011) and Reed et al. (2014) applied ACS algorithm to the VRP; the latter authors concluded that this might be the most successful soft computing approach for routing problems.

3.2.3. VRP Variants

Due to the economic importance of the problem, vehicle routing holds a central place in distribution management and is managed on a daily basis by tens of thousands of carriers worldwide (Laporte et al., 2013). Several variants of the basic problem have been put forward, due to the variety of constraints and complexity encountered in real-life problems.

A system may include more than one depot, a homogeneous or heterogeneous fleet of vehicles, or deterministic or stochastic demand. There are other variables to consider, such as time windows during which the customer has or can be served, the capacity of the vehicle, maximum duration of driving periods, or even budgets. The higher the number of restrictions imposed by the problem, the greater the approach to reality (Ferrucci, 2013). VRP variants arise when these constraints are added to the traditional version of the problem.

The most studied and common VRP variant is the capacitated VRP (CVRP), where capacity constrains exist. Demand of the system is deterministic and cannot be split (Toth et a., 2002d); there is demand associated with all customers, concerning only one type of product that must be collected, or delivered (Reed et al., 2014). The fleet of the vehicles is homogeneous, is based at a single depot, and each vehicle have a capacity that cannot be exceeded (Baldacci, et al., 2004) – the sum of the demands of the vertices visited by a circuit cannot exceed Q. When each vehicle if full (or empty) it returns to the depot. The objective is to minimize the total cost (reducing the number of routes, their length or travel time), serving all customers. Capacity is in fact an issue that all real routing problems have to deal; therefore, the following variations are also CVRP variants:

i) **Vehicle Routing Problem with Time Windows (VRPTW):** In this problem, each customer i is associated with a time interval $[a_i, b_i]$ (Toth et al., 2002d). This time window (TW) is the period of time during which deliveries can be made to a specific customer; its limits are the earliest allowed arrival time (e_i), and the latest allowed arrival time (l_i) (Berov, 2016). This type of VRP arises in a wide range of practical problems, such as school bus routing, mail, newspaper delivery, fuel oil delivery and municipal waste collection (Tan et al., 2001). Nikolic et al. (2013) and Barbucha (2014) published some recent studies on this topic.

ii) **Periodic Vehicle Routing Problem (PVRP):** This problem takes into account several planning days, unlike the CVRP, with customers that require service on multiple days during the planning period (Carotenuto et al., 2015). In order to find the set of minimum routes for each day, the PVRP aims to determine the appropriate day combination for each customer (Cacchiani et al., 2014), delivering or collecting the required quantity of products. PVRPs are applied to waste collection problems (Teixeira et al., 2004) or in retail distribution of fuel oils (Cacchiani et al., 2014).

iii) **Multi-Depot Vehicle Routing Problem (MDVRP):** This type of routing problems consider the existence of more than one depot per system, unlike the VRP variants already described. Because there are additional depots for receiving and storing the products, it has to be determined which one serves which customers, i.e., prior to the routing and scheduling problems, there is a grouping phase (Ho et al., 2008). Chao et al. (1993) studied MDVRP in the Soft Drink Industry, and Pooley (1994) detailed a case study within the Food Industry.

iv) **Multi-Compartment Vehicle Routing Problem (MCVRP):** In this type of problem customers request the delivery, or collection, of different products that cannot be commingled during transport. In such cases, vehicles with multiple compartments can be used to co-transport the products. This is the VRP variant considered for this study, which will be approached in detail in section 3.2.3.1.

Due to the complexity of problems and the number of constrains needed to consider, many combinations between the ones already mentioned arise in the literature. There are some extensions worth mentioning, such as: the Multi-Depot Periodic VRP – MDPVRP applied in the utilities sector (Hadjiconstantinou et al., 1998); the PVRP with Time Windows – PVRPTW, solved by an improved ACS heuristic (Yu et al., 2011); the Multi-product MDVRP applied in the frozen food delivery sector (Zhang et al., 2014).

Until now, all variants considered a homogenous fleet; however, in real life, a company may have a fleet with different vehicles types, with distinct capacities and costs (see Subramanian et al., 2012). So far, it has also been considered that in one route products would either be collected or delivered, yet each customer can be associated with two quantities, representing the demand of goods to be delivered and other the ones to be picked up at its location (Toth et al., 2002e), adding more challenges to the problem and to capacity management.

In the deterministic VRP, routes are planned in such a way that the vehicle always has enough capacity to satisfy all customers' demands. The situation is different when demands are stochastic, i.e., unknown. The study of VRP with Stochastic Demand (VRPSD) introduces randomness into combinatorial problems as a way of describing new real problems in which most of the information and data cannot be known beforehand (Juan et al., 2011).

3.2.3.1. Multi-Compartment Vehicle Routing Problem

As previously mentioned, this dissertation aims to study the impact of having a fleet of vehicles with more than one compartment, allowing each vehicle to collect more than one type of recyclable MSW in every vehicle route. MSW, after being sorted at the source by customers, can be collected simultaneously. In the literature, this problem is referred to as a Multi-Compartment Vehicle Routing Problem (MCVRP).

The MCVRP is a NP-hard problem and is formulated like a CVRP, represented by a complete undirected graph (see page 23). However, there are more constrains to consider: notation for this problem is based in Henke et al. (2015). For every node of the system (except for depots) exists a non-negative demand for each of product type (P): $s_{ip}(i \in V\backslash\{0\}, p \in P)$, where $V = (v_0, v_1, \dots, v_n)$ is the set of nodes (vertices).

Regarding transportation, K identical vehicles are available at a depot, each with a capacity of Q, that can be split between a limited number of m compartments, $1 > m \leq |P|$, each with a capacity of q; it is assumed $q_{ip} \leq Q_p$ for all i, p, $(q \in Q)$, $(p \in P)$. This division will allow loading products of different types at their location and keep them separated during the transport. When the vehicle is unable to make a further move without one or more compartments becoming overfull, it returns to the depot. A location can be visited more than one time in order to pick-up different product types (when for one location $|P| > m$); however, each demand q_{ip} has to be loaded in total in the same vehicle route (this VRP variant does not consider split collection). The MCVRP reduces to a CVRP when $P = 1$.

To determine the set of routes (n) in a MCVRP that minimize the total cost of all edges and where the vehicles capacity is not exceeded, there are some decisions to be made, as follows (Henke et al., 2015) – the first two are specific to this kind of problem, while the last two are generic for every VRP:

i) Assignment of product types that every vehicle can collect, and therefore the number of compartments;
ii) Determination of the compartment sizes, and therefore the capacity of each one;
iii) Assignment of supplies to each of the vehicles (implicitly includes clustering);
iv) Route sequence for every vehicle (routing).

Taking the collection of MSW sector as an example, the advantage of the MCVRP is that, in theory, only one vehicle is required to collect all products from the customer, or collection points. However, the amount of each product collected must be balanced so that all compartments fill at the same rate; otherwise, the vehicle may end up a route with its capacity not optimized – the system loses its advantage (Worrell et al., 2011).

Figure 3.5 illustrates the difference between single-material routes (traditional VRP) and multi-material routes (modelled with the MCVRP).

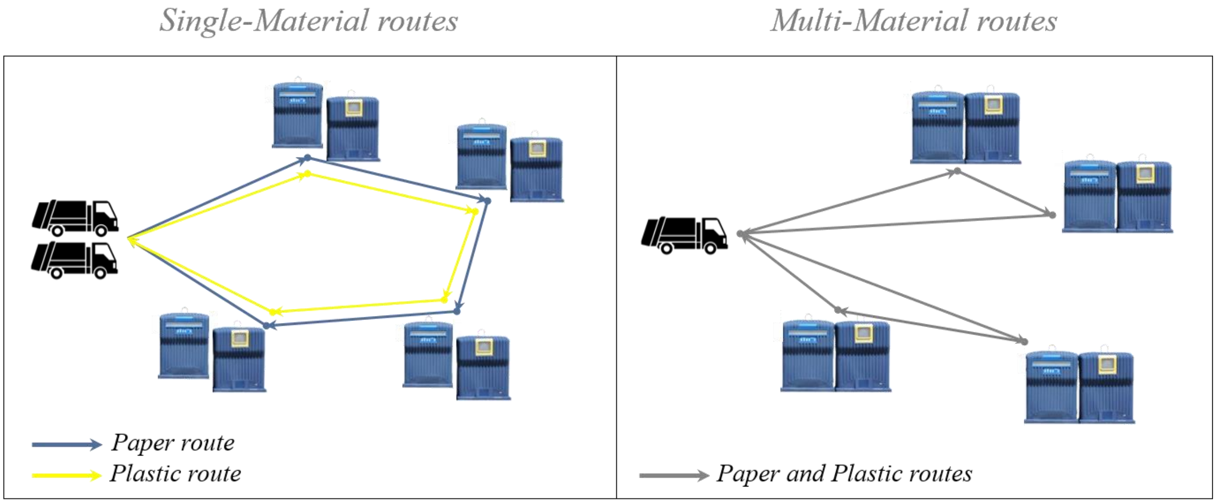


Figure 3.5 - Illustration of single-material routes *versus* multi-material routes (adapted from Oliveira et al., 2015)

Although not extensively discussed in the literature, the MCVRP have been applied to some sectors, as the fuel distribution where this VRP variant has been frequently addressed. Van Der Bruggen et al. (1995), Avella et al. (2004) and Cornillier et al. (2012) are some of the authors that published papers on this sector, considering trucks with several tanks (compartments) of different capacities to deliver fuel to retailers. Coelho et al. (2015) published one of the most recent papers about the fuel distribution problem, where the authors define and compare four variants of the multi-compartment delivery problem, solved in a multi-period and in an inventory-routing setting.

The distribution of food products has also been tackled in the literature. Chajakis et al. (2003) applied the MCVRP in the distribution of food products to convenience stores. El Fallahi et al. (2008) applied the MCVRP to the distribution of two products of cattle food to farms, solving it with three algorithms: a savings-based heuristic, a memetic algorithm and a TS procedure. The authors tested two possibilities of delivery: one where both products had to be delivered at the same time (same route), and another one where products were delivered in different moments (different routes). Mendoza et al. (2010) used the set of instances proposed by El Fallahi et al. (2008) and studied the MCVRP with stochastic demands (MCVRPSD).

Muyldermans et al. (2010) presented a LS procedure for the MCVRP applied to the waste collection industry, improved by route improvement heuristic, such as the two-point move. The authors concluded that co-collection is better than separate collection, and the benefits increases when: i) the number of commodities increases; ii) the vehicle capacity increases; iii) items are less bulky; iv) all clients request all commodities**;** v) the depot is more centrally located in the service area. The authors point out, however, that imbalances in commodity demands have a negative impact on the benefits of co-collection.

Reed et al. (2014) and Abdulkader et al. (2015) studied the MCVRP using an ACS, applying it to the collection of household waste by curbside and to garbage collection, respectively. The latter authors concluded that, although the travel cost per trip using single-compartmented vehicles is smaller, the total cost is higher because every customer has to be visited as many times as the number of products of the system.

Lahyani et al. (2015) presented a mathematical model based on the olive oil collection problem in Tunisia that can be applied to a variety of other industries. The authors proposed a branch-and-cut algorithm to solve a Multi-product (three grades of oil), Multi-period MCVRP. In turn, Wang et al. (2014) approach the MCVRP to the reality of many companies that operate a heterogeneous fleet of Vehicles.

Henke et al. (2015) added a new variable to the MCVRP: the size of the compartments can vary discretely, i.e., "…the walls separating the compartments from each other can only be introduced in specific, predefined positions" (Henke et al., 2015). They formulated a MCVRP with Flexible Compartment Sizes (MCVRP-FCS), implementing it to a real case where glass of different colours has to be collected and kept separated during transportation.

Oliveira et al. (2015) developed a cluster first – route second heuristic to solve a MCVRP in the collection of two different materials (paper/cardboard, and plastic/metal) of Valorsul. Although savings were obtained, the authors concluded that the cluster phase should be improved. This dissertation aims to pursue the work developed by Oliveira et al. (2015).

4. Methodology

The current chapter outlines the methodology applied to the development of this work. Figure 4.1 presents the sequence of phases on which this work was built on.

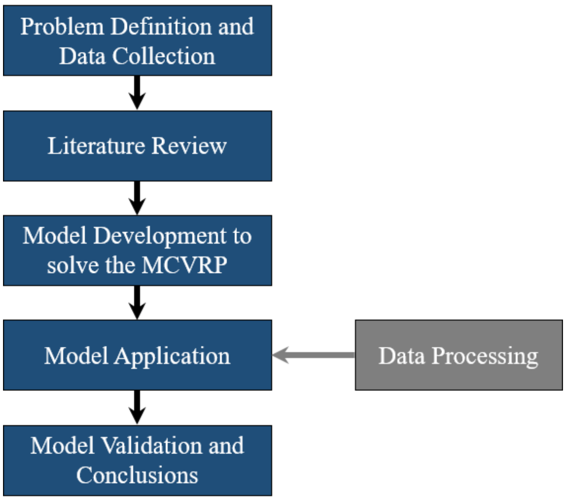


Figure 4.1 - Scheme of the methodology implemented

Collection costs represent about 70% of the total cost of a recyclable waste collection system (Ramos et al., 2014), and in Portugal there are approximately 40 000 *ecopontos* throughout all country to collect. This dissertation aims to study the impact of using vehicles with multiple compartments on the collection of recyclable MSW.

To do so, data about Valorsul – the company that supports the case study – was collected in order to understand how its system is operated, and with which resources. Moreover, the waste sector itself was analysed to have a comprehensive view of its operating mode.

Two main research questions were then formulated, as presented before, which this work intends to answer: 1) "*Which collection points are eligible to be visited by a multi-compartmented vehicle?*"; 2) "*What is the impact of the use of vehicles with multiple compartments on the distance travelled of a recyclable MSW collection system, when compared to the traditional method?*".

Given these research questions, literature on logistics, transportation and routing was reviewed. In a broad sense, the basic rule of a routing problem is that one vehicle starts its trip with an empty tank and ends it with a full tank, travelling the minimum distance and time possible (Abdelli et al., 2016). However, there are many constrains and variables to consider, such as the features of the road network, the characteristics of the fleet and of the points to visit, as well as labour conditions (Carvalho, 2010b). The more information a company has in advance about all of them, the better the planning.

