Solution approaches for the Smart Waste Collection Routing Problem

Gustavo Souza Marques

Thesis to obtain the Master of Science Degree in

Industrial Engineering and Management

Supervisor: Prof. Tânia Rodrigues Pereira Ramos

Examination Committee

Chairperson: Prof. Tânia Pinto Varela

Supervisor: Prof. Tânia Rodrigues Pereira Ramos

Member of the committee: Prof. Rui Manuel Moura de Carvalho Oliveira

January 2021

Declaration
I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Declaração
Declaro que o presente documento é um trabalho original da minha autoria e que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

ACKNOWLEDGEMENTS

First of all, I would like to express my sincere gratitude to professor Tânia Ramos whose guidance, support and encouragement has been invaluable throughout this investigation from day one. Secondly to Carolina Morais and Raquel Aguiar for their continued help, bundle of laughs and numerous meetings that made it easier to go through that journey. This was with no doubt the best team I could ask for.

To my family for all the unconditional support and for providing me the strength I needed to overcome some of the challenging moments. Finally, I cannot forget to thank to all the friends I made during my journey in Instituto Superior Técnico that, somehow, contributed to this dissertation.

ABSTRACT

Waste collection companies often face inefficiency in their operations, mostly associated with the highly difficulty in predicting the bins waste accumulation. These fluctuations are linked with the presence of uncertainty in the system, which leads to an excessive travelling kilometer usually to collect a small amount of waste. One way to reduce the uncertainty is to explore electronic devices to access real-time information on the bins fill-level and, thus, optimize the collection routes.

This problem is known in the literature as the Smart Waste Collection Routing Problem (SWCRP) and some approaches were already proposed to deal with it (Aguiar et al., in press; Ramos et al., 2018). The SWCRP was approached in both works as a Vehicle Routing Problem with Profits (VRPP) and therefore, the present dissertation aims to improve those works addressing some issues that were not considered beforehand, such as the route balance. Three operational management approaches are introduced to define dynamic routes considering real-time information about the bins fill-levels. In addition to the route balance, another branch is investigated to study how to select the bins to be considered by the model. Besides the option that complies all bins, a pre-selection procedure is explored combining the VRPP model with a heuristic method.

The solution method is applied in a real-world case study where a potential increase in the operational profit is achieved by up to 450%. Moreover, it is concluded that the solution method can also allow an improvement of up to 69% in the operations efficiency.

KEY-WORDS: Smart waste collection routing problem, Sensors, Real-time information, Optimization, Recycling.

RESUMO

As empresas de recolha de resíduos enfrentam frequentemente ineficiência nas suas operações, principalmente associada à grande dificuldade em prever a acumulação de resíduos nos contentores. Estas flutuações estão ligadas à presença de incerteza no sistema, o que leva a um excesso de quilómetros percorridos normalmente para recolher uma pequena quantidade de resíduos. Uma forma de reduzir a incerteza é explorar dispositivos eletrónicos para aceder a informações em tempo-real sobre o nível de enchimento dos contentores e, assim, otimizar as rotas de recolha.

Este problema é conhecido na literatura como *Smart Waste Collection Routing Problem* (SWCRP) ao qual algumas abordagens já foram propostas (Aguiar et al., in press; Ramos et al., 2018). O SWCRP foi abordado em ambos os trabalhos como um *Vehicle Routing Problem with Profits* (VRPP) e, portanto, a presente dissertação visa aprimorar estes trabalhos abordando questões que não foram consideradas anteriormente, tais como o *route balance*. São introduzidas três abordagens de gestão operacional para definir rotas dinâmicas, considerando a informação em tempo-real sobre os níveis de enchimento dos contentores. Além do *route balance*, é investigado outro ramo a fim de estudar como selecionar os contentores a serem considerados pelo modelo. É explorado um procedimento de pré-seleção, combinando o modelo VRPP com um método heurístico.

O método de solução é aplicado num estudo de caso do mundo real onde um potencial aumento do lucro operacional é alcançado em até 450%. Além disso, conclui-se que o método de solução pode permitir uma melhoria de até 69% na eficiência das operações.

PALAVRAS-CHAVE: *Smart waste collection routing problem*, Sensores, Informação em tempo-real, Otimização, Reciclagem.

LIST OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABREVIATIONS

APA – Portuguese Environment Agency (Agência Portuguesa do Ambiente)

CARP – Capacitated Arc Routing Problem

CDR – Waste Derived Fuel (Combustível Derivado de Resíduos)

CVRP – Capacitated Vehicle Routing Problem

ECAL – Cardboard Packaging for Liquid Foods (Embalagens de Cartão para Alimentos Líquidos)

EGF – Environment Global Facilities

GAMS – General Algebraic Modeling System

GIS – Geographic Information System

ICT – Information and Communication Technologies

IoT – Internet of Things

MCVRP – Multi-Compartment Vehicle Routing Problem

MILP – Mixed Integer Linear Programming

MSW – Municipal Solid Waste

PERSU – Strategic Plan for Urban Solid Waste (Plano Estratégico de Resíduos Sólidos Urbanos)

PRO Europe – Packaging Recovery Organisation Europe

PVRP – Periodic Vehicle Routing Problem

SGRU – Municipal Waste Management Systems (Sistema de Gestão de Resíduos Urbanos)

SIGRE – Integrated Packaging Waste Management System (Sistema Integrado de Gestão de Resíduos de Embalagens)

SPV – Sociedade Ponto Verde

SWCRP – Smart Waste Collection Routing Problem

VRPP – Vehicle Routing Problem with Profits

1. INTRODUCTION

The first chapter is intended to explain the context and motivation of the dissertation, define the objectives, detail the methodology and lastly, present the dissertation's structure. The chapter is divided into four sections: Section 1.1 will present the contextualization of the problem along with the motivation to address it. Section 1.2 highlight the objectives of the dissertation's development. Section 1.3 clarifies the methodology followed to comply with the objectives. And Section 1.4 presents the dissertation outline so that the reader gets a global view on how the subject will be structured.

1.1 Context and Motivation

Over the decades, the dramatic population growth and expansion of cities has been constantly observed and, as a result, influencing the waste production generated by citizens. Waste is an environmental problem that can be considered as a consequence of the human activity, which daily generates more and more waste due to the embedded nature of consumption (Beliën et al., 2014; Gutberlet, 2018). However, the management of this waste is a complex task that compels the absorption of a large amount of resources and causes an important and substantial impact on the environment (Ghiani et al., 2014). Thus, the demand of exploring solutions for the waste management optimization rises not only to provide access to environmental benefits but as well as in terms of economic benefits and improvement of the associated procedures (Beliën et al., 2014; Ghiani et al., 2014; Gilardino et al., 2017).

According to the Portuguese Environment Agency (APA), when considering mainland Portugal, it is possible to observe that the total waste production has reached approximately 4.94 million tons in 2018 (an increase of 4.2% compared to 2017). Also, it is indicated that Portugal presents a growing trend in waste generation occurring since 2014 (Agência Portuguesa do Ambiente, 2019). However, the collection of this waste is associated with high transportation costs and inefficiency in the use of resources. This because it is common to have uncertainty in the system caused by the highly variation of the amount of municipal solid waste, often leading the vehicles to visit only partially full bins (Nuortio et al., 2006; Ramos et al., 2018). Therefore, to deal with this uncertainty and the increase production of waste, it is important to design of an efficient waste collection system which, despite its difficult accomplishment and numerous decisions involved, different methods have been developed using Operational Research techniques along with advances in Information and Communication Technologies (ICT). The new era of Web and Internet of Things introduces the proliferation of smart devices to monitor, collect and transmit real-time information, since its constant change leads to great uncertainty in terms of operations. In this way, the increase availability of devices that provide real-time information is responsible for a new paradigm of logistics and transportation systems, enabling operational researchers to focus on the development of optimal planning models (Anagnostopoulos et al., 2017; Powell & Jaillet, 1995).

Taking into account the aforementioned considerations, the ambition of the present dissertation is to provide an improvement in the waste collection operations field, based on the Smart Waste Collection Routing Problem (SWCRP) introduced by Ramos et al., 2018. The SWCRP proposes the definition of dynamic routes using real-time information about the bins fill-level through an ICT device. The methodologies developed in this dissertation will be applied in a real case study that describes the collection operations of ERSUC, a company responsible for the recyclable waste collection system in 36 Portuguese municipalities. Currently, ERSUC's faces a problem regarding its operation's efficiency that, supported by quantitative data, shows the majority collection of empty or low fill-levels bins. Hence, the focus here is to increase the waste collection operations' efficiency by optimizing the collection routes taking into account the information sent by the ICT devices.

1.2 Objectives

This dissertation has as main objective to develop solution methods for approaching the waste collection routing problem supported by ICT devices in the system, namely, the SWCRP. As mentioned above, the methodologies here introduced will be tested based on a real case study which exposes the problem faced by ERSUC, a waste collection company that has noticed an inefficient performance of its operations. Therefore, in order to achieve the primary objective, several secondary objectives were defined and are described below:

- Understand the waste management sector in Portugal, analyse the evolution over time and present their main targets currently in action.
- Characterize the service provided by ERSUC, defining their currently procedure to perform the collection of recyclable waste.
- Address the challenges faced in its collection operations to identify the main issues.
- Investigate the relevant modelling and optimization methodologies related with the waste collection field, mainly focusing on routing problems.
- Research new technologies and others prominent trends applied in the waste collection operations.
- Develop new solution methodologies, based on the existing literature contributions.
- Implement the methodologies to real instances explored and analyse the potential impact of the different scenarios in terms of operations performance, especially their profitability and feasibility.

1.3 Dissertation Methodology

In order to accomplish the established objectives, the methodology applied in this dissertation was divided into several steps. Figure 1 displays the steps ordered according to the dissertation development sequence. Furthermore, the methodology followed for approaching each step will be detailed. The first two steps are related to the initial five objectives mentioned above and besides providing the contextualization of the problem, it supports the definition of the most appropriate methodology to follow. The subsequent steps are related to the remaining objectives and concerns the development and implementation of the solution approaches, as well as the results obtained, which is the aim of this dissertation.

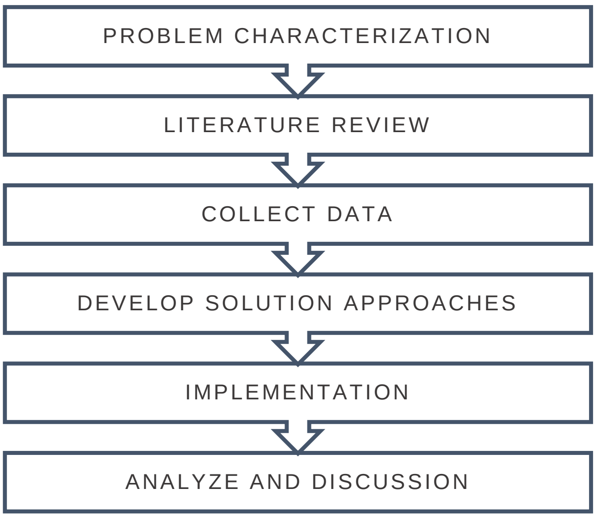

Figure 1 - Main steps for the dissertation's methodology

The initial step, PROBLEM CHARACTERIZATION, intends to describe the case study under analyses, a fundamental step for definition and characterization of ERSUC's problem. Thus, it is important to understand the history and applications of the waste management sector in Portugal, as well as to describe the service provided by the company, including its background and current market positioning. A research was then conducted using the Google search database, featuring several papers, articles, and web pages about the waste management sector. Additionally, it was identified which companies are currently active in the Portuguese market. For gathering specific information about ERSUC, the company's official website was exploited as a source, which then made it possible to highlight other entities directly related to its activity and, thus, support the need to also describe their activities (again, through access to the official websites). Moreover, the direct contact with the company was required to collect some specific information regarding its operations, such as number of vehicles and bins, which are the circuits currently performed, amount of waste annually collected, challenges and issues identified by the company, among others. By processing all information gathered, it was possible to better understand the problem at hand, clarify the logistical challenges faced by the company and, therefore, define the potential contributions of the dissertation.

Regarding the REVIEW OF LITERATURE, the main purpose is to create a knowledge base to support the problem analysis, investigating what are the issues considered relevant for the dissertation. Such purpose was approached by exploring a research process through the scientific-technical bibliographic databases Web of Science and Science Direct. Concepts, definitions, and investigations were addressed using the following keywords: municipal solid waste management, waste collection, route planning, modeling, and optimization.

The next step, COLLECT DATA, refers to the phase of collecting and processing the data gathered. To simulate ERSUC's operations it is necessary to acquire important information regarding its performance. It was taken into account the real location and distances of the depot and all bins here considered. Also, for a more accurate stipulation of the parameters, it is necessary to gather some specific information such as the bins and vehicle capacity, vehicle average speed, travel cost per distance unit, bins average collection time, bins fill-level, among others. Lastly, information about the packaging recycling market was also included. The processing part is only applied to certain information that is considered to be in a raw state, and therefore a processing method has to be applied to make this information viable for use, such as for the bins fill-levels.

The DEVELOP SOLUTION APPROACHES step focuses on designing the solution approaches based on the most appropriate methodology for the problem. The approaches should be able to define dynamic collection routes, considering real-time information on the individual fill-level of each bin, and optimize the collection sequence. As such, the objectives underlying the approaches are to prevent the bins from overflow and to maximize the operation's profit (maximizing the amount of waste to be collected while minimizing the distance travelled).

Afterwards, the IMPLEMENTATION step deals with the application of the solution approaches in a General Algebraic Modeling System (GAMS) software, which will be tested with the collected data.

The final step, ANALYZE AND DISCUSSION, consists in interpreting the results obtained by testing the solution approaches, debating the suitability of each one based on its performance.

1.4 Outline

After briefly describe the problem, the objective and the methodology of this work, the present section introduces the dissertation outline, which is structured under the following chapters:

- INTRODUCTION: The first chapter describes the problem background and motivation for addressing it, followed by the dissertation objectives and which research methodology should be used to achieve these objectives. At the end, the outline of the dissertation is presented, which is the current section.
- PROBLEM DESCRIPTION: The second chapter characterizes the problem addressed by presenting the history and evolution behind waste management operations in Portugal, since the first strategy plan proposed to the current situation. It is then specified for the packaging recycling sector where is presented the recycling rates objectives and the

Green Dot Society's role on the procedures and partnerships with the so-called Municipal Waste Management Systems (SGRU). Next, the real case under study is described based upon the paper/cardboard collection operations of the Portuguese waste management company ERSUC for Soure and Condeixa municipalities. After framing the problem with ERSUC's particular case, it is concluded how the dissertation can contribute to face the issues and challenges identified.

- LITERATURE REVIEW: The third chapter is intended to cover the review of definitions, concepts and methodologies already developed in the waste collection sector. The review is done according to the problem identified in the previous chapter and, therefore, focuses on the optimization of route operations. Lastly, emerging technologies and relevant trends related to the case study under analysis are also investigated.
- METHODOLOGY: The fourth chapter provides the methodology considered most appropriate to solve the problem analyzed according to the conclusions of the literature review chapter. The definition and characterization of the solution method is then presented. Three solution approaches are proposed based on the SWCRP, introduced by Ramos et al., 2018, and two branches are explored: (1) A heuristic to pre-select which bins should be considered (Bins Selection Rules); and (2) The consideration of workloads (Route Balance).
- RESULTS: The fifth chapter presents the results obtained after applying the solution method. It is described the initial phase of the data collection and processing method, the current situation of each test instance, and the assumptions and estimations considered for the parameters applied. Lastly, the performance of the solution approaches is analyzed along with their branches. It is intended to verify which is the most promising approach and how such branches can influence the quality of the solution.
- CONCLUSIONS AND FUTURE WORK: The sixth chapter discusses the dissertation's conclusions and proposes possible future work in the field.

2. PROBLEM DESCRIPTION

The present chapter aims to describe the problem under study and to present a broad review of the scope associated with such thematic. Initially, Section 2.1 address the Portuguese waste management history and evolution over the years, together with the corresponding goals set for the field. Section 2.2 introduces the strategies and policies regarding the packaging recycling sector for Portugal, with emphasis on the proposed targets. In addition, an analysis of the current situation is also developed here. Section 2.3 describes the case study undertaken for this dissertation, presenting the company at hand, its operation activity and the problem currently faced by them. Lastly, the conclusions are presented in Section 2.4 summarising the information obtained from the elaboration of the current chapter.

2.1 Waste Management in Portugal

When dealing with any kind of issue, it is essential to update the practices being performed as time goes by. Due to the constant evolution regarding factors associated to human behavior and the increasing world population, it becomes necessary to seek new courses of action so as to improve the social lifestyle in both economic and environmental fields. In this work, the main subject addressed is included in the municipal solid waste management field that, as a whole, encompasses all the processes related to the collection and treatment of the municipal solid waste (MSW) produced and the structures associated with its operations. MSW production can be defined as the wastes derived from consumer goods after consumption or transformation, i.e. no matter if they can be recycled or not, it refers to all solid materials used in domestic consumption (Russo, 2003).

The MSW management in Portugal was previously conducted by the municipalities themselves until 1996, which only carried out the collection operation and disposal of the MSW without any type of sorting or control in terms of environmental and public health issues. As a result, Portugal's politicians have noted a sharp delay regarding the practices conducted by most of the European Union member states, which led in 1996 the prioritization in solving such a situation (Trotta, 2011). Thus, the first national plan for the MSW sector was developed and approved in this year. The “Strategic Plan for Municipal Solid Waste” (PERSU I) consisted in establishing the organization, regulation and infrastructure of the MSW and would be implemented in the following year, comprising a 10-year horizon for action and having as main objectives for the year of 2005 (Agência Portuguesa do Ambiente, 2020b):

- Ending the waste final disposal method in the landfills (where approximately 80% of the produced waste was disposed of) and the environmental recovery of these areas.
- To enable the management of municipal waste through multi-municipal and intermunicipal systems.

- To create infrastructures for treatment, recovery, and disposal of municipal waste.
- Construction and implementation of foundations to support the recycling activity/process and allow multi-material selective collection performance.

Figure 2 shows the differences between the targets set in PERSU I for 2005 and the actual results obtained for the same year. Although some aspects did not reach the quantitative targets that were established, the implementation of PERSU I was generally considered a positive step for Portugal, leading to an institutional and structural revolution of the MSW sector. Such strategic plan made it possible not only the selective collection systems introduction (through eco-centers and eco points networks creation), but also the implementation of multi-municipal and inter-municipal MSW management systems, based on the construction of infrastructures such as: Landfills, transfer stations, sorting centers, organic valorization units and incineration units. In addition, it is important to mention that Figure 2 does not demonstrate one of the main objectives proposed by PERSU I that was successfully achieved in a considerably short period of time, the complete shutdown of the landfills previously used for disposal of all waste produced (Ministério do Ambiente Ordenamento do Território e do Desenvolvimento Regional, 2007).

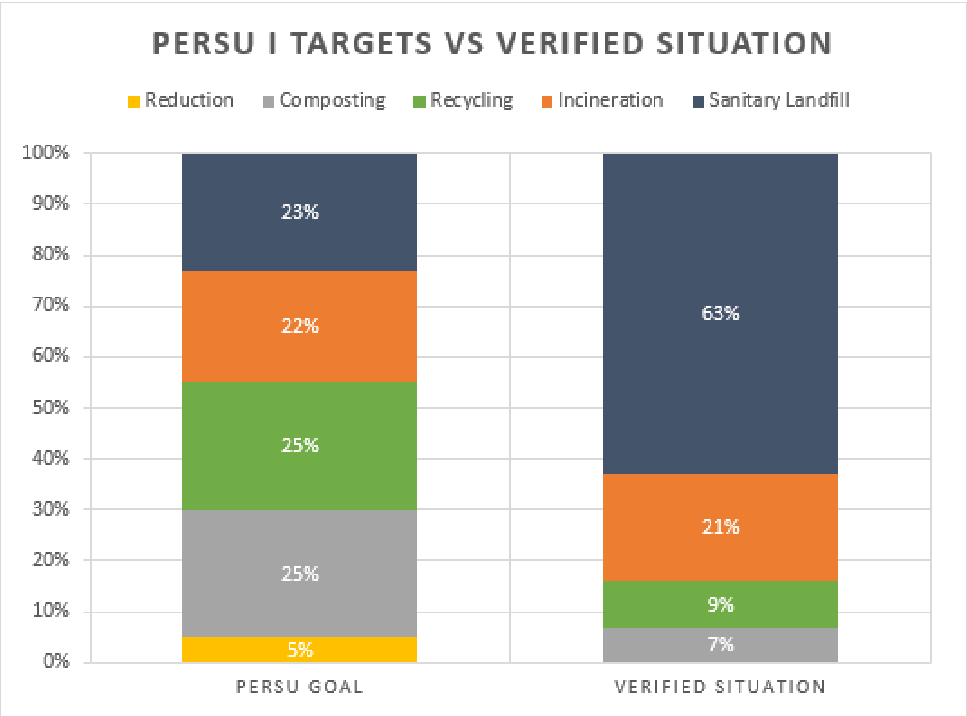

Figure 2 – PERSU I targets for 2005 vs Verified situation in 2005 (Adapted from PERSU II, 2007)

In 2006, a new strategic plan for the MSW was approved, the PERSU II. The plan was developed considering the monitoring and review of the previous plan's performance and aims to define the strategies by setting the priorities and targets regarding the MSW sector management (Ministério do Ambiente Ordenamento do Território e do Desenvolvimento Regional, 2007). Thus, by updating the course of action, PERSU II became the strategic management tool for the time horizon between 2007 and 2016, focusing on intensifying the policies and practices of reduction, recycling, and reutilization of the MSW. Additionally, it was also ensuring the monitoring of the main MSW management infrastructures, namely the centers of treatment and disposal of wastes (Nunes, 2017). Meanwhile, mid-term evaluations are performed over the time horizon of each PERSU and, according to the 2012 mid-term evaluation of the PERSU II, a significant deviation was verified from the targets proposed for 2020. This was mainly justified on the basis of two factors observed by the PERSU's management support group: (1) the continued use of sanitary landfills has remained predominant for the MSW disposal; And (2) the operations for capitation dedicated only to selective collection was considerably far from what was proposed. Therefore, they concluded that such a plan was not suitable to be taken as strategic action until 2016, hence requiring a reformulation of the plan earlier than the pre-established schedule (Agência Portuguesa do Ambiente, 2014a).

The PERSU 2020 was then developed, aligning the aspects mentioned above with more appropriate targets for the planning horizon from 2014 to 2020. The new reference tool established a vision, objectives, global and specific targets for the MSW management policy alongside with measures for implementation and strategic action (Agência Portuguesa do Ambiente, 2014b). However, similarly to the previous plans, mid-term evaluations were part of the action plan and, once again, it was verified that the behavior of some fundamental factors tended to be insufficient to achieve the proposed targets. The 2017 mid-term evaluation of the PERSU 2020 promoted the need for adjustments in the MSW national strategy policy, leading to a new plan: The PERSU 2020+. Note that such a plan does not repeal the previous one and thus, what is being considered in the PERSU 2020 but not adjusted in the present PERSU 2020+, remains in effect (Agência Portuguesa do Ambiente, 2020b).

2.2 Packaging Recycling

The concept of recycling refers to any recovery operation involving materials that constitute waste through which transformation processes are perform to a final origin of new products, materials or substances, not including energy recovery and the reprocessing of materials intended for use as fuel or filling operations (Ministério do Ambiente Ordenamento do Território e do Desenvolvimento Regional, 2011). Regarding the concept of municipal waste, it represents two types of waste: those considered as undifferentiated collection and those considered as selective collection of households, comprising materials such as paper/cardboard, glass, plastics, bio waste, wood, textiles, among others (Agência Portuguesa do Ambiente, 2020b).

This work focuses on the recyclability of materials classified as packaging, defined as "any and all products made of materials of any nature used to contain, protect, move, handle, deliver and display goods, both raw materials and processed products, from the producer to the user or consumer, including all 'disposable' items used for the same purposes" (Sociedade Ponto Verde, 2020a). The Sociedade Ponto Verde (SPV) is licensed by the Packaging Recovery Organization Europe (PRO Europe), an organization formed by the European environmental organizations that supervise household packaging waste management using mainly the trademark "The Green Dot" as a financing symbol (Packaging Recovery Organisation Europe, 2020). In Portugal, the SPV promotes the selective collection, recovery and recycling of packaging, organizing and managing the processes of recovery of packaging waste through the Integrated Packaging Waste Management System (SIGRE) (Sociedade Ponto Verde, 2020a). Under the SIGRE, the licensed entities are subject to the management principles and objectives established in Decree-Law no. 152-D/2017, of 11 December, concerning aspects related to the organization and management of packaging and packaging waste in a cycle that contemplates the return, recovery and recycling of non-reusable packaging waste in addition to the volume reduction of waste deposited in sanitary landfills. According to the APA, the SIGRE encompasses the structuring of the selective collection network, the financing costs of sorting, storage, transport, treatment, and recovery of packaging waste deposited in the selective collection networks. Furthermore, it also supervises the accomplishment of collection targets and minimum recovery goals (Agência Portuguesa do Ambiente, 2020a). The success of SIGRE requires, however, the coordination of responsibilities between the various partners involved in the system, in order to complete and ensure the efficient performance of the cycle. Figure 3 demonstrates the elements that constitute the SIGRE cycle whereby each partner has a fundamental role. Through the cooperation between them, SPV considers that such a process can offer a prospect of almost infinite sustainability (Sociedade Ponto Verde, 2020b).

Figure 3 - SIGRE's operating cycle (Adapted from Sociedade Ponto Verde, 2020)

The Packers/Importers that adhere to SPV declare the packaging they place on the national market; however, the recycling and recovery operations are performed by SPV. Based on the Green Dot Value table, unit values per kg are provided for each type of non-reusable packaging material, allowing the packer to calculate his annual contribution by multiplying the quantities of packaging placed on the market with the respective Green Dot Value. SPV then establishes partnerships with the Municipal Systems and/or its Concessionary Companies, i.e., SGRUs, which act according to a pre-established intervention area and, thus, become responsible for operating the selective collection and sorting of packaging waste coming from the citizen/consumer separation within their area. The SPV remunerates the SGRUs through a Counterpart Value calculated for each type of packaging material and based on the intervention area of the SGRUs, distinguishing for the Continent, Azores, and Madeira (in conformity with the legislation in effect). This value tends to support the accrual costs related to the operations of selective collection and sorting activities managed by the SGRUs. The waste is then provided to the SPV that sends it for recovery and recycling through the waste sale to Collectors/Recyclers companies who participated in a competition processes to be responsible for part of the waste take-back. Such a procedure is supported by a Take-back Value paid by the Collectors/Recyclers in exchange of the waste received and includes a definition of the waste status according to some technical specifications pre-established. However, if the waste is identified as being in breach of these specifications, the SPV then pays for the take-back procedure assuming then a negative Take-Back Value. Table 1 displays the quantities taken back for packaging waste managed by SPV in 2018. As can be seen, approximately 332,000 tonnes of waste were taken back and whereby 93% is derived from selective collection (Sociedade Ponto Verde, 2018).

Table 1 - Tonnes of packaging waste taken back by SPV in 2018 (Adapted from Sociedade Ponto Verde, 2018)

ORIGINS	GLASS	PAPER / CARDBOARD	ECAL	PLASTIC	STELL / ALUMINIUM	WOOD	TOTAL
Selective Collection	161 345	89 183	4 947	46 255	5 584	4	307 317
Undifferentiated Collection	235	982	1 486	8 636	12 863	0	24 201
Total Urban Flow	**161 580**	**90 165**	**6 433**	**54 891**	**18 447**	**4**	**331 518**

Under the goals and targets for the packaging waste recycling, Portugal is committed to achieve an increase in collection, recycling, and recovery rates (both global and sectoral), and to meet the following targets showed in Table 2. According to the Decree-Law no. 152-D/2017, of 11 December, it was established a minimum recovery rate of 60% (in weight) whereby at least 55% must correspond to recycling, in line with minimum targets for each sector. Also, this Decree-Law transposes the internal legal order of the Directive 94/62/EC that sets the targets achievement by the end of 2011. The Directive (EU) 2018/852 of the European Parliament and of the Council of

30 May 2018 establishes the preparation of Member States for reutilisation and recycling of 65% of the packaging waste by 2025 and, for 2030, it is expected the recycling of at least 70% (see Table 2). However, until the adoption of the new targets set by Directive 2018/852, it is assumed the achievement of the targets defined for 2011 to be in effect (Parlamento Europeu e do Concelho, 2018).

Table 2 - Recycling rate targets according to each Directive (Adapted from Parlamento Europeu e do Concelho, 2018)

DIRECTIVE	YEAR	RECYCLING RATES					
		GLASS	PAPER / CARDBOARD	PLASTIC	STELL	ALUMINIUM	WOOD
94/62/EC	2011	60%	60%	22.5%	50%		15%
2018/852	2025	70%	75%	50%	70%	50%	25%
	2030	75%	85%	55%	80%	60%	30%

Next, Figure 4 summarises the amount of packaging waste produced, as well as the respective recycling and recovery rates achieved by Portugal over the years. The evolution of these factors shows that initially there was a growth phase in waste production which reached its peak by 2008. A decrease is observed to occur until 2013 followed by a reversal of this trend, showing again a growth period until 2017. The recovery rate represented in Figure 4 includes the combined percentages of recycling and energy recovery operations that, according to the data, in the last

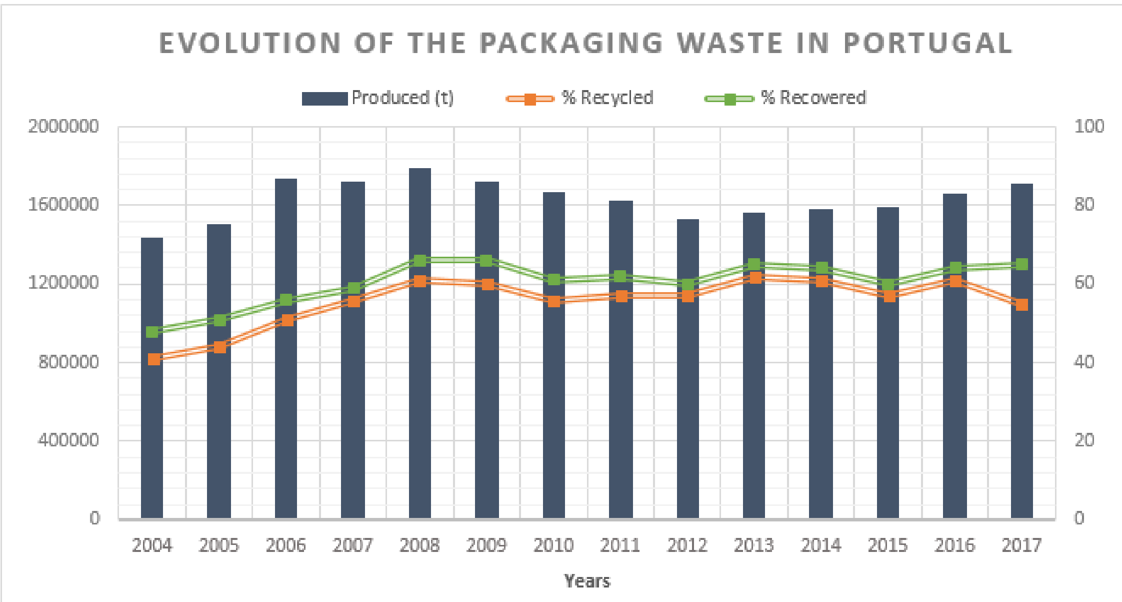

Figure 4 - Evolution of the packaging waste produced, recycled, and recovered in Portugal (Source: Agência Portuguesa do Ambiente, 2019)

two years has been increasing, reaching 65% by 2017, in contrast to the packaging recycling rate which decreased to 55%.