As for the studies applied to waste collection systems, it was found that most of them address the traditional method, where single-material routes are performed to visit collection points, i.e., a single compartment vehicle is used to collect each material individually. Real-life applications of the problem in study – the Multi-Compartment Vehicle Routing Problem (MCVRP) – are seldom studied, although this problem has been getting more attention from the academia in recent years. Muyldermans et al. (2010) concluded that imbalances in commodity demands have a negative impact on the benefits of co-collection, and Reed et al. (2014) and Abdulkader et al. (2015) determined that the MCVRP is more cost-effective than the single-material collections.

The topic and the company analysed in this dissertation were approached by Oliveira et al. (2015). The authors studied a specific region of the area where Valorsul operates and considered that all *ecopontos* within that region were eligible to be visited by a multi-compartment vehicle. Although savings were obtained, the authors concluded that the cluster phase should be improved. This dissertation aims to take this opportunity by developing a new model that ultimately analyses the impact of using vehicles with multi compartments on the distance travelled.

The model developed is divided in several phases. First, it identifies which materials are worth being collected by a multi-compartment vehicle, based on the similarity of densities between materials. Secondly, and to answer the first research question, the model identifies which collection points are worth being visited by the type of vehicles in study, from the existing network of Valorsul – to do so, a decision making process is approached. This analysis was performed since, based on the data provided by Valorsul, it was acknowledged that collection points have differences between themselves that may justify using different types of vehicles within the same region, such as demand and capacity installed.

After establishing which materials to collect and collection points to visit, the model clusters all *ecopontos* and calculates the optimal routes for each cluster – which means that the actual collection system is completely reconfigured. To do so, the model combines a heuristic for the clustering phase, and the use of an exact algorithm for the routing phase (hybrid model).

In order to apply the developed model to the case study, data collected by Valorsul had to be processed. Historical data from the 2^{nd} of January of 2013 to the 14^{th} of June of 2013 were provided by Valorsul in MS Excel sheets, and contained information about:

i) Types of material collected;

ii) Collection points (number of containers per material, their capacity, and geographical location);

iii) Collection shifts performed (all single-material routes): total amount of MSW collected per route, its visit sequence, duration, distance travelled, and the filling level of every container;

iv) Fleet of vehicles.

These data were necessary to calculate the parameters that the proposed model uses, such as the predictable daily filling rates per collection point, the capacity installed of each one and the theoretical distances between all nodes in the system. The processing of data was done using MS Excel, as well as most of the model implementation. Only the calculation of the optimal visit sequence (solved as a TSP) was done using GAMS (General Algebraic Modelling System). The mathematical formulation for the TSP is based on the work of Baldacci et al. (2004).

In the end, to verify the obtained solution, a model validation is proposed in order to answer the second research question and evaluate the benefits of the model and draw some conclusions. This validation will be performed by analysing a specific region of Valorsul.

5. Proposed Model to Solve the MCVRP

The model proposed to solve the MCVRP in this chapter is based on the literature reviewed, Valorsul operation and infrastructure, and aims to answer the research questions presented in section 1.2, page 4.

It is intended that this model can be adapted and applied to other MSW collection systems than the one Valorsul operates, although it was constructed based on the latter. In this chapter, the proposed model is presented in a generic way and in the next chapter applied to the case study.

5.1. Problem Description

The objective of this model is to set routes that minimize the distance travelled in the collection of recyclable MSW, using vehicles with multi-compartments, i.e., vehicles that collect more than one material per visit.

5.1.1. Data Required

i) Location of collection points;

ii) Location of depots (or the place where vehicles are based);

iii) Location of intermediate stations or sorting centres where vehicles have to pass by, stop or unload, if applicable, and different than the depots;

iv) Distance between all visiting points in the system (collection points, depots, stations, sorting centres, etc.);

v) Number of containers per material in every collection points, and their capacity;

vi) Amount to collect per material in every collection point;

vii) Type of vehicles available, and their capacity;

viii) Time required at each collection point to load the vehicle;

ix) Time required to unload the vehicle at the depot (or similar location).

5.1.2. To Determine

i) The materials that are advantageous to collect with multi-compartment vehicles;

ii) The collection points that are eligible to be visit by multi-compartment vehicles;

iii) The number of collection points per cluster;

iv) The size of the vehicle compartments for every cluster;

v) The amount of MSW collected per route;

vi) The distance travelled in every route.

5.2. Model Description

Figure 5.1 summarizes the proposed hybrid model for the collection of MSW with vehicles with multiple compartments (MCVRP). It has four different phases: firstly, the materials to be collected by a multi-compartment vehicle are decided (phase 1); secondly, the sites that are worth visiting with this type of vehicles are established (phase 2). Then, all visiting points are divided into groups, so that their visit sequence can be designed (phase 3). Finally, the model is validated, comparing the obtained solution with a VRP one (phase 4). Each phase will be explained in detail in the next sections.

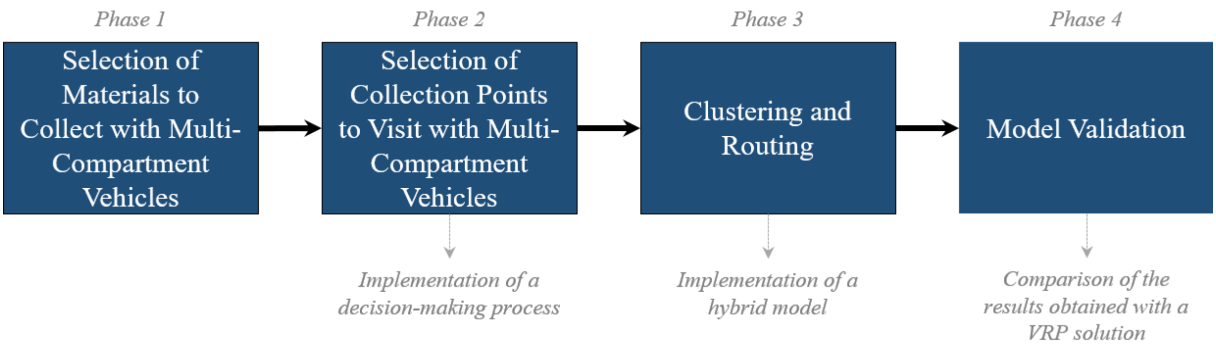


Figure 5.1 - Illustration of the proposed model

The second phase aims to answer to the first research question ("*Which collection points are eligible to be visited by a multi-compartmented vehicle?*"). Phase 3 aims to solve the second one, with the answer being given in the fourth one ("*What is the impact of the use of vehicles with multiple compartments in the distance travelled of a recyclable MSW collection system, when compared to the traditional method?*").

The proposed model is a hybrid one, which combines a heuristic with an exact algorithm (phase 3). The development of a heuristic to group collection points is related to the problem size, which includes a large number of restrictions (vehicles capacity, work schedule, and number and capacity of drop-off containers) and variables (demand, i.e., filling rates of the drop-off containers), giving more flexibility to the problem and achieving a good solution in less time than if an exact algorithm was used. On the other hand, routing is performed with an exact method due to the existence of software able to compute optimal results in an acceptable time, especially when the size of the instances is small (Laporte et al., 2013).

5.2.1. Phase 1: Selection of Materials to Collect with Multi-Compartment Vehicles

Multi-compartment vehicles are used to collect and distribute different kind of materials. El Fallahi et al. (2008) described the delivery process of cattle food; Lahyani et al. (2015) described the collection of olive oil; other authors focused on waste collection. Since the vehicle capacity is split between two or more materials, the less volume a material occupies inside the vehicle, the greater the advantage of this VRP variant; thus, it is important to know their density.

The density (ρ) of a substance is its mass (m) per unit volume (V), i.e., is the ratio between its mass and how much space it occupies, $\rho = \frac{m}{V}$; typically, it is expressed in kg/m^3. The more similar is the density between materials, the greater the advantage in applying this VRP variant.

5.2.2. Phase 2: Selection of Collection Points to Visit with Multi-Compartment Vehicles

Depending on the filling rate of the materials and the capacity installed for each one (number and volume capacity of the drop-off containers), using vehicles with one compartment may be more advantageous than vehicles with multiple ones; the opposite is also true. Prior to the cluster and routing phases, this model suggests a decision making process to select which collection points are worth being visited with a multi-compartment vehicle, and which ones are not. Firstly, the criteria to evaluate each *ecoponto* is presented, and then the decision making process used to decide which ones are eligible for the MCVRP is formulated.

5.2.2.1. Criteria

Based on the information collected about the waste sector and on the literature reviewed, two main criteria were identified to analyse collection points and decide which ones are worth to visit with a multi-compartment vehicle:

1. Daily Filling Rate per Material, per *Ecoponto*;
2. Capacity Installed per *Ecoponto*

The first criterion (1) is related to the customer behaviour and intends to access the relation between the volume of waste to be collected for each material, per *ecoponto*. As for the second one (2), it is related to the capacity installed by the service provider to collect any material, per *ecoponto*, and can be subdivided into three criteria: volume capacity in m^3 (2.1), number of containers (2.2), and the difference between the number of containers per material 2.3. Both criteria intend to ensure that the vehicle compartments have, in the end of one route, similar occupancy/usage rates (multi-material analysis).

Criterion 1: Daily Filling Rate per Material, per *Ecoponto*

As previously mentioned, the more similar the density of materials, the greater the advantage in applying the MCVRP. Besides, materials demand should also be similar since imbalances between them have a negative impact on the benefits of co-collection (Muyldermans et al., 2010). Furthermore, Worrell et al. (2011) stated that all compartments of one vehicle must fill at the same rate, and this is the principle that supports this criterion. Although customer behaviour is unknown, companies responsible for the collection of MSW are able to predict the demand per material and per collection point, based on historical data.

Formula 5.1 is the one used to assess criterion 1; it compares, between each pair of materials (m_i, m_j), the ratio between the space (volume) that each material collected in the same *ecoponto* e occupies inside the vehicle ($L_{e,mi,mj}$). Demand in this model is addressed as the daily filling rate; thus, for each *ecoponto* e visited and material m_i, its daily filling rate (f_{e,m_i}) is divided by its density (ρ) inside the vehicle – that may or may not be different than its density inside the container; for example, if the vehicle has pressing function, the density of materials increase.

$$L_{e,mi,mj} = \frac{\frac{f_{e,m_i}}{\rho(inside\ the\ vehicle)_{m_i}}}{\frac{f_{e,m_j}}{\rho(inside\ the\ vehicle)_{m_j}}} \tag{5.1}$$

Valorsul predicts that, in order to have advantage in implementing the MCVRP for a set of materials collected simultaneously in the same *ecoponto*, no material can occupy (in volume) more than the double or less than half the space inside the vehicle of other material collected. Thus, for every pair of materials compared within the same *ecoponto*, the result of formula 5.1 must comply with the condition $0{,}5 \leq L_{e,mi,mj} \leq 2$, i.e., one cannot occupy less than half (0,5) and more than double (2) than the other one inside the vehicle.

Criterion 2: Capacity Installed per *Ecoponto*

The main idea behind criterion 2 is about reducing the risk of having too much MSW to collect per *ecoponto*, due to less available space inside the vehicle for each material.

Drop-off containers for the disposal of recyclable MSW are placed according to population density and commercial activities, i.e., according to the predicted amount of waste produced in the area one *ecoponto* serves; thus, the capacity installed is not standardized and there are differences between them. The proposed model considers that the less capacity one collection point has, the better. This assumption is based on the information given by Valorsul and on the literature reviewed – Carvalho (2010b), for example highlighted that one of the variables to consider when solving a routing problem is the characteristic of the points to visit (see section 3.1.1).

There are three sub-criteria that intend to evaluate each *ecoponto* individually in relation to its capacity, and all intend to highlight which collection points have less capacity installed, i.e., the ones that have less available space for the disposal of MSW. Moreover, they also aim to analyse the similarity between the capacity installed per material in each *ecoponto*.

Sub-Criterion 2.1 Volume Capacity of Containers

A collection system may have containers with different capacities spread out in its service area. In order to reduce the risk of completely filling the vehicle compartments too soon – i.e., with few *ecopontos* visited –, the proposed model assumes that there is greater benefit when multi-compartment vehicles visit collection points with the containers that have the smallest capacity of all system.

Sub-Criterion 2.2 Number of Containers per Material

The number of containers per material follow the same principle. For example, if one collection point has two containers for one material and they are both completely full when collected, they will occupy more space inside the vehicle when compared to another *ecoponto* with only one container completely full. Regarding this factor, the proposed model assumes that there is greater benefit when multi-compartment vehicles visit collection points with only one container per material.

Sub-Criterion 2.3 Difference between the Number of Containers per Material

The difference between the number of containers per material is the last condition to consider regarding the capacity installed of one *ecoponto*. Having more capacity installed for one material within the same collection point increases the risk of having more of that material to collect than the other one, even if the predicted amount to collect for both is similar – if the densities of the materials are similar, the vehicle will most likely fill the compartments at different rates. The proposed model assumes that there is greater benefit when multi-compartment vehicles visit collection points with the same number of containers per material (1 or more).

5.2.2.2. Decision Making Process

The proposed model aims to decide which collection points are worth visiting with multi-compartment vehicles, and which ones are not. After gathering all information from Valorsul, and analysing the reviewed literature, a step-by-step decision making process was formulated, inspired by the graphic representation of the Vroom-Yetton-Jago decision model (Vroom and Yetton, 1973).

The decision tree presented in Figure 5.2 has four questions that intend to evaluate every *ecoponto* individually. Only those collection points that have at least one container for each material selected in the previous phase are considered.