Since the focus for analysis in this work lie on ERSUC's current operation for collection of the paper/cardboard material type, Figure 5 present a temporal evolution of the recycling rate of packaging waste for such material, together with the targets established by the directives in effect for 2011 and 2025. Generally speaking, a decrease in the recycling rate can be observed since 2008, when the highest value of 88% of recycled waste for paper/cardboard was reached. However, it remains above the proposed by Directive 94/64/EC which sets the target of 60% by 2011. As previously mentioned, once these targets were reached, the adoption of new ones established by the Directive 2018/852 would come into effect for achievement by 2025 (in this case, 75%) and, despite having been already achieved in 2007, 2008 and 2009, it is observed that was not possible to maintain such achievement for the following years.

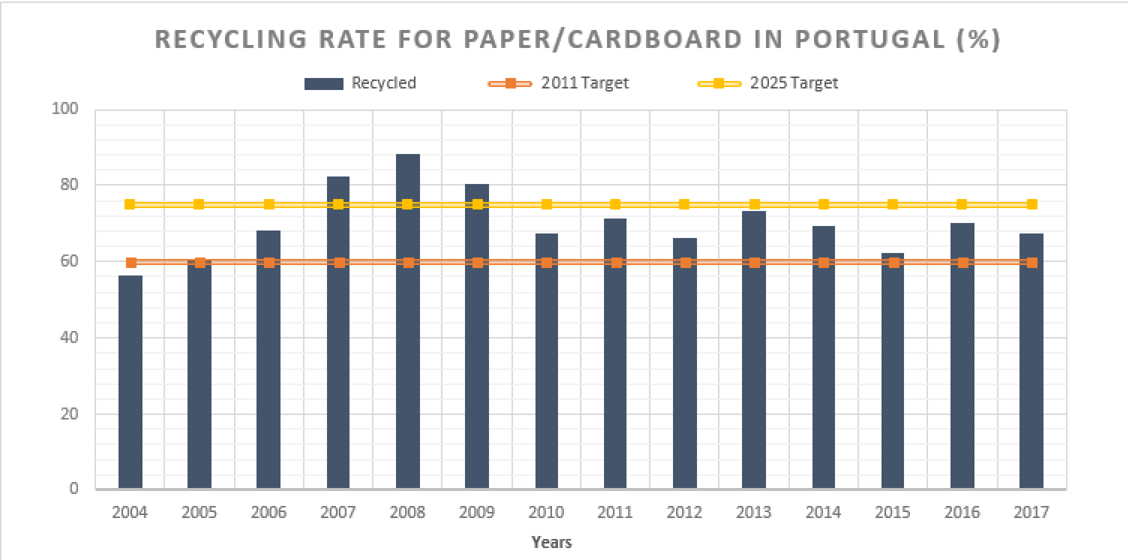

Figure 5 - Paper/cardboard recycling rate and targets for Portugal (Adapted from Agência Portuguesa do Ambiente, 2019)

2.3 ERSUC's Case

The SGRU under study refers to the company ERSUC - Resíduos Sólidos do Centro, S.A., which belongs to the Environment Global Facilities (EGF) group, a European company leader in waste treatment and recovery services in Portugal. EGF treats around 3.3 million tonnes per year of municipal waste through its 174 municipalities of operating area and is considered to be a reference company for the environmental sector, ensuring the performance of sustainable operations and following the environmental standards (Environment Global Facilities, 2019). Figure 6 shows all SRGUs belonging to the EGF group in Portugal, based on their operating area.

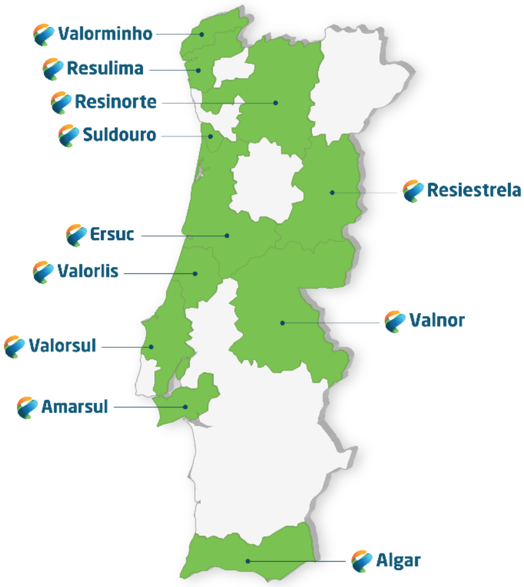

Figure 6 - SGRUs members of the EGF group in Portugal (Source: EGF, 2020)

ERSUC's activity is located in the Central Coast of Continental Portugal and covers an area of 7000 km^2, equivalent to 7.9% of the national territory. Serving around one million inhabitants, the company treats more than 300,000 tons of waste per year through its facilities, which includes Transfer Stations, Eco-centres, Mechanical and Biological Treatment Plants, Biogas Energy Recovery Plants, Sorting Stations, Support Sanitary Landfills and CDR Production Plants. In Figure 7, such facilities are presented according to their respective locations (ERSUC, 2020).

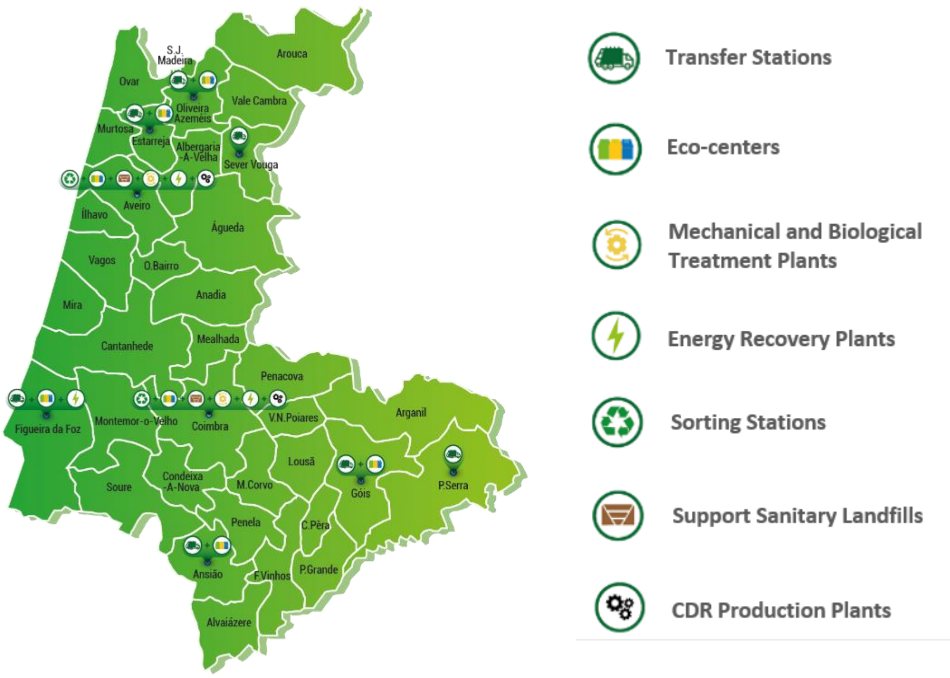

Figure 7 - ERSUC's facilities (Adapted from ERSUC's official website)

Responsible for the selective collection of packaging waste in 36 Municipalities, ERSUC assumes the following collection methods adapted to the needs of each geographical area and target group: eco-points, door-to-door, or voluntary deliveries. The selective collection of disposed waste at the eco-points is organised by static circuits that are performed according to a pre-established frequency, considering the number of bins in each circuit and their waste production. Additionally, in order to promote an increase in the selective collection, ERSUC provides for free the door-to-door service dedicated to the collection of recyclable materials produced by small businesses. This because in most cases such waste is not properly disposed, following the practice of disposal in the undifferentiated waste bins or outside the eco-points (ERSUC, 2020). According to the data provided by ERSUC, their operations for the selective collection of packaging waste performed in 2019 a total of 15 207 circuits through 44 vehicles that travelled around 1.8 million kilometres and attended the collection of more than 5 600 eco-points. As a result, approximately 21 500 tons of packaging waste were collected in this year, which represents an 11% increase when comparing with the amount collected by the company in 2018. Table 3 shows the numbers of elements used by ERSUC's selective collection to accomplish such results, divided by the two major action areas that the company performs its operation, Aveiro and Coimbra.

Table 3 - ERSUC’s selective collection elements in 2019 (Source: Ramos, T. R. P., 2020)

ERSUC’S ELEMENTS	AVEIRO	COIMBRA	TOTAL
Municipalities	15	21	**36**
Vehicles	22	22	**44**
Drivers	34	33	**67**
Daily Circuits	36	30	**66**
Eco-points Visited	2 818	2 786	**5 604**

Since one of the purposes of this work is to analyse and improve ERSUC’s performance operations, it is essential to understand the challenges and issues that the company is currently dealing in its operations. Through the direct contact with ERSUC, the following issues have been identified:

- Uncertainty regarding the eco-points filling levels.
- Eco-points filling behaviour affected by seasonality.
- Very extensive collection area.
- Existence of collection zones at long distances from the Aveiro and Coimbra plants.
- Difficulty in creating new circuits.
- Variability in the duration of the routes.
- Work schedules conjugation.

As mentioned above, although ERSUC has achieved an 11% increase in the weight collected from 2018 to 2019, there is a large margin of improvement for the company's collection operations. Analysing the issues identified by ERSUC, we can see that most of them are related to the uncertainty regarding the bins fill-levels status and to the fact that the operations are carried out statically, through predefined routes. Without access to additional information into the system, the company is unable to optimize its routes as a function of the bins fill-level variation, which represents an extreme challenge to simply base its operations on prediction (since it is subject to many variables including dealing with seasonality and the waste producers' unpredictable behaviour). Moreover, regardless of any occurrence, its large action area needs to be covered, implying an inefficient usage of the company's resources as well as the influence on factors related to the creation of new and improved routes, considered by ERSUC as a complex and slow process. In addition, the company highlights the fact that there is variability in terms of the routes' duration, which affects the fulfilment of the daily workload per employee (7 hours/day) and consequently hampers the work scheduling process.

For the development of this work, ERSUC provided several data regarding its collection operations in the three municipalities mentioned above. Table 4 presents some statistics collected by the company in 2017.

Table 4 - ERSUC's paper/cardboard collection in 2017

DESCRIPTION	SOURE	CONDEIXA	COIMBRA
Number of routes performed	105	66	993
Weight collected (kg)	104 080	122 120	1 612 360
Distance travelled (km)	16 457	8 066	82 007
Ratio (kg/km)	6.3	15.1	19.7
Average collection time	6h20m	6h17m	6h07m
Minimum collection time	5h06m	4h57m	4h08m
Maximum collection time	7h34m	7h19m	8h27m
Average vehicles usage rate (%)	45%	84%	74%

For the three municipalities shown in Table 4, it is reasonable to say that the company's operation at that time is characterized by a variation in the performance efficiency. Both for the kg per km ratio and average vehicles usage rate, it is possible to observe a fluctuation behavior of the values per area. Moreover, ERSUC' s routes were built so as not to exceed the collection team's workload (7 hours/day) and such constraint is observed to be usually respected since, on average, the collection time does not exceed the 7 hours per day. However, when analyzing the minimum and maximum collection times, some values are quite far from the average collection time presented, perhaps influenced by non-controllable factors such as traffic (in the case of a time above average) or visiting empty bins (in the case of a time below average).

To enable the analysis of ERSUC's operations efficiency, a data collection process was performed in order to monitor the bins waste accumulation. The process consisted in a manual recording conducted by ERSUC's collection team upon arrival to the bin, classifying the bins fill-level through visual inspection. Six classes were defined to describe the bins possible status based on their percentage of filling, whereby it could be considered as EMPTY (0%), LOW FILLING (0% - 25%), MEDIUM LOW FILLING (25% - 50%), MEDIUM HIGH FILLING (50% - 75%), HIGH FILLING (75% - 100%) or FULL/OVERFLOW (<100%). Since ERSUC's operating area is deemed extensive, the data collection process was applied only to part of the company's operation, as it is considered to be a representative area. Thus, ERSUC decided to analyze the following municipalities: Soure, Condeixa and Coimbra. Furthermore, one type of recyclable material was selected for study, the paper/cardboard. Such a decision lies in the fact that the collection of glass has been discarded for being characterized as an operation with low filling rates. Regarding the remaining recyclable materials (paper/cardboard and plastic/metal), it would not matter to choose either one of them considering that both share the same filling rates characteristics. Table 5 displays the bins fill-levels recorded for paper/cardboard material in Soure, Condeixa and Coimbra municipalities, encompassing an analysis period between April 2 and April 29 of 2019. It is possible to verify that 48% of the visited/collected bins showed an empty or considerably low fill-level, being represented respectively by the classes 0% and between 0% and 25%. In addition, only 12% of the bins were collected with a fill-level higher or equal to 75%. These are conclusive to state that ERSUC faces a particular problem regarding its operations' performance whereby almost the majority of the bins collected by them are basically empty.

Table 5 - Number of bins fill-levels recorded per class and municipality

CLASS	SOURE	CONDEIXA	COIMBRA	TOTAL	(%)
0%	0	55	529	584	**10%**
0% - 25%	203	286	1 681	2 170	**38%**
25% - 50%	138	129	898	1 165	**20%**
50% - 75%	65	145	936	1 146	**20%**
75% - 100%	36	53	595	684	**12%**
> 100%	0	0	0	0	**0%**

As a possible solution and representing one of the purposes of this work, ERSUC is willing to proceed with the implementation of volumetric sensors in the bins to, thereby, allow the company to gain data access about the bins fill status on a real-time basis. It is expected that the introduction of the device in the system will reduce the operation uncertainty since it intends to eliminate the doubt related with the bins waste accumulation and, therefore, improve the collection operation by using resources more efficiently. ERSUC intends to know the impact of implementing the volumetric sensors in its bins which is defined by the access evaluation to potential benefits that would justify their installation, namely in terms of minimizing the distance travelled and maximizing the weight collected, so that its service level is improved or maintained. For that purpose, ERSUC established that the most important key performance indicators (KPIs) for assessment are related to the efficiency, productivity and profitability of the operation, namely the vehicles usage rate, the kg per km ratio and the total profit, respectively. Since the company does not operate directly with its customers, the service level mentioned here refers to the prevention of the bins overflow which, if unsuccessful, can be considered as disturbing or in some cases even dangerous for the population. Furthermore, ERSUC is interested in exploring the possibility of merging two municipalities in order to assess the benefits of considering them simultaneously instead of operating separately. Lastly, the company also seeks to know how to define the collection routes considering the additional information provided by the sensors.

2.4 Problem Description's Conclusions

As the population increases over the years, it is inevitable that the waste generated by people will not follow the same behavior. It becomes essential to ensure that the waste treatment practices are performed in an efficient way, considering the principles of good management and environmental sustainability. However, although we live in a time of rising environmental awareness, it is still predominant an inadequate behavior of using, exploring and consuming goods without any concern about the final destination of our waste or the consequences that a large-scale waste production can cause. In addition to the continuing responsibility of raising citizens/consumers awareness for the adoption of sustainable practices, it is important that the companies active in the market aim to implement policies and procedures that provide a more efficient and sustainable activity. The waste collection management is an area of great potential for research and development of new operational methods. A dynamic and more precise collection provides benefits at both environmental and economic levels, having as main purpose to provide a service that allows a higher amount of collected waste (or even the same) within a shorter distance travelled. Therefore, a more efficient collection can result in a better resources allocation and lower CO_2 emissions derived from the collection vehicles. There is, however, a great degree of uncertainty associated when dealing with people, i.e., the waste producers. To design an almost 'always' functional operation, waste companies face the challenge of predicting waste accumulation that in turn depends on people's behaviors.

As such, it is concluded in this chapter that ERSUC performs an inefficient operation caused by the travelling of many kilometers for the collection of bins usually empty or presenting a low waste fill. Also, part of the company's operation was characterized as a variable behavior in route lengths, kg per km ratios and in the efficient use of the collection vehicles capacity. To overcome these situations, the present work aims to analyze the adoption of a new procedure to reduce the uncertainty inherent to the waste accumulation and measure the impact of implementing volumetric sensors on ERSUC's bins. Simulating a hypothetical situation that translates the information transmitted by the sensors, it would be possible to estimate the potential benefits and support the decision to invest in such a solution. Additionally, the simulation where the company has access to real-time information regarding the bins filling status can also support the exploration of a route planning procedure operating in a dynamic way. To conclude, as the company faces a situation where it is wasting valuable time and resources, this work intends to explore a solution that allows ERSUC to take advantage of new benefits, mitigate most of the issues identified and, therefore, exploit the opportunity to operate a more profitable performance.

3. LITERATURE REVIEW

Chapter 3 is intended to present the research process carried out through the scientific-technical bibliographic databases Web of Science and Science Direct. A literature review was elaborated for the concepts considered relevant for the dissertation development. As such, the chapter begins by exploring the developments for modelling the urban solid waste collection in section 3.1. Next, section 3.2 provides a comparison between methodologies for static and dynamic waste collection planning. Section 3.3 addresses the investigations on the concept of a waste collection performed with the presence of components in the system, identified as "smart". Also, the section addresses the practices of route balance formulation previously done on the waste collection context. For closing, section 3.4 describes the conclusions achieved with this chapter development.

3.1 Modelling the Municipal Solid Waste Collection

Waste management practices range from separation and collection operations to recovery and recycling operations (Jatinkumar et al., 2018). However, lately an increasing number of studies have focused on waste collection as this operation is characterized by high transportation costs and inefficient usage of resources since vehicles often visit empty bins that are only partially full. If waste collection efficiency increases, gains in both economic and environmental perspectives can be achieved (McLeod & Cherrett, 2008; Ramos et al., 2018). Operational research techniques can serve as support tool to evaluate complex tasks and systems that cannot be analytically performed or experimented in the real-world, thus, using these techniques to improve the efficiency of waste collection (Bing et al., 2016; Law, 2007).

A literature research on modelling of municipal solid waste logistics is developed by (Bing et al., 2016), based on three elements: Network Design, Collection and Routing, and Sustainability. Here, only the review of Collection and Routing will be highlighted and discussed. According to the authors, the different modeling practices of the municipal waste collection and routing problem are addressed under the following aspects:

- COLLECTION TYPE: The MSW collection usually derives from two main approaches for routing modeling: arc-routing and node-routing. These approaches are associated with the type of collection performed which, in terms of execution, can differ as curbside collection (considers the mandatory visit in all arcs) or drop off collection (considers the mandatory visit in all central spots). In this work the curbside collection type is investigated, which is often modeled as arc-routing. The works of Amponsah & Salhi, 2004; Bautista et al., 2008; and Mora et al., 2013; are examples of the waste collection problem formulated as a capacitated arc routing problem (CARP). Although very similar, the mathematical models proposed by the authors have different factors under consideration, such as the minimization of environmental impact (Amponsah & Salhi, 2004; Mora et al., 2013) and the addition of turn constraints related to street junctions and traffic signals (Bautista et al., 2008). For other types of modeling methods, the works of Baptista et al., 2002; Karadimas & Loumos, 2007; Nuortio et al., 2006; are highlighted, exploring the waste collection problem through the node-routing approach, guided variable neighborhood thresholding metaheuristic, and the ant colony algorithm, respectively.

- WASTE STREAMS COLLECTED: Considering the number of waste streams collected in a route, the problem can be modeled through the capacitated vehicle routing problem (CVRP) - collection performed by type in separate routes, i.e., separate collection; or through the Multi-Compartment Vehicle Routing Problem (MCVRP) - two or more types can be collected simultaneously, i.e., co-collection. According to Bing et al., 2016, the CVRP is a widely studied problem and, for recent surveys, the work of Golden, 2008 and Laporte, 2009 is suggested. For the MCVRP, Muyldermans & Pang, 2010 is referred where the benefits of co-collection are investigated over separate collection on the basis of literature instances. Through a local research procedure, it is concluded that the improvement over separate collection increases due to different factors and, according to the commodities demand, their imbalances reduce the benefits of the co-collection.

- COLLECTION FREQUENCIES: In waste collection networks, some sites may be visited every day while others may be visited only on specific days, for instance. The problem associated with the variation of collection frequencies can be modeled as a periodic vehicle routing problem (PVRP) and, for example, the works of Angelelli, 2002; Tung & Pinnoi, 2000; and Teixeira et al., 2004 are referred by the author. The works here mentioned address the development of a PVRP heuristic algorithms applied in waste collection systems to minimize the vehicles distance traveled and, therefore, access the benefits on an economic level.

- DYNAMIC CHARACTERISTICS: Regarding the design of models for dynamic route planning, Johansson, 2006 is highlighted for concluding that operating dynamic (instead of static and pre-defined) routes can benefit the waste collection system, both in terms of distance and hauling reductions, as well as the associated operational costs. Faccio et al., 2011 and Anghinolfi et al., 2013 were also mentioned for exploring the dynamic optimization of waste collection but including additional data input to describe the amount of waste generated. Such a feature can be exploited by the authors through the application of Information and Communication Technologies (ICT) in the system where, particularly, Faccio et al., 2011 uses sensor devices and Anghinolfi et al., 2013 uses a simulation model based on Geographic Information System (GIS).

Lastly, Bing et al., 2016 refers to some variants that were also studied for the waste collection problem, citing the works of Bektas & Laporte, 2011; Benjamin & Beasley, 2010; Groot et al., 2014; Ramos et al., 2014a; Ramos & Oliveira, 2010; that, respectively, explore the following types of cases: Reduction of travel distance along with different aspects such as operations pollution, fuel, amount of journeys and associated costs; Existence of multiple disposal facilities and one depot for vehicle station only; Inclusion of an emission cost for the economic and environmental impact estimation; The planning of recycling waste collection systems according to economic and environmental concerns; and Multiple depots with dynamic service areas to be defined during collection routes.

Since 2016, many other authors have proposed ways of dealing with waste collection and routing through mathematical models. Among them, the following works are highlighted:

Santibañez-Aguilar et al., 2017 proposes a mathematical model to designing a waste management system for optimal planning. The model selects the number and location of system entities together with the definition of their capacities and material flows, encompassing collection and transport, handling, storage, and sales operations, and taking into account the dynamic behavior associated to variables and parameters. Saeidi-Mobarakeh et al., 2019 addresses the hazardous waste management which, through a reformulation of the developed bi-level model in a Mixed Integer Linear Programming (MILP) formulation, considers the following hierarchy: (1) Government policies for planning and controlling waste management infrastructure; and (2) The decision on waste collection plans for minimizing total operational cost. The goal lies in achieving the optimal practices regarding collection, treatment, and disposal operations. It is important to mention the additional development of a mechanism to repair the viability of routes and, as a suggestion for future research, the author recommends the focus on solution methods that offer higher computational efficiency. Considering the aim to improve sustainability in the waste management systems operations, Asefi et al., 2019; Gilardino et al., 2017; and Harijani et al., 2017 are highlighted. Gilardino et al., 2017 introduces the life cycle concept into the model to identify collection sites and create an effective route system. The vehicles' temporal availability, its minimization and the total distance travelled are considered factors which, according to the results achieved, allowed the author to conclude that the optimization of waste collection can offer significant reductions in the environmental impact. Asefi et al., 2019 establishes the integrated solid waste management (integration of all components associated with the system) and introduces an optimization model with heterogenous fleet and multiple depots. The vehicles, besides being associated to a particular depot, are classified into types according to their capacities and compatibility with the waste being collected. Harijani et al., 2017 proposes a system approach to build an integrated network for recycling and disposal (involving decisions related to the facilities selection, location and capacity, waste allocation, transportation between facilities and recycled materials distribution). On the other hand, modelling approaches may have other types of branches combined with cost reduction (associated with the operations of municipal waste management systems). Bruecker et al., 2018 presents the introduction of a service level restriction for developing shift schedules and collection routes. Lastly, Yousefloo & Babazadeh, 2019 is highlighted for performing an investigation targeting the risks related to the system so as to design an MSW management network. The author characterizes the main works developed in MSW management modeling field classifying in two types of problems, network design and collection operations. To perform a more in-depth literature review, focused on waste collection modeling, it will first be reviewed the work of Johansson, 2006, previously mentioned by Bing et al., 2016 for addressing the benefits of practicing a traditional collection, i.e. static, versus the concept application of dynamism.

3.2 Static vs Dynamic Waste Collection Planning

The planning approach considered traditionally refers to the design of a static operation, where fixed routes are performed according to a predetermined collection frequency (Johansson, 2006). However, it is possible to observe a significant interest for dynamic planning approaches since transportation and logistics environment are associated with uncertainty and dynamic characteristics. Also, static approaches cannot deal with such characteristics, especially due to the dynamic nature of Internet of Things (IoT) potentiality (Anagnostopoulos et al., 2015; Powell & Jaillet, 1995). In order to evaluate the different policies regarding the effects of static versus dynamic scheduling and routing performance, Johansson, 2006 studied the waste management system through analytical modelling and discrete-event simulation. The author concluded that the association of collection operations with dynamism enables the achievement of economic benefits and the operation's improvement; this because the uncertainty associated to demand is reduced. Such a conclusion is shown in Figure 8, where the percentages of potential savings according to two planning policies, the static system versus the dynamic system, is demonstrated. Potential savings are calculated using bins filling rates as a function of their average and standard deviations for a system that includes 10 bins and operates 24 hours a day, 7 days a week (Johansson, 2006).

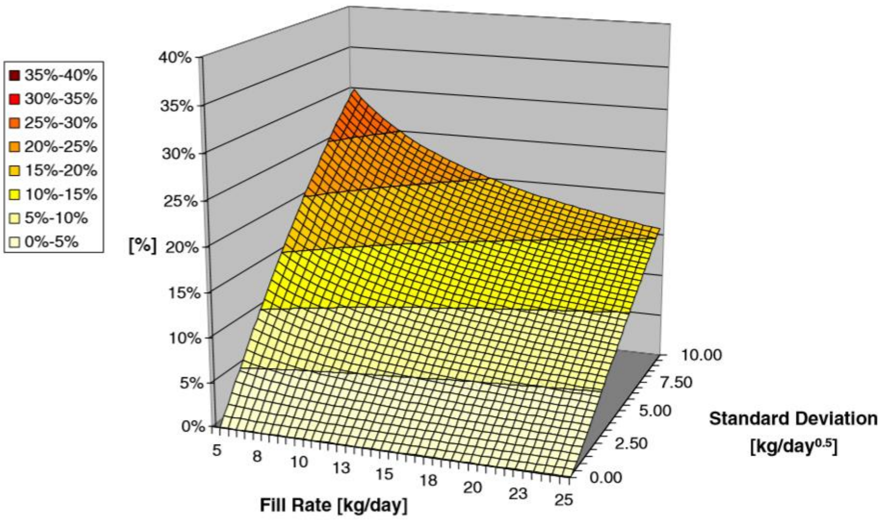

Figure 8 - Savings potential for dynamic scheduling and routing versus static scheduling and routing (Source: Johansson 2006)

As we can see, Figure 8 supports the conclusion made by Johansson that dynamic planning offers the best savings potential compared to static planning, in particular for systems with high variation and low mean filling rates (while the potential of systems with low variation is clearly neglected). Thus, the literature on traditional waste collection, i.e., considering a static routing planning, is not an object of study for this dissertation. For the investigation of static route planning, the works of Angelelli, 2002; Baptista et al., 2002; Shih & Chang, 2001; Tung & Pinnoi, 2000; Zografos & Androutsopoulos, 2004; are pointed out as examples.

The dynamic collection planning is usually associated with data acquisition technologies, which makes it possible to assess real-time information about waste bins fill-levels, enabling the reduction of the uncertainty associated to waste accumulation (Anagnostopoulos et al., 2015; Ramos et al., 2018). As Powell & Jaillet, 1995 stated, dynamic modeling practices place tremendous demands on access to real-time data. The provision of such information is only allowed by the exploitation of devices called “smart” that, when used in waste collection systems, enable tracking procedures, route optimization and, in some cases, even for service provisioning (Hong et al., 2014).

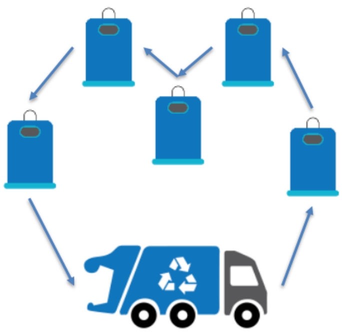

Figure 9 - Static route performance

(Adapted from Ramos, T. R. P., 2020)

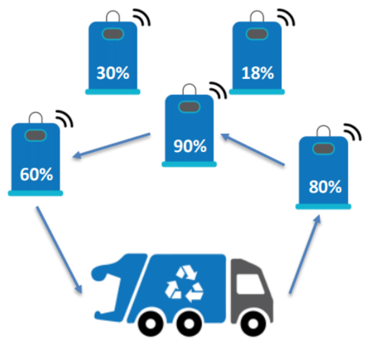

Figure 10 - Dynamic route performance

(Adapted from Ramos, T. R. P., 2020)

Figure 9 and Figure 10 displays the representation of a static collection versus a dynamic collection, respectively. In the static collection we can observe that there is no information about the bins waste accumulation, requiring the vehicles to perform a route where all associated bins are visited and collected. Normally, each route has a number of assigned bins and thus the route will always be performed in exactly the same way. For dynamic collection, in this case it is possible to observe the availability of additional information to the system, where the bins levels are known in advance. This allows a more efficient route performance, by collecting only those bins considered as "important " (i.e., bins with a higher filling rate).

In conclusion, a more efficient system can be achieved with the replacement of the static collection paradigm for a dynamically one, allowing access to economics and environmental benefits such as reduction in the distance traveled and carbon emissions, fewer numbers of bins collected and, consequently, reduction in operating costs. This conclusion is mainly supported due the fact that the old methodology does not consider the bins' actual filling level to perform the collection. However, in the new methodology, the availability of information in a real-time basis allows the filling level to be defined using smart components, thus making it possible to design routes that visit only the necessary waste bins and that do not visit empty waste bins (Johansson, 2006; Ramos et al., 2018)

The literature review on these smart components, i.e., the smart enabling technologies, is presented in the next section that focuses on investigations about dynamic waste collection coupled with technologies, here called as the Smart Waste Collection.

3.3 Smart Waste Collection

The addition of a smart concept applied in waste management is defined by the use of smart enabling technologies to improve monitoring, collection, separation and transport operations in order to perform more efficiently, effectively and sustainably (Zhang et al., 2019). This kind of additional capability is offered by the exploitation of ICT that allow the development of dynamic solutions through the production of sensors, actuators and IoT technologies, which can be installed in bins in order to reduce the associated uncertainty (Jatinkumar et al., 2018). Therefore, a literature review on these components is presented, particularly focusing data acquisition technologies and their applications in collection/routing optimization.

3.3.1 Smart Enabling Technologies

The use of smart devices as a key enabling technology is addressed by Anagnostopoulos et al., 2017 through the development of a comprehensive survey on the utilization of ICT generally applied in waste management models. Hannan et al., 2015 developed a review within the smart waste management context in which the available ICTs and their use is explored for problem solving. Through the respective categorization of planning, monitoring, collection and management operations for solid waste, the author divides the ICTs into four classes: (1) Spatial technologies, (2) Identification technologies, (3) Data Acquisition technologies, and (4) Data Communication technologies. Esmaeilian et al., 2018 addresses the future of waste management in smart and sustainable cities and conducts a literature review focused on the last three classes recognized by Hannan et al., 2015. According to the author, these classes has received more attention in waste management literature. In addition, four categories are recognized for technologies applied in smart waste management systems: the development of data acquisition and sensor-based technologies; communication and data transmission technologies, field experiment technology and technologies for setting and scheduling truck routes. It is concluded that the studies reviewed by the author have focused primarily on making monitoring, separation, and collection more efficient with the help of sensor-enabled solutions. Finally, the work of Zhang et al., 2019 is pointed out where the barriers of smart waste management to the circular economy in China are identified and, according to the work of Esmaeilian et al., 2018, the author provides an overview of the principles and strategies in waste management based on the main smart enabling technologies used. Focusing on detailing data acquisition technologies, Zhang et al., 2019 states that there has been an increased interest in supporting the waste management system through dynamic planning models, and the development of data acquisition and sensor-based technologies is eventually used to guarantee access to bin fill levels. Rovetta et al., 2009 presents the combination of distributed sensor technology with a GIS as the basis for application of the municipal solid waste monitoring. A set of sensors were installed in a sample containing 15 bins to test and evaluate the application. As a result, the authors conclude that such implementation provides quantitative data regarding the waste inside each bin, allowing the future establishment of appropriate waste management's policies. Faccio et al., 2011 proposes a real-time traceability data routing model where a minimum level of replenishment is pre-established in order to first define which bins are going to be collected, i.e., that have reached the imposed level, and then optimize the route performed according to the set of bins to be visited. To contribute toward the optimization of waste collection coupled with smart components, Mamun et al., 2015 provides an investigation on the concept of real time intelligent bin status monitoring system through the proposal and implementation of a theoretical model using Rule Based Decision Algorithms. The work of Mamun et al., 2015 relies on the so-called smart bins, which update their status in relation to the filling level and transmit the information to a server when any change in volume is verified. In conclusion, the author states that such system is efficient and allows the decision of which bins should be collected and which should not, enabling later the use of this information to optimize collection routes reducing costs and carbon emissions. Recently, Liu et al., 2019 proposes a dynamic optimization method that uses real-time information for smart vehicles and logistics tasks. The authors demonstrated the effectiveness of the method developed for cost reduction, improvement of vehicle utilization rate and fuel consumption, and the high efficiency of logistics services when faced with the real-time concept.

It is possible to conclude that modelling dynamic collection operations is explored in conjunction with smart enabling technologies, especially to gain access to real-time information. As already mentioned, this is justified due to the high uncertainty associated with bins filling levels (Ramos et al., 2018). Thus, the next section will address the concept of smart waste routing problem, aimed at modelling routing problems when real-time data is accessible.

3.3.2 Smart Waste Routing Problem

When considering the dynamic collection coupled with real-time information the following studies are highlighted: Mes, 2012 uses the discrete event simulation to evaluate the opportunities of dynamic waste collection with sensors that describe the level of bin filling. Applying a real case study, options of dynamic planning methodologies are compared with the static planning, in order to quantify the benefits of implementing the new methodology as well as those of investing in sensors. In the analyzed case, the company owns most of the bins equipped with motion sensors, technology that allows the counting of lid openings and, consequently, allows the deposit estimation in each bin. The problem lies in the fact that the deposition volumes fluctuate strongly which, by associating uncertainty in the operations, leads to a collection of bins with relatively low filling average. It is concluded that major improvements can be achieved in terms of logistical cost efficiency and customer satisfaction. Anagnostopoulos et al., 2015 studies dynamic waste collection architecture based on data retrieved by sensors. The author considers the possibility of immediate collection in high priority areas, defined according to the focus on sensitive citizens groups where the presence of waste is considered dangerous or has negative effects on the quality of human life. Through the management of the trade-off between cost and performance of immediate collection, the author proposes a system that responds to the demand identified by sensor observations and alerts in high priority areas by forcing vehicles to deviate from the regular collection path and prioritize the bin collection alerted by the sensor. Thus, the author seeks to provide efficient solutions to the dynamic waste collection problem by responding in high priority areas with an optimum reaction, minimizing the time required while maintaining the expected average performance level. Gutierrez et al., 2015 addresses the benefits and drawbacks of providing intelligence to trashcans through sensors that enable the reading, collection, and transmission of waste volume for the waste collection strategies management in a dynamic and efficient way. The benefits of the dynamic system proposed by the author are investigated through simulation, optimizing the selection of which bins should be daily collected and comparing such system with approaches to waste collection by sectors considered traditional. In this way, route optimization algorithms allow the best route design considering the bins previously selected and the minimization of the distance traveled. However, Anagnostopoulos et al., 2015; Gutierrez et al., 2015; Mes, 2012; only explore a minimization of the distance travelled during collection, not considering the profit that may be attained. Recently, Ramos et al., 2018 explored the profit maximization (maximizing the amount of waste to be collected while minimizing the distance travelled). It is introduced the Smart Waste Collection Routing Problem (SWCRP) as a proposal for the optimization of recyclable waste collection operations. According to the authors, waste collection companies often deal with high transportation costs and inefficiency in the use of resources, since it is verified that the vehicles visit only partially full bins. To overcome such a situation, the hypothesis of coupling volumetric sensors to the system is investigated in order to enable the transmission of real-time information regarding the bins' filling level and to introduce the attractiveness concept for choosing which bins are worth to collect it. Based on the information available, different approaches are proposed to define dynamic routes through a Vehicle Routing Problem with Profits (VRPP) mathematical model that, as mentioned above, maximizes the profit associated with the collection of recyclable waste. Therefore, in order to define dynamics routes considering the additional information from the sensors, Ramos et al., 2018 proposed three different operational management approaches:

1) LIMITED APPROACH: The combination of a CVRP model with a Cluster First-Route Second heuristic method is proposed, where bins are selected through a rule that considers a minimum filling level. It is then imposed the collection of bins that comply with such a rule, i.e., that present a value above the pre-established filling level threshold. Thus, the model defines the best collection sequence for each day, optimizing the routes to be defined.

2) Smart collection approach: The concept of attractiveness is introduce considering the bins that are worth to collect through their fill-levels. A VRPP mathematical model is then proposed to define the daily set of bins selected and compose the best sequence to collect it, maximizing the profit for each day.
3) Smarter collection approach: A heuristic method is proposed to decide the best days to operate a route according to the pre-established service level. For each day, is defined the dynamic set of bins with the same model and methodology applied in the second approach. The VRPP is then run for the selected days.

The three approaches are compared by evaluating the following KPIs: distance travelled; amount of waste collected; profit; kg per km ratio; and vehicle usage rate. Since the work of Ramos et al., 2018 is based on real information from a waste management company, the approaches are compared with the current situation performed through the KPIs values. As a result, the third operational management approach proves to be the most efficient, achieving an improvement of operations and reducing uncertainty in the system. However, the authors dealt with high computational time and the presence of gaps between the integer solution and the lower bound found by CPLEX after the total computational time, providing opportunities for future work developments. Aguiar et al., in press addressed the limitations of SWCRP and proposed the decomposition of the problem through an optimization-based heuristic. The purpose was to reduce computational time and improve the quality of solutions through the Cluster First-Route Second methodology. Two phases were defined: (1) a heuristic is applied in order to dynamically reduce the numbers of bins; That is, a construction set is formed considering only bins with fill-levels above a predetermined threshold (M) as input for the second phase. (2) The subproblem previously defined is modeled as a VRPP and then solved; The results were compared with real data from a case study and demonstrated the achievement of optimal solutions in a reasonable time, enhancing the proposed method in economic and environmental terms. As future work, the author proposes to study the value of M considering the number of vehicles as a variable (Ramos et al., 2018). However, a gap in the literature has been identified to which no workload is considered. For instance, the approach found to be the most efficient provides two routes with widely differing lengths in a given day. Figure 11 shows the two routes simulated on the same day for one of the bests scenarios analyzed (scenario 3.B). As we can see, the first route travels across the sample space, visiting several bins geographically spread, while the second route visits only a “niche” of bins close to the depot. When researching works that include workload constraints in the SWCRP context, no such consideration was identified. However, some work has been done on the waste collection management context. Ramos & Oliveira, 2011, introduces a heuristic approach to design routes considering two objectives: (1) minimizing variable costs and (2) balancing the workload on depots in an equitable manner. Kim et al., 2006 applies a pre-routing phase through a clustering-based procedure to improve the route compactness and workload balancing. Ramos et al., 2014b presents a multi-objective procedure to obtain a set of

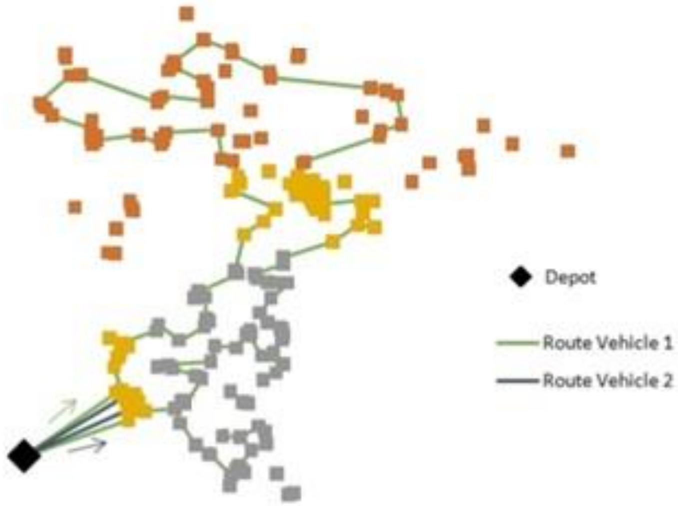

Figure 11 - Collection routes of scenario 3.B for day 8 (Adapted from Ramos et al., 2018)

solutions considering economic, environmental, and social objectives. One objective is to balance the workload by minimizing the maximum duration of the routes. Matl et al., 2019 investigates the workload equity in vehicle routing and states that minimizing the maximum route duration, or the route length are the two most commonly used measures of equity. When considering the route duration length, the minimization of the difference between the minimum and maximum route duration is taken into account, thus reflecting a more comprehensive view of equity. Therefore, this is the most appropriate measure for this work.

3.4 Chapter Conclusions

The present chapter has characterized the scope and evolution of several investigations based on the existing literature, with the purpose of defining an effective methodology to apply in the future case study. Initially, waste management modeling was explored, focusing on applications related to collection operations. In addition, the existing methodologies for planning and optimization of dynamic routes were investigated. Due to the increasing search for optimization of processes and procedures, it is possible to verify that the dynamism concept associated to collection routes can provide numerous benefits at the economic and environmental levels. Therefore, it arises the need to explore the additional components that allow the design of dynamic routes in the waste management systems, the ones considered here as smart enabling technologies. According to the revised literature, there are many types of available technologies. In particular, sensory components are often applied to transmit the bins fill-level, enabling a reduction of the high uncertainty inherent to such information.

Based on the works above described, it can be concluded that the dynamism applied in waste collection planning presents great potential for development. It is observed that usually the procedure to select the bins to be collected are based only on the weight, and not on the operation's economic terms. Moreover, the investigation of models that uses real-time information to optimize collection routes is an area of significant importance for further exploration. Therefore, Ramos et al., 2018 work is the most appropriate methodology to approach the problem future analyze, considering its introduction to the selection of bins by the profit aspect and their use of a sensor device to transmit the bins fill-level. Additionally, the fact that some of its limitations have already been improved by Aguiar et al., in press and the potentiality of the proposed method was proven, helps the decision to apply the development of both works as bases to the dissertation's methodology, thus, extending the SWCRP. However, it was observed that no workload restrictions are considered in both works. To explore the identified gap and, representing one of the purposes of this work, it was concluded that the most appropriate route balance measure would be considering the routes' duration length.

4. METHODOLOGY

The current chapter describes the methodology proposed to solve the problem in hand. The chapter is divided into five sections: First, in section 4.1, a framework is summarized in order to clarify the differences between the methodology adopted in the previous work developed by Ramos et al., 2018 and Aguiar et al., in press with the one that will be performed in this dissertation. Section 4.2 explains in detail the approaches explored herein as a method of solving the problem previously addressed. Also, in this same section, it is presented the VRPP mathematical formulation used to construct the route definition algorithm. Sections 4.3 and 4.4 then describe the different branches established to combine with the VRPP model that were explored, namely the route balance and the bins selection rules. Lastly, section 4.5 presents a scenario tree in order to summarize the possible scenarios, resulting from the methodology used, that will be explored in Chapter 5.

4.1 Framework Overview

As defined in the literature review section, the most appropriate methodology to apply is based on the work of Ramos et al., 2018, which introduces the smart waste collection routing problem. According to the authors' conclusions and the further work presented by Aguiar et al., in press, the following aspects are described to clarify the differences and additions raised in the current study:

1) Operational management approaches: The work of Ramos et al., 2018 proposed three different operational management approaches as a solution to the Smart Waste Collection Routing Problem. However, only two of them are considered as relevant for us to address it, which are: the smart collection (in the present work named "Everyday" to emphasize the fact that the model is run everyday) and the smarter collection (in the present work named "Myopic") approaches. Such a decision is justified by the fact that Ramos et al., 2018 demonstrated that the so-called limited approach when tested on a real-world environment does not provide an efficient performance compared to the other approaches proposed, making the extension of the limited approach pointless for future development.

2) Input parameter: The second aspect was carried out by shaping the way the model considers and analyzes the input parameter that describes the bins fill level status at the beginning of the day. Figure 12 shows the difference between what the work of Ramos et al., 2018 considered to collect and what it will be now consider. As we can see, previously it was assumed that only the daily initial bins fill-level would be collected, i.e., the volumetric sensors information provided at the beginning of the day. Such assumption is, however, unreasonable to apply since the collection of all bins in the system is

established to occur at the end of the day. Therefore, the model must consider that it would collect the initial fill level plus an estimated daily filling value.

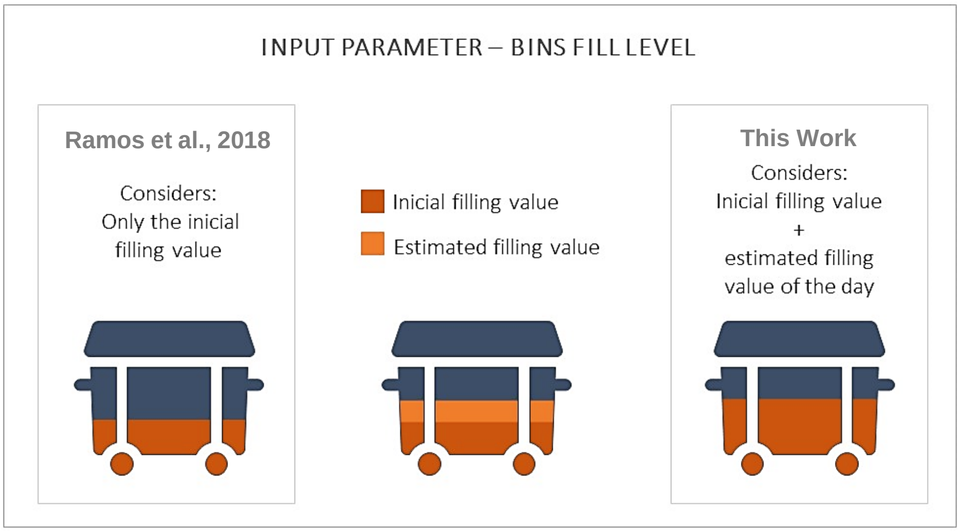

Figure 12 - Input parameter before versus now (Source: author)

3) CLUSTER FIRST - ROUTE SECOND: Since in Ramos et al., 2018 high computational time and gaps was observed, Aguiar et al., in press develops a further work exploring an optimization-based heuristic to reduce the number of bins being inputted in the model, the Cluster First-Route Second approach. In Aguiar et al., in press, a dynamic subset is designed only to restrict the number of bins inputted in the model, where the model decides which ones will be collected considering the condition of preventing overflow of any bin from the subset. The method applied in Aguiar et al., in press proved to be successful, delivering optimal solutions in a reasonable time and opening opportunities to further explorations. In this way, based on the methodology applied by Aguiar et al., in press, a new bins selection rule is here introduced in order to explore the dynamic ways of inputting bins into the model. Hopefully, it is expected that such an analysis will help to determine a better method to reduce the computational time while also improving the solution quality.

4) BINS SELECTION RULES: Under the methodology of Aguiar et al., in press, the construction of the dynamic subset is determined by the bins fill-level, selecting the bins according to a predetermined threshold. Considering this step as a type of selection rule, we will explore three types of bins selection rules: Inputting all the bins from the initial set; Inputting by fill-level (as in Aguiar et al., in press); And inputting through the relation between fill-level and distance, a new type of selection rule introduced here based on a two-step procedure that first creates a subset by the bins fill-level and then aggregates adjoining bins (by a predetermined distance limit) to the subset. Further in this chapter, the types of bins selection rules explored will be better described in section 4.3.

5) DURATION: In Ramos et al., 2018, no restrictions are applied to the route's duration, thus not considering the time element into the model.. Since this study deals with a real-world problem, some specifications must be considered as a way to be more realistic when simulating the problem. In this way, it is justifiable to add restrictions in terms of duration of the routes to achieve feasible solutions that, here, such a definition will be made considering the ERSUC collection team's workload.

6) ROUTE BALANCE: With the duration limit now being considered, the need for applying methods to constrain the solution routes arise and, therefore, the route balance concept will be introduced into the model. It is intended that such a concept will induce the model to perform routes in a balanced way, complying with the pre-established duration limits. Hence, discrepancies in the route lengths are eliminated and, therefore, the possible imbalance of the routes are minimized. The route balance concept will be further detailed below in section 4.4.

Considering the differences and additions previously mentioned, the present work proposes three new approaches for solving the problem here addressed, having as main goal to design a bin collecting sequence that considers real-time information obtained by the volumetric sensors, which describes the daily bins fill levels per bin. This information enables the dynamic design of daily routes in order to collect only certain bins from the initial set, relying heavily on preventing waste overflow in the operation. As in the work of Ramos et al., 2018, the base model is a VRPP where the objective function maximizes the profit from the collection operation by balancing the amount of waste collected with the total distance travelled for each route. However, this is only possible since the current work considers the simulation of waste collection applied to recyclable materials, thus allowing a monetary value to be associated with its collection (In the next chapter, the values assumed for each parameter it is presented as well as their sources). That way, a revenue value for the weight collected is considered and a transportation cost for the distance traveled is established, enabling the monetization of profit as their difference. Considering a predefined planning horizon of 28 days for the simulation, another aspect that influences the total profit obtained is the number of routes required to avoid overflows that, when efficiently minimized, it is expected to result in a better overall outcome.

Two important questions are explored in this work: "When" to run the VRPP model? And "What" should be the time horizon to consider in the VRPP model? To answer to those questions, three approaches were considered: The First Approach will run the VRPP model every day and just visualize only the current day, respecting the conditions to prevent any bin overflow and maximizing the profit for each day – this approach is called "EVERYDAY"; The Second Approach will run the model only for those days when there is risk of overflow by visualizing the current day plus the following day, respecting the same conditions mentioned above– this approach is called "MYOPIC". The last approach explored is the Third Approach that can visualize ahead within the planning horizon period. Just as the second approach, the model will be run only for those days when it is expected that some bin from the initial set shows a risk of overflowing and the same conditions previously mentioned are applied – this approach is called "LOOK AHEAD". It is noteworthy that all three base approaches consider estimated filling values when visualizing the future: For the first approach this is observed in the current day's filling considered; For the second approach, besides the current day's filling, it is also observed in the values considered for the following day. And for the third approach, it is all the values of the days ahead that the model will visualize, besides the current day's filling. The three approaches will be detailed at section 4.2.

In addition, two branches are going to be explored which will be combined with the base approaches, namely the **Route Balance** and the **Bins Selection Rules**. As mentioned above, the Route Balance concept is used to allow the VRPP model to be restricted in terms of duration of the routes, introducing the time element to be considered by the model. This is explained at section 4.4. Meanwhile, the Bins Selection Rules is explored to distinguish the input methods regarding the bins from the initial set. Besides the base option of inputting the model with all bins (which will provide the optimal solution but do not ensure efficient computational times), the Cluster First-Route Second is here applied based on the work of Aguiar et al., in press and a new type of rule is introduced. This is further explained at section 4.3.

4.2 Operational Management Approaches

4.2.1 First Approach: Everyday

The Everyday Approach works by receiving the real-time information from the sensors about the fill level of each bin i on the morning of each day t (S_i^t). In order to prepare the model for no overflow, a parameter $\hat{a}_i$ is initially estimated to describe the bins filling rate based on historical data. To calculate such parameter, an average daily filling rate (am_i) and a standard deviation (σ_i) for each bin is previously calculated also based on historical data which, together with a predefined safety factor value (Z), results in the definition of $\hat{a}_i$ by the following expression: $\hat{a}_i = am_i + Z\sigma_i$. The procedure to obtain the average filling rate and the standard deviation for each bin will be detailed in Chapter 5. Due to the fact that the sensors describe the bins status at the exact moment, it is initially established that the model will acquire this information in the morning in order to allow the VRPP model to run and present the routes for the day. This information is defined as the bins initial fill level (S_i^t). Next, it is necessary to estimate the bins final fill level for each day (F_i^t), since it is also established that all bins would be collected hypothetically at the end of day t. Therefore, to obtain F_i^t, the bins initial fill level S_i^t must be added to their estimated filling rate $\hat{a}_i$ ($F_i^t = S_i^t + \hat{a}_i$). Such information is used as an input for the VRPP model and will support the definition of a dynamic subset F of bins that satisfy the following capacity condition: $F_i^t \geq 100$. The value 100 represents the bin's maximum capacity, making the condition mentioned above a form of validation if any bin from the initial set present a risk of overflow. If verified, a route will be performed to collect all bins that comply with such condition, i.e., contained in subset F. However, the model does not consider collecting only those bins that are mandatory, but will additionally define which bins are profitable to visit according to the route that would be performed to collect the ones contained in subset F. In this approach, the VRPP model will be run every day, regardless of whether bin is expected to be overflowed or not.

Summarizing, the Everyday Approach primarily takes into account the prevention of overflows by considering the initial fill level and the estimated daily filling rate. Secondly, the model optimizes the bin's collection sequence maximizing the profit to perform the collection, given the transportation cost associated to picking up each bin and restricted to collect all the bins expected to overflow. Lastly, the model will be run every day performing a collection route on those days when it is verified that some bin is at risk of overflowing.

For a better overview, a flowchart has been constructed describing how the model operates under this approach (Figure 13).

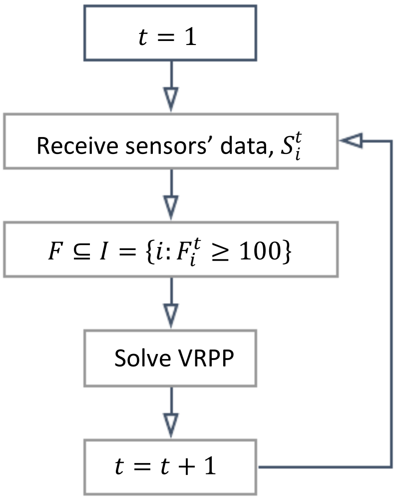

Figure 13 - Everyday Approach flowchart (Source: author)

4.2.2: Second Approach: Myopic

The Myopic Approach operates like the Everyday Approach except for two differences:

- Adopting a conservative stance, the model relies not only on the estimated filling rate of the day but also on an additional estimation for the following day. Thereby, it is verified if there is at least one bin expected to overflow either on day t and day $t + 1$;
- The other difference consists of the condition that the model does not run every day but only for those days on which it is estimated to occur an overflow considering the addition of the following day filling rate.

Initially, the VRPP model is inputted with the initial fill level provided by the sensors (S_i^t) and add an estimated filling rate ($\hat{a}_i$) for the current day t and the following day $t + 1$, which is calculated based on historical data. A parameter F_i^{t+1} is then estimated regarding the expected bins final fill level at the end of day $t+1$. With the addition of considering the following day filling values, it is possible to avoid in a consequent way the need to perform collections on consecutive days. Thus, the values for the bins final fill level are calculated by the sum of their initial level with the filling rates of the current and following day ($F_i^{t+1} = S_i^t + 2\hat{a}_i + Z\sqrt{2}\sigma_i$). Since the model will not run every day, such parameter is used to create a collection condition that will also works to define which days the model will run. The condition states that if at least one bin is expected to overflow – status in which the bin is considered to be at or above maximum capacity ($F_i^{t+1} \geq 100$), a collection route must be performed and thus, the model will be run. A Subset F is then formed with the bins that are mandatory to be collected and, as the Everyday Approach, the model will also consider visit bins from the initial set taking into account the profitability associated and the initially route that would be required to collect those ones contained in subset F. The methodology of the Myopic Approach is outlined in a flowchart represented in Figure 14.

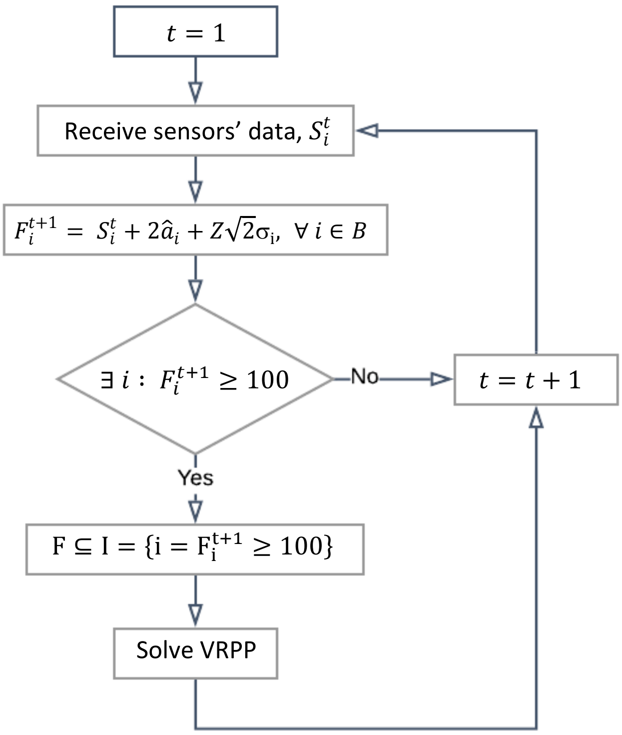

Figure 14 - Myopic Approach flowchart (Source: author)

4.2.3 Third Approach: Look Ahead

Considering the Myopic Approach that visualizes the expected filling rates for the following day $t+1$, an alternative approach was tested, predefining the next day of collection based on the bins that will be collected on the current day t.

Initially this alternative approach works exactly like the Myopic Approach, where is estimated the bins final fill level for the next day ($F_i^{t+1} = S_i^t + 2\hat{a}_i + Z\sqrt{2}\sigma_i$), i.e. taking into account the sensor data about the initial fill level per bin (S_i^t) plus their estimated filling values for both current and next day. If the capacity condition $F_i^{t+1} \geq 100$ is verified, i.e., some bin presents a risk of overflow by reaching or exceeding its maximum capacity, a collection route will be performed. If not verified, the VRPP model is not run, and the procedure is repeated for the following day. The approaches differ in the case of being verified there are bins required to be collected. Here, a filling value $SAux_i$ is simulated on the current day t to describe the bins expected fill level for the next days (t'). For the bins that are verified to violate the capacity condition on the current day t, the model will hypothetically collect and a value equal to zero is then considered as their new initial fill level, simulating that they have been collected on day t. For those that are not initially required to collect, their initial fill level S_i^t is kept for the future estimations. In both cases, the estimated filling rate ($\hat{a}_i$) is daily added to simulate the bins fill level at the end of each day ($F_i^{t'+1}$).

Thus, the model estimates what would be the next day which the bins that violates the capacity condition on day t will present a risk of overflow again, considering that they were hypothetically collected. From those bins, the one verified to overflow sooner defines the next day of collection (nc) and, therefore, a subset F is formed encompassing all the bins that are mandatory to be collected between the current day and the next predefined day of collection. Then, the model is forced to collect all bins contained on subset F so that, supposedly, no collections will be required in the estimated time between the two collections. As in the Everyday and Myopic Approaches, it is also possible for the model to consider visit bins that are not mandatory to be collected, taking into account, as mentioned before, the profitability and the route required to collect the ones contained in subset F.