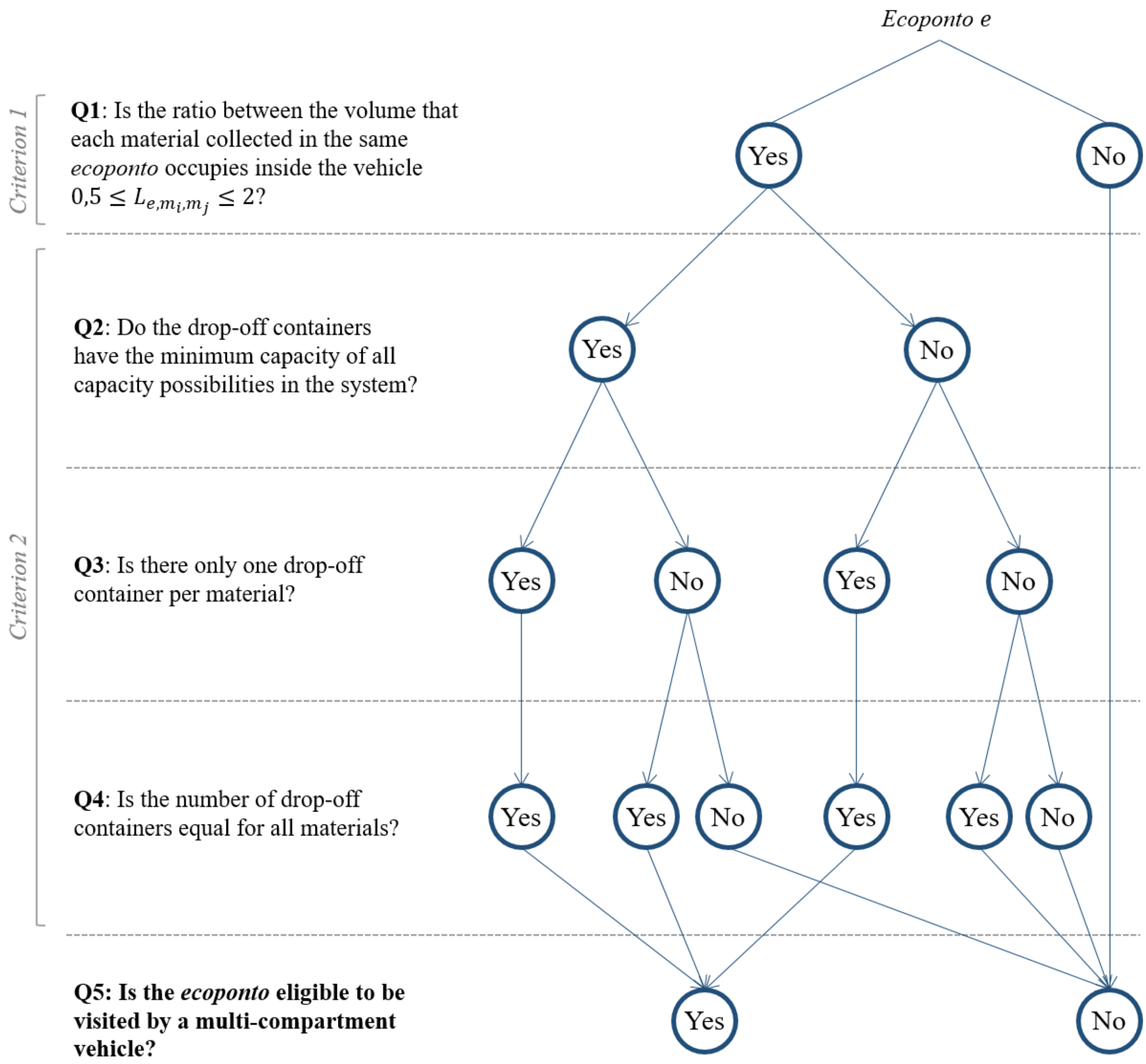


Figure 5.2 – Illustration of the Decision Tree that selects which collection points are eligible to be visited by a multi-compartment vehicle

First question (Q1) aims to understand if any material collected in one *ecoponto* occupies less than the double or more than half the space inside the vehicle of other material collected simultaneously (criterion 1). Since this question evaluates demand (which is variable and only predictable based on historical data), it was established that if one collection point does not comply with the parameter established for criterion 1 (answer “No”), then it is automatically not eligible to be visited by a multi-compartment vehicle. If, however, it complies (answer “Yes”), then at least two capacity installed criteria – questions 2 (Q2), 3 (Q3) and 4 (Q4) – have to be fulfilled (meaning that the answer to at least two of these questions have to be “Yes”).

These four questions combined intent to evaluate every *ecoponto*, by the listed order, resulting in a final decision for each one – question 5 (Q5): “Is the *ecoponto* (in analysis) eligible to be visited by a multi-compartment vehicle?”.

There are three possibilities for one collection point to be eligible – the first question has always to be “Yes”, and in only 1 path all questions have a positive answer; the other two possibilities only fulfil two of the three capacity installed criteria.

5.2.3. Phase 3: Clustering and Routing

After selecting the nodes to visit in the decision making process, *ecopontos* have to be grouped together (forming clusters), and their visit sequence defined (routing). Figure 5.3 illustrates the heuristic developed to solve the MCVRP.

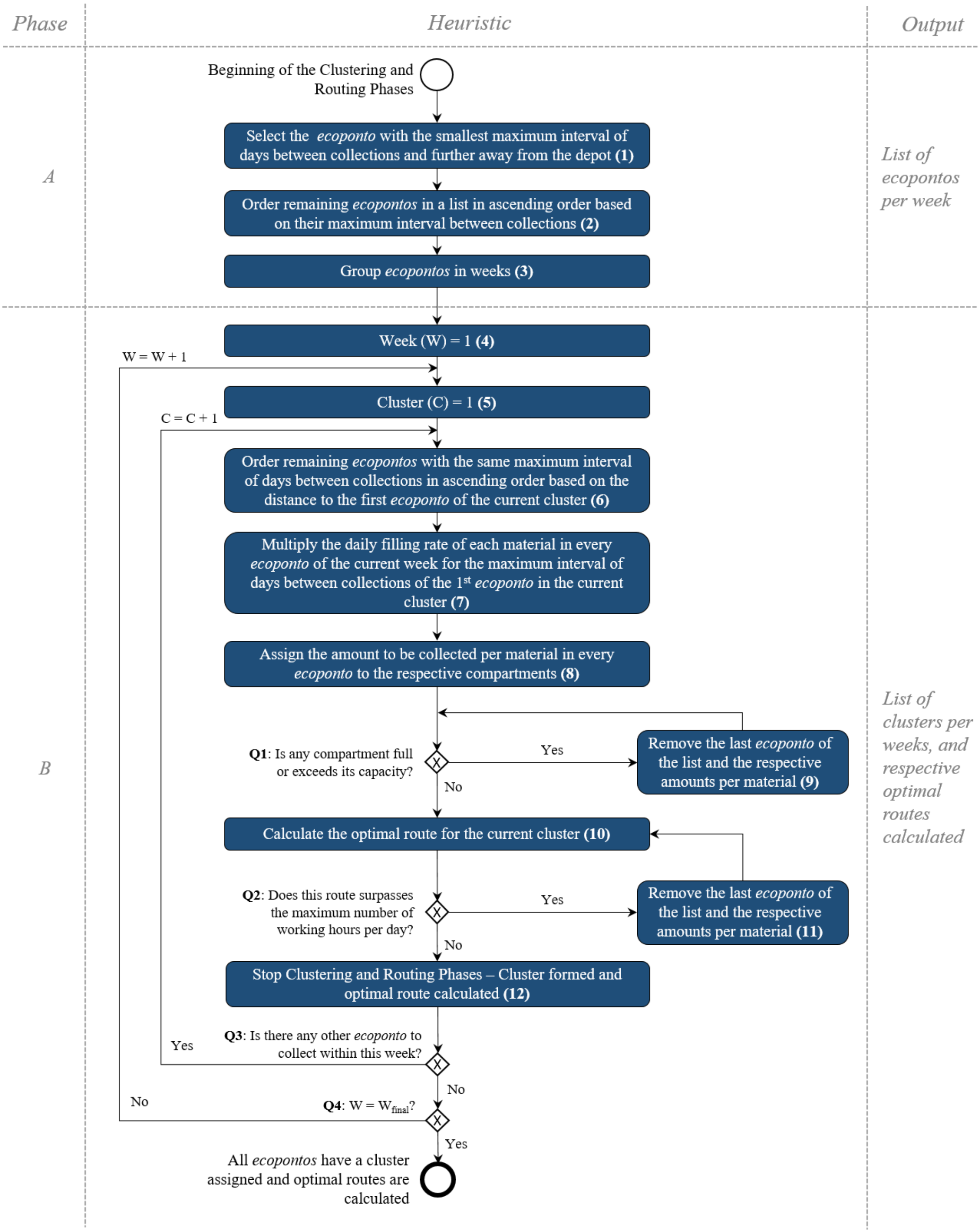


Figure 5.3 - Flowchart of the MCVRP Heuristic developed

The heuristic schematized in Figure 5.3 decides simultaneously each cluster and route, considers that the collection system is served by only one depot (every route starts and ends at the same point), and that routing is static. In addition, one route has to be completed within one day, and the number of routes scheduled depends on the duration of routes and the number of vehicles available per day. To define clusters the heuristic takes into account the daily filling rate per material of each *ecoponto*, the capacity of the vehicle compartments for each material, and the distance between collection points, and between these and the depot.

Before forming any cluster, one vehicle has to be assigned and the compartments defined (in number and size). Regarding the number of compartments inside the vehicle, it has to be equal to the number of materials to collect; as for the size of each one, it should be based on the amount predicted that each route will collect, per material – the bigger the amount predicted per material, the bigger the respective compartment. However, they can only vary in predefined positions (as stated in Henke et al., 2015). This model does not suggest an exact way to calculate the size of each one; instead, this topic is approached with a sensitivity analysis in the next chapter that assesses the better vehicle configuration for every route.

Phase A

Firstly, the maximum interval of days between collections has to be calculated for each *ecoponto*. This value represents the maximum interval of time one *ecoponto* does not have to be visited, so that its capacity installed is not surpassed. Since the MCVRP collects more than one material simultaneously, the maximum interval of days between collections of one collection point is the smallest maximum interval of days between collections considering all materials, since this is the one that exhausts its capacity first.

Phase A starts by selecting the *ecoponto* with the smallest maximum interval of days between collections. In case there is more than one *ecoponto* with this same value, the one further away from the depot must be selected – the collection point that fulfils both conditions is the one that will be included into the first cluster (1). It also defines the maximum interval of days between collections of the cluster being formed, i.e., all *ecopontos* assigned to this cluster will be visited when the first has to be collected (so it never surpasses its capacity installed).

Next, all remaining collection points in the system have to be sorted in ascending order with respect to their maximum interval of days between collections (2). The goal is that the next collection points to be included to the current cluster being formed are the ones with the smallest maximum interval of days between collections.

One of the main features of waste collection problems is that containers have different filling rates. Low filing rates mean that collection points have to be visited with a longer time interval between collections, while *ecopontos* with high filing rates have to be visited more frequently. For example, one *ecoponto* that reaches its maximum capacity in 7 days has a higher weekly filling rate than one container that only reaches its maximum capacity in 14 days – the filling speed is half of the first one.

To tackle this, the last step in this phase is to group *ecopontos* in weeks (3), so that clusters have collection points with similar filling rates. The output of this phase is a list per week, where all *ecopontos* are ranked in ascending order with respect to their maximum interval of days between collections.

Phase B

With all collection points grouped in weeks, for week *W* (4) and cluster *C* (5), all *ecopontos* with the same maximum interval of days between collections are sorted in ascending order in relation to the distance to the collection point that begun the cluster (6), in order to form clusters with *ecopontos* near each other. After having all *ecopontos* ranked, the amount to be collected per collection point has to be calculated, adding the multiplication of the daily filling rate of each material by the value of the maximum interval of days between collections of the cluster (7). The amount of each material to be collected of all *ecopontos* in week *W* have to be added to the respective compartment (8).

At this point, it is assessed if any of the compartments exceeds its capacity (Q1). If it does ("Yes"), then the last *ecoponto* on the list has to be removed from the cluster, and the quantity to collect in this point not considered (9). The compartments filling rates are assessed again until none of them have their capacity overfilled ("No").

When the vehicle has at least one of the compartments full, the optimal sequence of visits has to be defined (10). To define the optimal route, a TSP is solved. The mathematical formulation for the TSP is based on the work of Baldacci et al. (2004) and was implemented in GAMS 23.7 and solved through the CPLEX Optimizer 12.3.0.

Based on the results obtained, it is assessed if the route surpasses the maximum number of working hours per day (Q2). To calculate the time it takes a route to be completed, this model considers the following parameters: i) travel speed inside and outside cities; ii) time for collecting containers (time to walk to the containers, bring them to the truck and back to their place, and time to manoeuver the vehicle crane); iii) time for unloading the vehicle at the end of each route.

If the route surpasses the available time ("Yes" to Q2), then the last *ecoponto* and the respective amounts added to the cluster have to be removed (11), and the optimal route for the cluster recalculated (10). This iteration happens until the route of the cluster do not exceeds the available time to perform it ("No" to Q2). In such case, the clustering and routing phases stop, forming a cluster and having its optimal route calculated in respect to time and distance (12).

If there are still more *ecopontos* to collect in week *W* ("Yes" to Q3), another cluster for that week begins to be formed. If "No", but there is still other *ecopontos* to cluster in the following weeks ("No" to Q4), the model goes back to the beginning of phase B. If the last week was the final one ("Yes" to Q4), then the heuristic ends.

The output of phase B is a list with all clusters formed, and their respective optimal routes calculated regarding time and distance.

5.2.4. Phase 4: Model Validation

To verify the benefits of this model, single-material routes are defined for the same population of collection points in study. To do so, the collection points are also grouped together by week (Phase A) and for each week, a CVRP with duration constraints is solved, obtaining the optimal routes for each week. The mathematical formulation for the CVRP is based on the work of Baldacci et al. (2004) and Ramos et al. (2013), and was implemented in GAMS 23.7 and solved through the CPLEX Optimizer 12.3.0.

6. Model Application to the Case Study

6.1. Data Analysis

As stated before, Valorsul provided data about:

i) Types of material collected;

ii) Collection points (number of containers per material, their capacity, and geographical location);

iii) Collection shifts performed (all single-material routes): total amount of MSW collected per route, its visit sequence, duration, distance travelled and vehicle used; and the filling level of every container per visit.

These data were analysed in order to gather the required inputs to apply the proposed model.

During the analysis of the data provided in Excel, some outliers were identified, such as: i) some *ecopontos* did not had the geographic coordinates available – they were found using *Google Maps* and *Google Street View*; ii) some shifts were found registered with incorrect years (1990, 2007 and 2008), and some were registered twice; for this reason they were not considered; iii) the time horizon for each material collection was different, analysing only the common period (from the 2nd of January of 2013 to the 14th of June of 2013).

6.1.1. Type of MSW in study

Valorsul is responsible for the collection of Paper and/Cardboard (PC), Plastic and/Metal (PM) and Glass (G), whose densities inside the containers and vehicles are shown in Table 6.1.

Table 6.1 - Density of the materials collected by Valorsul inside the respective containers, and inside collection vehicles (Lopes, 2014)

Type of Material	Density inside the deposit containers (kg/m³)	Density in the collection vehicles (kg/m³)
Paper and/Cardboard	40	250
Plastic and/Metal	20	150
Glass	300	600

The density of Glass is 7,5 higher than the one of PC and 15 times higher than the density of PM. It means that considering 3 products with the same mass, one of each material, the glass one has a much smaller volume, i.e., for the same weight, glass occupies much less space.

Furthermore, the gain of space when compressing glass is reduced due to the high density of this material (Oliveira, 2014). Since it is more advantageous to collect materials with similar densities when using vehicles with multi-compartments, the materials in study are PC and PM.

6.1.2. Collection Points

As referred in section 2.2.1.2, in 2013 Valorsul had 2515 *ecopontos*. These locations are not standard or random: containers are placed in specific locations accordingly to the needs of the population. Table 6.2 shows the different compositions of *ecopontos*, according to the types of containers per material they can have.

Table 6.2 – Different compositions of *ecopontos*, per types of container each one has – Paper and/Cardboard (PC), Plastic and/Metal (PM), Glass (G)

Composition of *ecopontos* per types of container		Total	
1	PC	17	0,7%
2	PM	2	0,1%
3	G	363	14,4%
4	PC + PM	31	1,2%
5	PC + G	15	0,6%
6	PM + G	4	0,2%
7	PC + PM + G	2083	82,8%
Total		2515	

As shown in Table 6.2, approximately 83% of all *ecopontos* have at least one container for Paper and/Cardboard (PC), one for Plastic and/Metal (PM) and another one for Glass (G) (composition number 7). Regarding the materials in study – PC and PM –, only composition number 3 does not have containers for at least one of them.

Considering all three types of materials Valorsul collects, these 2515 locations have 6959 drop-off container, spread out across 138 parishes, in 14 different municipalities. However, not all of them have the same capacity.

6.1.2.1. Capacity of Containers

Valorsul operates containers with three different capacities: 2,5 m^3, 3 m^3 and 5 m^3 (based on the data provided, it is assumed that all containers within one *ecoponto* have the same capacity). – see Table 6.3.

Table 6.3 - Number of containers per capacity, and number of *ecopontos* with such type of containers (per material and totals)

Container Capacity	2,5 m³		3 m³		5 m³		Total number of containers
Material	Number of containers	Number of *ecopontos* with this type of container	Number of containers	Number of *ecopontos* with this type of container	Number of containers	Number of *ecopontos* with this type of container	
Paper and/Cardboard	1920	1829	306	289	28	28	2254
Plastic and/Metal	1880	1809	301	285	26	26	2207
Subtotal	3800	85,2%	607	13,6%	54	1,2%	4461
Glass	2135	2104	335	334	28	27	2498
Total	5935	85,3%	942	13,5%	82	1,2%	6959

Out of 6959, only 4461 containers are destined for the disposal of PC and PM. Approximately 85% of these are containers of 2,5 m^3; the ones with a capacity of 5 m^3 are the least used, representing approximately 1,20%. Although similar, the number of containers of PC and PM of any capacity is not the same, which is revealing of the fact that not all *ecopontos* have both containers, and/or that some have more than one per material.

Table 6.4 presents the conversion from capacity in volume (m^3) to capacity in weight (kg), for the different types of containers of PC and PM. Glass will not be mentioned anymore.

Table 6.4 - Capacity in weight (kg) of PC and PM containers with volumes of 2,5 m³, 3m³ and 5 m³

Type of Material	Capacity (kg) a container of 2,5 m³	Capacity (kg) a container of 3 m³	Capacity (kg) a container of 5 m³
Paper and/Cardboard	100	120	200
Plastic and/Metal	50	60	100

6.1.2.2. Configuration of *ecopontos*

Table 6.5 presents the 9 configurations of the *ecopontos* with containers for PC and PM according to the number that exist of each material, and the percentage of *ecopontos* per each configuration. Almost 95% of *ecopontos* with containers for the deposit of PC and PM have only one for each material.

Table 6.5 - Configurations of *ecopontos* of Valorsul with at least one container for Paper and/Cardboard and one Plastic and/Metal

Configuration	Number of containers				Percentage of ecopontos per configuration
	Paper and/ Cardboard	Plastic and/ Metal	Diference (in absolute)	Total number of containers	
1	1	1	0	2	94,47%
2	2	1	1	3	1,51%
3	1	2	1	3	0,85%
4	2	2	0	4	2,84%
5	3	1	2	4	0,05%
6	3	2	1	5	0,09%
7	2	3	1	5	0,09%
8	3	3	0	6	0,05%
9	7	2	5	9	0,05%

6.1.2.3. Daily Filling Rate per *Ecoponto*, per Material

To solve the proposed heuristic, the daily filling rate in every *ecoponto* e for each material m_i has to be known (f_{e,m_i}) in percentage (%) and weight (kg). To do so, the amount of MSW collected, the average filling level, and the average interval of time between collections per material m_i have to be calculated for every *ecoponto* e. Such analysis was only performed for the materials in study (PC and PM), and was used to estimate the amount to collect per material in every visit, in volume (m^3) and weight (kg), and the maximum interval of time between visits to one *ecoponto*.

To better understand how all these calculations were made, shift number 18120 was chosen as an example (from the 969 shifts analysed). Table 6.6 shows a summary of the operation of this shift, performed on the 26th of February of 2013, where 64 *ecopontos* were visited in approximately 6 hours and a half, collecting a total of 2480 kg of Paper and/Cardboard. The vehicle used was the V11 (see page 13 for information about the fleet), and it travelled 138 km.

Table 6.6 - Summary of the operation of shift 18120

Shift	Material	Date	Vehicle	Total amount collected	Total distance	Hours travelled	Number of *ecopontos*	Number of containers
18120	PC	26/02/2013	V11	2480 kg	138 km	6h22m	62	64

Amount of MSW collected per *Ecoponto*, per Material

As previously mentioned in section 2.2.1.3, every time a container is collected its filling level is recorded, using five possible measures: i) empty (0%); ii) less than half (25%); iii) half (50%); iv) more than half (75%); v) full (100%). As for the amount in kilograms (kg), there is only information on the total waste collected per route – the truck is weighed when comes back to the CTRO after visiting all assigned collection points. This information and the values of density provided by Valorsul of PC and PM (ρ_{PC} = 40 kg/m^3; ρ_{PM} = 20 kg/m^3; see densities in Table 6.1, page 49) were used to calculate the amount collected per *ecoponto*.

The formula to calculate the amount collected per *ecoponto* and per material follows (6.1a), where A_{e,m_i} is the amount collected in *ecoponto* e of the material m_i; ρ_{m_i} is the density of material m_i; C_{e,m_i} is the total capacity of all containers of material m_i in *ecoponto* e; and FL_{e,m_i} the average filling level of all containers of material m_i in *ecoponto* e.

$$A_{e,m_i}(kg) = \rho_{m_i} * C_{e,m_i} * FL_{e,m_i} \tag{6.1a}$$

To better understand it, part of the visit sequence performed in shift 18120 is listed in Table 6.7, as well as information about the filling level of each container collected.

Table 6.7 - Part of the visit sequence of shift 18120

Hour (hh:mm:ss)	Ecoponto	Container	Container capacity (m³)	Filling level (%)	Amount collected (kg)
…	…	…	…	…	…
19:25:20	1590	P0800	2,5	0%	0
19:25:33	1590	P2257	2,5	25%	25
19:27:00	578	T_P0021	2,5	0%	0
19:29:48	2293	P2306	2,5	50%	50
19:39:38	574	P0438	2,5	50%	50
…	…	…	…	…	…

The vehicle used in shift 18120 collected, for example, 50 kg of PC in *ecoponto* 2293 (marked in grey in Table 6.7), calculated as follows in formula 6.1b.

$$A_{2293,PC} = 40 * 2{,}5 * 50\% \Leftrightarrow A_1 = 50\ kg \tag{6.1b}$$

This *ecoponto* has only one container for the deposit of PC. However, there are collection points with more than one container per material, such as 1590, with containers P0800 and P2257 – see Table 6.7. The formula presented (6.1a) contemplates that in such cases all containers are analysed as if they were only one.

Average Filling Level per *Ecoponto*, per Material

Since routes are not static – i.e., one container is not necessarily visited at a constant interval of days –, the average filling level was calculated using the weighted mean from the records provided by Valorsul.

To exemplify how calculations were done, Table 6.8 shows a list with the 13 visits made to container P2306, placed at *ecoponto* 2293, within the period considered.

Table 6.8 - Information about the filling level and amount of MSW deposited in container P2306 of *ecoponto* 2293 per visit

Number of visit	Date (dd/mm/yy)	Interval of days since last visit	Filling level (%)	Amount deposited (kg)
1	07/01/2013	0	50%	50
2	18/01/2013	11	75%	75
3	14/02/2013	27	100%	100
4	26/02/2013	12	50%	50
5	22/03/2013	24	75%	75
6	02/04/2013	11	0%	0
7	11/04/2013	9	75%	75
8	22/04/2013	11	25%	25
9	02/05/2013	10	100%	100
10	14/05/2013	12	50%	50
11	24/05/2013	10	75%	75
12	04/06/2013	11	50%	50
13	14/06/2013	10	100%	100

Total of days between the first and last visit: 158

Average filling level (weighted): 68,2%

To calculate the average filling level for this container, firstly it is multiplied the filling level of each visit by the respective interval of days since the last visit. Then, the sum of this multiplication for all visits is divided by the number of days between the first and the last visit. Thus, the average filling level of container P2306 is 68,2%. Since the capacity of this container is 2,5 m^3, the average amount collected of PC is 68,2 kg (40 $kg/m^3 * 2{,}5\ m^3 * 68{,}2\%$).

Typically, as mentioned in section 2.2.1.3, the filling level is registered by excess what may cause a deviation from reality in the calculation of the average filling level.

Average Interval of Time between Collections per *Ecoponto*, per Material

To calculate the average interval of time between collections, the number of days between the first and the last visits is divided by the number of collections subtracted by 1.

When applied to container being used as an example – P2306 – the average interval of time between collections is 13,17 days (158/(13-1)).

Daily Filling Rate per *Ecoponto*, per Material

With all the previous data and calculations, it is possible to find the daily filling rate per *ecoponto* (f_{e,m_i}), calculated by dividing the average filling level per container for the average interval of time between collections.

Container P2306, for example, has on average a filling level of 68,20%, with approximately 68kg of Paper and/Cardboard deposited every 13,17 days. This represents a daily filling rate of 5,18% ($f_{2293,PC} =$ 68,2%/13,17 days).

In terms of volume (m^3) the daily filling rate translates into 0,13 m^3 of PC deposited per day (5,18% $*$ 2,5 m^3, where 2,5 m^3 is the capacity of *ecoponto* 2293 for the deposit of this material). The daily amount deposited per day is 5,18 kg (40 kg/m^3 $*$ 2,5 m^3 $*$ 5,18%).

Maximum Interval of Time between Collections per *Ecoponto*

In order to calculate the maximum interval of time between collections for every *ecoponto*, the daily filling rate of all materials to collect simultaneously in the same location has to be known. The material that reaches its capacity first defines the maximum interval of time between collections of its collection point.

Besides container P2306, *ecoponto* 2293 has also one container for the deposit of PM. The maximum capacity of PC is achieved in 19 days ($100\%/f_{2293,PC}$), with $f_{2293,PC} =$ 5,18%, and of PM in 15 days ($100\%/f_{2293,PM}$), with $f_{2293,PM} =$ 6,58%. These values represent the maximum interval of time between collections for each one of the materials, so that none of them surpass its capacity in the respective collection point. Since PM has the smaller maximum interval between collections, it defines the maximum interval of *ecoponto* 2293 (15 days).

Valorsul has established that no collection point can be visited with an interval between collections longer than 5 weeks, unless there is a significant amount of containers to collect within a specific week. This means that, although the proposed heuristic clusters *ecopontos* per week, all the ones after $W = 5$ may be move to this week if the number of containers is low. Valorsul assumes this value since throughout time the difference on the filling rate per week tends to decrease, meaning that the difference on the amount collected between combining weeks and not combining also decrease in time.

Figure 6.1 illustrates what was just described. It considers 14 different *ecopontos* (A to N), each one with a different interval between collections: *ecoponto* A has an interval of 1 week, *ecoponto* 2 has one of 2 weeks, and so on. While the difference between the daily filling rates of *ecopontos* A and B is of 50%, the difference between *ecopontos* M and N is only of 1%. The difference on the weekly filling rate between two consecutive weeks tend to zero, meaning that throughout time there is advantage in combining weeks with longer interval of time between collections.

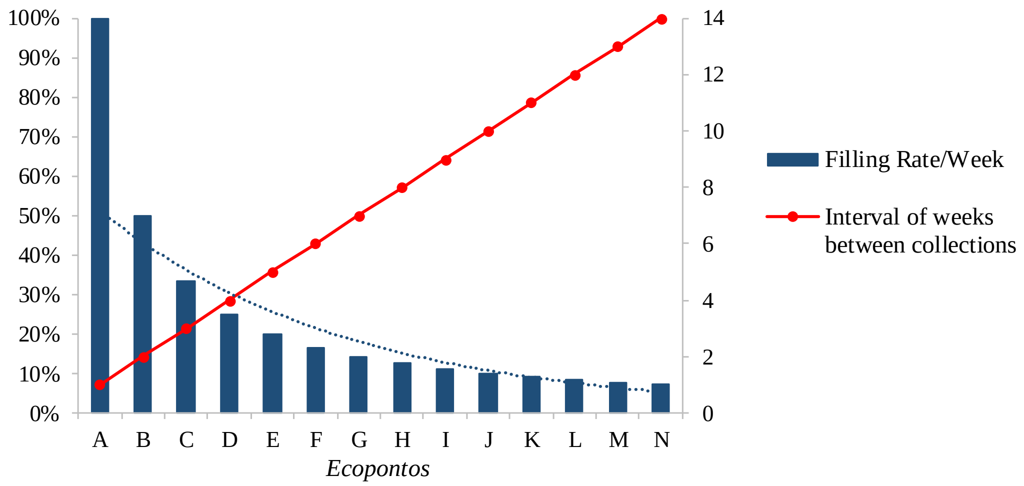


Figure 6.1 - Illustration of the tendency of the weekly filling rate throughout time

6.1.3. Fleet of Vehicles

Table 6.9 presents the only available vehicles for the collection of the materials in study – types II, III and IV (see page 13 for more information about the fleet). All of them have pressing function, which means that the density of PC and PM increase after collection: the one of PC has an increase of 6,25 times (from 40 to 250 kg/m^3) and the one of PM of 7,5 times (from 20 to 150 kg/m^3).