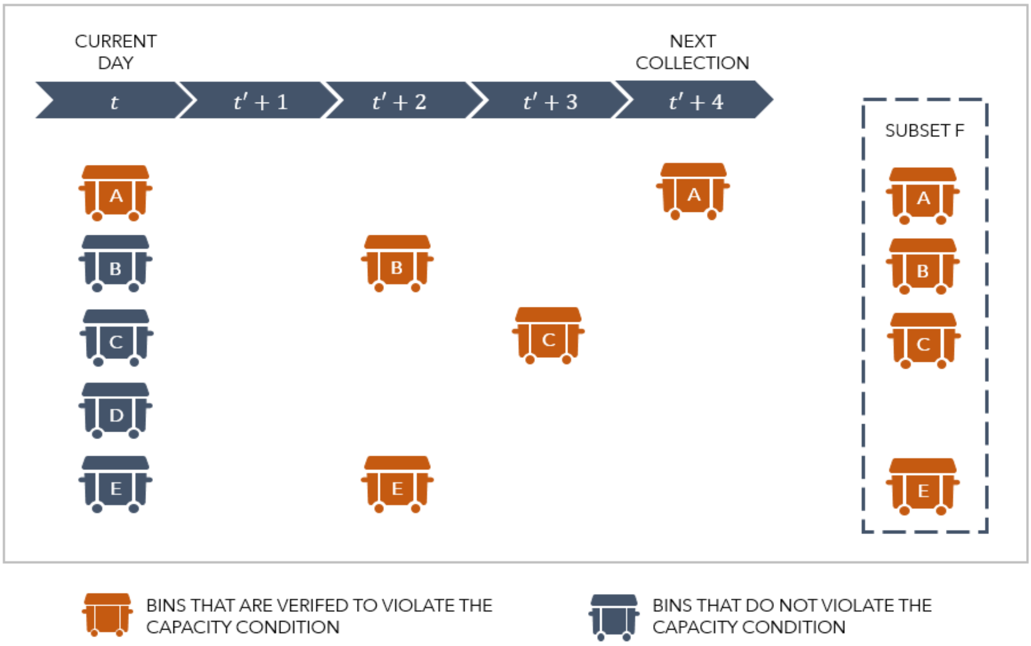

Figure 15 - Procedure illustration of the Look Ahead Approach (Source: author)

To better understand the complexity of this approach, Figure 15 represents an illustration of the procedure being applied. Suppose that the initial set of bins consists in five bins, from A to E. On the current day t, it was verified the violation of the capacity condition by bin A. Therefore, as in the previous approaches, it is mandatory the performance of a collection route where the content of bin A is hypothetically emptied, simulating its collection on that day. Moving on for the next day $t' + 1$, no risk of overflow is verified (considering the day before and the simulation of the bins fill-level), so no changes are made. For day $t' + 2$, two bins violate the capacity condition: B and E. Therefore, they are hypothetically collected, replacing their fill-levels by 0. The same happens on the next day $t' + 3$ with bin C. On day $t' + 4$ it can be verified that bin A presents a risk of overflow, violating the capacity condition again, after we have simulated its collection on day t. This situation represents a stopping point since it means that a route will have to be performed for its collection, thus pre-defining the next day of collection. In general, all bins that are expected to overflow between the current day and the next pre-defined collection day are required to be collected so that no collection is necessary to perform between the two days. These bins constitute the subset called F. However, it is important to highlight that in addition to them, the model can choose to collect other non-obligatory bins according to the profit associated.

The issue behind the Look Ahead Approach is not to ensure an effective level of service since its operation procedure is totally based on filling estimations. The longer the estimated period is, the greater the degree of uncertainty to be considered and, consequently, lesser is the reliability associated with the results, i.e., it is likely that, with the daily updating of the actual fill level, an additional collection will be necessary to collect some bins that were unexpectedly filled up. A flowchart showing how the Look Ahead Approach works is represented on Figure 16.

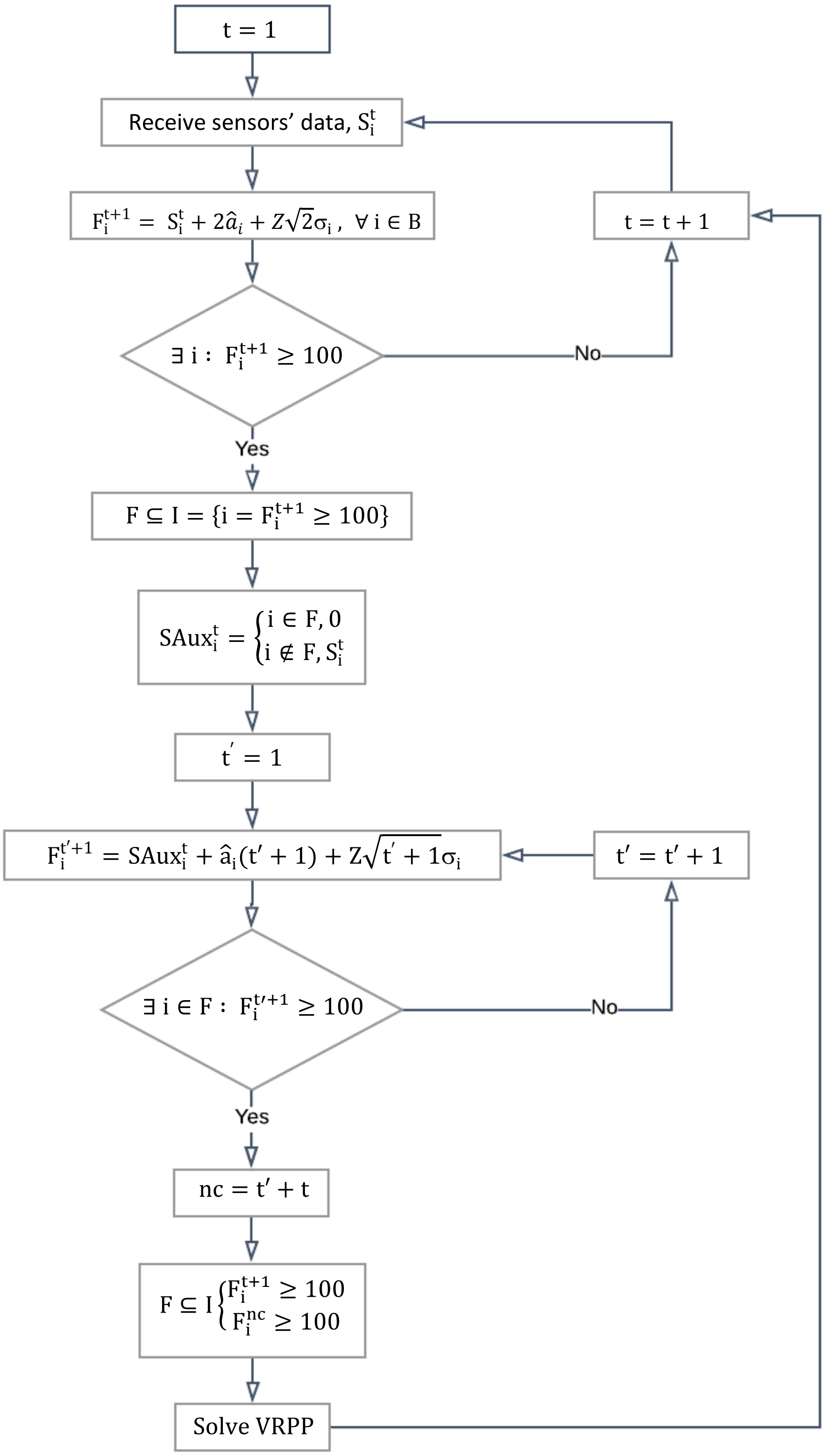

Figure 16 - Look Ahead Approach flowchart (Source: author)

4.2.4 VRPP Formulation

Since the problem addressed in this work is an operational decision, the route definition algorithm is constructed in order to decide which route sequence should be performed for each day after receiving the real-time daily information on the bins fill-level, considering that they are transmitted by the sensors in the morning of the current day.

Ramos et al., 2018 proposed a VRPP mathematical model that selects for each day which bins are worth collecting based on their attractiveness, that is, which the model considers attractive to collect in order to maximize the amount of waste collected while minimizing the total distance traveled. This formulation is based on the two-commodity flow proposed by Baldacci et al., 2004 which considers the use of two flow variables, y_{ij} and y_{ji}, to represent in the collection operation the waste carried by the vehicle when it crosses the edge (i, j). In case the vehicle travels from i to j, flow y_{ij} represents the vehicle's load while flow y_{ji} represents the vehicle's available space. Thus, for each route is simulated two paths to be performed, where each one is associated by a flow variable. Although there are two flows occurring, they represent the same path but in opposite ways, being necessary to initially define a replica for the real depot here called, the copy depot. The path associated to the flow variable y_{ij}, that is, the one considering the vehicle load, represents the journey from node 0 (real depot) to node $n + 1$ (copy depot). The path associated with the flow variable y_{ji}, which considers the vehicle available space, represents the journey from node $n + 1$ (copy depot) to node 0 (real depot).

Since the model seeks to maximize the profits associated with the operations, a monetary penalty (Ω) was applied to the objective function upon the daily number of vehicles/routes used in its solutions. The model is then restricted to perform more than one route, i.e., more than one vehicle, only if such solution provides profit.

Sets

$I = 0, 1, 2, \dots, n + 1 : set\ of\ n\ waste\ bins\ and\ the\ real\ depot\ 0\ and\ the\ copy$
$depot\ n + 1$

$B \subseteq I :\ subset\ of\ n\ waste\ bins$

$F \subseteq I : dinamic\ subset\ of\ waste\ bins\ that\ are\ mandatory\ to\ collect\ it$

Parameters

C: $travelling\ cost\ per\ distance\ unit\ (in\ €/km)$

Sp: $selling\ price\ per\ kg\ of\ a\ recyclable\ material\ (in\ €/kg)$

Ω: $penalty\ for\ the\ use\ of\ the\ vehicles\ (in\ €)$

Q: $vehicle\ weight\ capacity\ (in\ kg)$

G: $waste\ density\ (in\ kg/m^3)$

E_i: $volume\ capacity\ of\ bin\ i\ (in\ m^3)$

E_iG: $weight\ capacity\ of\ bin\ i\ (in\ kg)$

d_{ij}: $distance\ between\ node\ i\ and\ node\ j\ (in\ km)$

S_i^t: $fill\ level\ in\ percentage\ of\ volume\ of\ bin\ i\ at\ the\ beginning\ of\ day\ t\ (sensors\ data)$

a_i^t: $daily\ filling\ rate\ of\ bin\ i\ at\ day\ t\ (in\ percentage\ of\ volume/day)$

am_i: $avarege\ filling\ rate\ of\ bin\ i\ (in\ percentage\ of\ volume)$

Z: $safety\ factor$

σ_i: $standard\ deviation\ of\ bin\ i\ (in\ kg)$

$\hat{a}_i$: $estimated\ filling\ rate\ of\ bin\ i\ given\ by\ am_i + Z\sigma_i\ (in\ percentage\ of\ volume)$

F_i^t: $expected\ fill\ level\ in\ percentage\ of\ volume\ of\ bin\ i\ at\ the\ end\ of\ day\ t\ (S_i^t + \hat{a}_i)$

W_i: $weight\ to\ be\ collected\ from\ bin\ i\ given\ by\ [(S_i^t + \hat{a}_i)E_i G]\ (in\ kg)$

Decision variables

x_{ij}: $binary\ variable\ indicating\ if\ edge\ (i,j)\ is\ visited, (i,j\ \in I)$

y_{ij}: $positive\ variable\ representing\ the\ flow\ between\ node\ i\ and\ node\ j, (i,j\ \in I)$

g_i: $binary\ variable\ indicating\ if\ bin\ i\ is\ visited\ (i \in B)$

k: $integer\ variable\ on\ the\ number\ of\ vehicles\ to\ use$

Model

$$max\ P = Sp\sum_{i\in B} W_i g_i - (0.5(C\sum_{i\in I}\sum_{j\in I\ (j\neq i)} x_{ij}d_{ij}) + k\Omega) \tag{1}$$

s.t.

$$\sum_{i,j\in B(j\neq i)} (y_{ij} - y_{ji}) = 2W_i g_i \tag{2}$$

$$\sum_{i\in B} y_{in+1} = \sum_{i\in B} W_i g_i \tag{3}$$

$$\sum_{j\in B} y_{n+1j} = Q\sum_{i,j\in B(j\neq i)} x_{ij} - \sum_{i\in B} W_i g_i \tag{4}$$

$$\sum_{i\in B} y_{i0} = Q\sum_{i,j\in B(j\neq i)} x_{ij} \tag{5}$$

$$\sum_{j\in B} y_{0j} = 0 \tag{6}$$

$$\sum_{i,j\in B(i\neq j)} x_{ij} = 2g_j \tag{7}$$

$$y_{ij} + y_{ji} = Qx_{ij}, \forall\ i,j \in I\ (i \neq j) \tag{8}$$

$$g_i = 1, \forall i \in F \tag{9}$$

$$x_{ij}, g_i \in \{0,1\}, \forall i,j \in I\ (i \neq j) \tag{10}$$

$$y_{ij} \in \mathfrak{R}^+, \forall i, j \in I \ (i \neq j) \tag{11}$$

$$k \in \mathfrak{J}^+ \tag{12}$$

The OBJECTIVE FUNCTION (1) maximizes the profit (P) obtained through the difference between the revenue generated from the sale of collected waste and the cost of transportation to collect it (considered as a linear function of the distance traveled). Also, the transportation cost includes the aforementioned penalty for the number of vehicles used.

Regarding the constraints reflected in the model:

- CONSTRAINT (2): Since the model is based on the two-commodity flow formulation, a restriction is required to ensure that the difference between the inflow and outflow of each bin visited by each vehicle is equal to twice the estimated weight.
- CONSTRAINT (3): Ensures that the total inflow of the copy depot is equal to the total weight of the visited bins.
- CONSTRAINT (4): Ensures that the total outflow of the copy depot is equal to the residual capacity of the collection vehicle.
- CONSTRAINT (5): Ensures that the total inflow of the real depot is equal to the capacity of the collection vehicle.
- CONSTRAINT (6): Ensures that the total depot outflow of the real depot is equal to zero (starting point with empty vehicle).
- CONSTRAINT (7): Ensures that there are two incident edges on each bin.
- CONSTRAINT (8): Ensures that the sum of the flows for each edge (i, j) must be equal to the capacity of the vehicle if the edge is crossed by the vehicle.
- CONSTRAINT (9): Ensures that a bin that is about to overflow, based on information provided, will not remain in this state as a visit is imposed.
- CONSTRAINTS (10), (11) and (12): Variables domain.

4.3 Bins Selection Rules

One of the major challenges faced when dealing with a VRPP model applied over a real-world problem is the computation time required to achieve an optimal or close-to-optimal solution. Given the nature of the problem at hand, it is essential that the routes derived from the model are designed as quickly as possible to meet the circumstances of the real world. In the present work, such challenge is faced since the procedure for receiving the bins fill-level data is established to be transmitted by the sensors in the morning. Consequently, it becomes necessary to ensure that the model is capable to provide a good solution in a time-efficient way so that, if required, the collection team can start the operation as soon as possible after receiving the sensors data.

In order to establish the possibilities for dealing with the computational time issue, a bins selection rules were developed taking advantage of the fact that the computational time varies significantly as a function of the number of bins considered by the model. Thus, besides the base option that complies all bins contained in the initial set, a pre-selection procedure is explored in this work by combining the VRPP model with a heuristic method, aligned with the one in Aguiar et al., in press. This initial step will restrict the number of bins to be inputted into the model in order to achieve a solution close to the optimum and considerably good while decreasing the computational time. However, it is important to mention that is necessary to perform a sensitive analysis for determine an appropriate threshold value, which happens to be case-study dependent.

Three types of selection rules were analyzed: (1) Considering all bins; (2) Considering only some bins by fill-level; and (3) Considering only some bins by the relation between distance and fill-level. The last two rules correspond to the procedure using a heuristic method to construct a bins dynamic set that the model will consider for each day of collection. Therefore, in both cases a subset L is added to the VRPP model in order to encompass the bins resulting from the selection rule applied. Based on the color code displayed below in Figure 17, a description of each bins selection rules applied in this work is given as follows:

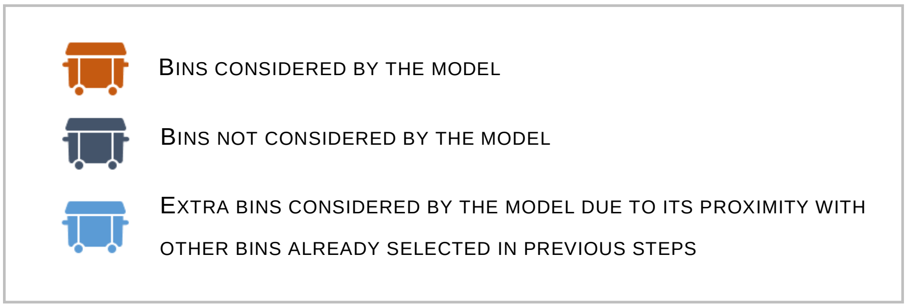

Figure 17 - Color code applied for the illustration of the bins selection rules (Source: author)

1) CONSIDERING ALL BINS: No restrictions or pre-selection methods are applied in this case, therefore, all bins contained in the initial set in inputted every day to the model (See Figure 17 and Figure 18).

Figure 18 - Exemplification of the first bins selection rule (Source: author)

2) CONSIDERING ONLY SOME BINS BY FILL-LEVEL: In addition to the bins that are mandatory to be collected, i.e., that present a risk of overflow, the model is inputted with other bins from the initial set that satisfies the condition of having the fill-level above a predetermined threshold (M). Thus, all the bins that are observed in this condition are inputted to the model together with those that are mandatory, creating a dynamic set for each day of collection (See Figure 17 and Figure 19).

Figure 19 - Exemplification of the second bins selection rule (Source: author)

3) CONSIDERING ONLY SOME BINS BY THE RELATION BETWEEN DISTANCE AND FILL-LEVEL: Under this type of selection, a dynamic set is initially constructed exactly as described in the previous point, considering the bins fill-level that complies with the predetermined threshold M. Then, a second procedure is performed only for those bins contained in the dynamic set and determines according to a second predetermined threshold (R), the distance between these bins with the other bins that are not contained in the dynamic set initially constructed. As a result, the model will be inputted with a new updated dynamical set that includes additional bins according to their distance relation with those already pre-selected through the fill-level condition (See Figure 17 and Figure 20).

Figure 20 - Exemplification of the third bins selection rule (Source: author)

4.4 Route Balance

Since the VRPP model proposed by Ramos et al. 2018 does not consider the "time" element, i.e., it does not apply any constraints regarding the routes' durations. Thus, a branch of the VRPP model previously presented is implemented in order to include the Route Balance in the formulation. As concluded in the literature review, the most appropriate measure for the present work is to consider the difference between the longest and shortest routes length. Therefore, the objective is not only to maximize the profit but also to minimize the routes' length difference.

To apply the Route Balance, it is initially necessary to establish a maximum and minimum values as a limitation for the route's duration. With the time element being now taken into account, it is also necessary to establish parameters that allow the model to simulate the time required to perform the collection routes, such as the average speed of the vehicle fleet and the average time to collect the bins. In addition, a new way of penalty has been introduced in the objective function which, instead of penalizing for the number of vehicles used, now penalizes for violating the duration limit values. Thus, since the VRPP model maximizes profit, the model will be influenced to avoid performing routes that exceed the established values. Below, it is possible to see the model formulation with the Route Balance concept to which a new set for the vehicles is added and new restrictions are applied.

New Sets

$Dd \subseteq I : real\ depot$

$Ad \subseteq I : copy\ depot$

$V = 1, 2, \dots, k : set\ of\ available\ vehicles$

New Parameters

$\Omega: penalty\ for\ the\ for\ the\ range\ of\ route\ durations\ (in\ €/h)$

$Hl: minimum\ duration\ for\ routes\ (in\ h)$

$Hu: maximum\ duration\ for\ routes\ (in\ h)$

$Av: vehicles\ average\ speed\ (in\ km/h)$

$Ac: average\ waste\ bin\ collection\ time\ (in\ h)$

Decision variables

$x_{ijv}: binary\ variable\ indicating\ if\ edge\ (i,j)\ is\ visited\ by\ vehicle\ v, (i,j\ \in I,\ v \in\ V)$

$y_{ij}: positive\ variable\ representing\ the\ flow\ between\ node\ i\ and\ node\ j, (i,j\ \in I)$

$g_{iv}: binary\ variable\ indicating\ if\ bin\ i\ is\ visited\ by\ vehicle\ v\ (i \in B, v \in\ V)$

$maxv: positive\ variable\ assuming\ the\ maximal\ route\ duration\ value$

$minv: positive\ variable\ assuming\ the\ minimal\ route\ duration\ value$

Model

$$max\ P = Sp \sum_{i \in B} \sum_{v \in V} W_i g_{iv} - (0.5(C \sum_{i \in I} \sum_{j \in I\ (j \neq i)} \sum_{v \in V} x_{ijv} d_{ij}) + \Omega(maxv - minv) \tag{1}$$

s.t.

$$maxv \geq \sum_{i \in I} \sum_{j \in I} 0.5 \frac{(x_{ijv} d_{ij})}{Av} + Ac \sum_{i \in B} g_{iv}\ , \forall v \in V \tag{2}$$

$$minv \leq \sum_{i \in I} \sum_{j \in I} 0.5 \frac{(x_{ijv} d_{ij})}{Av} + Ac \sum_{i \in B} g_{iv} + BigM(1 - \sum_{i \in Dd} \sum_{j \in B} x_{ijv})\ , \forall v \in V \tag{3}$$

$$\sum_{i \in I} \sum_{j \in I} 0.5 \frac{(x_{ijv} d_{ij})}{Av} + Ac \sum_{i \in B} g_{iv} \leq Hu\ , \forall v \in V \tag{4}$$

$$\sum_{i \in I} \sum_{j \in I} 0.5 \frac{(x_{ijv} d_{ij})}{Av} + Ac \sum_{i \in B} g_{iv} + BigM(1 - \sum_{i \in Dd} \sum_{j \in B} x_{ijv}) \geq Hl\ , \forall v \in V \tag{5}$$

$$\sum_{i,j \in B (j \neq i)} (y_{ij} - y_{ji}) = 2W_i \sum_{v \in V} g_{iv}\ , \forall i \in B \tag{6}$$

$$\sum_{i \in B} y_{ij} = \sum_{i \in B} \sum_{v \in V} W_i g_{iv}\ , \forall j \in Ad \tag{7}$$

$$\sum_{i \in B} y_{ji} = Q \sum_{i \in B} \sum_{v \in V} x_{ijv} - \sum_{i \in B} \sum_{v \in V} W_i g_{iv}\ , \forall j \in Ad \tag{8}$$

$$\sum_{j \in B} y_{ji} = Q \sum_{j \in B} \sum_{v \in V} x_{ijv}\ , \forall i \in Dd \tag{9}$$

$$\sum_{j \in B} y_{0j} = 0\ , \forall i \in Dd \tag{10}$$

$$\sum_{j \in B} x_{ij} + \sum_{j \in B} x_{ji} = 4 g_{iv}\ , \forall i \in B, v \in V \tag{11}$$

$$y_{ij} + y_{ji} = Q \sum_{v \in V} x_{ijv}\ , \quad \forall i,j \in I \tag{12}$$

$$\sum_{v \in V} g_{iv} = 1, \forall i \in F \tag{13}$$

$$\sum_{v \in V} g_{iv} \leq 1, \forall i \in B \tag{14}$$

$$\sum_{j \in B} 0.5\left(x_{ijv} + x_{jiv}\right) \leq 1, \forall i \in Dd, v \in V \tag{15}$$

$$g_{iv} = \sum_{j \in B} x_{ijv}\ , \forall i \in Dd, v \in V \tag{16}$$

$$g_{jv} \leq g_{iv}, \forall i \in Dd, j \in B, v \in V \tag{17}$$

$$x_{ijv}, g_{iv} \in \{0,1\}, \forall i, j \in I \ (i \neq j), v \in V \tag{18}$$

$$y_{ij}, maxv, minv \in \Re^{+}, \forall i, j \in I \ (i \neq j) \tag{19}$$

The OBJECTIVE FUNCTION (1) maximizes the profit (P) just as in the previous model, through the difference between the revenue generated from selling the collected waste and the cost of transportation to collect it (considered as a linear function of the distance traveled). Besides the introduction of the set V of vehicles, here the transportation cost includes the new type of penalization that considers the equilibrium of the routes' durations. Thus, it penalizes for each hour of difference between the longest and shortest route durations of the solution.

Regarding the constraints reflected in the model, all the constraints previously presented for the VRPP model without route balance has the same meaning, so there is no need to describe them again. Next, the additional constraints to include the route balance formulation into the model are described:

- CONSTRAINT (2): Determine the maximum route duration.
- CONSTRAINT (3): Determine the minimum route duration.
- CONSTRAINT (4): Ensures that the maximum route duration is not exceeded.
- CONSTRAINT (5): Ensures that the minimum route duration is satisfied.
- CONSTRAINT (14): Ensures that a bin must be visited by at most one vehicle.
- CONSTRAINT (15): Ensures that a vehicle leaves the depot no more than once.
- CONSTRAINT (16): Attribute a value to the variable g_{iv} which must be equal to 1 if the vehicle leaves the depot, and 0 otherwise.
- CONSTRAINT (17): Ensures that a bin can only be visited by a vehicle which has left the depot.
- CONSTRAINTS (18) and (19): Variable domains.

.

4.5 Scenario Tree

The methodology adopted in this work enables the development of various scenarios that will be tested and explored in Chapter 5. A scenario tree was then constructed to summarize and allow an overview of all the possible ramifications achieved by combining the approaches previously described with the route balance and the bins selection rules branches.

The scenarios are initially differentiated by three branches according with the approach that is being applied: The EVERYDAY APPROACH, the MYOPIC APPROACH, or the LOOK AHEAD APPROACH. The approaches are then decomposed depending on whether the concept of route balance is applied, creating for each one of them two different branches to be explore: With or without the route balance. Furthermore, based on the bins selection rule applied, each branch from the route balance is dismembered into three new branches: Considering all bins (named All), considering only some bins according to the fill-level (named M), or considering only some bins according to the relation between the distance and the fill-level (named R). In Figure 21 it is possible to visualize the scenario tree constructed in order to clarify the ramification of all possible scenarios here taken into account.

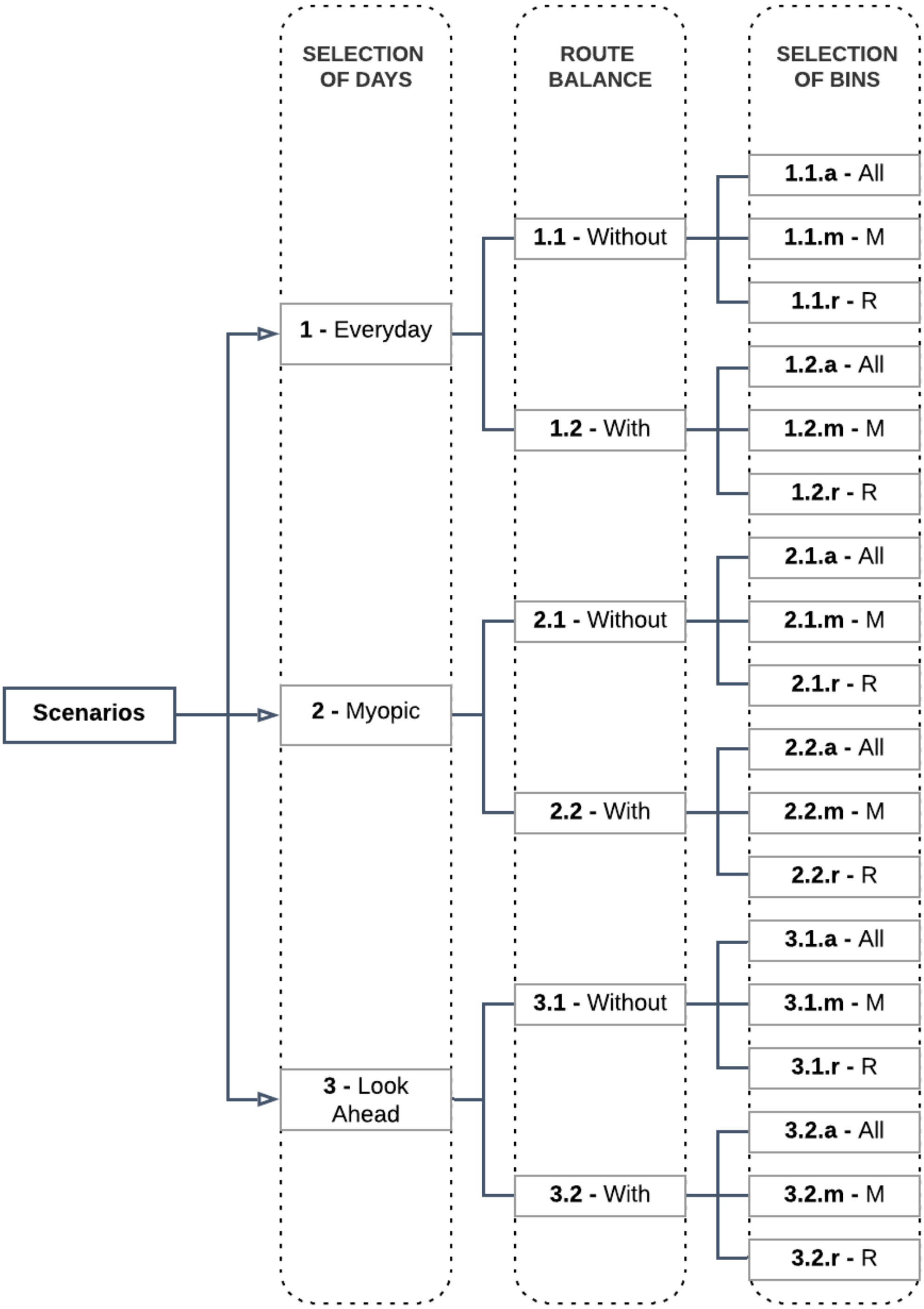

Figure 21 - Scenario tree

5. RESULTS

The present chapter focuses on the discussion of the results obtained by applying the methodology previously presented, using real instances from ERSUC's case study. The mathematical model was implemented in GAMS 24.6.1 language on an Intel Xeon CPU X5680 @ 3.33 GHz, restricted by a computational time limit of 14 400 seconds. Additionally, for comparison purpose, the current situation and each scenario analyzed here has a time horizon defined to encompass the period of 28 days, from April 2 to April 29.

Section 5.1 describes the data collection procedure and its processing, whereby two methods were tested in order to determine the most appropriate one. Section 5.2 characterizes the parameters used in this work. Section 5.3 presents Soure's results analysis, the first instance analyzed (with 98 bins). Section 5.4 presents Condeixa's results analysis, the second instance analyzed (with 121 bins). Section 5.5 presents Soure + Condeixa results analysis, the third and last instance analyzed (with 219 bins). Section 5.6 presents the chapter's conclusions.

5.1 Data Collection and Processing

In collaboration with ERSUC, a data collection process was started in order to monitor the bins filling behavior in Soure and Condeixa municipalities. The data was gathered in the year of 2019 covering a monitoring period from 15 February to 30 September where, for this work, three different instances are initially defined based on their dimensions in terms of number of bins: Soure, Condeixa, and Soure together with Condeixa. They can be considered as a small, medium, and large instances, respectively.