Table 6.9 - Types of vehicles available for the collection of the materials in study

Type of vehicle	Number of vehicles available per day	Type of material	Weight capacity (kg)	Volume capacity (m^3)	Density that satisfies both volume and weight capacity (kg/m^3)	Maximum weight capacity[i] (kg)
II	2	PC	13 945	20	697	20 * 250 = 5 000
		PM				20 * 150 = 3 000
III	5	PC	5 580	20	279	20 * 250 = 5 000
		PM				20 * 150 = 3 000
IV	2	PC	4 465	15	298	15 * 250 = 3 750
		PM				15 * 150 = 2 250

[i]Calculation based on the data provided by Valorsul about materials density with pressing function (kg); formula used: $volume\ capacity\ of\ the\ vehicle\ (m^3) * \rho_{m_i}(kg/m^3) = maximum\ weight\ capacity\ (kg)$

Values presented in column "Density that satisfies both volume and weight capacity (kg/m^3)" reveal that all vehicles are restricted by volume, since they are higher than the values of density provided by Valorsul for each material in study Valorsul ($\rho_{PC} = 250$ kg/m^3; $\rho_{PM} = 150$ kg/m^3).

Types II and III can collect a maximum of 5000 kg of PC, and 3000 kg of PM, while vehicles of type IV can collect a maximum of 3750 kg of PC and 2250 kg of PM (considering single compartmented vehicles). Due to the fact that vehicles of types II and III are the ones with more capacity (in volume and weight), this is the only one to be considered from now on. Therefore, in every route the maximum volume capacity per vehicle is 20 m^3.

Since this model formulates multi-material routes, the vehicle has more than one compartment and its weight capacity has to be split between them; as this MCVRP model suggests, the number of compartments (kc) is equal to the number of materials in study (2). Instead of defining in advance one capacity limit for each compartment, a sensitivity analysis is performed to address this topic further on. Figure 6.2 illustrates the three different configurations tested in every MCVRP, in order to establish which one suits better each route. This analysis follows the principle presented in Henke et al., 2015: the size of compartments can vary in predefined positions, between routes (MCVRP-FCS). The first configuration divides the vehicle exactly in half; the second one gives more volume capacity to PC; and configuration number 3 gives more volume capacity to PM.

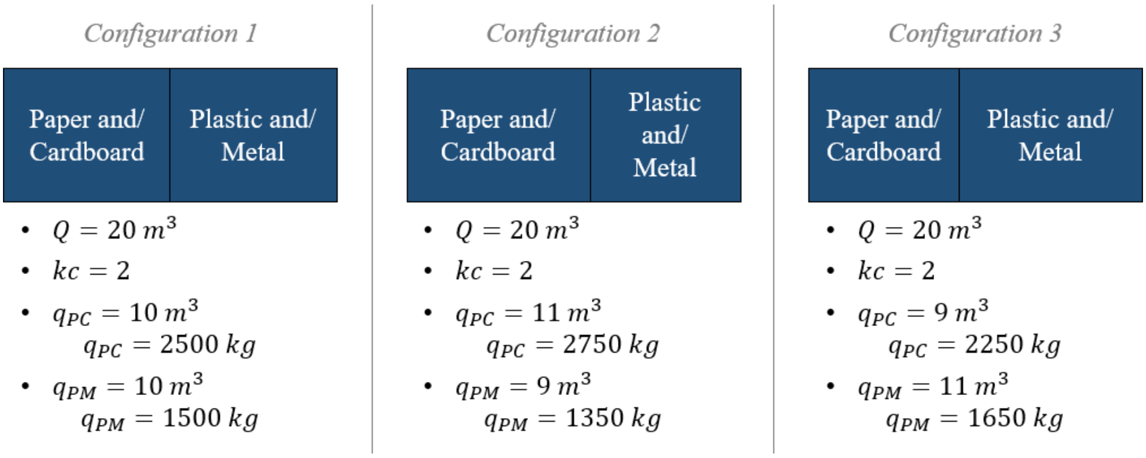


Figure 6.2 - Illustration of the three possible configurations for the vehicle compartments

6.1.4. Route Duration

Valorsul's drivers and assistants work 8 hours per day – within this time the vehicle has to leave and get back to the depot (CTRO). Collection is only performed on weekdays.

To calculate the route duration there are two parameters to consider: i) operation times (to collect each container and unload the vehicle); ii) travel time between all locations visited. Data regarding these parameters was provided by Valorsul.

Regarding operation times (i): the time spent to collect each container is 1 minute and 45 seconds (which includes the time to walk to the containers, bring them to the truck and back to their place, and time to manoeuver the vehicle crane); the time for unloading the vehicle at the depot is estimated at 15 minutes.

The travel time depends on the distance travelled per route and the average speed the vehicles travels. Within cities the travel speed considered is 30 km/h, and outside is 60 km/h, according to the company. It is assumed that vehicles run only with these two speeds, meaning that between collection points in the same city the travel speed considered is 30 km/h, and when the vehicle moves from one city to another the travel speed is 60 km/h.

6.1.5. Distances

To solve any VRP it is fundamental to know, among other aspects (see VRP – section 3.2), the distance between all vertices of the system ($d_{i,j}$), i.e., between all *ecopontos* and between these collection points and the only depot for the western region of Valorsul, the CTRO.

Valorsul provided the geographical location for all *ecopontos*, but not the distance between all of them. Although possible to find them in *Google Maps*, due to the high number of collection points in study the Euclidean distance (6.2) was used instead to calculate them:

$$D_{i,j} = \sqrt{(lon_i - lon_j)^2 + (lat_i - lat_j)^2} \tag{6.2}$$

The Euclidean distance assumes that the distance between 2 points (i, j) is the length of the line segment connecting them (i.e., straight-line distance). Since the formula gives its result in degrees, the conversion to kilometres (km) is obtained by multiplying it by $(2\pi * 6378 \text{ km} * \cos 39^{o})/360^{o} \simeq 86{,}51$(Lopes, 2014), where 6378km is the equatorial radius of the earth and 39° is the latitude of approximately 97% of all *ecopontos* of Valorsul (the remaining ones are positioned at 38°).

In addition, since the aim is to calculate road distances, the formula must be corrected with a multiplier, referred to as a circuity factor (CF), to approximate the result to the actual travel distance (Ballou et al., 2002). To calculate the CF, it was compared the actual road distance of 100 randomly pairs of *ecopontos* with the Euclidean distance. Actual road distances were found in *Google Maps*, on the 3rd of August of 2016, Wednesday, between 11am and 12pm, a period with no record of accidents: i) it was considered the shortest route, and not the fastest; ii) tolls and highways were avoided.

Table 6.10 shows the sum of the actual distance travelled of all 100 pairs of *ecopontos* looked for in *Google Maps* and its comparison with different CF, being the first one proposed by Simchi-Levy et al., 2008 ([i]).

Table 6.10 - Comparison between the actual road distances of 100 randomly chosen routes with different circuit factors

Criteria	Google Maps	Euclidean Distance with CF=1.3[i]	Euclidean Distance with CF=1.4	Euclidean Distance with CF=1.5	Euclidean Distance with CF=1.58	Euclidean Distance with CF=1.6
Total distance travelled (km)	4 133	3 341,81	3 598,87	3 855,93	4 061,58	4 112,99
Average match per route (%)	-	81,96%	88,26%	94,57%	99,61%	100,87%
Average deviation per route (km)	-	7,94	5,55	3,70	3,36	3,39

From all CF studied the one chosen was the one with the smallest average deviation, in this case, CF=1,58. As for the row "Average match per route (%)", it stands for the correspondence on average between the distance travelled in every route and the value calculated with each CF (see Appendix B).

Valorsul also provided information about the distance travelled for all routes performed in the period considered, which totals 969 shifts. To support the decision on CF, the Euclidean distance with a CF of 1,58 was applied in all routes to calculate the distance travelled.

The results achieved by this comparison are shown in Table 6.11. It is concluded that there is a total difference of 3846,42 km between the distance calculated with the Euclidean formula and the data provided by Valorsul about the 969 shifts. The average number of km travelled per shift is approximately 4 km higher. These results are considered not relevant and the CF of 1,58 is, therefore, considered accurate.

Table 6.11 - Comparison between the real distance travelled to perform 969 shifts, and the Euclidean Distance calculated with a circuit factor of 1,58 for the same shifts

Criteria	Valorsul data	Euclidean Distance (CF=1,58)	Difference (in absolute)
Total distance travelled (km)	133 501	137 347,40	3 846,40
Average of km/shift	137,77	141,74	3,97

By result, the formula used to calculate distances between all vertices was:

$$D_{ij}(km) = \sqrt{(lon_a - lon_b)^2 + (lat_a - lat_b)^2} * 86{,}51 * 1{,}58 \qquad (6.3)$$

Lopes (2014) also studied the collection system of Valorsul, but approach the topic of distance differently, considering each parish a collection site (one cluster), and an average distance between all collection points (1 km). Although this approach has allowed the author to work with less *ecopontos* (equal to the number of parishes where Valorsul operates), the real location and distance between them may have been detracted. For this reason, this study considers all *ecopontos* individually.

6.1.6. Region in Study

The 14 municipalities where Valorsul collects selective MSW have in total 2712 km^2. By drawing a circle around the CTRO – the only depot of the system and, therefore, the first and last point of every route –, it is possible to conclude that there is an asymmetry in the operating region: some municipalities are very far away from the depot (such as Alcobaça and Nazaré), which has significant impact on the distance travelled. These two municipalities, marked in green in Figure 6.3, form the so-called Remote Area (RA) and is the region that will be studied. The RA was chosen since vehicles have to travel many kilometres due to great distance between collection points and the CTRO. If the number of times needed to travel to this remote area is reduced due to better route planning, savings in the distance travelled to collect all *ecopontos* are expected to be achieved.

This region has in total 466 *ecopontos*, whereas only 360 have at least one container for the deposit of Paper and/ Cardboard, and one for Plastic and/ Metal – representing 17% of the total collection points of Valorsul with such feature. The other 106 *ecopontos* (466-360) exclusively have containers for the deposit of Glass and will not be considered.

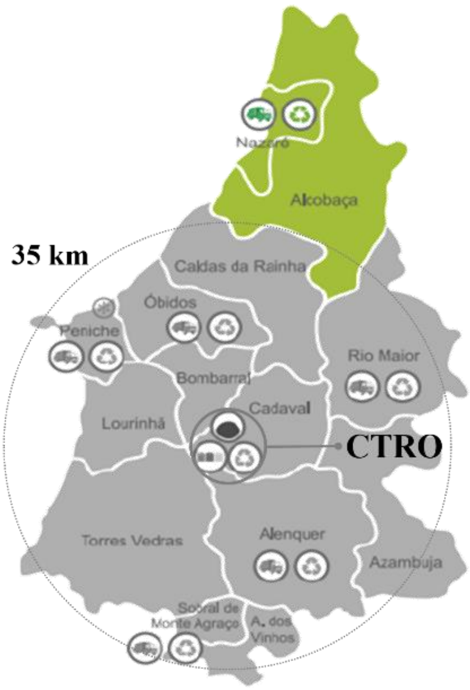


Figure 6.3 - Illustration of the Remote Area of Valorsul (marked in green)

6.2. Results

After gathering all required inputs to apply the model, the results found for each phase of the proposed model are presented in this section.

6.2.1. Phase 1: Selection of Materials to Collect with Multi-Compartment Vehicles

As mentioned in section 6.1.1, the materials selected to collect with multi-compartment vehicles are Paper and/Cardboard and Plastic and/Metal, due to the similarity between their densities. Therefore, each vehicle needs to have two compartments, one for each material.

6.2.2. Phase 2: Selection of Collection Points to Visit with Multi-Compartment Vehicles

Since the main advantage of the MCVRP is to visit the same location fewer times, only the collection points that have at least one container for PC and one for PM can be eligible to be visited by a vehicle with multiple compartments. Out of the 2515 *ecopontos* Valorsul operates, only 2114 fulfil this condition – the ones marked in green in Table 6.12: drop-off containers for PC and PM, and the ones that have containers for both and for Glass.

Table 6.12 - Compositions of *ecopontos* eligible to be implemented in the proposed model per types of container

Composition of *ecopontos* per types of container		Total	
1	PC	17	0,7%
2	PM	2	0,1%
3	G	363	14,4%
4	PC + PM	31	1,2%
5	PC + G	15	0,6%
6	PM + G	4	0,2%
7	PC + PM + G	2083	82,8%
Total		2515	
Total eligible		2114	

To decide which *ecopontos* are eligible to be visited by a multi-compartment vehicle out of the 2114, the proposed decision making process is applied.

To answer question 1 (Q1) formula 6.1 adapts criterion 1 to the case study. It compares the ratio between the volume each material (PC and PM) occupies inside the vehicle after simultaneous collection.

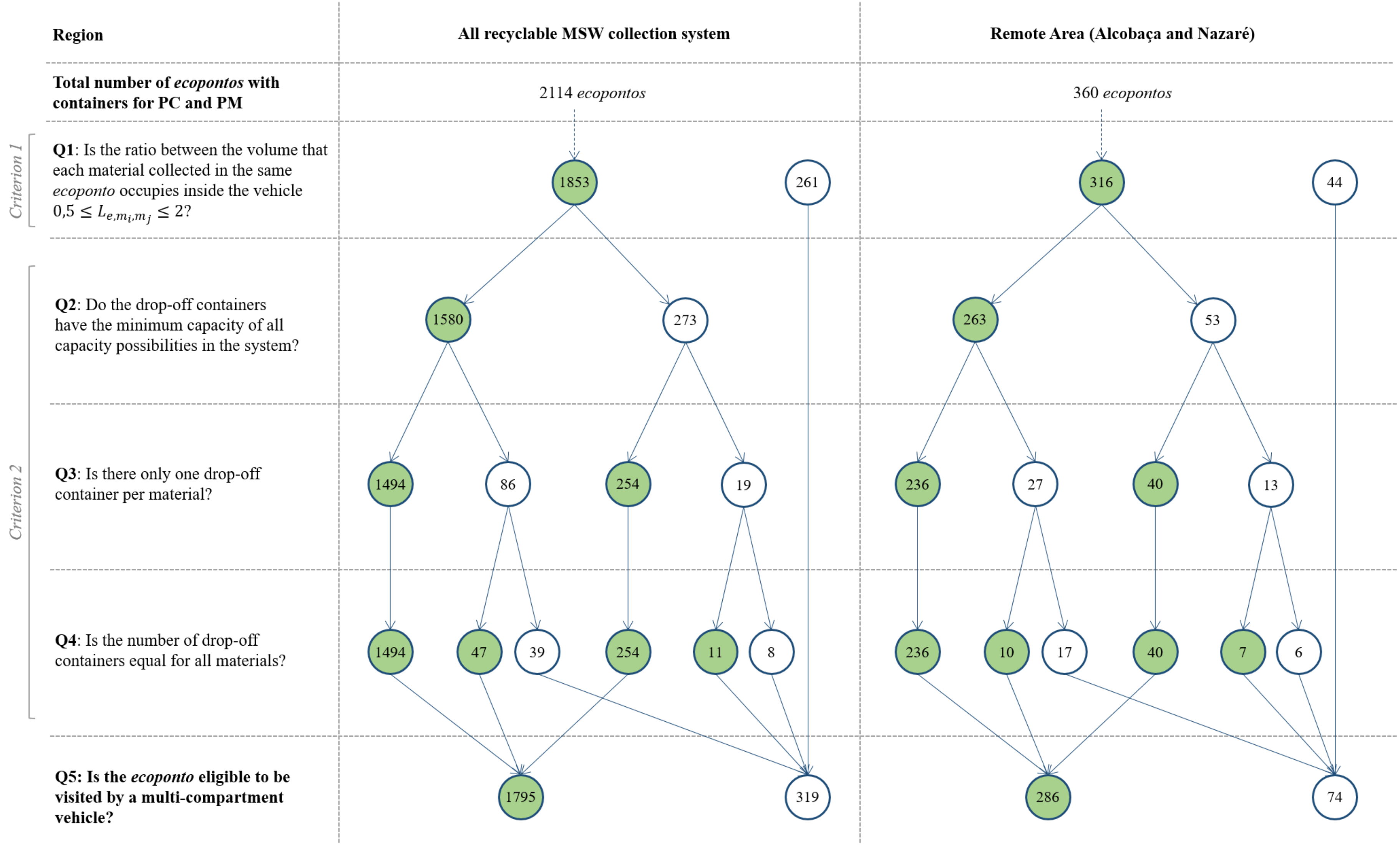
$$L_{e,PC,PM} = \frac{\frac{f_{e,PC}}{250\ kg/m^3}}{\frac{f_{e,PM}}{150\ kg/m^3}} \tag{6.1}$$

The daily filling rate per *ecoponto* and per material (f_{e,m_i}) was calculated as explained in section 6.1.2.3, based on data provided by Valorsul. The values considered for the density of each material inside the vehicle can be consulted in Table 6.1, page 49 ($\rho(inside\ the\ vehicle)_{PC} = 250\ kg/m^3$; $\rho(inside\ the\ vehicle)_{PM} = 20\ kg/m^3$). Results reveal that only 1853 out of 2114 *ecopontos* fulfil the required condition for this criterion, $0{,}5\ \leq L_{e,m_i,m_j} \leq 2$, meaning that there are automatically 261 ($2114 - 1853$) collection points not eligible.

For the remaining *ecopontos* (1853), at least two conditions regarding capacity installed have to be fulfilled to be eligible (criterion 2), as established in the decision making process.

Figure 6.4 presents the results obtained by the application of the decision making process. Two decision trees are presented: one for all *ecopontos* operated by Valorsul, and one for the region in study (RA); in both cases only *ecopontos* with at least one container for PC and for PM are considered. For each possible answer ("Yes" or "No") for each question, the number of *ecopontos* are presented.

Considering the total number of *ecopontos* eligible to be implemented to the MCVRP in all recyclable MSW collection system of Valorsul, 15% are excluded with this decision making process. As for the RA, the region in study, the percentage of not eligible collection points is 21%.



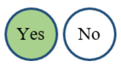


Figure 6.4 - Results obtained in the decision making process for the all system of Valorsul, and for the region in study

6.2.3. Phase 3: Clustering and Routing

Clustering and Routing phases are only applied to the 286 containers considered eligible to be visited by a multi-compartment vehicle in the RA – see Figure 6.4 in the previous page.

MS Excel was used to execute phases A and B of the proposed model, as well as to calculate the distance travelled and duration of every route. The visit sequence of each one was defined using GAMS, in order to obtain the optimal route for every cluster in terms of distance travelled.

Phase A

The heuristic states that *ecopontos* have to be grouped in weeks, so that the ones collected in the same route have similar filling rates. Thus, the first step was to create a list with the *ecopontos* that are going to be collected by multi-compartment vehicles, per week. In all of them, the first *ecoponto* is the one with the smallest maximum interval of days between collections of the respective week. The remaining *ecopontos* were then sorted in ascending order, based on their respective maximum interval of days between collections. Table 6.13 shows how many *ecopontos* have to be collected per week.

Table 6.13 - Number of ecopontos divided per week

Week	Number of *ecopontos*	Percentage (%)
1	17	5,94%
2	148	51,75%
3	72	25,17%
4	24	8,39%
5	11	3,85%
6	5	1,75%
7	2	0,70%
8	2	0,70%
9	2	0,70%
10	1	0,35%
11	1	0,35%
13	1	0,35%
Total	286	100%

Week	Number of *ecopontos*	Percentage (%)
1	17	5,94%
2	148	51,75%
3	72	25,17%
4	24	8,39%
5	25	8,74%
Total	286	100%

Since is established by the company that no *ecoponto* can be visited with an interval between collections longer than 5 weeks (see page 56), as shown in Table 6.13 the collection points marked in red were all added to week 5. This adjustment improved the percentage of *ecopontos* that have to be collected in week 5 (from 1,75% to 8,74%), avoiding the definition of routes with few *ecopontos* to collect.

To develop the lists of Table 6.13 it was considered that the first day of the year is on a Monday, which means, for example, that one *ecoponto* with a maximum interval between collections of 4 days has to be visited for the first time in week 1, $W = 1$, ranging between days 1 and 7. There are 17 collection points that have to be visited in the first week (approximately 6% of the total). Week 2 is the one with the highest percentage of *ecopontos* with 51,75% of the total being collected. The list on the right of Table 6.13 reveals that approximately 96% of the total number of collection points have to be visited between weeks 2 and 5.

If no capacity constraint was being considered, the number of clusters for the MCVRP would be equal to the number of different weeks (5).

Phase B

Table 6.14 illustrates the table developed to define clusters for the MCVRP. It shows cluster 1 and part of cluster 2; *ecopontos* 1425 and 1256 are the ones that start each cluster, respectively – both have simultaneously the smallest maximum interval of days between collections and the higher distance to the depot of their week. These *ecopontos* also define the maximum interval of days between collections of their clusters.

Table 6.14 - Illustration of the list developed for the MCVRP to define clusters

Cluster		*Ecoponto*	City	Week	Maximum interval of days between collections	Distance to the farthest *ecoponto* from the depot (km)	PC Compartment		PM Compartment	
#	Maximum interval of days between collections						Cumulative volume (m^3)	Cumulative weight (kg)	Cumulative weight (kg)	Cumulative weight (kg)
1	6	**1425**	**Alcobaça**	**1**	**6**	**0**	0,22	54,02	0,32	47,94
		1207	Alcobaça	1	6	1,73	0,48	121,10	0,65	96,88
		1084	Benedita	1	6	18,30	0,80	199,91	0,93	140,17
		2386	Alcobaça	1	7	0,71	1,07	267,56	1,26	188,68
		1211	Alcobaça	1	7	0,76	1,40	349,63	1,46	218,67
		1426	Alcobaça	1	7	0,98	1,59	396,48	1,74	260,97
		1197	Alcobaça	1	**7**	1,02	1,86	465,37	2,03	303,83
		1209	Alcobaça	1	**7**	1,11	2,05	513,66	2,30	345,30
		1200	Alcobaça	1	**7**	1,15	2,36	590,64	2,57	385,37
		1201	Alcobaça	1	**7**	1,25	2,68	668,93	2,83	424,47
		1208	Alcobaça	1	7	1,32	3,28	820,57	3,40	510,19
		781	Alcobaça	1	7	1,34	3,59	896,78	3,66	549,57
		1526	Alcobaça	1	7	1,84	3,90	975,33	3,89	583,45
		1206	Alcobaça	1	7	2,00	4,12	1 029,31	4,17	625,41
		1109	Turquel	1	7	13,12	4,43	1 106,50	4,48	671,58
		1087	Benedita	1	7	18,29	4,70	1 176,06	4,74	711,52
		1086	Benedita	1	7	18,34	4,99	1 246,26	5,00	750,06
2	8	**1256**	**Pedemeira**	**2**	**8**	**0**	0,27	67,75	0,37	55,03
…		…	…	…	…	…	…	…	…	…

Table 6.14 also contains in its last four columns information about the filling level of each compartment obtained by multiplying the daily filling rate of each material for the maximum interval of days between collections of the cluster. These columns aim to control the capacity limit of the vehicle compartments and perform a sensitivity analysis on their configuration.

Table 6.15 presents the results obtained for the clustering and routing phases for the MCVRP. The 286 *ecopontos* to visit with a multi-compartment vehicle are distributed in 11 clusters (routes). The average distance travelled per each one is approximately 178,8 km, in 4 hours and 50 minutes, and the average filling rate per vehicle is 71,69%.

In total, the 11 MCVRP clusters/routes translate into 328 routes per year, to a total of 56 081,43 km travelled. The amount of Paper and/Cardboard collected is 70% higher than the amount of Plastic and/Metal in weight (kg). Considering that the filing level of both compartments per every route is not significantly different, the difference on the amount collected per year per material is due to the density of each material inside the vehicle (PC has a density 60% higher than the one PM has inside the vehicle).

Most clusters perform well; some have nearly optimal (100%) filling rates: clusters 2, 3, 4, 5, 7 and 8 have an average of 97,68% of vehicle occupation, being the ones with the longest routes (in time and distance). Cluster 10 also achieved fine results, with an occupation of approximately 70%. Cluster 11 achieved an occupation rate of approximately 60% and cluster 1 of 50% (as an example, the route of this cluster is presented in Appendix C).

The clusters that perform worst are the ones marked in red in Table 6.15: cluster 6 has a vehicle occupation rate of 13,28% and cluster 9 has an occupation rate of 10,71%. These poorly performances are due to the fact that both clusters have few *ecopontos* assigned to each other (5 and 4, respectively), jeopardizing the average of *ecopontos* visited per cluster. In order to assess if there was any gain in the distance travelled, these two clusters were grouped with cluster 1 (since the vehicle is only half full). Thus, this new cluster would have 26 *ecopontos* (17+5+4) and in one year a vehicle would travel 8694,4 km to collect them all. It represents a gain of 3600,49 km per year: (7605,65+2866,24+1883,60) – 8694,4 km. Compared to Cluster 1, the increase of km/route would be of 16,71km. This improvement suggests that a minimum number of *ecopontos* per cluster should be established in order to avoid having vehicles with low filling rates, travelling unnecessary kilometres.

Table 6.15 - Results obtained for the MCVRP for the collection of Paper and/Cardboard and Plastic and/Metal

Cluster	Maximum interval of days between collections	Week	Analysis per route			Analysis per year				Vehicle			
			Number of *ecopontos* visited	Distance travelled per route (km)	Duration	Number of routes per year	Distance travelled per year (km)	Amount of PC collected per year (kg)	Amount of PM collected per year (kg)	Vehicle configuration	PC compartment filling rate (%)	PM compartment filling rate (%)	Vehicle filling rate (%)
1	6	1	17	117,01	3h13min	65	7 605,65	75 814,36	45 628,80	1	49,85%	50,00%	49,93%
2	8	2	41	178,17	5h36min	51	9 086,67	99 689,67	73 346,36	3	97,91%	98,24%	98,09%
3	11	2	32	188,76	5h18min	34	6 417,84	73 308,79	50 405,15	3	99,83%	93,60%	96,41%
4	12	2	34	195,52	5h49min	31	6 061,12	67 180,88	49 208,07	3	98,98%	98,86%	98,91%
5	13	2	36	211,83	5h56min	28	5 931,24	66 152,61	46 919,82	3	99,95%	96,67%	98,14%
6	14	2	5	110,24	2h22min	26	2 866,24	9 960,45	6 041,73	1	13,21%	13,35%	13,28%
7	15	3	33	212,52	6h01min	25	5 313,00	52 354,82	36 843,27	3	98,32%	94,35%	96,14%
8	17	3	35	214,56	5h56min	22	4 720,32	47 523,09	34 163,00	3	99,46%	97,50%	98,38%
9	21	3	4	110,8	2h17min	17	1 883,60	4 525,61	3 289,96	1	9,69%	11,74%	10,71%
10	22	4	24	213,27	5h14min	17	3 625,59	27 772,20	17 751,43	1	67,51%	71,92%	69,72%
11	29	5	25	214,18	5h35min	12	2 570,16	16 966,85	10 575,57	1	57,72%	59,96%	58,84%
Average			**26**	**178,81**	**4h50min**	**30**	-	-	-	-	**72,04%**	**71,47%**	**71,69%**
Total			**286**	-	-	**328**	**56 081,43**	**541 249,34**	**374 173,15**	-	-	-	-

Cluster 1 is the one with the smallest maximum interval of days between collections, meaning that this is the one that has to be visited more often (65 times in one year). However, cluster 2 is the one with the longest distance travelled per year, even being performed 14 times less than cluster 1. This is due to the fact that cluster 2 has more 24 *ecopontos* than cluster 1 (41 – 17). Disregarding clusters 6 and 9, the one with the minimum distance travelled per year is cluster 11, achieved in 12 visits. This cluster also has the highest maximum interval of days between collections. On average, each cluster is visited 30 times (see Table 6.15), which represents a visit every 12 days.

The results obtained in Table 6.15 for the number of visits per year and the amount of PC and PM collected per year are based on the real interval of days between collections, instead of the maximum interval of days between collections.

Valorsul only operates during weekdays (from Monday to Friday), which means that the interval of days between collections of one *ecoponto* may not be constant. The real interval of days between collections was calculated considering three assumptions: i) the first day of the year is Monday; ii) each month has 30 days; iii) 1 year has 360 days (360 days $*$ 12 months).