The purpose here is to simulate the real reading of the bin's fill-level that would be transmitted by volumetric sensors and, thus, assess the benefits of designing collection routes with updated information on waste fill-levels. However, the data provided by ERSUC is not "clean", possessing several inaccuracies and demanding further analysis on how to process it. Firstly, let us describe the procedure used to obtain the raw data: through manual records, the collection team of ERSUC classified the bins fill-level (by a visual assessment) into one of four classes regarding the percentage of volume capacity filled with waste, as displayed in Table 6. As the simulation requires a precise reading from a sensor, it was assumed that the corresponding value hypothetically transmitted by the sensor would be the average of the recorded class as also displayed in Table 6. For example, in the case that it was classified between 0% and 25%, the assumed value for sensor transmission was 12.5%.

Table 6 - Classes of the bins fill-level

0% - 25%	25% - 50%	50% - 75%	75% - 100%
12.5%	37.5%	62.5%	87.5%

These manual records were filled by the drivers upon arrival to the bin, immediately before the collection. In ERSUC's operation, a route is performed for each material type but often, in each location, there are bins of the three material types. It was also established by ERSUC that the driver of a material-specific route should also "check" all bins in the same site and record their filling level, so that a more continuous data set is obtained. Consequently, it was later considered useful to classify the manual records into "readings" and "checks". Readings are considered to be the manual records, performed by the driver responsible to collect that material; and "checks" are the manual records performed by drivers collecting other material types. Nevertheless, it is highly relevant to highlight the existence of inaccuracies regarding these two types of manual records. More specifically, there were inconsistencies between "readings" and "checks". In periods between two readings, there would be cases when the "check" between two collections would present a higher value that the "reading", which is impossible when there is no collection between the "check" and the "reading" recorded just before collection. This can partially be explained by the subjectivity of judgements on fill levels performed by different drivers. Also, waste surface is rarely flat, also contributing to the subjectivity of fill level assessment. Beyond the subjectivity of assessment, it has previously been demonstrated that the reliability of a "reading" is considerably greater than that of a "check" (Brouwer et al. Submitted). In order to simulate the sensor readings, these two factors contributed to the definition of two types of methods that differ according to what was considered to process the raw data provided by ERSUC.

1) Considering both "readings" and "checks" as accurate: Under this method it is possible to observe cases where the "checks" and the "readings" had the same fill-level. For these cases, it was assumed that, between the days effectuated the "check" and the "reading", there was no waste deposited on the bins. Such situation leads to the occurrence of fill peaks that do not match with what is expected for the bins filling to behave. It happens because, when considering that no waste has been deposited for days, the bin fill-level will suddenly reach a considerably high value, resulting in a peak. In addition, inconsistencies between "readings" and "checks" were also detected where the highest fill-level was assumed.
2) Considering only the "reading" records as accurate: Here, by eliminating the "check" values from the data processing, situations of inconsistency and fill peaks were consequently eliminated. As a result, the bins eventually behaved in a linear growth as initially expected.

Generally speaking, for both methods the data processing was basically the same: It started handled the raw data and calculating a daily filling average for each bin. For days when the data was incomplete, this average value was used to estimate the bins fill level. Therefore, with all the data from the “readings” and (or) “checks” complete, a linear function was assumed to estimate the bins fill-level over the intermediate days between the “readings” and ”checks” (or just between the “readings” if the second method was applied). To assess the two methods, a test was performed with the VRPP model for the MYOPIC APPROACH considering all bins as selection rule and no route balance. The data obtained by applying each method was inputted into the model and run, both for the same planning horizon of 28 days (i.e., between April 2 and April 29). Such test is reliable to assess because the impact of these methods lies in the determination of the real values for each bin daily fill level, as well in the average daily fill-level and the standard deviation of the daily fill level. Therefore, the estimated weight and the actual weight collected will be vary between methods, and their consequences regarding the planning horizon are assessed, in order to validate the best option. The test results for method 1 and 2 are displayed in Figure 22.

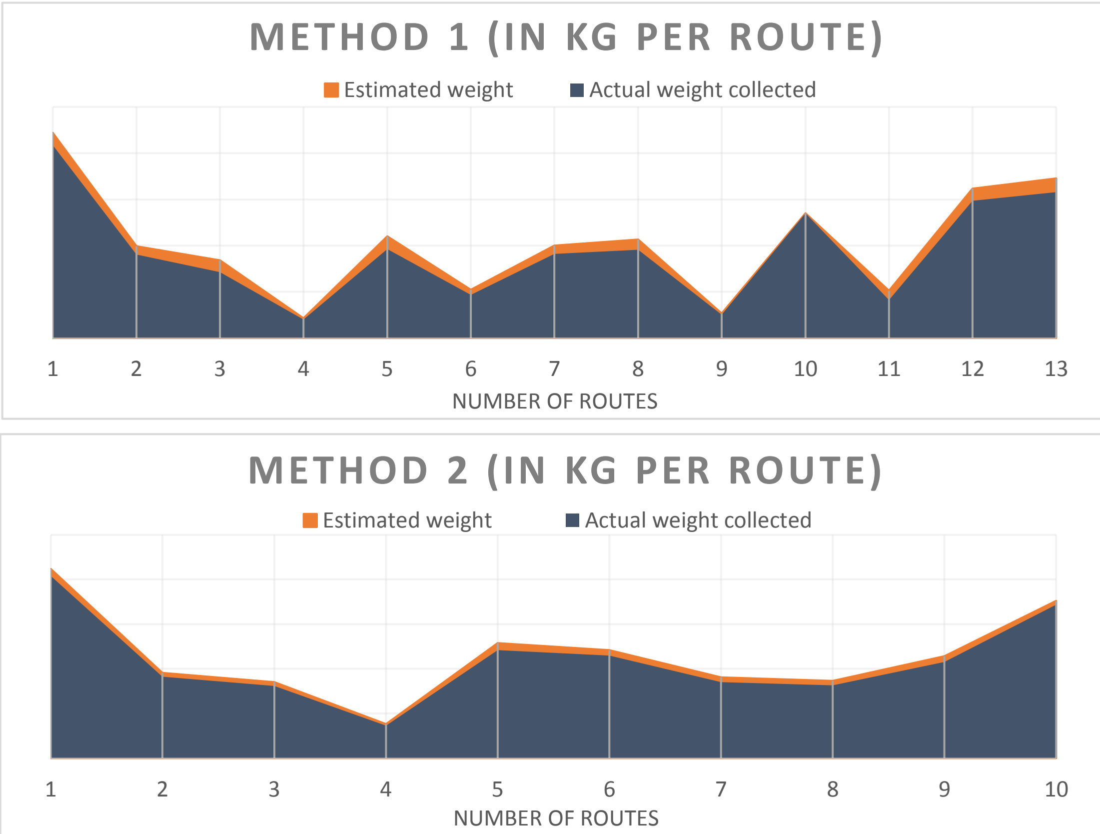

Figure 22 - Results for the data processing method 1 and 2

As expected, the method that provided the most reliable results for the data processing was method 2, which discards the “checks” values. This can be justified by the fact that method 2 presents a closer approximation between the expected weight to be collected (orange function in Figure 22) and the actual weight collected (blue function in the same figure). In addition, since the assessment was made for the same planning horizon, method 2 provides a solution with less collection operations required (10 vs. 13 routes). The reason for this decrease lies in the fact that the additional number of collections is related to the high volatility of the bins fill-levels. As previously mentioned, by not considering the "checks", filling peaks are eliminated making the data more stable and closer to reality. In conclusion, method 2 is the most accurate and, therefore, is the one chosen to process the data in this work.

5.2 Parameters

To better describe all the parameters and their source , the present section summarizes the values adopted to simulate the problem in hand. Table 7 describes each one of them along with their respective value and source. The parameters with the symbol "*" are exclusive to the model formulation with the route balance concept applied.

Table 7 - Parameters values and sources

PARAMETERS	DESCRIPTION	VALUES	SOURCE
$\boldsymbol{G}$	Waste density	29.5 kg/m^3	ERSUC
$\boldsymbol{E_i}$	Volume capacity of bin i	2.5 m^3	ERSUC
$\boldsymbol{S_i^t}$	Fill-level in percentage of volume of bin i at the beginning of day t	Drivers records	ERSUC
$\boldsymbol{a_i^t}$	Daily filling rate of bin i at day t	Calculated	-
$\boldsymbol{am_i}$	Average filling rate of bin i	Calculated	-
σ_i	Standard deviation of bin i	Calculated	-
$\boldsymbol{Z}$	Safety factor	0.84	-
$\boldsymbol{Q}$	Vehicle weight capacity	2200 kg	ERSUC
$\boldsymbol{d_{ij}}$	Distance between node i and node j	Real distances	Google Maps
$\boldsymbol{M}$	Fill-level threshold	30 %	-
$\boldsymbol{R}$	Distance threshold	2 km	-
$\boldsymbol{C}$	Travelling cost per distance unit	1 €$/km$	ERSUC
$\boldsymbol{Sp}$	Selling price per kg of a recyclable material	121 €$/ton$	Novo Verde
$\boldsymbol{Av}$	Vehicles average speed	40 km/h	ERSUC
$\boldsymbol{Ac}$	Average waste bin collection time	0.05 h	ERSUC
$\boldsymbol{\Omega}$	Penalty for the use of the vehicles	0.1 €	-
$\boldsymbol{Hl}$*	Minimum duration for routes	4 h	-
$\boldsymbol{Hu}$*	Maximum duration for routes	7 h	ERSUC
$\boldsymbol{\Omega}$*	Penalty for the range of route duration	30 €$/h$	-

According to ERSUC, the volume capacity of bin i (E_i) is 2.5 m^3 and the waste density (G), i.e., the paper/cardboard inside the bin is considered to be 29.5 kg/m^3. The bins fill-level (S_i^t) or, in other words, the amount of waste in bin i on day t, is calculated so as to simulate the values that the sensors will transmit for each day. For the first day $t = 1$, this value was set according to the processing of the manual records data filled by ERSUC's collection team, as explained previously in section 5.1. Once processed, the data was translated into kg. During the data processing phase, the daily filling rate of bin i (a_i^t) was calculated for each day t of the planning horizon. The average filling rate (am_i) and the standard deviation (σ_i) of bin i were then calculated considering the period from 2 April to 20 July. In order to adopt a conservative view, the safety factor (Z) selected was 0.84. The vehicle capacity (Q) was also achieved according to ERSUC's data, which determined it to be 2200 kg. For each instance analyzed, the geographic coordinates of the bins and the associated depot are well known where, using real values from Google Maps, the distance between each departure and arrival node (d_{ij}) was considered and determined. By applying the different types of the bins selection rules, a sensitivity analysis was performed to define the most appropriate values. For the second selection rule that considers the bins according to the fill-level (M), the threshold of 30 % was selected. For the third bins selection rule that considers the relation between fill-level and distance (R), the threshold of 2 km was selected.

In the context of recyclable waste collection, profit is achieved through the difference between the amount of weight collected and the distance traveled. Thus, in order to translate such measures into monetary value, the following financial counterpart values were taken into account in the present work: According to ERSUC, the transportation cost (C) is 1 $€/km$; According to the waste management entity Novo Verde, the revenue for each ton of paper/cardboard collected and sorted is 173 $€/ton$. However, it is important to consider that the selling price covers the costs of collection and sorting operations, assuming that 70% of the total cost is related to the collection operation (Ramos et al., 2014c). Considering that we are going to analyze only the collection operation, the selling price per kg of a recyclable material (Sp) is adjusted to 121 $€/ton$ $(70\% \times 173€/ton)$. According to ERSUC, the collection vehicle travels at an average speed (Av) of 40 km/h and the average time to collect each bin (Ac) is about 0.05 h (3 minutes). To force the model to allocate the minimum number of vehicles, a penalty for the use of vehicles (Ω) is set using the small value of 0.1 €. However, such a penalty is only applied in the formulation of the model without route balance. This because when the route balance is applied, a new set is introduced for the vehicles. Thus, a different type of penalty is considered for the route balance model penalizing now by the route's duration range (Ω*), established to be 30 $€/h$. Lastly, the other two exclusive parameters of the model formulation with route balance were defined to determine the minimum (Hl*) and maximum (Hu*) duration of the routes, set to be 4 h and 7 h respectively.

5.3 Soure Analysis

For the instances' scenarios results, the total and average values will be presented to which the total values represent the sum of each route perform in the time horizon and the averages can be found per collection day. It is important to mention that: (1) The distance travelled was calculated by the sum of the real distances between each bin location visited; (2) The vehicles usage rate was calculated considering the parameter vehicle weight capacity that, just like the vehicle average speed and the average waste bin collection time, is a well-known value according to ERSUC's data; and (3) The duration of the routes was obtained by the following expression: $(\text{Distance}/\text{Average vehicle speed}) + (\text{Average waste bin collection time} \times \text{Number of bins collected})$. For a more in-depth analysis, all the scenarios results are detailed in the attachments.

5.3.1 Current Situation

Currently, ERSUC conducts its waste collection operation in a static way. With a homogeneous fleet of vehicles and a single depot, the routes performed by the company are composed of predefined circuits that remain unchanged regardless of any additional information. Although ERSUC operates the waste collection for all recyclable materials, in this work we only consider the collection of paper/cardboard. For this type of waste,

Figure 23 illustrate the two periodical static circuits currently performed by the company for Soure municipality, circuit A with 48 bins and circuit with 50 bins, resulting in a total of 98 bins for this instance. The workload established by ERSUC is no more than 7 hours per day and, when the circuits are performed, all bins associated are visited.

Figure 23 - Map of ERSUC´s paper/cardboard circuits for Soure

To be able to compare the current situation with the scenarios analysis that will be further explored, a planning horizon of 28 days was established, i.e., from April 2 to April 29. Table 8 displays the results of Soure's current situation for the collection of paper/cardboard. It can be observed that 9 routes are performed in the analyzed period and, in total, this operation allowed the collection of approximately 10 700 kg while travelling a distance about 1 380 km. Moreover, the operation is characterized by an average loss of 10 € per collection day and a low vehicle usage rate which, on average, shows that only 54% of the vehicle capacity is actually used.

Table 8 - Soure's current situation

KPI	TOTAL (28 days)	AVERAGE (per collection day)
Number of routes	9	-
Vehicles used	9	1
Attended bins	425	47
Weight (kg)	10 731	1 192
Distance (km)	1 386	154
Ratio (kg/km)	-	7.8
Shift duration (h)	-	6.2
Vehicles usage rate (%)	-	54%
Profit (€)	-86	-10

Another relevant analysis to introduce refers to the status of the bins fill-level at the moment they were collected. Table 9 - Bins fill-levels for circuits A and Table 9 encompass the data from the manual records of all 9 routes made in the planning horizon, differing for each circuit how many filling classes was observed by ERSUC's collection team. It is possible to verify that almost 50% of the visited bins were classified as having a fill-level between 0% to 25%, meaning that most of the bins are collected when they present a considerably low fill-level.

Table 9 - Bins fill-levels for circuits A and B

CLASS	CIRCUIT A	CIRCUIT B	TOTAL	(%)
0% - 25%	97	106	203	46%
25% - 50%	96	42	138	31%
50% - 75%	35	30	65	15%
75% - 100%	22	14	36	8%

5.3.2 Base Scenarios Results

To better systematize the comparisons between the various scenarios and thus provide a clearer insight, a subset called base scenarios was defined for initial analysis. The base scenarios are composed by three scenarios that are potentially the optimum situation of each approach: Scenario 1.1.A for the EVERYDAY APPROACH, 2.1.A for the MYOPIC APPROACH and 3.1.A for the LOOK AHEAD APPROACH (see Figure 21, page 47). The present work introduces two possible branches that can restrict the solution either by the number of bins being inputted into the model or by the duration limits. When only considering scenarios where the route balance is not applied and the model is inputted by all bins (i.e., first bins selection rule), we can assume that they have no general restrictions, being the optimal scenarios for each approach. However, such a definition can only be corroborated in the present analysis because it is applied to an instance considered small. Table 10 displays the results obtained by simulating the base scenarios.

Table 10 – Soure's base scenarios results

KPI		SCENARIO 1.1.A Everyday	SCENARIO 2.1.A Myopic	SCENARIO 3.1.A Look Ahead
TOTAL	Profit (€)	134	344	400
	Number of routes	8	7	5
	Attended bins	543	434	346
	Weight (kg)	10 641	11 186	10 158
	Distance (Km)	1 155	1 010	830
AVERAGE	Duration (h)	7.0	6.7	7.6
	Ratio (Kg/Km)	9.4	10.8	12.5
	Vehicles used	1	1	1
	Vehicles usage rate (%)	60	73	92
	Computational time (s)	6 311	2 233	3 903
	Gap	3.4	0.7	0.0

Comparing the base scenarios results, it is possible to see that scenario 1.1.A presents the lower values for the vehicle usage rate (60 vs. 73 vs. 92%) and the kg per km ratio (9.4 vs. 10.8 vs. 12.5) which, consequently, affects its reduced total profit (134 vs. 344 vs. 400€). Therefore, here we can verify a significant improvement performed by scenarios 2.1.A and 3.1.A over scenario 1.1.A. However, when dealing with real-world problems, it is important to analyze the average computational times and average gaps to assess whether certain values are sustainable or not according to reality. Thus, the time required to reach a solution is often crucial and, considering the ERSUC's case being analyzed, it is essential that the scenarios developed here has the capability to provide a solution as quickly as possible and as close to the optimal. For the base scenarios, we can notice a large discrepancy in the computational time required for scenario 1.1.A when compared to the other scenarios (6 311 vs. 2 233 and 3 903 seconds). Furthermore, the same can be observed for the gap values reached by them (3.4 vs. 0.7 vs. 0.0) i.e., the difference between the integer solution and the lower bound found by CPLEX after the total computational time. However, these values represent the average per collection day, considering all the collection days performed during the time horizon.

As a global conclusion, it is possible to state that scenario 1.1.A presented the worst performance considering the KPIs analyzed, being significantly inferior to the performances achieved in scenarios 2.1.A and 3.1.A. Therefore, since scenario 1.1.A represents the nearest optimal situation for the EVERYDAY APPROACH, it can be concluded that all the scenarios in the EVERYDAY APPROACH are useless for future development.

5.3.3 Non-base Scenarios Results

Following the scenario tree, a second set was defined: the non-base scenarios. Here, regardless of whether the route balance concept is applied, or which bins selection rule is considered, the remaining scenarios are introduced. To a better visualization, the scenario tree is displayed in Figure 24 deferred by a color scale to represent the category that each scenario belongs to and, in addition, it is already updated with the conclusions previously reached in the previously section. Thus, orange represents the scenarios that will not be explored, while blue represents the scenarios already analyzed, i.e., the base scenarios, and lastly, yellow represents the scenarios that will be analyzed in the present section, namely the non-base scenarios.

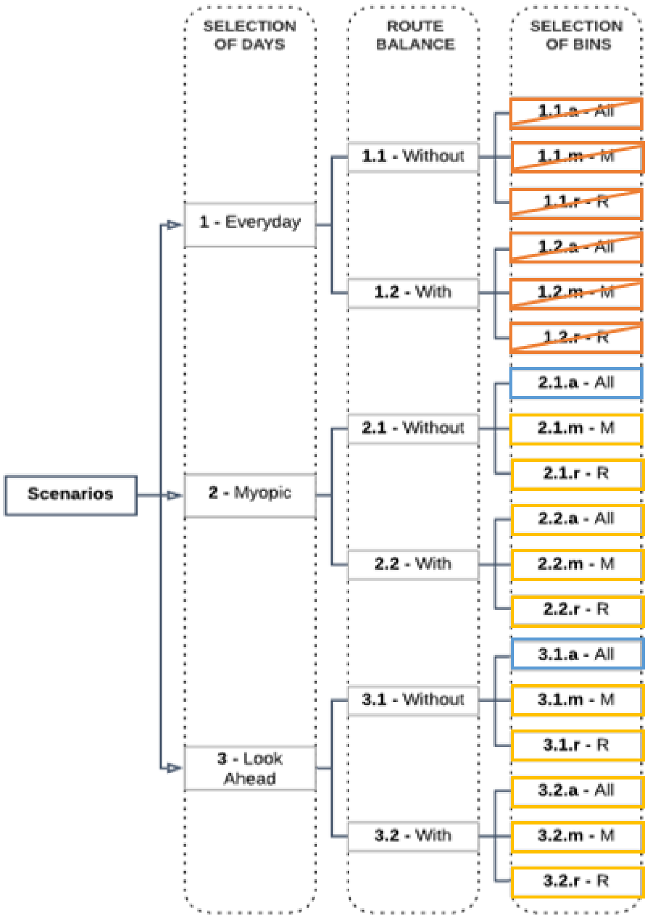

Figure 24 - Updated scenario tree with the base and non-base scenarios

For a better overview of the non-base scenarios performance, two tables were developed summarizing all the results obtained for the most relevant KPIs to analyze here. The two tables represent a subdivision of the scenarios according to the presence of route balance in the VRPP model formulation. Thus, Table 11 shows the performance of the non-base scenarios without the route balance applied, while Table 12 shows the performance of the ones with the route balance applied. For more details on the scenarios results see Attachment 1.

Table 11 - Main KPI's results for the non-base scenarios without route balance

KPI		2.1.M Myopic	2.1.R Myopic	3.1.M Look Ahead	3.1.R Look Ahead
TOTA	Profit (€)	474	359	360	431
	Number of routes	6	7	5	6
AVERAGE	Ratio (Kg/Km)	13.2	10.8	12.1	12
	Vehicles usage rate (%)	82	71	89	90
	Computational time (s)	1 847	36	23	153
	Gap	0.0	0.0	0.0	0.0

Table 12 - Main KPI's results for the non-base scenarios with route balance

KPI		2.2.A Myopic	2.2.M Myopic	2.2.R Myopic	3.2.A Look Ahead	3.2.M Look Ahead	3.2.R Look Ahead
TOTAL	Profit (€)	315	405	312	475	341	342
	Number of routes	7	7	7	6	7	7
AVERAGE	Ratio (Kg/Km)	11.1	12	10.9	13.3	11.5	11.7
	Vehicles usage rate (%)	71	73	70	86	77	85
	Computational time (s)	12 775	2 643	6 699	14 400	6 131	10 392
	Gap	9.7	0.3	0.7	6.0	17.5	30.4

First, let us look at the results of Table 11. Considering only the scenarios that follow the MYOPIC APPROACH methodology (2.1.M and 2.1.R), except for the average computational time, all KPIs had better values for scenario 2.1.M, the one that considers the bins selection by the fill-level (i.e., the second bin selection rule). Due to its high kg per km ratio and vehicle utilization rate, when compared to scenario 2.1.R, scenario 2.1.M achieved a better solution by providing one less route for the same planning horizon (6 vs. 7) and therefore, reaching a substantial increase in the total profit (474 vs. 359€). For the scenarios that follow the LOOK AHEAD APPROACH methodology (3.1.M and 3.1.R), a very similar outcome is observed in terms of kg per km ratio, vehicle usage rate and computational time averages. However, a significant difference for the total profit was observed between the scenarios. Scenario 3.1.R, which considers the bins selection by the fill-level/distance relation (i.e., the third bins selection rule), presents a total profit higher than scenario 3.1.M (431 vs. 360€). This is justifiable due to its solution obtain one more route but maintain the average for the kg per km ratio and the vehicle usage rate, providing more profit to the collection operation.

Now looking at Table 12, it is possible to see that generally three of the scenarios have a significantly high value in terms of average computational time, namely scenarios 2.2.A, 3.2.A and 3.2.R. Although scenario 3.2.A has the best overall performance in all the remaining KPI's of this set, the three scenarios referred above become irrelevant for an in-depth analysis since an average computational time as high as those achieved is not a viable solution for the problem at hand. In addition, such values can imply the presence of solutions where optimality was not proved, i.e., with a significant gap. A specific analysis according to the approach type is also developed here as follows: For the MYOPIC APPROACH scenarios (2.2.A, 2.2.M and 2.2.R) it is evident that scenario 2.2.M provides by far the best performance in all KPIs analyzed. For the LOOK AHEAD APPROACH scenarios (3.2.A, 3.2.M and 3.2.R), the best performance is the one of scenario 3.2.A for providing a higher profit (475 vs. 341 vs. 342€) and lower number of routes (6 vs. 7 vs. 7). This is justifiable since the scenario also achieved the higher kg per km ratio (13.3 vs. 11.5 vs. 11.7) and vehicle usage rate average (86 vs. 77 vs. 85%) when compared with the other scenarios. Nevertheless, as previously mentioned, the average computational time plays a major role in the assessment of the approaches, and two of the three scenarios here analyzed for the LOOK AHEAD APPROACH presented a significant value for the average computational time (scenarios 3.2.A and 3.2.R). Therefore, it is possible to conclude that the scenario with the best overall performance in this case becomes scenario 3.2.M which, despite presenting a median performance in the KPIs, is the only one from the LOOK AHEAD APPROACH that obtained an acceptable average computational time (6 131 vs. 14 400 vs. 10 392 seconds).

5.3.4 Soure’s Scenarios Overall Comparison

So far it has been analyzed which scenarios presented the best performances when applied for Soure's instance. Previously, it was established that scenarios that had an average computational time considered not viable for the problem at hand were discarded for future simulations. Such procedure is justifiable since if for a small instance it is observed that they present high values, in larger instances such behavior will be consequently amplified. Thus, Figure 25 displays the updated scenario tree with only those scenarios that prove to be worth developing for the next instances.

To conclude the analysis of the scenarios, the present section aims to provide an overall comparison of the scenarios performances with the current situation faced by ERSUC. As such, it is expected to conclude whether there was improvement in the company's collection operations and, moreover, which scenario presented the best performance for this instance.

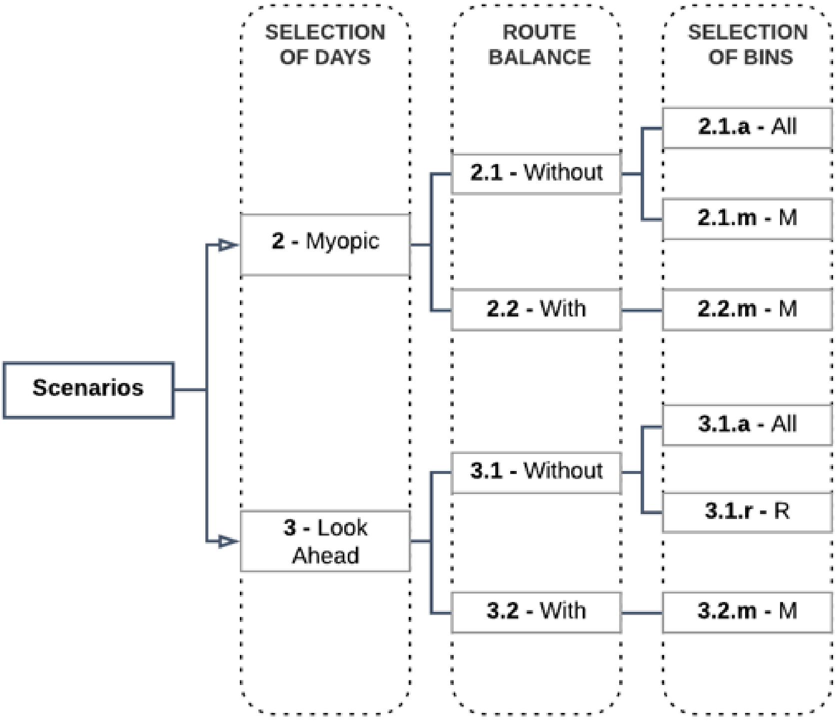

Figure 25 - Updated scenario tree with the best scenarios

The following analysis is made according to the indicators considered as most relevant for the assessment of the system's performance. As previously mentioned, ERSUC believes that the most important KPIs for analysis are those mainly related to the operation's efficiency, productivity and profitability. Therefore, here we will analyze the average vehicles usage rate, the average kg per km ratio and, lastly, the operation's total profit. Figure 26 shows the aforementioned KPIs for the current situation (CS) and for those scenarios considered to be the best scenarios.

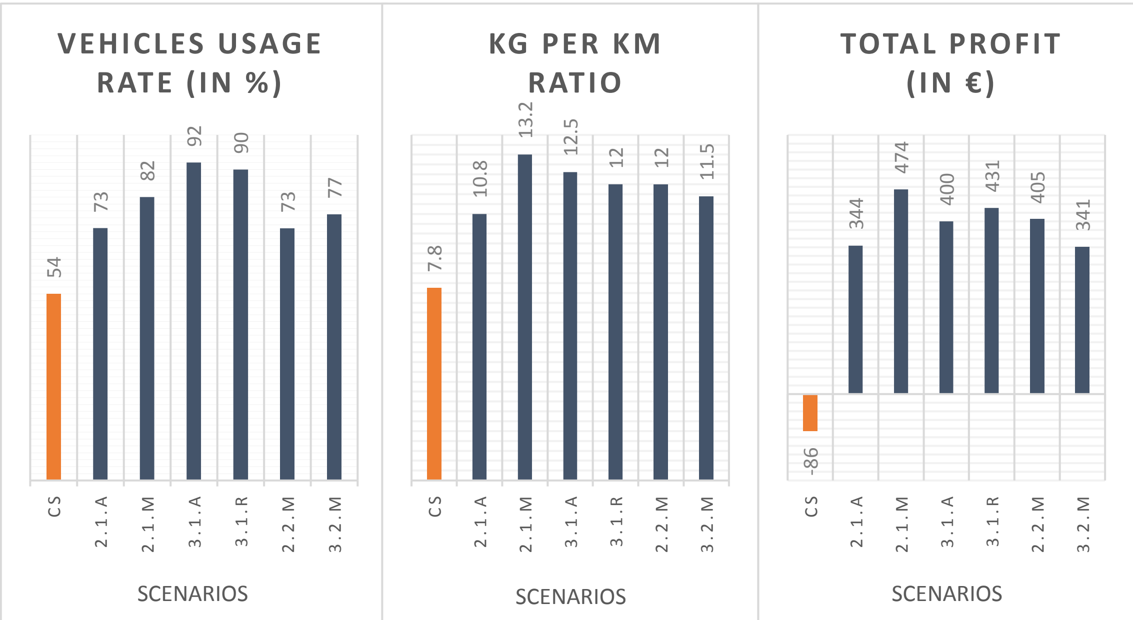

Figure 26 - Main KPIs comparison for Soure

Through Figure 26, it is possible to observe that, for the presented KPIs, all the simulated scenarios had a better performance compared to the current situation faced by the company. However, looking only at the scenarios results, it is noteworthy that scenarios 2.1.A and 3.1.A (considered at first to be the nearest optimal scenarios of the MYOPIC and LOOK AHEAD approaches, respectively) do not provide the best overall results when compared to other scenarios of the same approaches. For the MYOPIC APPROACH scenarios, this is justified since that scenario 2.1.A performs an “extra route” right on the following day of the first route performed, which is not usual to occur considering that all bins in this case are inputted into the model, i.e., first bins selection rule. However, in an in-depth analysis of the scenarios results (see attachment 1), it is possible to verify that a particular bin is not collected on the first route performed and, by not being collected, it presents a risk of overflow on the following day, forcing the model to perform the “extra route”. Since only one bin is required to be collected for the “extra route” and most of the bins were already collected the day before, such situation did not result in a favorable outcome for scenario 2.1.A, reducing its performance in the KPIs analyzed. In addition, as scenarios 2.1.M and 2.2.M follows the second bins selection rule methodology, i.e., inputting the model not with all bins but only those above a filling threshold, the “extra route” is eliminated since the bin that becomes required to collect it and forces a route to occur is already collected by the first route. For the LOOK AHEAD APPROACH scenarios, this can be justified by two aspects: (1) scenario 3.1.R, by considering the relation between distance and fill-level, i.e., third bins selection rule, allows the model to consider bins close to other bins, which enables the collection of additional waste without significantly increasing the distance travelled to do so. And (2) a route is additionally performed by scenario 3.1.R when compared to scenario 3.1.A which, analyzing its results (see attachment 1), it is possible to verify that the average vehicles usage rate and the kg per km ratio were maintained, leading to a favorable route for its solution.

Lastly, although no scenario shows a dominant performance, it is possible to conclude that scenario 2.1.M presents the best performance for Soure's instance. This conclusion is supported by the fact that scenario 2.1.M achieves the highest kg per km ratio (13.2) and provides the highest total profit obtained (474€). Moreover, despite not showing the most efficient vehicles usage rate, it remained among the best results of this KPI, only behind scenarios 3.1.A and 3.1.R. Such behavior is reasonable since these scenarios use the LOOK AHEAD APPROACH methodology, which, as the name says, can see ahead and cluster the bins collection, thus achieving a high vehicles usage rate per collection. Considering only the route-balanced scenarios (2.2.M and 3.2.M), scenario 2.2.M presents the best results for the kg per km ratio (12) and total profit (405€). Therefore, it becomes the most attractive scenario with route balance for Soure’s instance.

5.4 Condeixa Analysis

5.4.1 Current Situation

The operation performed by ERSUC to collect paper/cardboard in Condeixa is done through two periodic circuits, circuit C with 66 bins and circuit D with 55 bins. As previously seen for Soure's instance, the operation is carried out in a static way where all bins are visited when their associated circuit is performed (regardless of any information). This instance contains 121 bins in total and Figure 27 shows a map displaying all Condeixa's bins per circuit.

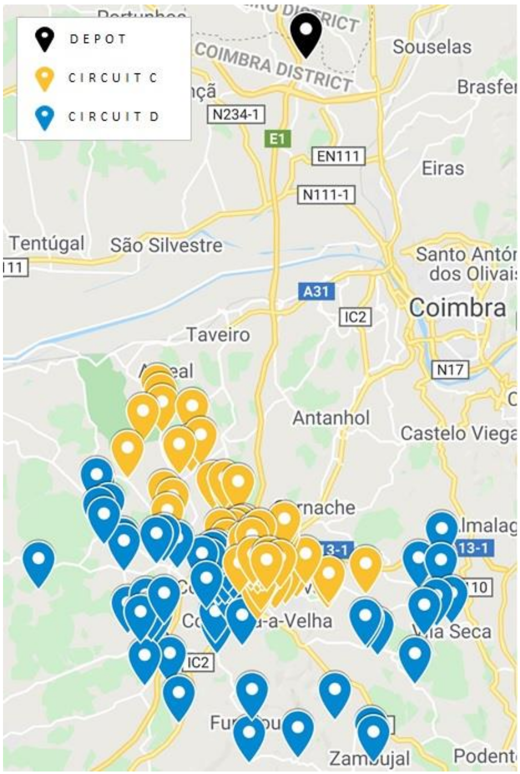

Figure 27 - Map of ERSUC´s paper/cardboard circuits for Condeixa

Table 13 presents the total and average results of Condeixa's current situation. When analyzing the results on Table 13, it is possible to see that 10 routes were performed for the planning horizon, collecting in total 16 145 kg of waste while travelling a distance around 1 213 km. Two factors are important for discussion here: (1) Although the operation shows an average profit of 74€ per route, in an in-depth analysis (see attachment 2) it is verified that 2 of the 10 routes presented loss to the company; and (2) On average, only about 73% of the vehicle's total capacity was actually used. Both factors support the conclusion that, despite performing a profitable operation as a whole, there is a great margin for improvement to be explored here. This because an increase in the vehicles usage rate can allow a more efficiently performance of the routes that directly affect each one of them at an economic level. Moreover, may even lead to an operation with fewer number of routes required for the same period of time.

Table 13 - Condeixa's current situation

KPI	TOTAL (28 days)	AVERAGE (per collection day)
Number of routes	10	-
Vehicles used	10	1
Attended bins	614	61
Weight (kg)	16 145	1 614
Distance (Km)	1 213	121
Duration (h)	-	6.1
Ratio (Kg/Km)	-	14.1
Vehicles usage rate (%)	-	73
Profit (€)	742	74

Lastly, it is also interesting to analyze the bins fill-levels status at the time of their collection. Table 14 summarizes the records of the bins fill-levels per circuit for all routes performed in the planning horizon. When looking at the percentages of each class, it is possible to verify that most of the bins collected by the company showed a considerably low fill-level, just as previously observed in Soure. More than 50% of the bins were classified as having a low fill-level at the moment of their collection, i.e., somewhere between 0 and 25%. Meanwhile, only 8% of the bins were classified as full, i.e., somewhere between 75 and 100%.

Table 14 - Bins fill-levels for circuits C and D

CLASS	CIRCUIT C	CIRCUIT D	TOTAL	(%)
0% - 25%	192	149	341	51%
25% - 50%	63	66	138	19%
50% - 75%	97	48	65	22%
75% - 100%	37	16	36	8%

5.4.2 Condeixa Scenarios Results

Since it was previously concluded that certain scenarios are not valid to continue exploring, the remaining scenarios will be here analyzed for Condeixa's instant. Among the three initial approaches, only two of them were considered relevant for further analysis: The MYOPIC APPROACH and the LOOK AHEAD APPROACH. Moreover, as already mentioned, within these approaches there are scenarios that, by proving a poor performance for a small instance, it is expected that such occurrence will be amplified in a larger instance. Thus, for each approach only three scenarios are considered worth to explore, resulting in a total of six scenarios for analysis.

As for Soure's instance, the results analysis is divided into scenarios without route balance (Table 15) and with route balance (Table 16).

Table 15 - Condeixa' s results for scenarios without route balance

KPI		SCENARIO 2.1.A Myopic	SCENARIO 2.1.M Myopic	SCENARIO 3.1.A Look Ahead	SCENARIO 3.1.R Look Ahead
TOTAL	Profit (€)	1 237	1 190	1 236	1 242
	Number of routes	10	10	10	10
	Attended bins	574	445	574	535
	Weight (kg)	17 942	17 183	17 930	17 627
	Distance (Km)	936	891	936	893
AVERAGE	Min shift duration (h)	4.9	4.1	4.6	4.1
	Max shift duration (h)	5.8	5.3	5.8	5.6
	Ratio (Kg/Km)	19.2	20.1	19.2	19.7
	Vehicles used	2	1	2	2
	Vehicles usage rate (%)	82	81	82	80
	Computational time (s)	10 472	1 991	10 580	6 156
	Gap	0.0	0.0	0.0	0.0

First, looking only at the scenarios that follow the MYOPIC APPROACH (2.1.A and 2.1.M), both scenarios differ only in the type of bins selection rule used. Scenario 2.1.A considers all bins to input the model, i.e., first bins selection rule, while scenario 2.1.M dynamically considers certain bins according to their fill-level, i.e., second bins selection rule. As previously explained in section 4.3 the bins selection rules were developed in order to establish the possibilities to deal with issues regarding the computational time and, here, we can verify it prosper applicability. By not having restrictions about which bins to consider, scenario 2.1.A provides a more profitable performance (1 237 vs. 1 190 €) but, as expected, obtains a much higher average computational time (10 472 vs. 1 991 seconds). The prosper application of the second bins selection rule can be justified by the fact that a large discrepancy is observed in the computational time of the two scenarios but there is no significant impact on other KPI, maintaining the quality of the solution. In conclusion, scenario 2.1.M not only achieved a higher kg/km ratio (20.1 vs. 19.2) but obtained only 1% difference in the vehicle usage rate average (81 vs. 82%), providing a more efficient performance when compared to scenario 2.1.A. Now looking at the scenarios that follow the LOOK AHEAD APPROACH (3.1.A and 3.1.R), it is visible that no major difference can be found between them, so let us just highlight what is important to mention here: Although the results are very similar, scenario 3.1.R obtained a higher kg/km ratio (19.7 vs. 19.2) and, therefore, higher profit for the planning horizon (1 242 vs. 1 236 €). Due to the bins selection rule applied in this scenario, i.e., the third selection rule, these results can be justifiable by the fact that the rule considers not only the bins mandatory to collect (those which are expected to overflow) but also the ones around them. Thus, it possible to collect more waste while the distance travelled to do so is practically minimal. Such methodology also allowed the significant decrease in the average computational time required to achieve the optimal routes solutions (6 156 vs. 10 580 seconds). This because the third bins selection rule also reduces the possibilities of solution by giving to the model cluster bins with the ones mandatory to collect. Generally, the model will opt to collect bins close to other bins since, as mentioned above, it will collect more waste at a minimum distance. Considered the aspects previously described and, although scenario 3.1.A is considered the optimal situation of the LOOK AHEAD APPROACH, it is possible to state that scenario 3.1.R becomes more attractive in terms of performance than scenario 3.1.A.

We then proceed to analyze the two previously selected scenarios that shown the best performances for modelling with the route balance concept applied. Table 16 presents the scenarios results that follow a methodology with route balance, namely scenarios 2.2.M and 3.2.M which have the same bins selection rule applied, i.e., the second one, but different approaches: The MYOPIC APPROACH for scenario 2.2.M and the LOOK AHEAD APPROACH for scenario 3.2.M.

Table 16 - Condeixa' s results for scenarios with route balance

KPI		SCENARIO 2.2.M Myopic	SCENARIO 3.2.M Look Ahead
TOTAL	Profit (€)	1 189	1 117
	Number of routes	9	10
	Attended bins	449	428
	Weight (kg)	16 910	17 132
	Distance (Km)	859	958
AVERAGE	Min shift duration (h)	4.8	4.5
	Max shift duration (h)	5.1	4.5
	Ratio (Kg/Km)	20.7	18.2
	Vehicles used	1	2
	Vehicles usage rate (%)	86	78
	Computational time (s)	6 860	14 162
	Gap	1.1	4.2

Although both scenarios have similar results, scenario 2.2.M presents a better performance for the kg/km ratio (20.7 vs. 18.2), the vehicle usage rate (86 vs. 78%) and the total profit achieved (1 189 vs. 1 117€). Regarding the computational time required, scenario 2.2.M maintains the best performance achieving a lower average computational time (6 860 vs. 14 162 seconds) and thus, allowing a decrease in the gap value (1.1 vs. 4.2). It is also important to mention that although scenario 2.2.M shows a small variation between the routes' minimum and maximum duration, scenario 3.2.M shows no variation, reaching a solution where the routes have practically the same duration. However, this is not enough to state that scenario 3.2.M presents the best performance since, for the other KPIs analyzed, such behavior is not verified. Therefore, it can be concluded that scenario 2.2.M operates a more attractive performance when compared to scenario 3.2.M.

5.4.3 Condeixa Scenarios Overall Comparison

Summarizing the conclusions obtained above for Condeixa's instance, it was proved the prosperous application of the bins selection rules whereby the purpose of reducing the computational time is achieved without significantly affecting the solution's quality. In fact, given the problem complexity and the instance size, in some cases even improved the scenarios performance. Thus, it was also concluded that:

- For the scenarios without route balance, scenario 2.1.M provided the best performance.
- For the scenarios with route balance, scenario 2.2.M provided the best performance.

The purpose of this section is therefore to conclude on three aspects: (1) Whether the scenarios presented a better performance than the current situation; (2) Determine the best overall scenario for Condeixa's instance; and (3) Assess the route balance impact on the solutions in terms of route duration variability. Figure 28 shows the performance of each scenario and the current situation (CS) for the main KPIs that are related to the profit obtained in their operation: Average ratio of kg per km; Average vehicle usage rate; and Total profit.

Figure 28 - Main KPIs comparison for Condeixa

Initially, according to the KPIs presented in Figure 28, it is possible to conclude that all scenarios in Condeixa's instance achieved a more favorable performance when compared to the current situation. However, to compare only the scenario results, it is necessary to consider the KPIs related to the solution method, namely the computational time and gap. Therefore, Figure 29 shows a graph with the scenario's performance for the average computational time and gap.

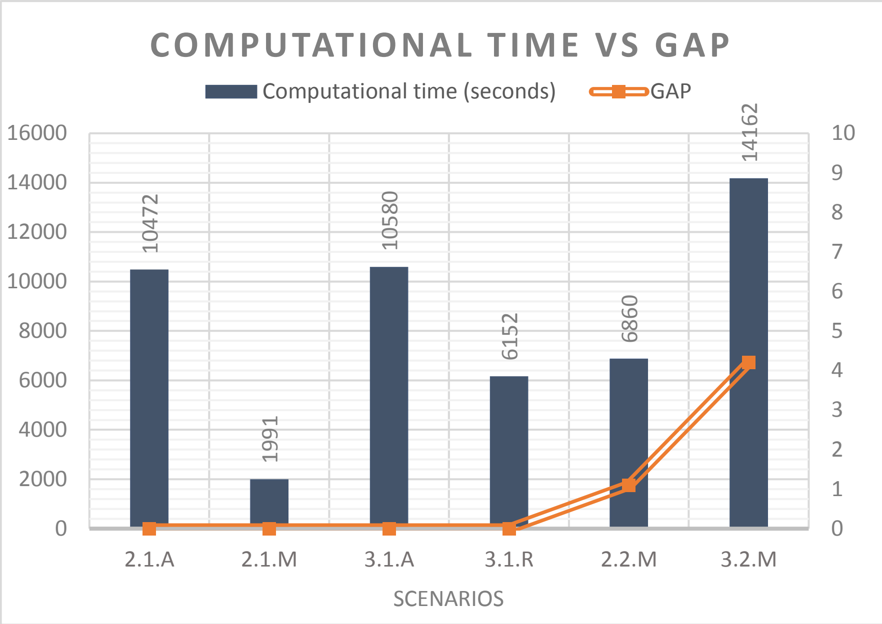

Figure 29 - Computational time and GAP comparison for Condeixa

Considering the above Figure 28 and Figure 29, the following aspects are highlighted:

- The highest total profits were achieved by scenarios that consider the first and third bins selection rules. This is reasonable since the first rule considers all bins, inputting the model with the maximum number of bins, and the third rule considers bins close to the mandatories to collect, allowing a higher collection of waste for a practically minimum distance.
- Scenario 3.2.M had the worst performance in all the KPIs analyzed.
- Scenario 2.2.M presents the best average vehicles usage rate (86%) and the best average kg per km ratio (20.7), but an intermediate performance in the average computational time (6 860 seconds) and gap (1.1).
- Scenario 2.1.M presents an intermediate performance for the vehicles usage rate (81%) and a considerably good performance in the kg per km ratio (20.1). Moreover, this is the scenario with the lowest average computational time (1 991 seconds) and no gap was observed in its solutions.

These results support the conclusions previously obtained. It is expected that scenarios with route balance will have a higher computational time and gap in the solutions since its application restricts the solutions in terms of route duration, making the model more demanding and complex. Thus, if we consider the computational time more significant than other KPIs (given the nature of the problem at hand being a real-world problem), scenario 2.1.M becomes the most attractive for Condeixa's instance. Lastly, it is worth to study how much the route balance is impacting the solutions in terms of route duration. Figure 30 introduces a graph with the difference between the minimum and maximum average route duration per scenario.

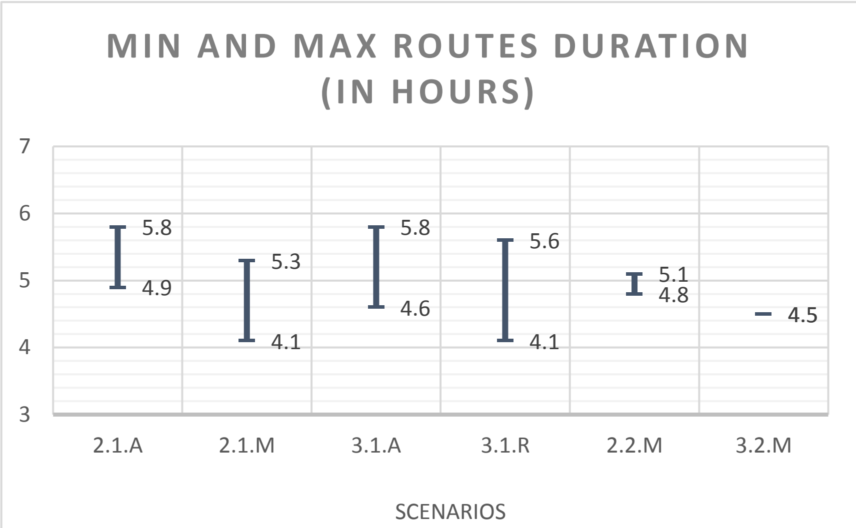

Figure 30 - Variation of the routes' average duration for Condeixa

As expected, scenarios that include the route balance concept in their formulation (2.2.M and 3.2.M) provide greater precision regarding the routes' average duration. Moreover, scenario 3.2.M was the most precise and did not present any variation in its solution. For the scenarios without route balance, scenario 2.1.A provides the lowest average variation. Thus, here we can verify the successful application of the route balance concept that, although it may affect the solution's quality and the performance in other KPIs, significantly reduces the variations in the routes' durations. However, it is noteworthy that scenarios without the concept applied showed no major discrepancy in the duration of the routes and not exceeded the collection team's workload (7 hours/day).

5.5 Soure + Condeixa Analysis

Since ERSUC does not perform the collection operation of Soure and Condeixa together as a whole, the current situation corresponds to the sum of both municipalities (Table 8 + Table 13). As already mentioned, the merging of the two municipalities was applied in order to assess the benefits of considering them simultaneously instead of operating separately. Therefore, we proceed to the presentation of the results for Soure + Condeixa' s instance, containing 219 bins.

5.5.1 Soure + Condeixa Scenarios Results

As before, the analysis of the scenarios will be divided into two parts, depending on whether the route balance concept is applied. Table 17 presents the results for the scenarios that do not apply the route balance in the model, namely scenarios 2.1.A, 2.1.M, 3.1.A and 3.1.R.

Table 17 - Soure + Condeixa' s results for scenarios without route balance

KPI		SCENARIO 2.1.A Myopic	SCENARIO 2.1.M Myopic	SCENARIO 3.1.A Look Ahead	SCENARIO 3.1.R Look Ahead
TOTAL	Profit (€)	1 595	1 589	1 526	1 632
	Number of routes	14	14	15	16
	Attended bins	950	724	989	1 065
	Weight (kg)	26 969	26 957	27 726	29 574
	Distance (Km)	1 670	1 675	1 831	1 949
AVERAGE	Min shift duration (h)	4.9	5.1	4.7	6.0
	Max shift duration (h)	7.9	6.3	7.9	7.4
	Ratio (Kg/Km)	16.2	15.6	15.1	14.9
	Vehicles used	3	2	3	2
	Vehicles usage rate (%)	88	87	84	84
	Computational time (s)	14 400	6 839	14 400	14 400
	Gap	3.2	1.0	4.3	3.5

When comparing the four scenarios presented above, it can be observed that the scenarios following the MYOPIC APPROACH methodology (2.1.A and 2.1.M) provides a better performance for the kg per km average ratio (16.2 and 15.6 vs. 15.1 vs. 14.9) and the average vehicles usage rate (88 and 87 vs. 84 %). In addition, these are the scenarios with the lowest gap obtained in their solutions (3.2 and 1.0 vs. 4.3 vs. 3.5). Since the present instance represents the largest instance studied in this work, it is expected that the maximum computational time established (14 400 seconds) will eventually be achieved by the scenarios and, as a consequence, will lead to gap in the solutions. It is worth noting that, despite presenting gap, scenario 2.1.M obtains the lowest value (1.0) and is the only scenario that did not reach the maximum computational time on all days of collections performed. This can be justified by its average computational time remaining below the established limit, which is 14 400 seconds. Lastly, scenario 3.1.R presents the highest total operating profit (1 632 €) and as already mentioned, this is a reasonable result since the scenario applies the third selection rule, enabling the collection of more waste at a shorter distance and, therefore, increasing the operation's profit.

Table 18 presents the results with route balance obtained when simulating scenarios 2.2.M and 3.2.M. These scenarios are designed with a more complex and demanding model due to two reasons: (1) The present instance has the initial set with the largest number of bins; and (2) It includes the route balance application into the model. Thus, when the model was run with the pre-established computational time limit of 14 400 seconds, none of the scenarios achieved solutions. To overcome this situation, the model was then solved considering now a maximum limit of 36 000 seconds. However, since the LOOK AHEAD APPROACH requires a model even more complex when compared to the MYOPIC APPROACH, by combining with the two factors previously mentioned, such an alteration was not able to accomplish a solution for scenario 3.2.M (that follows the LOOK AHEAD APPROACH methodology). Therefore, it is not possible to apply a comparison in this situation. The performance of scenario 3.2.M will be analyzed in the next section for the main KPIs considered relevant in this work. It is noteworthy that, despite not reaching the new computational time limit for every day performed (36 000 seconds per collection day), the scenario reaches a significant average value of 25 276 seconds.

Table 18 - Soure + Condeixa' s results for scenarios with route balance

KPI		SCENARIO 2.2.M Myopic	SCENARIO 3.2.M Look Ahead
TOTAL	Profit (€)	1 526	NO SOLUTION
	Number of routes	16	
	Attended bins	743	
	Weight (kg)	28 792	
	Distance (Km)	1 961	
AVERAGE	Min shift duration (h)	5.4	NO SOLUTION
	Max shift duration (h)	5.4	
	Ratio (Kg/Km)	14.0	
	Vehicles used	2	
	Vehicles usage rate (%)	77	
	Computational time (s)	25 276	
	Gap	14.5	

5.5.2 Soure + Condeixa Overall Comparison

So far, scenario 2.1.M was considered to provide the best overall performance while scenario 3.1.R presented the operation with the highest total profit for the planning horizon. To complement the analyses, all scenarios simulated for the present instance (2.1.A, 2.1.M, 3.1.A, 3.1.R and 2.2.M) are globally compared for the main KPIs together with the current situation (CS), assumed to be the sum of the two municipalities. Figure 31 displays the current situation and the scenario results for the KPIs kg per km average ratio, average vehicles usage rate and total profit. Figure 32 introduces the scenarios' computational time versus the gap achieved (both on average). As we can see in Figure 31, all the scenarios present a superior performance over the current situation assumed for Soure + Condeixa. Also, although it does not provide the best results for the three KPIs analyzed, scenario 2.1.M presents the best computational time and gap (see Figure 32). In the detailed analysis of the results, it was observed that, despite scenario 3.1.R having the highest total operating profit, it shows a lower average profit per collection day when compared to scenario 2.1.M (see attachment 3). Moreover, scenario 2.1.M presented the higher average kg per km ratio (15.6 vs. 14.9) and vehicles usage rate (87 vs. 84%), both KPIs strongly related to operation's efficiency and profitability. Also, by eliminating scenario 2.2.M from the analysis, the comparison would be only between the route-balanced scenarios and such a comparison have already been made in the previous section. Therefore, the conclusion that scenario 2.1.M provide the best performance for the present instance is maintained.

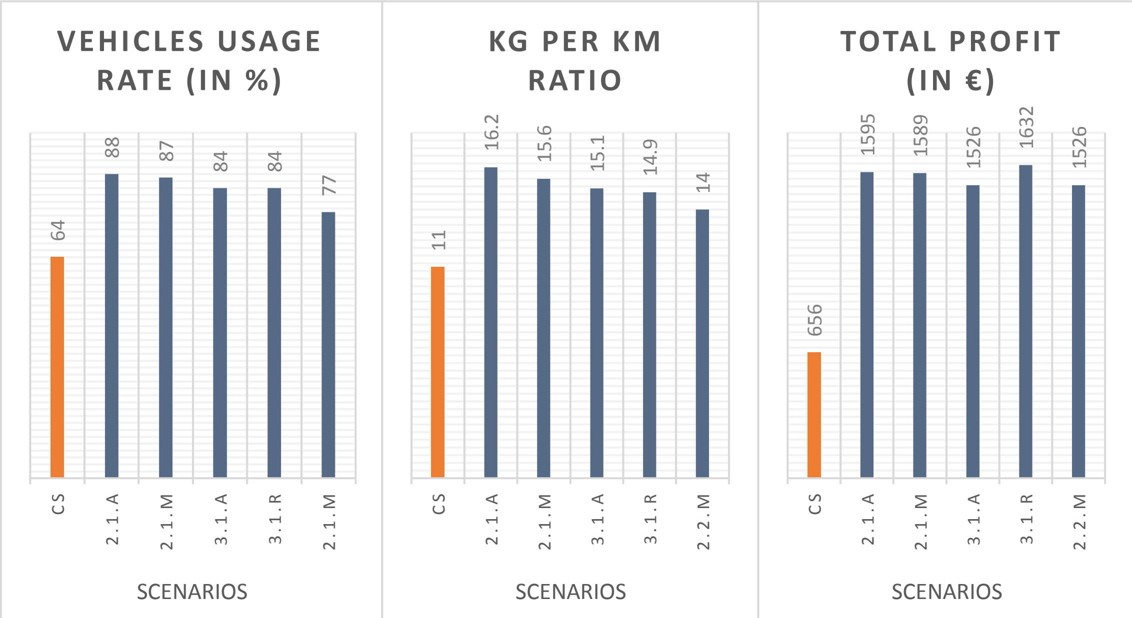

Figure 31 - Main KPIs comparison for Soure + Condeixa

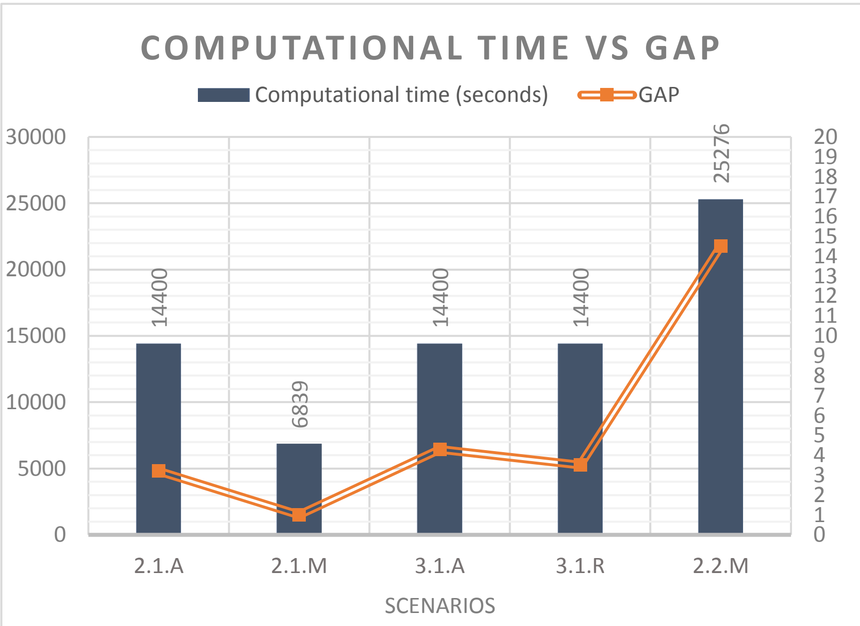

Figure 32 - Computational time and GAP comparison for Soure + Condeixa

Next, to verify if the route balance application into the model satisfies the purpose of providing more balanced routes, Figure 33 displays the scenario's average maximum and minimum duration of the routes. As expect, scenario 2.2.M by applying route balance constraints, does not show any variation in its solutions, being the most accurate result achieved. Thus, the scenario respects the two conditions set by the route balance formulation which: (1) restricts the solutions in terms of maximum and minimum collection time allowed, 7 and 4 hours, respectively; and (2) whenever using two or more vehicles for a collection day, the routes must be designed as balanced as possible.

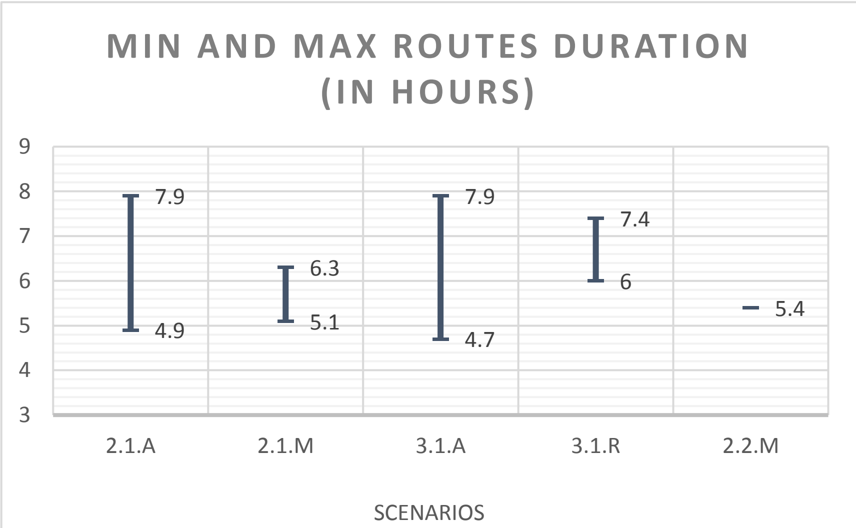

Figure 33 - Variation of the routes' average duration for Soure + Condeixa

For scenarios without route balance (2.1.A, 2.1.M, 3.1.A and 3.1.R), none of them presented an average duration below the minimum limit considered in the route balance formulation, even without the additional constraints to force the conditions previously mentioned. However, since we are looking at average values, in the detailed analysis of the results it is possible to observe the performance of routes with less than 4 hours of duration (see attachment 3). Regarding the maximum limit, we can see that scenario 2.1.M is the only one which does not exceed the 7 hours' average duration, also providing the smallest variation of all scenarios (without considering the scenario with route balance, 2.2.M).

As in the previously instances, it can be concluded that scenario 2.1.M provides the most adequate and attractive performance for Soure + Condeixa's instance. Since scenario 2.2.M is the only one to provide a route-balanced solution, it becomes the best scenario of this type and also proves that scenario 3.2.M does not support a large sized instance (by not achieving a solution, even with the increase of the daily computational time limit).