Figure 6.5 illustrates the calculation of the real interval between collections for an *ecoponto* with a maximum interval between collection of 5 days. Numbers marked with a star (*) represent the days this *ecoponto* would be visited if Valorsul operated 7 days per week; numbers marked in green represent the real day when this *ecoponto* has to be visited so that no container surpasses its maximum capacity.

Month 1

week	M	T	W	T	F	S	S
1	1	2	3	4	5*	6	7
2	8	9	10*	11	12	13	14
3	15*	16	17	18	19	20*	21
4	22	23	24	25*	26	27	28
5	29	30*					

Month 2

week	M	T	W	T	F	S	S
5			1	2	3	4	5*
6	6	7	8	9	10*	11	12
7	13	14	15*	16	17	18	19
8	20*	21	22	23	24	25*	26
9	27	28	29	30*			

Month 3

week	M	T	W	T	F	S	S
9					1	2	3
10	4	5*	6	7	8	9	10*
11	11	12	13	14	15*	16	17
12	18	19	20*	21	22	23	24
13	25*	26	27	28	29	30*	

Figure 6.5 - Explanation of the calculation of the real interval of days between collections

In theory, this collection point would be visited 72 times in a year (360/5 $\simeq$ 72). In week 3 of the first month, however, this *ecoponto* would have to be visited on a Saturday, which is not possible; therefore, the visit would move to the previous Friday so that the capacity of the *ecoponto* is not surpassed. This adjustment represents an increase of 6 more visits in the period of one year (360 days), to a total of 78 visits, representing a frequency of approximately 4,61 days (360/78).

Due to this restriction – 5 working days per week –, the values of the compartments filling rates presented in Table 6.15 are the maximum each cluster can achieve; a cluster may be visited one or two days sooner than expected, resulting in less amount collected per material, and consequently in a smaller filling rate (%).

Lastly, the sensitivity analysis used to determine which configuration of the vehicle compartments suits better each route is analysed.

Routes with materials with filling rates close to 100% may benefit from adjusting the capacity of the vehicle compartments, so that more *ecopontos* can be included in the cluster. Configuration 1, the one with the vehicle divided in exactly half, was applied to all clusters where none of the compartments reached an occupation rate close to 100% (1, 6, 9, 10 and 11). As for clusters 2, 3, 4, 5, 7 and 8, configuration 3 was used (q_{PC} = 2250 kg; q_{PM} = 1650kg). Results for the referred 6 clusters are presented in Table 6.16, as the number of *ecopontos* each cluster would have if only their configuration would change.

Table 6.16 - Results of the sensitivity analysis regarding the size of the compartments of Paper and/Cardboard, and Plastic and/Metal (number of *ecopontos*, per cluster, per configuration)

Cluster	Configuration 1		Configuration 2		Configuration 3	
	q_{PC} = 2500 kg	q_{PM} = 1500 kg	q_{PC} = 2750 kg	q_{PM} = 1350 kg	q_{PC} = 2250 kg	q_{PM} = 1650 kg
	q_{PC} = 10 m^3	q_{PM} = 10 m^3	q_{PC} = 11 m^3	q_{PM} = 9 m^3	q_{PC} = 9 m^3	q_{PM} = 11 m^3
2	37		33		41	
3	31		27		32	
4	31		27		34	
5	33		30		36	
7	31		28		33	
8	32		29		35	

As seen, the best option for all analysed clusters is configuration 3, since it assigns more *ecopontos* for each cluster, than the other two configurations. On average, it assigns more 3 containers than configuration 1, and 6 more than configuration 2.

Configuration 3 has more volume for Plastic and/Metal (11 m^3) than for Paper and/Cardboard (9 m^3). This is revealing of the fact that, in these cases, the amount deposited of PM is restraining the formation of clusters, more than the amount of PC. Due to the lower density of PM, the respective compartment needs more available volume inside the vehicle so that the weight of the both materials is more balanced. Even if this condition was approached with the decision making process in criterion 1, this adjustment in the size of the compartments is beneficial because demand, i.e. amount deposited of both materials, is inevitably different.

6.2.4. Phase 4: Model Validation

In order to validate the proposed model, the results obtained for the MCVRP are compared with the results for the VRP.

Firstly, all collection points were grouped into weeks based on their maximum interval of days between collections, meaning that the results for Phase A are the same. However, Phase B (Clustering and Routing) was totally replaced by an exact method, where a mathematical formulation for the CVRP was implemented in GAMS and solved using the CPLEX solver. This means that the author had no impact on the way clusters were defined. The same inputs (times, speeds, distances and demand) considered for the MCVRP were given to the software to calculate, for each week, the number of optimal routes and minimize the number of kilometers travelled in the respective week – see Table 6.17.

Table 6.17 - Results obtained for the VRP for the collection of Paper and/Cardboard and Plastic and/Metal

Routing Problem	Week	Maximum interval of days between collections	Number of clusters/ routes	Total number of *ecopontos* visited	Total distance travelled (km)	Distance travelled per year (km)
VRP PC	1	7	1	7	114,29	5 943,08
VRP PM	1	6	1	15	116,90	7 598,50
VRP PC	2	8	1	48	182,34	9 299,34
VRP PM	2	8	3	145	413,01	21 063,51
VRP PC	3	15	2	100	359,64	8 991,00
VRP PM	3	15	2	75	336,09	8 402,25
VRP PC	4	22	2	60	332,85	5 658,45
VRP PM	4	22	1	23	201,79	3 430,43
VRP PC	5	29	2	71	350,09	4 201,08
VRP PM	5	29	1	28	215,31	2 583,72
Average			-	57	262,23	-
Total			16	572 (286*2)	-	77 171,36

Due to high number of collection points and the limited processing capacity of the computer used, the clusters formed for the VRP for PM in week 2 and for the VRP for PC in week 3 have a 6% gap (difference between the lower bound and upper bound in the branch-and-bound algorithm used by the CPLEX solver) achieved within a time limit of 4 hours. All the others were proven to be optimal solutions (gap = 0%) – see in Appendix D the routes for week 1.

Results show that to collect all 286 *ecopontos* in single-material routes it is necessary 5 more clusters than in the MCVRP, and the average distance travelled per route increases in approximately 30%; since there is less time spent per collection point and the vehicle has more capacity for one material, 6 more *ecopontos* are visited per route than in the MCVRP). As for the distance travelled, the VRP solution requires more 21 089,93 km to collect all 286 *ecopontos* than the solution obtained for the MCVRP. This represents an increase of 38%, approximately, confirming that the MCVRP, in this application, is more beneficial than the VRP.

7. Conclusions and Future Research

7.1. Conclusions

The problem of waste collection has a remarkable importance in the preservation of the environment, however, it is crucial for companies responsible for it that such service can be cost-effective. In fact, collection and transportation of MSW represent a major part of the budget in waste management (Ramos et al., 2014; Abdelli et al, 2016). Thus, this work proposed an optimisation of the collection of two recyclable packaging materials – Paper and/Cardboard (PC) and Plastic and/Metal (PM) – using vehicles with multiple compartments.

The development of this dissertation begun by studying the waste sector and the company that supports the case study presented, Valorsul, which only operates single compartment vehicles. This step was followed by a review of the existing literature on transportation and routing management, with focus on the current methodologies and alternatives to solve the Multi-Compartment Vehicle Routing Problem (MCVRP). Pursuing the work developed by Oliveira et al. (2015), two research questions were formulated.

The first question addressed is related to the characteristics of *ecopontos*, and aims to select which ones are worth being visited by a multi-compartment vehicle ("*Which collection points are eligible to be visited by a multi-compartmented vehicle?*"). The answer was given considering two criteria. The first one concerns demand and was supported by the fact that, since in the MCVRP more than one material is collected simultaneously, all vehicle compartments should fill at the same rate to optimize its capacity (Muyldermans et al., 2010; Worrell et al., 2011). To predict the filling rates of every *ecoponto* (demand), data about Valorsul was used. The second criterion was mostly based on the existing network of collection points of Valorsul, and intended to analyse the differences on the capacity installed between *ecopontos*, regarding their capacity and number of containers per material. The principle assumed was that the less capacity installed one collection point has, the better. Approximately 85% of the total number of collection points with at least one container for PC and PM were considered eligible to be visited by a multi-compartment vehicle; in the region in study – the municipalities of Alcobaça and Nazaré – a smaller percentage of collection points was considered eligible (80%).

The second question formulated – "*What is the impact of the use of vehicles with multiple compartments in the distance travelled of a recyclable MSW collection system, when compared* *to the traditional method?*" – was answered with the development of a hybrid model, where each cluster represents one different route. The proposed heuristic formed clusters based on the similarity of the filling rates between *ecopontos* (calculated based on the data provided by Valorsul) and only between those selected eligible to be visited by a multi-compartment vehicle. Simultaneously, the size of the compartments for every route was defined (out of three possible configurations). Then, with the use of a modelling software (GAMS), the optimal visit sequence for each cluster was found.

To answer the latter question, this model was applied to a specific region. The solution obtained was then compared to the traditional method – single-material routes –, and the results of this application have shown that the use of multi-compartments vehicles enables a reduction in the distance travelled. Gains of approximately 38% were achieved when comparing the solutions obtained between the MCVRP and the VRP, with both assuring that collection points never surpass its capacity limit. This result has direct impact on the cost structure of a company as Valorsul, highly dependent on the cost of fuel. Results obtained were much better than the savings obtained by Oliveira et al. (2015) – a decrease in the total distance travelled of 5%; however, the authors studied a different region within the system of Valorsul.

As for the sensitivity analysis performed on the size of the compartments, it is concluded that the use of vehicles with multiple compartments can be improved if the partition between compartments can be moved between routes, instead of having one specific configuration for all of them. This flexibility was found in Henke et al. (2015) and allows the vehicle to adapt better to the predicted amount of MSW it has to collect on its routes.

Nonetheless, this study, as any other, has some limitations that may have influenced the results obtained, even if some assumptions were necessary to be considered. For instances, the average filling level was calculated based on the records provided by Valorsul for each container; however, as mentioned, filling levels are typically registered by excess, and there are only 5 possible measures (0%; 25%; 50%; 75%; 100%). This way of determining the filling level is not accurate and causes a deviation from reality, which ends up jeopardizing the company's data for the calculation of the predicted amount to collect per collection point. As for the values of density used of PC and PM they were considered constant.

Specifically regarding the decision making process, it was assumed for the first criterion ("Daily Filling Rate per Material, per *Ecoponto*") that in order to have advantage in implementing the MCVRP for a set of materials, no material can occupy (in volume) more than the double or less than half the space inside the vehicle of other material collected. These values were found using data provided by Valorsul. As for criterion 2 ("Capacity Installed per *Ecoponto*"), it was assumed that all sub criteria had the same importance, which may have disregarded some collection points worth being visited by a multi-compartment vehicle.

Concerning the Clustering and Routing Phases: *ecopontos* were clustered based on their similarity between filling levels and these values could not be accurate, as mentioned before. Variations in the amount deposited may change the number of *ecopontos* visited per route (making one vehicle return to the depot with less MSW than predicted, or sooner than expected if its capacity limit is reached sooner – 6 out 11 routes of the MCVRP solution have filling rates close to 100% and any increase in the predicted amount to collect may change these clusters.

Moreover, clusters were organized in weeks and no consideration was done regarding a minimum number of *ecopontos* per cluster, what end up creating clusters with a reduced number of collection points (2 out of 11 clusters have less than 10 *ecopontos* in the MCVRP). As for the distances between all nodes in the system, the Euclidean distance was used, corrected with a circuit factor calculated specifically for the area where Valorsul operates; however, the values of these distances are only approximate, and not the real ones. Regarding the calculation of the duration of the route, it was not considered street navigation and conditions (if the traffic is heavy, if there are many stop signs and/or traffic lights) and the acceleration. The number of vehicles available per day was also not considered, and therefore did not restrict the results obtained. As for the region chosen to implement the proposed model, it is a remote location that represents only 17% of the collection points with at least one container for the deposit of PC and one for PM of Valorsul system, which prevents the application to have scale.

Finally, the model validation only compared collection points considered worth being visited by a multi-compartment vehicle. *Ecopontos* considered not eligible in the decision making process may have been added to the study in order to have analysed a sample more similar to a real collection system (more variety).

One may argue that the comparison between the proposed model (which uses a heuristic) and the optimal routes achieved for the VRPs may not be fair. However, if gains were achieved even between a heuristic method and an exact algorithm, it is concluded that this MCVRP model is effective, fulfilling the objective herein proposed – a reduction on the distance travelled with the use of vehicles with multiple compartments when compared to the current method used by Valorsul (single-material routes).

7.2. Suggestions for Future Research

The MCVRP is seldom studied in the literature. With the development of heuristics and the effort to improve them, the quality of the MCVRP solution increases, making it more appealing to the be implemented in the industry of waste (or any other). Only with more research on this topic the real advantages and disadvantages of the use of vehicles with multi-compartments can be perceived. Some improvements or additional studies are indicated in this chapter for future research in order to enhance the implementation of the MCVRP and of the proposed heuristic.

First of all, it would be pertinent to analyse if the acquisition of vehicles with multi-compartments are economically feasible for Valorsul, or, in alternative, the adaptation of the existing vehicles (in-house or not). Secondly, the quality of the data should also be a focus for the company. Worrell et al. (2011) stated that the holy grail in the world of MSW is to be able to determine how much waste is generated; to do so, the filling level of each container must be correctly measured every time each one is emptied. Since the current method is not accurate, Valorsul may study the possibility of implementing a system (as RFID chips, which are already used) to record the exact amount of waste collected per container.

Regarding the proposed model in specific, some suggestions for future research are presented:

i) Another way of dealing with the criteria implemented in the decision making process may be the use of a weighted combination of multiple criteria – a multi-criteria analysis may improve the selection of the best collection points worth being visited by multi-compartment vehicles. Criteria should also be review, conducting a sensitivity analysis to validate, for example, the condition used for criterion 1 ($0{,}5 \leq L_{e,mi,mj} \leq 2$).
ii) For the cluster phase it is suggested that a minimum number of *ecopontos* per cluster is defined, in order to avoid the definition of clusters with few collection points. Moreover, the division into weeks may also be approached: routing, in some cases, can go from static to dynamic. Some collection points may be added to one cluster from time to time (considering that there is capacity), instead of creating a specific route for them, or grouping them into a cluster with a lower frequency and ending up visiting them more than required.
iii) The size of each compartment is a crucial factor in the study of the MCVRP; therefore, it is recommended to study this topic in more depth, especially the variant that considers the use of flexible compartments (MCVRP-FCS; Henke et al., 2015).
iv) To support the results obtained in this study, the heuristic proposed can be implemented to the entire system of Valorsul, analyzing how it performs from region to region.