5.6 Final Discussion

For the three instances analyzed, the scenario that follows the myopic approach and applies the second bins selection rule (by fill-level), i.e., 2.1.M, was found to be the most promising scenario in terms of performance. The same happened for the scenarios with the route balance concept applied to which it was verified that the best performance is provided by scenario 2.2.M. Therefore, the next analyses will be developed considering the results of scenarios 2.1.M and 2.2.M.

As already mentioned, one of the purposes of this work is to assess how the two municipalities under analysis will operate as one. Table 19 presents the results comparison of the best scenarios when applied to Soure and Condeixa separately and together (Soure + Condeixa).

Table 19 - Soure e Condeixa VS Soure + Condeixa

2.1.M		KPI	2.2.M	
Soure e Condeixa	Soure + Condeixa		Soure e Condeixa	Soure + Condeixa
1 594	1 526	Profit (€)	1 664	1 589
16	16	Number of routes	16	14
28 087	28 792	Weight (kg)	27 995	26 957
1 808	1 961	Distance (Km)	1 726	1 675
16.6	14.0	Ratio (Kg/Km)	16.9	15.6
80	77	Vehicles usage rate (%)	82	87

It is expected that operating Soure and Condeixa simultaneously would be result in a more profitable outcome. However, we can see that for both scenarios (with and without route balance), operating Soure and Condeixa separately presents not only a higher profit (1 594 vs. 1 526 and 1 664 vs. 1 589€), but also a higher kg/km ratio (16.6 vs. 14.0 and 16.9 vs. 15.6). Regarding the vehicles usage rate, scenario 2.1.M maintains the best performance for operating Soure and Condeixa separately (80 vs. 77%). Under scenario 2.2.M, such behavior cannot be verified (82 vs. 87%). Moreover, given the larger size of Soure + Condeixa' s instance, its solutions presented a higher gap value to which the maximum computational time was reached for most of the days. This means that the solutions were more distant from the optimal solution when compared with the results for Soure and Condeixa, affecting the accuracy of the presented comparison. Considering the aforementioned aspects, it is possible to say that operating Soure and Condeixa separately is not only more profitable but also can improve the performance in other KPIs. However, we have to take into account the fact that Soure + Condeixa dimension has influenced the results achieved.

The next analysis focuses on the bins fill-levels status at the time of collection. As mentioned in Chapter 2, ERSUC noticed that they constantly visit empty or mostly empty bins in their collection operations. In fact, the fill-levels of the current situation faced by the company were previously presented for Soure and Condeixa instances. For the medium sized instance (Condeixa), Figure 34 introduces the difference between the bins fill-levels in the current situation versus in the best scenarios simulated (2.1.M and 2.2M).

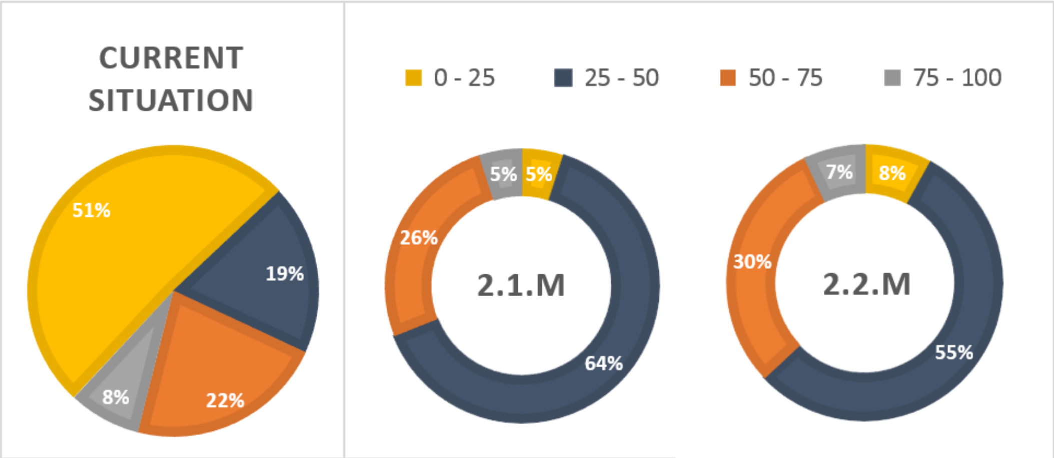

Figure 34 - Bins fill-levels at the moment of collection for Condeixa

As we can see, the solution method applied by both scenarios drastically minimized the collection of bins with a fill-level between 0 and 25% (51 vs. 5 and 8%). It is also observed that the majority of the collections performed are now between 25 and 50%. This result is reasonable since the approaches' methodology is based on the condition of preventing overflow by performing a collection when any bin is at risk of overflow. For the collection of these bins and to improve the operation profitability, the model chooses to visit partially full bins that become attractive considering the ones mandatory to collect. As a result, it is expected that the scenarios' outcome will not be majority for higher fill-levels.

For example, Figure 35 presents the first two routes obtained from Condeixa's 2.1.M scenario. Route 1 predicts the overflow of two bins while Route 2 predicts three bins at risk. In both cases, these bins show a fill-level between 75 and 100%. However, the remaining bins visited have been considered according to two aspects: (1) the selection rule applied to which, in this case, eliminates bins with a fill-level below 30% (forming a subset); and (2) the path to be followed in order to collect the bins at risk. Thus, the attractiveness of the bins after the subset is formed is not only based on the fill-level but also on the impact in terms of the operation's profit, i.e., considering the weight/distance ratio.

Lastly, since one of the main objectives of the present work is the prevention of overflows, it is important to mention that all the simulated scenarios in this work had no overflow bins when considering the difference between the estimated weight and the actual weight being collected.

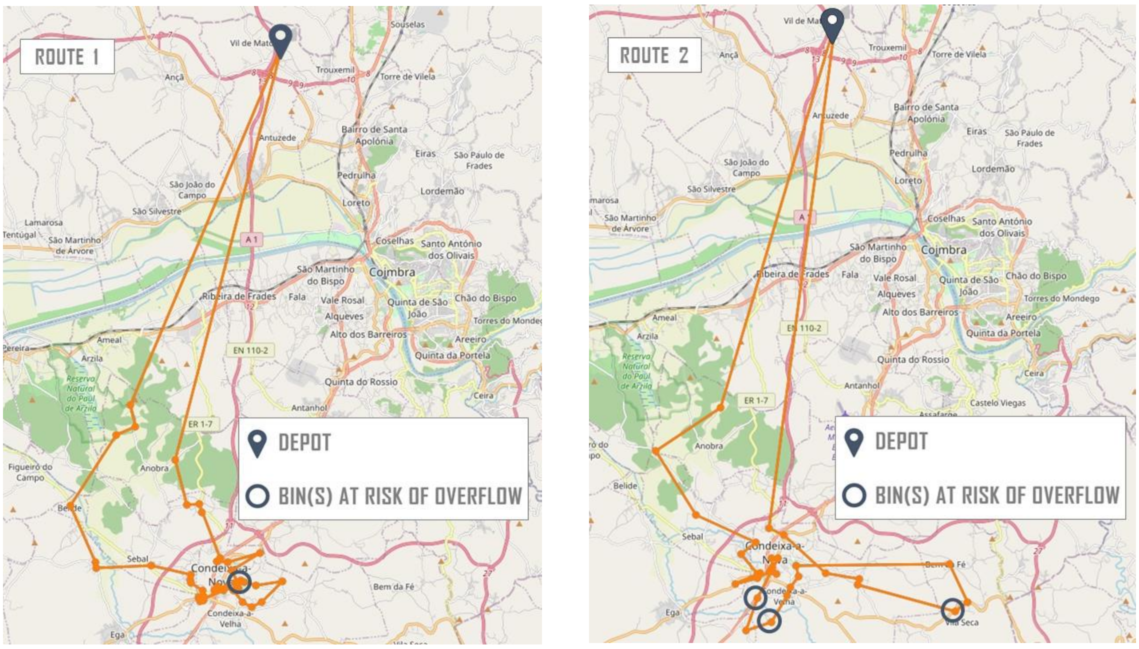

Figure 35 - Scenario 2.1.M first and second routes for Condeixa

5.7 Chapter Conclusions

This section presents the main findings of the solution method when applied to the waste collection context. Using real-world instances, three approaches and three types of branches have been tested.

For the first and smaller instance, the Everyday Approach showed a significantly poorer result compared to the other two approaches. As already mentioned, larger instances tend to amplify the performance behavior of smaller instances and, in this way, the decision to discard the Everyday Approach for future developments was supported. The same occurred for the branches under investigation where, combined with the approaches, a type of triage phase was performed in order to define which scenarios were worth considering. As a result, a total of six types of scenarios were defined, encompassing all the three branches introduced. Among the scenarios analyzed, the most attractive solution found for each instance was unanimous, having scenario 2.1.M as the best without route balance and scenario 2.2.M as the best with route balance applied. Although it does not consider the time element in its formulation, i.e., it has no restrictions on the duration of routes, it was observed that scenario 2.1.M does not violate the minimum and maximum duration limits established in the route balance formulation (on average). However, this does not guarantee that the limits are respected for the routes simulated. In fact, such violation was observed for the instances of Condeixa and Soure + Condeixa. For the route-balanced scenarios, no violation of the restrictions was observed and, moreover, the solutions have shown a minimal or no variation at all in the average duration of the routes. This demonstrates that the route balance concept was generally well formulated, respecting the two purposes of its application, which are: (1) minimize the variation of the route's duration and (2) restrict the duration according to a minimum and maximum pre-established limit.

Regarding the bins selection rule branch, the two rules that build a subset through a heuristic procedure (M and R) have proved to be very effective. As mentioned, the goal of dynamically pre-selecting the bins that the model will consider was to reduce the computational time needed to provide the optimal or close to optimal solution. The second selection rule (M) was found to be the most attractive one considering the impact on the main KPIs under analysis. However, it is important to note that the third rule (R) has demonstrated, in some cases, the potential for achieving a higher total profit when compared to scenarios that apply the second rule.

Another aspect explored in this work was the inefficiency of ERSUC's operations in collecting/visiting empty or practically empty bins. With the application of the solution method, it was possible to improve the bins fill-levels upon the time of collection, mostly from the first category (0 - 25%) to the second category (25 - 50%). This result is quite natural since there are usually only a few bins at risk of overflow and, therefore, a larger number of bins are visited considering the path to collect the mandatory ones and the profit maximization of the operation. Furthermore, all the simulated scenarios do not visit empty bins, which already represents a great improvement in terms of efficiency. It is also noteworthy that the solution method has provided a significant improvement in terms of the operation's profitability when compared to the current situation faced by the company. For the municipalities of Soure and Condeixa, quantitative data show that the improvement in the operations' total profit was about 450% and 60%, respectively (both considering the best scenario result, 2.1.M).

Lastly, the analyses of Soure and Condeixa being operated simultaneously were applied. Against what was expected, the best results achieved were for the operation of the municipalities separately. However, we have to consider that the clusterization of the municipalities creates a considerably large instance, implying higher gap values in its solutions and therefore, negatively influencing the performance of the scenarios in the analyzed KPIs.

6. CONCLUSIONS

Nowadays we live in a time of constant search for optimization of processes and environmental awareness around the world. The waste produced by human activity is an environmental problem of great concern due to the dramatic population growth and expansion of cities. The companies responsible for the management of this waste face major challenges in their collection processes, being mainly associated with uncertainty about the accumulation of waste in the bins and it is often operated through forecasts. As a result, the presence of uncertainty in the system leads to inefficiency in the use of their resources, to which excessive kilometers are typically taken for the collection of bins whose fill-level is low or even empty. One way to reduce this uncertainty is to explore electronic devices to access real-time information about the bins fill-levels and, therefore, optimize the collection routes based on this information.

In this way, the present dissertation intended to continue the work of Ramos et al., 2018 and Aguiar et al., in press in the exploration of the SWCRP, improving the approaches introduced and addressing some issues that have not yet been considered. The solution method was applied to a real case study (ERSUC) where three different sized instances were defined, and the following conclusions were reached:

- Operational management approaches: The approaches explored in this work are based on three types of methodology: (1) The Everyday approach that considers only the current day; (2) The Myopic approach that considers the current day plus the next day; and (3) The Look ahead approach that, as the name implies, is able to consider ahead in the time horizon. The Everyday approach demonstrated the worst performance for the smallest analyzed instance and therefore the discard for future development was supported based on the amplified behavior of the approaches at larger instances. The Myopic approach was considered the most attractive approach in terms of performance while the Look Ahead approach demonstrated an intermediate performance. It is important to note that this conclusion is supported by the analysis of several KPIs linked to efficiency, profitability, and computational performance. Thus, the Myopic approach presented in general the best results for the vehicle usage rate, kg per km ratio, total profit, computational time, and gap. However, the Look Ahead approach had compatible results with the Myopic approach and in some cases provided a higher operational profit. Still, its worse computational performance influenced the choice of the most attractive approach. The relevance of providing solutions as quickly as possible and as close to the optimum was strongly considered in this work since we are dealing with real world problem and it is necessary to take into account whether certain values are sustainable or not according to reality. Thus, due to the complexity and demanding methodology, the Look Ahead approach requires a longer computational time and consequently presents higher gaps, decreasing the quality of its solutions. In fact, for the largest instance it did not provide a solution when applied with the route balance formulation, even with the extension of the computational time allowed.

- BINS SELECTION RULES: Different ways of choosing which bins should be inputted into the model have been studied through three selection rules. As expected, the first rule that considers all bins in the initial set showed poor results in the computational time performance, influencing the gap values in its solutions, and thus decreasing their quality. The second selection rule that considers the bins by fill-level demonstrated an effective applicability whereby a significant reduction in the computational time required to reach a solution was observed. In addition, the second rule allowed the improvement of some KPIs analyzed due to their closer proximity to the optimal solution. The third and final rule did not generally stand out in any of the analyzed instances, consistently providing an average performance when compared to the other selection rules. However, it is worth pointing out that its methodology considers bins close to those mandatory to collect and in this way, enabled the increase in the operational profit. Our objective function seeks to maximize the operational profit obtained through the ratio between the weight collected and the distance traveled. Thus, the third rule takes advantage of the opportunity to collect more weight while the distance to do so is practically minimal.
- ROUTE BALANCE: By introducing the "time" element into the model formulation, some changes were necessary to apply as well as the addition of constraints regarding the routes' duration. In this work, the route balance concept was applied restricting the solutions in terms of duration through a predefined minimum and maximum limit. As expected, due to the higher complexity of the route-balanced scenarios, their performance was affected in the KPIs analyzed. The presence of such a concept led to higher gap values in the solutions and thus, justifies the slightly lower performance of the scenarios in the KPIs. However, the two purposes were successfully achieved by the model whereby it was possible to verify that the route-balanced scenarios presented solutions with a minimum or no variation at all regarding the average routes' duration and none of the solutions violated the predefined limits. Therefore, the conclusion that the route balance concept was generally well formulated in this work is supported.

Summarizing the main findings, scenarios 2.1.M and 2.2.M were defined as the most attractive scenarios for the case study under analysis, respectively without and with the route balance concept applied. One of the objectives of this work was to maintain the service level of the waste collection operation, namely in the prevention of bins overflow. This was verified for all simulated scenarios and under no circumstances was observed bins in overflow, demonstrating the effectiveness of the model formulation in this matter. A further issue discussed was the fill-level status of bins at the moment of collection. As already mentioned, one of the main issues in the waste management field is the travel of excessive kilometers for the collection of nearly or totally empty bins. The solution method showed an improvement regarding the status of the bins fill-levels collected by the model. It was observed the eradication in visiting empty bins and moreover, the upgrade in the majority category of the collected bins (from 0-25% to 25-50%). Lastly, it was discussed the clustering of the two municipalities analyzed in the present dissertation, Soure and Condeixa, so that they can be operated simultaneously. Such analysis originated from the interest of the waste management company ERSUC, which represents the real case study applied in this work. According to the results achieved, the best operational option remained to perform the collection by considering the municipalities separately. However, it is important to mention that having Soure and Condeixa combined, a considerably large instance is formed, which impacts on the quality of the simulated solutions due to the computational time limit and therefore gap.

As mentioned above, the real case study applied in this dissertation refers to the waste collection operations of the company ERSUC. The company noticed that it is currently facing inefficiency in its performance and therefore is interested in exploring the potential benefits of implementing volumetric sensors in the bins in order to gain access to real-time information regarding their fill-levels. Two relevant aspects for ERSUC's management have already been addressed above, namely the possibility of improving the status of the bins fill-levels collected (successfully achieved by the solution method) and the operational decision to manage the municipalities of Soure and Condeixa separately. For the scenarios considered as most attractive in this work (2.1.M and 2.2.M), the following quantitative data were achieved:

- IMPACT OF IMPLEMENTING VOLUMETRIC SENSORS: The real case study analyzed in the present work is mainly focused on the assessment of implementing volumetric sensors in the bins on request of ERSUC. Therefore, when comparing the current situation faced by the company with the best scenarios, the solution method estimates an improvement potential of 451% and 60% in terms of operational profitability for Soure and Condeixa, respectively. Regarding the efficiency and productivity of the operations, a potential increase in the vehicle's capacity utilization and the kg per km ratio was also achieved for both municipalities. For Soure, the results showed a 52% increase in the vehicles usage rate and 69% in the kg per km ratio. For Condeixa, the increase was of 18% and 47%, respectively. These factors support the conclusion that the implementation of volumetric sensors in the bins offers great potential for ERSUC, both in terms of profitability and operational efficiency.
- IMPACT OF THE ROUTE BALANCE: When considering the route balance option, it is expected that the operational profit will be lower due to the additional constraints on the collection routes. For Soure, such expectation was verified which estimates that the route balance implies a 15% decrease in the operational profit. However, this was not verified for Condeixa where the income was pretty much the same as the option without route balance.

For future work, it is suggested to investigate other methods to solve larger problems (such as the Soure + Condeixa instance), namely metaheuristics. The same applies to the third bins selection rule that was introduced in this work, i.e., the one that considers the bins by the relation between fill-level and distance. This because its methodology has shown a great potential to increase the collection's operational profit and yet it has not excelled itself among others KPIs. Lastly, regarding the VRPP model developed, it should be noted that its formulation does not consider traffic and street conditions. For example, schools usually have time constraints for the movement of special vehicles such as buses or collection trucks.

REFERENCES

Agência Portuguesa do Ambiente. (2014a). *Avaliação Ambiental do PERSU 2020: Relatório Ambiental Preliminar*. http://www.apambiente.pt/_zdata/AAE/PERSU 2020_RA_preliminar_25_08_14.pdf

Agência Portuguesa do Ambiente. (2014b). *Plano Estratégico para os Resíduos Sólidos Urbanos 2020: Versão de trabalho prévia à consulta pública e à Avaliação Ambiental Estratégica*. http://apambiente.pt/_zdata/DESTAQUES/2014/RelatorioPropostaPERSU2020_Fev14_v2 .pdf

Agência Portuguesa do Ambiente. (2019). *MUNICIPAL WASTE PRODUCTION AND MANAGEMENT*. https://rea.apambiente.pt/content/municipal-waste-production-and-management?language=en

Agência Portuguesa do Ambiente. (2020a). *Embalagens e Resíduos de Embalagens*. https://apambiente.pt/index.php?ref=16&subref=84&sub2ref=197&sub3ref=276

Agência Portuguesa do Ambiente. (2020b). *Reflexão Estratégica e Ajustamentos às medidas do PERSU 2020*.

Aguiar, A. R., Morais, C. S. De, Pereira, T. R., & Barbosa-Póvoa, A. P. (in press). *Searching for a solution method for the Smart Waste Collection Routing Problem*. Springer Proceedings in Mathematics & Statistics, in publication.

Amponsah, S. K., & Salhi, S. (2004). The investigation of a class of capacitated arc routing problems : the collection of garbage in developing countries. *Waste Management*, *24*, 711–721. https://doi.org/10.1016/j.wasman.2004.01.008

Anagnostopoulos, T., Kolomvatsos, K., Anagnostopoulos, C., Zaslavsky, A., & Hadjiefthymiades, S. (2015). The Journal of Systems and Software Assessing dynamic models for high priority waste collection in smart cities. *The Journal of Systems & Software*, *110*, 178–192. https://doi.org/10.1016/j.jss.2015.08.049

Anagnostopoulos, T., Zaslavsky, A., & Member, S. (2017). Challenges and Opportunities of Waste Management in IoT-Enabled Smart Cities : A Survey. *In IEEE Transactions on Sustainable Computing*, 2(3), 275-289. https://doi.org/10.1109/TSUSC.2017.2691049

Angelelli, E. (2002). The application of a vehicle routing model to a waste-collection problem : two case studies. *Journal of the Operational Research Society*. 53, 944–952. https://doi.org/10.1057/palgrave.jors.2601402

Anghinolfi, D., Paolucci, M., Robba, M., & Celeste, A. (2013). A dynamic optimization model for solid waste recycling. *Waste Management*, *33*(2), 287–296.

https://doi.org/10.1016/j.wasman.2012.10.006

Asefi, H., Shahparvari, S., & Chhetri, P. (2019). Integrated Municipal Solid Waste Management under uncertainty : A tri-echelon city logistics and transportation context. *Sustainable Cities and Society*, *50*(June), 101606. https://doi.org/10.1016/j.scs.2019.101606

Baldacci, R., Hadjiconstantinou, E., & Mingozzi, A. (2004). An exact algorithm for the capacitated vehicle routing problem based on a two-commodity network flow formulation. *Operations Research*, *52*(5), 723–738. https://doi.org/10.1287/opre.1040.0111

Baptista, S., Oliveira, R. C., & Zúquete, E. (2002). Discrete Optimization A period vehicle routing case study. *European Journal of Operational Research*, *139*, 220–229. https://doi.org/10.1016/S0377-2217(01)00363-0

Bautista, J., Fernández, E., & Pereira, J. (2008). Solving an urban waste collection problem using ants heuristics. *Computers & Operations Research, 35*, 3020–3033. https://doi.org/10.1016/j.cor.2007.01.029

Bektas, T., & Laporte, G. (2011). The Pollution-Routing Problem Tolga Bektas. *Transportation Research Part B: Methodological*, *45*, 1232–1250. https://doi.org/10.1016/j.trb.2011.02.004

Beliën, J., Boeck, L. De, Ackere, J. Van, Beliën, J., Boeck, L. De, & Ackere, J. Van. (2014). Municipal Solid Waste Collection and Management Municipal Solid Waste Collection and Management Problems : A Literature Review. *Transportation Science*, 48. https://doi.org/10.1287/trsc.1120.0448

Benjamin, A. M., & Beasley, J. E. (2010). Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. *Computers and Operations Research*, *37*(12), 2270–2280. https://doi.org/10.1016/j.cor.2010.03.019

Bing, X., Bloemhof, J. M., Rodrigues, T., Ramos, P., Barbosa-povoa, A. P., Yew, C., & Vorst, J. G. A. J. Van Der. (2016). Research challenges in municipal solid waste logistics management. *Waste Management*, 1–9. https://doi.org/10.1016/j.wasman.2015.11.025

Brouwer Y., Ramos T.R.P., Barbosa-Póvoa A.P. & Antunes A.P. (Submitted). Waste bin monitoring: is sensorization the best approach?. Submitted to Waste Management.

Bruecker, P. De, Belien, J., Boeck, L. De, Jaeger, S. De, & Demeulemeester, E. (2018). A model enhancement approach for optimizing the integrated shift scheduling and vehicle routing problem in waste collection. *European Journal of Operational Research*, 266(1), 278-290. https://doi.org/10.1016/j.ejor.2017.08.059

Environment Global Facilities. (2019). *Newsletter EGF nº3*. https://www.egf.pt/media/13114/egf-news-abr19.pdf

ERSUC. (2020). *Recolha Seletiva*. http://ersuc.pt/

Esmaeilian, B., Wang, B., Lewis, K., Duarte, F., Ratti, C., & Behdad, S. (2018). The future of waste management in smart and sustainable cities : A review and concept paper. *Waste Management*, *81*, 177–195. https://doi.org/10.1016/j.wasman.2018.09.047

Faccio, M., Persona, A., & Zanin, G. (2011). Waste collection multi objective model with real time traceability data. *Waste Management*, *31*(12), 2391–2405. https://doi.org/10.1016/j.wasman.2011.07.005

Ghiani, G., Laganà, D., Manni, E., Musmanno, R., & Vigo, D. (2014). Computers & Operations Research Operations research in solid waste management : A survey of strategic and tactical issues. *Computers and Operation Research*, *44*, 22–32. https://doi.org/10.1016/j.cor.2013.10.006

Gilardino, A., Rojas, J., Mattos, H., Larrea-gallegos, G., & Vázquez-rowe, I. (2017). Combining operational research and Life Cycle Assessment to optimize municipal solid waste collection in a district in Lima (Peru). *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2017.04.005

Golden, R. L. (2008). William Osler'S "the Nervousness of American Women." *History of Psychology*, *11*(1), 1–14. https://doi.org/10.1037/1093-4510.11.1.1

Groot, J., Bing, X., Bos-brouwers, H., & Bloemhof-ruwaard, J. (2014). Resources , Conservation and Recycling A comprehensive waste collection cost model applied to post-consumer plastic packaging waste. *"Resources, Conservation & Recycling," 85*(2014), 79–87. https://doi.org/10.1016/j.resconrec.2013.10.019

Gutberlet, J. (2018). Waste in the City: Challenges and Opportunities for Urban Agglomerations. *Urban Agglomeration*. https://doi.org/10.5772/intechopen.72047

Gutierrez, J. M., Jensen, M., Henius, M., & Riaz, T. (2015). Smart Waste Collection System Based on Location Intelligence. *Procedia - Procedia Computer Science*, *61*, 120–127. https://doi.org/10.1016/j.procs.2015.09.170

Hannan, M. A., Al, A., Hussain, A., Basri, H., & Begum, R. A. (2015). A review on technologies and their usage in solid waste monitoring and management systems : Issues and challenges. *Waste Management*, *43*, 509–523. https://doi.org/10.1016/j.wasman.2015.05.033

Harijani, A. M., Mansour, S., Karimi, B., & Lee, C. (2017). Multi-period sustainable and integrated recycling network for municipal solid waste – A case study in Tehran. *Journal of Cleaner Production*, 151. https://doi.org/10.1016/j.jclepro.2017.03.030

Hong, I., Park, S., Lee, B., Lee, J., Jeong, D., & Park, S. (2014). IoT-Based Smart Garbage System for Efficient Food Waste Management. *The Scientific World Journal*, 646953. https://doi.org/10.1155/2014/646953

Jatinkumar, P., Anagnostopoulos, T., Zaslavsky, A., & Behdad, S. (2018). A stochastic optimization framework for planning of waste collection and value recovery operations in smart and sustainable cities. *Waste Management*, *78*, 104–114. https://doi.org/10.1016/j.wasman.2018.05.019

Johansson, O. M. (2006). The effect of dynamic scheduling and routing in a solid waste management system. *Waste management, 26*, 875–885. https://doi.org/10.1016/j.wasman.2005.09.004

Karadimas, N. V, & Loumos, V. G. (2007). Optimal solid waste collection routes identified by the ant colony system algorithm. *Waste Management & Research*, 25, 139–147. https://doi.org/10.1177/0734242X07071312

Kim, B. I., Kim, S., & Sahoo, S. (2006). Waste collection vehicle routing problem with time windows. *Computers and Operations Research*, *33*(12), 3624–3642. https://doi.org/10.1016/j.cor.2005.02.045

Laporte, G. (2009). Fifty years of vehicle routing. *Transportation Science*, *43*(4), 408–416. https://doi.org/10.1287/trsc.1090.0301

Law, A. M. (2007). *Simulation Modeling and Analysis* (4th edn).

Liu, S., Zhang, Y., Liu, Y., Wang, L., & Vincent, X. (2019). An ' Internet of Things ' enabled dynamic optimization method for smart vehicles and logistics tasks. *Journal of Cleaner Production*, *215*, 806–820. https://doi.org/10.1016/j.jclepro.2018.12.254

Mamun, M. A. Al, M A Hannan, A. H., & Basri, H. (2015). Theoretical Model and Implementation of a Real Time Intelligent Bin Status Monitoring System Using Rule Based Decision Algorithms. *Expert Systems With Applications*. https://doi.org/10.1016/j.eswa.2015.11.025

Matl, P, Hartl, R. F. and Vidal, T. (2019). Computers and Operations Research Workload equity in vehicle routing: the impact of alternative workload resources. *Computers and Operations Research*, 110, 116-129. https://doi.org/10.1016/j.cor.2019.05.016

McLeod, F., & Cherrett, T. (2008). Quantifying the transport impacts of domestic waste collection strategies. *Waste Management*, *28*(11), 2271–2278. https://doi.org/10.1016/j.wasman.2007.09.041

Mes, M. (2012). Using Simulation to Assess the Opportunities of Dynamic Waste Collection. In: Bangsow S. (eds) Use Cases of Discrete Event Simulation. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-28777-0_13

Ministério do Ambiente Ordenamento do Território e do Desenvolvimento Regional. (2007). Plano Estratégico para os Resíduos Sólidos Urbanos (PERSU II). In *Diário da República*.

Ministério do Ambiente Ordenamento do Território e do Desenvolvimento Regional. (2011). Decreto-Lei nº 73/2011 de 17 de Junho. *Diário Da República*.

Mora, C., Manzini, R., Gamberi, M., & Cascini, A. (2013). *Production Planning & Control : The Management of Operations Environmental and economic assessment for the optimal configuration of a sustainable solid waste collection system : a ' kerbside ' case study*. *October 2014*, 37–41. https://doi.org/10.1080/09537287.2012.750386

Muyldermans, L., & Pang, G. (2010). On the benefits of co-collection : Experiments with a multi-compartment vehicle routing algorithm. *European Journal of Operational Research*, *206*(1), 93–103. https://doi.org/10.1016/j.ejor.2010.02.020

Nunes, B. M. (2017). *Evolução e Situação Atual dos RSU em Portugal, Estudo de Caso - Comparação dos Sistemas de RSU em Sintra e Munster*. https://run.unl.pt/bitstream/10362/22036/1/DissertaçãoBernardoNunesRS U.pdf.

Nuortio, T., Kytojoki, J., Niska, H., & Braysy, O. (2006). Improved route planning and scheduling of waste collection and transport. *Expert Systems with Applications*, *30(2)*, 223–232. https://doi.org/10.1016/j.eswa.2005.07.009

Packaging Recovery Organisation Europe. (2020). *The Green Dot Trademark*. https://www.pro-e.org/the-green-dot-trademark

Parlamento Europeu e do Concelho. (2018). DIRETIVA (UE) 2018/852 DO PARLAMENTO EUROPEU E DO CONSELHO de 30 de maio de 2018 que altera a Diretiva 94/62/CE relativa a embalagens e resíduos de embalagens. *Jornal Oficial Da União Europeia*.