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Appendix A

Table A.1 - Distribution of Valorsul own containers for the deposit of Paper and/Cardboard, Plastic and/Metal, and Glass, per district, municipality and capacity

Material		Paper and/Cardboard (PC)					Plastic and/Metal (PM)					Glass (G)					Total	
Container capacity (m³)		2,5	3	5	Subtotal		2,5	3	5	Subtotal		2,5	3	5	Subtotal			
District	Municipality	#	#	#	#	%	#	#	#	#	%	#	#	#	#	%	#	%
Lisboa	Torres Vedras	360	71	7	438	19,4%	357	68	7	432	19,6%	427	74	7	508	20,3%	1378	19,8%
Leiria	Alcobaça	266	45	2	313	13,9%	256	43	2	301	13,6%	300	54	2	356	14,3%	970	13,9%
Leiria	Caldas da Rainha	258	19	7	284	12,6%	255	20	7	282	12,8%	277	19	7	303	12,1%	869	12,5%
Lisboa	Alenquer	209	7	3	219	9,7%	208	7	3	218	9,9%	209	7	3	219	8,8%	656	9,4%
Leiria	Peniche	173	43	4	220	9,8%	159	42	2	203	9,2%	191	42	4	237	9,5%	660	9,5%
Lisboa	Lourinhã	146	35	0	181	8,0%	140	37	0	177	8,0%	146	34	0	180	7,2%	538	7,7%
Lisboa	Azambuja	107	10	1	118	5,2%	104	10	1	115	5,2%	123	13	1	137	5,5%	370	5,3%
Santarém	Rio Maior	106	6	0	112	5,0%	106	6	0	112	5,1%	110	9	0	119	4,8%	343	4,9%
Lisboa	Cadaval	68	27	1	96	4,3%	68	25	1	94	4,3%	74	29	1	104	4,2%	294	4,2%
Leiria	Bombarral	68	11	1	80	3,5%	69	10	1	80	3,6%	88	10	1	99	4,0%	259	3,7%
Leiria	Nazaré	58	18	1	77	3,4%	58	19	1	78	3,5%	74	26	1	101	4,0%	256	3,7%
Lisboa	Arruda dos Vinhos	56	7	0	63	2,8%	56	7	0	63	2,9%	69	9	0	78	3,1%	204	2,9%
Lisboa	S. M. Agraço	43	7	1	51	2,3%	42	7	1	50	2,3%	44	8	1	53	2,1%	154	2,2%
Leiria	Óbidos	2	0	0	2	0,1%	2	0	0	2	0,1%	3	1	0	4	0,2%	8	0,1%
Total		1 920	306	28	2 254	100%	1 880	301	26	2 207	100%	2 135	335	28	2 498	100%	6 959	100%

Appendix B

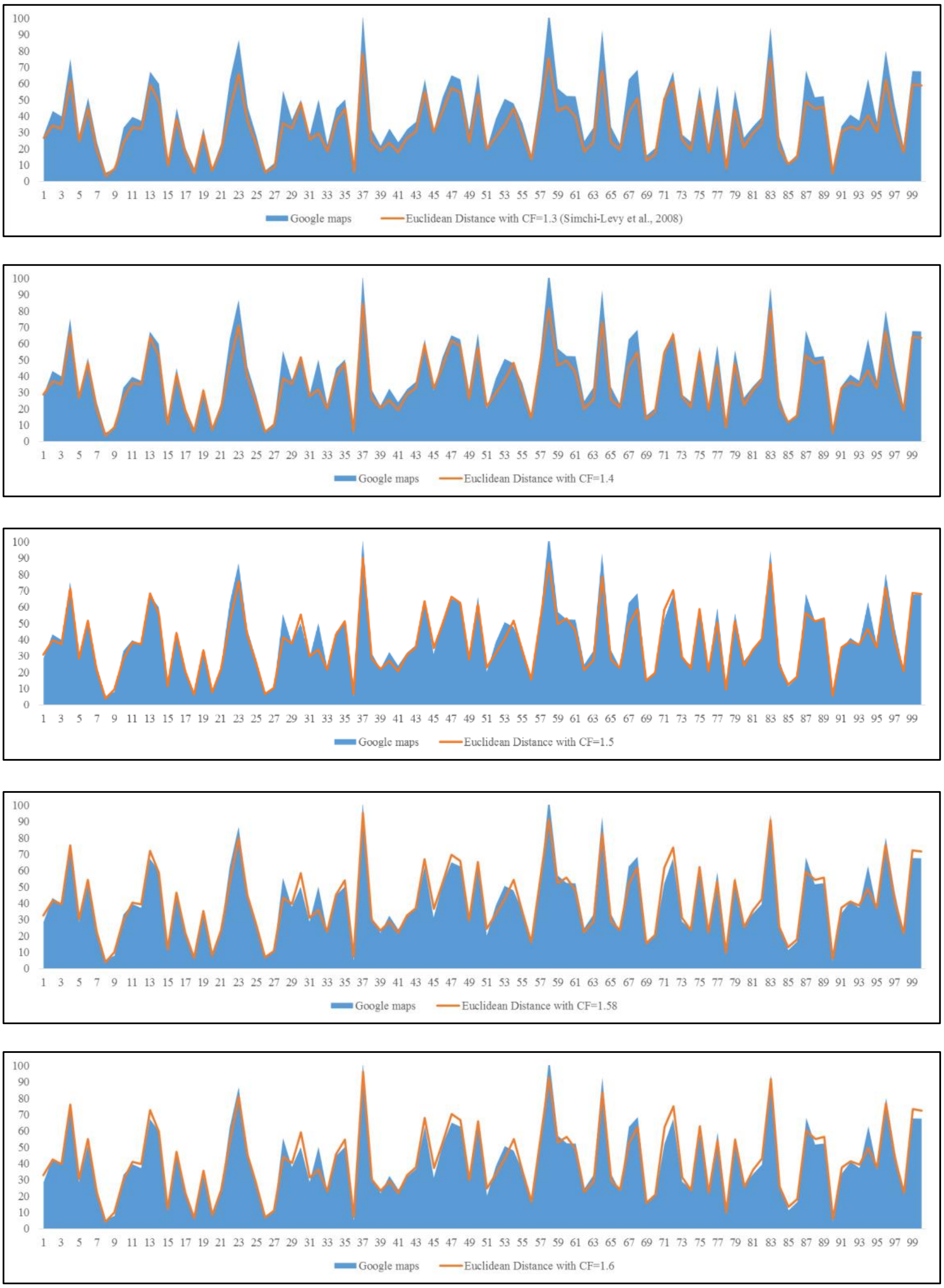

Figure B.1 - Graphical matches between the distance calculated in Google Maps (filled section in blue) and the same distance calculated with the Euclidean Distance formula, using as circuity factors 1,3; 1,4; 1,5; 1,58 (the chosen one, with 99,61% of match); and 1,6

Appendix C

Table C.1 - Visit sequence of cluster 1 of the MCVRP

From	Municipality ("From")	Parish ("From")	To	Number of containers collected	Travelled distance (km)	Duration (hh:mm:ss)
1	Cadaval	Pêro Moniz	1086	*Depot*	39,99	00:39:59
1086	Alcobaça	Benedita	1087	2	0,19	00:03:52
1087	Alcobaça	Benedita	1084	2	0,40	00:04:18
1084	Alcobaça	Benedita	1109	2	5,18	00:08:40
1109	Alcobaça	Turquel	1206	2	11,82	00:15:19
1206	Alcobaça	Alcobaça	1207	2	0,29	00:04:05
1207	Alcobaça	Alcobaça	1208	2	0,48	00:04:27
1208	Alcobaça	Alcobaça	1209	2	0,28	00:04:3
1209	Alcobaça	Alcobaça	1426	2	0,32	00:04:8
1426	Alcobaça	Alcobaça	1211	2	0,26	00:04:00
1211	Alcobaça	Alcobaça	1425	2	0,76	00:05:01
1425	Alcobaça	Alcobaça	2386	2	0,71	00:04:55
2386	Alcobaça	Alcobaça	1197	2	0,35	00:04:11
1197	Alcobaça	Alcobaça	1200	2	0,35	00:04:12
1200	Alcobaça	Alcobaça	1201	2	0,23	00:03:57
1201	Alcobaça	Alcobaça	781	2	0,23	00:03:57
781	Alcobaça	Alcobaça	1526	2	0,63	00:04:45
1526	Alcobaça	Alcobaça	1	2	54,55	01:09:33
Total				34	117,01	3h13min

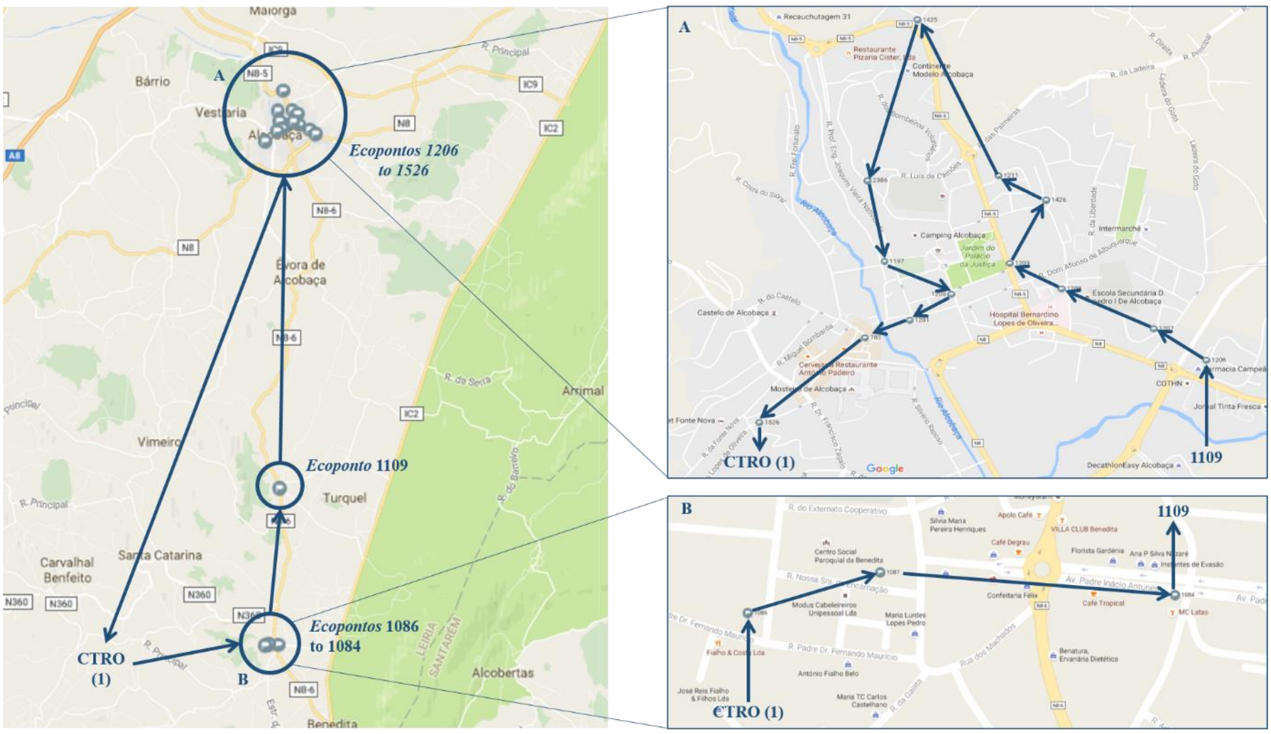

Figure C.1 - Illustration of the route of cluster 1 of the MCVRP

Note: Maps were extracted from *Google Maps*, and the location of CTRO (1) is merely illustrative

Appendix D

Table D.1 - Visit sequence of the cluster of week 1 of the VRP for PC

From	Municipality ("From")	Parish ("From")	To	Number of containers collected	Travelled distance (km)	Duration (hh:mm:ss)
1	Cadaval	Pêro Moniz	1526	*Depot*	54,55	00:54:34
1526	Alcobaça	Alcobaça	781	1	0,63	00:03:01
781	Alcobaça	Alcobaça	1201	1	0,23	00:02:13
1201	Alcobaça	Alcobaça	1200	1	0,23	00:02:13
1200	Alcobaça	Alcobaça	1211	1	0,54	00:02:51
1211	Alcobaça	Alcobaça	1208	1	0,56	00:02:53
1208	Alcobaça	Alcobaça	1084	1	17,21	00:18:58
1084	Alcobaça	Benedita	1	1	40,33	00:55:21
Total				7	114,29	2h22min

Table D.2 - Visit sequence of the cluster of week 1 of the VRP for PM

From	Municipality ("From")	Parish ("From")	To	Number of containers collected	Travelled distance (km)	Duration (hh:mm:ss)
1	Cadaval	Pêro Moniz	781	*Depot*	55,09	00:55:6
781	Alcobaça	Alcobaça	1201	1	0,23	00:02:13
1201	Alcobaça	Alcobaça	1200	1	0,23	00:02:13
1200	Alcobaça	Alcobaça	1197	1	0,35	00:02:28
1197	Alcobaça	Alcobaça	2386	1	0,35	00:02:27
2386	Alcobaça	Alcobaça	1425	1	0,71	00:03:11
1425	Alcobaça	Alcobaça	1426	1	0,98	00:03:43
1426	Alcobaça	Alcobaça	1209	1	0,32	00:02:24
1209	Alcobaça	Alcobaça	1208	1	0,28	00:02:19
1208	Alcobaça	Alcobaça	1207	1	0,48	00:02:43
1207	Alcobaça	Alcobaça	1206	1	0,29	00:02:20
1206	Alcobaça	Alcobaça	1109	1	11,82	00:13:34
1109	Alcobaça	Turquel	1084	1	5,18	00:06:56
1084	Alcobaça	Benedita	1087	1	0,40	00:02:34
1087	Alcobaça	Benedita	1086	1	0,19	00:02:08
1086	Alcobaça	Benedita	1	1	39,99	00:54:60
Total				15	116,90	2h42min