Powell, W. B., & Jaillet, P. (1995). Stochastic and Dynamic Networks and Routing. Handbooks in Operations Research and Management Science, 8(C), 141-295. https://doi.org/10.1016/S0927-0507(05)80107-0

Ramos, T. R. P., de Morais, C. S., & Barbosa-Póvoa, A. P. (2018). The smart waste collection routing problem: Alternative operational management approaches. *Expert Systems with Applications*, *103*, 146–158. https://doi.org/10.1016/j.eswa.2018.03.001

Ramos, T. R. P., Gomes, M. I. and Barbosa-Póvoa, A. P. (2014a). Economic and environmental concerns in planning recyclable waste collection systems. *Transportation Research Part E: Logistics and Transportation Review*, *62*, 34–54. https://doi.org/10.1016/j.tre.2013.12.002

Ramos, T. R. P., Gomes, M. I. and Barbosa-Póvoa, A. P. (2014b). Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. *Omega*, 48, 60-74. https://doi.org/10.1016/j.omega.2013.11.006

Ramos, T., Gomes, M. I., and Barbosa-Póvoa, A. P. (2014c). Assessing and improving management practices when planning packaging waste collection systems. *Resources, Conservation and Recycling*, 85, 116-129. https://doi.org/10.1016/j.resconrec.2013.12.013

Ramos, T. R. P., & Oliveira, R. C. (2011). Delimitation of service areas in reverse logistics networks with multiple depots. *Journal of the Operational Research Society*, *62*(7), 1198–

1210. https://doi.org/10.1057/jors.2010.83

Rovetta, A., Xiumin, F., Vicentini, F., Minghua, Z., Giusti, A., & Qichang, H. (2009). Early detection and evaluation of waste through sensorized containers for a collection monitoring application. *Waste Management*, *29*(12), 2939–2949. https://doi.org/10.1016/j.wasman.2009.08.016

Russo, M. A. T. (2003). *Tratamento de Resíduos Sólidos, Relatório da Universidade de Coimbra, Faculdade de Ciências e Tecnologia, Departamento de Engenharia Civil*. http://homepage.ufp.pt/madinis/RSol/Web/TARS.pdf

Saeidi-Mobarakeh, Z., Tavakkoli-Moghaddam, R., & Navabakhsh, M. (2019). A bi-level and robust optimization-based framework for a hazardous waste management problem : A real-world application. *Journal of Cleaner Production*, *252*, 119830. https://doi.org/10.1016/j.jclepro.2019.119830

Santibañez-Aguilar, J. E., Flores-Tlacuahuac, A., Rivera-Toledo, M., & Ponce-Ortega, J. M. (2017). Dynamic optimization for the planning of a waste management system involving multiple cities. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2017.07.063

Shih, L., & Chang, H. (2001). A routing and scheduling system for infectious waste collection. *Environmental Modeling & Assessment* 6, 261–269. https://doi.org/10.1023/A:1013342102025

Sociedade Ponto Verde. (2018). *Relatório de atividades da sociedade ponto verde 2018*.

Sociedade Ponto Verde. (2020a). *MANUAL SPV: PREENCHIMENTO DECLARAÇÃO ANUAL, EDIÇÃO 2020 V1.1*.

Sociedade Ponto Verde. (2020b). *SIGRE*. https://www.pontoverde.pt/como_funciona.php

Teixeira, J., Antunes, A. P., & de Sousa, J. P. (2004). Recyclable waste collection planning – a case study. *European Journal of Operational Research*, *158(3)*, 543–554. https://doi.org/10.1016/S0377-2217(03)00379-5

Trotta, P. (2011). A Gestão de Resíduos Sólidos Urbanos em Portugal. *VII Congresso Nacional de Excelência Em Gestão*. http://www.excelenciaemgestao.org/portals/2/documents/cneg7/anais/t11_0350_2173.pdf

Tung, D. V., & Pinnoi, A. (2000). Vehicle routing-scheduling for waste collection in Hanoi. *European Journal of Operational Research*, *125*, 449-468. https://doi.org/ 10.1016/S0377-2217(99)00408-7

Yousefloo, A., & Babazadeh, R. (2019). Designing an integrated municipal solid waste management network: A case study. *Journal of Cleaner Production*, 118824. https://doi.org/10.1016/j.jclepro.2019.118824

Zhang, A., Venkatesh, V. G., Liu, Y., Wan, M., & Qu, T. (2019). Barriers to smart waste management for a circular economy in China. Journal of Cleaner Production, 240, 118198. https://doi.org/10.1016/j.jclepro.2019.118198

Zografos, K. G., & Androutsopoulos, K. N. (2004). A heuristic algorithm for solving hazardous materials distribution problems. *European Journal of Operational Research* 152(2), 507–519. https://doi.org/10.1016/S0377-2217(03)00041-9

ATTACHMENTS

ATTACHMENT 1: SOURE'S RESULTS

Current Situation

KPI	1 2/Apr	2 3/Apr	8 9/Apr	10 11/Apr	14 15/Apr	19 20/Apr	22 23/Apr	25 26/Apr	28 29/Apr	Total	Average / collection day	Average / route
Circuit	A	B	A	B	A	A	B	A	B	-	-	-
Vehicles used	1	1	1	1	1	1	1	1	1	9	1	-
Attended bins	50	35	48	46	50	50	48	50	48	425	47	47
Overflowing bins	0	0	0	0	0	0	0	0	0	0	0	0
Weight (kg)	1531.1	1485.0	1103.5	1239.8	1198.9	1110.3	1365.	811.7	885.4	10730.8	1192.3	1192.3
Distance (km)	139.5	153.4	141.7	174.1	140.9	139.8	178.4	139.8	178.4	1385.9	154	154
Shift duration (h)	6.0	5.6	5.9	6.7	6.0	6.0	6.9	6.0	6.9	-	6.2	-
Ratio (Kg/Km)	11.0	9.7	7.8	7.1	8.5	7.9	7.7	5.8	5.0	-	7.8	-
Vehicles usage rate (%)	69.6	67.5	50.2	56.4	54.5	50.5	62.0	36.9	40.2	-	54.2	-
Profit (€)	46.0	26.4	-8.1	-24.0	4.3	-5.3	-13.1	-41.5	-71.2	**-86.4**	**-9.6**	**-9.6**

1.1.A

KPI	1 2/Apr	3 4/Apr	7 8/Apr	11 12/Apr	15 16/Apr	19 20/Apr	23 24/Apr	26 27/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	1	8	-	-
Vehicles used	1	1	1	1	1	1	1	1	8	1	-
Attended bins	57	78	70	73	65	60	66	74	543	68	68
Overflowing bins	0	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	2085.7	1259.3	1286.1	1287.1	1215.1	1049	1257.7	1200.5	10641	1330	1330
Distance (Km)	121.6	168.5	158.4	147.7	138.1	125.5	140.7	154.1	1155	144	144
Duration (h)	5.9	8.1	7.5	7.3	6.7	6.1	6.8	7.6	-	7.0	-
Ratio (Kg/Km)	17.2	7.5	8.1	8.7	8.8	8.4	8.9	7.8	-	9.4	-
Vehicles usage rate (%)	94.8	57.2	58.5	58.5	55.2	47.7	57.2	54.6	-	60	-
Computational time (s)	56	1370	605	14420	4768	14416	432	14420	50487	6311	-
GAP (%)	0.0	0.0	0.0	5.0	0.0	11.0	0.0	11.0	-	3.4	-
Profit (€)	131.0	-16.0	-2.7	8.2	9.0	1.5	11.6	-8.7	**134.0**	**16.7**	**17.0**

2.1.A

KPI	1 2/Apr	2 3/Apr	8 9/Apr	9 10/Apr	15 16/Apr	21 22/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	7	-	-
Vehicles used	1	1	1	1	1	1	1	7	1	-
Attended bins	57	64	83	7	74	82	67	434	62	62
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	2085.7	921.4	1949.7	257.2	2014.8	1884.4	2072.6	11185.8	1598.0	1598.0
Distance (Km)	121.6	155.3	173.5	91.0	156.1	172.4	140.5	1010.4	144.3	144.3
Duration (h)	5.9	7.1	8.5	2.6	7.6	8.4	6.9	-	6.7	-
Ratio (Kg/Km)	17.2	5.9	11.2	2.8	12.9	10.9	14.8	-	10.8	-
Vehicles usage rate (%)	94.8	41.9	88.6	11.7	91.6	85.7	94.2	-	72.6	-
Computational time (s)	85	14400	710	127	57	85	167	15631	2233	-
GAP (%)	0.0	5.0	0.0	0.0	0.0	0.0	0.0	-	0.7	-
Profit (€)	131.0	-43.7	62.6	-59.9	87.9	55.8	110.5	**344.2**	**49.2**	**49.2**

3.1.A

KPI	1 2/Apr	7 8/Apr	11 12/Apr	18 19/Apr	24 25/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	5	-	-
Vehicles used	1	1	1	1	1	5	1	-
Attended bins	48	62	84	68	84	346	69	69
Overflowing bins	0	0	0	0	0	0	0	0
Weight (Kg)	2104.4	2047.8	1972.8	2025.0	2007.8	10157.8	2031.6	2031.6
Distance (Km)	143.6	161.7	204.4	143.0	177.0	829.7	165.9	165.9
Duration (h)	6.0	7.1	9.3	7.0	8.6	-	7.6	-
Ratio (Kg/Km)	14.7	12.7	9.7	14.2	11.3	-	12.5	-
Vehicles usage rate (%)	95.7	93.1	89.7	92.0	91.3	-	92.3	-
Computational time (s)	4652	14404	253	39	165	19513	3903	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	111.2	86.3	34.5	102.2	66.1	**400.3**	**80.1**	**80.1**

2.1.M

KPI	1 2/Apr	6 7/Apr	9 10/Apr	16 17/Apr	21 22/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	6	-	-
Vehicles used	1	1	1	1	1	1	6	1	-
Attended bins	42	52	31	49	55	52	281	47	47
Overflowing bins	0	0	0	0	0	0	0	0	0
Weight (Kg)	2088.7	1783.0	894.3	2090.4	1851.0	2104.4	10811.8	1802.0	1802.0
Distance (Km)	138.4	150.9	137.7	120.1	165.3	122.8	835.2	139.2	139.2
Duration (h)	5.6	6.4	5.0	5.5	6.9	5.7	-	5.8	-
Ratio (Kg/Km)	15.1	11.8	6.5	17.4	11.2	17.1	-	13.2	-
Vehicles usage rate (%)	94.9	81.0	40.7	95.0	84.1	95.7	-	81.9	-
Computational time (s)	3	15	4	11021	17	20	11080	1847	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	114.5	65.0	-29.4	133.0	58.9	132.0	**474.0**	**79.0**	**79.0**

2.1.R

KPI	1 2/Apr	2 3/Apr	8 9/Apr	9 10/Apr	15 16/Apr	21 22/Apr	27 28/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	7	-	-
Vehicles used	1	1	1	1	1	1	1	7	1	-
Attended bins	55	17	69	5	64	70	64	344	49	49
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (kg)	2092.6	571.6	2043.9	214.2	2048.8	1982.8	1950.9	10904.8	1557.8	1557.8
Distance (Km)	122.7	129.3	160.7	89.1	146	165.2	148.8	961.8	137.4	137.4
Duration (h)	5.8	4.1	7.5	2.5	6.9	7.6	6.9	-	5.9	-
Ratio (Kg/Km)	17.1	4.4	12.7	2.4	14.0	12.0	13.1	-	10.8	-
Vehicles usage rate (%)	95.1	26.0	92.9	9.7	93.1	90.1	88.7	-	70.8	-
Computational time (s)	20	1	151	1	22	27	28	250	36	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	130.7	-60.1	86.8	-63.2	102.1	74.9	87.5	**358.8**	**51.0**	**51.0**

3.1.M

KPI	1 2/Apr	7 8/Apr	11 12/Apr	18 19/Apr	24 25/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	5	-	-
Vehicles used	1	1	1	1	1	5	1	-
Attended bins	43	57	80	48	59	287	57	57
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	2110.4	2062.5	1975.6	1716.6	1889.2	9754.3	1950.9	1950.9
Distance (km)	148.3	168.7	211.4	130.2	162.9	821.5	164.3	164.3
Duration (h)	5.9	7.1	9.3	5.7	7.0	-	7.0	-
Ratio (Kg/Km)	14.2	12.2	9.3	13.2	11.6	-	12.1	-
Vehicles usage rate (%)	95.9	93.8	89.8	78.0	85.9	-	88.7	-
Computational time (s)	23	51	20	2	18	114	23	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	-	0	-
Profit (€)	107.3	81.1	27.8	77.7	65.9	**359.8**	**72.0**	**72.0**

3.1.R

KPI	1 2/Apr	7 8/Apr	11 12/Apr	18 18/Apr	24 25/Apr	29 30/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	6	-	-
Vehicles used	1	1	1	1	1	1	6	1	-
Attended bins	48	61	87	56	73	71	396	66	66
Overflowing bins	0	0	0	0	0	0	0	0	0
Weight (kg)	2104.4	2056.5	1965.7	1762.8	2040.7	1946.8	11876.9	1979.5	1979.5
Distance (Km)	143.6	164.2	208.7	133.2	169	188.5	1007.2	167.9	167.9
Duration (h)	6.0	7.2	9.6	6.1	7.9	8.3	-	7.5	-
Ratio (Kg/Km)	14.7	12.5	9.4	13.2	12.1	10.3	-	12.0	-
Vehicles usage rate (%)	95.7	93.5	89.4	80.1	92.8	88.5	-	90.0	-
Computational time (s)	310	264	18	14	282	28	916	153	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	111.2	84.8	29.3	80.3	78.1	47.3	**431.1**	**71.8**	**71.8**

2.2.A

KPI	1 2/Apr	2 3/Apr	8 9/Apr	9 10/Apr	15 16/Apr	21 22/Apr	27 28/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	7	-	-
Vehicles used	1	1	1	1	1	1	1	7	1	-
Attended bins	58	63	68	60	68	69	66	452	65	65
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	2085.7	893.8	1727.0	720.1	1802.4	1728.2	1933.8	10891.0	1555.9	1555.9
Distance (Km)	121.6	151.6	143.8	152.1	141.3	143.6	149.8	1003.8	143.4	143.4
Duration (h)	5.9	6.9	7.0	6.8	6.9	7.0	7.0	-	6.8	-
Ratio (Kg/Km)	17.2	5.9	12.0	4.7	12.8	12.0	12.9	-	11.1	-
Vehicles usage rate (%)	94.8	40.6	78.5	32.7	81.9	78.6	87.9	-	70.7	-
Computational time (s)	4460	14400	14400	14400	12967	14400	14400	89427	12775	-
GAP (%)	0.0	27.0	2.7	27.0	0.0	3.0	8.0	-	9.7	-
Profit (€)	131.0	-43.4	65.3	-64.9	77.0	65.7	84.4	**315.1**	**45.0**	**45.0**

2.2.M

KPI	1 2/Apr	6 7/Apr	9 10/Apr	16 17/Apr	20 21/Apr	27 28/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	7	-	-
Vehicles used	1	1	1	1	1	1	1	7	1	-
Attended bins	43	53	32	51	46	54	19	298	43	43
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	2088.7	1783.0	894.3	2086.9	1543.4	2103.5	677.0	11176.8	1596.7	1596.7
Distance (Km)	138.4	150.9	137.7	120.2	158.5	116.8	126.4	948.9	135.6	135.6
Duration (h)	5.6	6.4	5.0	5.6	6.3	5.6	4.1	-	5.5	-
Ratio (Kg/Km)	15.1	11.8	6.5	17.4	9.7	18.	5.4	-	12.0	-
Vehicles usage rate (%)	94.9	81.0	40.7	94.9	70.2	95.6	30.8	-	72.6	-
Computational time (s)	51	535	916	14400	517	2073	7	18499	2643	-
GAP (%)	0.0	0.0	0.0	2.0	0.0	0.0	0.0	-	0.3	-
Profit (€)	114.5	65.0	-29.4	132.5	28.4	137.9	-44.4	**404.5**	**57.8**	**57.8**

2.2.R

KPI	1 2/Apr	2 3/Apr	8 9/Apr	9 10/Apr	15 16/Apr	21 22/Apr	27 28/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	7	-	-
Vehicles used	1	1	1	1	1	1	1	7	1	-
Attended bins	56	18	65	8	65	66	64	342	49	49
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (kg)	2092.6	571.6	1953.5	262.6	2057.4	1827.8	2022.5	10788.0	1541.1	1541.1
Distance (Km)	122.7	129.3	149.8	146.3	143.8	148.6	153.9	994.4	142.1	142.1
Duration (h)	5.9	4.1	7.0	4.1	6.8	7.0	7.0	-	6.0	-
Ratio (Kg/Km)	17.1	4.4	13.0	1.8	14.3	12.3	13.1	-	10.9	-
Vehicles usage rate (%)	95.1	26.0	88.8	11.9	93.5	83.1	91.9	-	70.1	-
Computational time (s)	2490	3	14400	1	12909	14400	2690	46893	6699	-
GAP (%)	0.0	0.0	1.0	0.0	0.0	4.0	0.0	-	0.7	-
Profit (€)	130.7	-60.1	86.8	-114.5	105.4	72.7	91.0	**312.0**	**44.6**	**44.6**

3.2.A

KPI	1 2/Apr	8 9/Apr	15 16/Apr	21 22/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	2	1	1	1	6	-	-
Vehicles used	1	2	1	1	1	6	1	-
Attended bins	50	97	69	63	63	342	68	57
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	2101.6	3138.5	1957.6	1691.8	2091.3	10980.8	2196	1830
Distance (km)	146.8	282.7	143.9	155.8	125.9	855.1	171.0	142.5
Min shift duration (h)	6.2	6.0	7.0	7.0	6.3	-	7	-
Max shift duration (h)	-	6.0	-	-	-	-	6.0	-
Ratio (Kg/Km)	14.3	11.1	13.6	10.9	16.6	-	13.3	-
Vehicles usage rate (%)	95.5	71.3	89.0	76.9	95.1	-	85.6	-
Computational time (s)	14400	14400	14400	14400	14400	72000	14400	-
GAP (%)	4.0	13.0	2.0	10.0	1.0	-	6.0	-
Profit (€)	107.7	97.4	93.2	49.1	127.4	**474.8**	**95**	**79.1**

3.2.M

KPI	1 2/Apr	7 8/Apr	11 12/Apr	18 19/Apr	25 26/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	2	1	1	1	7	-	-
Vehicles used	1	1	2	1	1	1	7	1	-
Attended bins	44	57	83	49	62	42	337	56	48
Overflowing bins	0	0	0	0	0	0	0	0	0
Weight (kg)	2110.4	2042.7	2010.6	1701.5	2055	1186	11106.2	1851.0	1586.6
Distance (km)	148.3	167.8	278.8	130.2	143.4	154.1	1023	170.4	146.1
Min shift duration (h)	5.9	7.0	5.5	5.7	6.7	6.0	-	6.1	-
Max shift duration (h)	-	-	5.6	-	-	-	-	5.6	-
Ratio (Kg/Km)	14.2	12.2	7.2	13.1	14.3	7.7	-	11.5	-
Vehicles usage rate (%)	95.9	92.9	45.7	77.3	93.4	53.9	-	76.5	-
Computational time (s)	55	14400	14400	27	7582	321	36785	6131	-
GAP (%)	0.0	5.0	100.0	0.0	0.0	0.0	-	17.5	-
Profit (€)	107.7	97.4	-35.3	75.9	105.5	-10.5	**340.7**	**56.8**	**48.7**

3.2.R

KPI	1 2/Apr	7 8/Apr	11 12/Apr	18 19/Apr	24 24/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	2	1	1	1	7	-	-
Vehicles used	1	1	2	1	1	1	7	1	-
Attended bins	49	58	87	56	65	64	379	63	54
Overflowing bins	0	0	0	0	0	0	0	0	0
Weight (kg)	2104.4	2054.9	1981.3	1735	1819.4	1584.5	11279.5	1879.9	1879.9
Distance (km)	143.6	165.4	284.4	130.9	147.2	152.8	1024.3	170.7	170.7
Min shift duration (h)	6.0	7.0	5.7	6.1	6.9	7.0	-	6.5	-
Max shift duration (h)	-	-	5.7	-	-	-	-	5.7	-
Ratio (Kg/Km)	14.7	12.4	7.0	13.3	12.4	10.4	-	11.7	-
Vehicles usage rate (%)	95.7	93.4	90.1	78.9	82.7	72.0	-	85.5	-
Computational time (s)	14400	14400	14400	2111	2640	14400	62351	10392	-
GAP (%)	1.3	5.0	168.6	0.0	0.0	7.5	-	30.4	-
Profit (€)	111.2	83.4	-44.5	79.2	73.1	39.1	**341.6**	**56.9**	**56.9**

Attachment 2: Condeixa's results

Current Situation

KPI	1 2/Apr	3 4/Apr	7 8/Apr	9 10/Apr	11 12/Apr	14 15/Apr	16 17/Apr	18 19/Apr	22 23/Apr	26 27/Apr	Total	Average / collection day	Average / route
Circuit	C	D	C	D	C	D	C	D	C	C	-	-	-
Vehicles used	1	1	1	1	1	1	1	1	1	1	10	1	-
Attended bins	65	56	65	56	65	56	65	56	65	65	614	61	61
Overflowing bins	0	0	0	0	0	0	0	0	0	0	0	0	0
Weight (kg)	1614.1	1180.6	2075.2	1789.3	1780.1	1660.2	2200.0	1309.7	1392.7	1143.7	16145.6	1614.6	1614.6
Distance (km)	99.6	143.9	104.0	144.0	101.8	148.9	97.5	174.1	102.0	97.3	1213.0	121.3	121.3
Shift duration (h)	5.7	6.4	5.8	6.4	5.8	6.5	5.7	7.2	5.8	5.7	-	6.1	-
Ratio (Kg/Km)	16.2	8.2	20.0	12.4	17.5	11.2	22.6	7.5	13.7	11.8	-	14.1	-
Vehicles usage rate (%)	73.4	53.7	94.3	81.3	80.9	75.5	100.0	59.5	63.3	52.0	-	73.4	-
Profit (€)	95.8	-0.9	147.3	72.7	113.8	52.2	168.9	-15.5	66.7	41.2	**742.3**	**74.2**	**74.2**

2.1.A

KPI	1 2/Apr	7 8/Apr	12 13/Apr	17 18/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	2	2	2	2	2	10	-	-
Vehicles used	2	2	2	2	2	10	2	-
Attended bins	109	120	116	112	117	574	115	57
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	3251.4	3948.4	3807.2	3651.2	3283.3	17941.5	3588.3	1794.2
Distance (km)	172.3	200.4	191.6	180.2	191.3	935.8	187.2	93.6
Min shift duration (h)	5.3	5.0	5.2	4.3	4.9	-	4.9	-
Max shift duration (h)	6.1	6.0	5.3	5.8	5.7	-	5.8	-
Ratio (Kg/Km)	18.9	19.7	19.9	20.3	17.2	-	19.2	-
Vehicles usage rate (%)	73.9	89.7	86.5	83.0	74.6	-	81.6	-
Computational time (s)	3227	9132	14400	14400	11199	52358	10472	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	221.4	277.8	269.5	262.0	206.3	**1237.0**	**247.4**	**123.7**

2.1.M

KPI	1 2/Apr	3 4/Apr	7 8/Apr	11 12/Apr	14 15/Apr	17 18/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	2	1	1	2	2	10	-	-
Vehicles used	1	1	2	1	1	2	2	10	1	-
Attended bins	40	30	102	59	60	88	66	445	64	45
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (kg)	2243.6	1043.4	3710.	2250.3	2298.6	2876.8	2759.9	17182.6	2454.7	1718.3
Distance (km)	79.3	91.5	192.2	86.4	104.1	191.9	146.	891.4	127.3	89.1
Min shift duration (h)	4.0	3.8	3.9	5.1	5.6	3.0	3.2	-	4.1	-
Max shift duration (h)	-	-	5.9	-	-	6.2	3.7	-	5.3	-
Ratio (Kg/Km)	28.3	11.4	19.3	26.	22.1	15.	18.9	-	20.1	-
Vehicles usage rate (%)	102.0	47.4	84.3	102.3	104.5	65.4	62.7	-	81.2	-
Computational time (s)	6	1	9350	63	91	4389	38	13938	1991	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	192.4	34.9	257.1	186.1	174.3	156.5	188.2	**1189.5**	**169.9**	**119.0**

3.1.A

KPI	1 2/Apr	7 8/Apr	12 13/Apr	17 18/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	2	2	2	2	2	10	-	-
Vehicles used	2	2	2	2	2	10	2	-
Attended bins	109	120	116	112	117	574	115	57
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	3251.4	3936.8	3807.2	3651.2	3283.3	17929.9	3586.0	1793.0
Distance (km)	172.3	200.4	191.6	180.2	191.3	935.8	187.2	93.6
Min shift duration (h)	3.6	4.9	5.0	4.3	5.0	-	4.6	-
Max shift duration (h)	6.1	6.1	5.6	5.8	5.6	-	5.8	-
Ratio (Kg/Km)	18.9	19.6	19.9	20.3	17.2	-	19.2	-
Vehicles usage rate (%)	73.9	89.5	86.5	83.0	74.6	-	81.5	-
Computational time (s)	3830	9435	14400	14400	10836	52901	10580	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	221.4	276.3	269.5	262.0	206.3	**1235.5**	**247.1**	**123.6**

3.1.R

KPI	1 2/Apr	7 8/Apr	12 13/Apr	17 18/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	2	2	2	2	2	10	-	-
Vehicles used	2	2	2	2	2	10	2	-
Attended bins	96	118	109	114	98	535	107	54
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	3103.3	4053.9	3686.1	3859.9	2923.8	17627.0	3525.4	1762.7
Distance (km)	164.4	198.4	177.8	195.8	156.3	892.7	178.5	89.3
Min shift duration (h)	3.9	4.8	3.9	4.7	3.4	-	4.1	-
Max shift duration (h)	5.0	6.0	5.9	5.8	5.3	-	5.6	-
Ratio (Kg/Km)	18.9	20.4	20.7	19.7	18.7	-	19.7	-
Vehicles usage rate (%)	70.5	92.1	83.8	87.7	66.5	-	80.1	-
Computational time (s)	945	12258	14400	2627	530	30760	6152	-
GAP (%)	0.0	0.0	0.0	0.0	0.0	-	0.0	-
Profit (€)	211.4	292.5	268.6	271.6	197.8	**1241.9**	**248.4**	**124.2**

2.2.M

KPI	1 2/Apr	3 4/Apr	7 8/Apr	11 12/Apr	14 15/Apr	17 18/Apr	19 20/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	1	1	1	1	1	1	1	1	9	-	-
Vehicles used	1	1	2	1	1	1	1	1	9	1	-
Attended bins	41	32	103	60	61	64	38	50	449	56	50
Overflowing bins	0	0	0	0	0	0	0	0	0	0	0
Weight (kg)	2243.6	1091.9	3655.4	2250.3	2298.6	2059.3	1262.6	2048.	16909.6	2113.7	1878.8
Distance (km)	80.0	100.1	199.6	86.4	104.1	90.3	121.6	76.7	858.7	107.3	95.4
Min shift duration (h)	4.0	4.1	5.1	5.2	5.6	5.5	4.9	4.4	-	4.8	-
Max shift duration (h)	-	-	5.1	-	-	-	-	-	-	5.1	-
Ratio (Kg/Km)	28.0	10.9	18.3	26.0	22.1	22.8	10.4	26.7	-	20.7	-
Vehicles usage rate (%)	102.0	49.6	83.1	102.3	104.5	93.6	57.4	93.1	-	85.7	-
Computational time (s)	380	33	14400	10663	14400	14400	48	558	54882	6860	-
GAP (%)	0.0	0.0	5.2	0.0	0.4	2.9	0.0	0.0	-	1.1	-
Profit (€)	191.7	32.2	243.1	186.1	174.2	159.1	31.3	171.4	**1189.1**	**148.6**	**132.1**

3.2.M

KPI	1 2/Apr	7 8/Apr	11 12/Apr	16 17/Apr	24 25/Apr	Total	Average / collection day	Average / route
Number of routes	2	2	2	2	2	10	-	-
Vehicles used	2	2	2	2	2	10	2	-
Attended bins	54	104	83	97	90	428	86	43
Overflowing bins	0	0	0	0	0	0	0	0
Weight (kg)	2632.9	4224.9	2954.1	4054.2	3266.2	17132.3	3426.5	1713.2
Distance (km)	216.0	179.5	198.3	175.5	188.8	958.1	191.6	95.8
Min shift duration (h)	4.1	4.8	4.5	4.6	4.6	-	4.5	-
Max shift duration (h)	4.1	4.8	4.6	4.6	4.6	-	4.5	-
Ratio (Kg/Km)	12.2	23.5	14.9	23.1	17.3	-	18.2	-
Vehicles usage rate (%)	59.8	96.0	67.1	92.1	74.2	-	77.9	-
Computational time (s)	13210	14400	14400	14400	14400	70810	14162	-
GAP (%)	0.0	3.0	11.5	2.8	3.7	-	4.2	-
Profit (€)	102.8	332.2	159.4	315.4	206.7	**1116.6**	**223.3**	**111.7**

ATTACHMENT 3: SOURE + CONDEIXA'S RESULTS

2.1.A

KPI	1 2/Apr	7 8/Apr	11 12/Apr	16 17/Apr	23 24/Apr	Total	Average / collection day	Average / route
Number of routes	3	3	2	3	3	14	-	-
Vehicles used	3	3	2	3	3	14	3	-
Attended bins	196	195	172	189	198	950	190	68
Overflowing bins	0	0	0	0	0	0	0	0
Weight (Kg)	6030.7	5728.8	4183.2	5808.4	5217.8	26969.0	5393.8	1926.4
Distance (Km)	356.2	364.4	247.5	337.1	365.7	1670.9	334.2	119.4
Min shift duration (h)	5.2	4.4	6.7	4.2	4.2	-	4.9	-
Max shift duration (h)	7.5	7.4	8.0	8.1	8.7	-	7.9	-
Ratio (Kg/Km)	16.9	15.7	16.9	17.2	14.3	-	16.2	-
Vehicles usage rate (%)	91.4	86.8	95.1	88.0	79.1	-	88.1	-
Computational time (s)	14400	14400	14400	14400	14400	72000	14400	-
GAP (%)	2.0	6.4	1.3	1.7	4.4	-	3.2	-
Profit (€)	374.1	329.4	259.0	366.3	266.2	**1595.0**	**319.0**	**113.9**

2.1.M

KPI	1 2/Apr	3 4/Apr	7 8/Apr	11 12/Apr	16 17/Apr	22 23/Apr	25 26/Apr	Total	Average / collection day	Average / route
Number of routes	2	1	3	2	3	2	1	14	-	-
Vehicles used	2	1	3	2	3	2	1	14	2	-
Attended bins	82	45	158	117	146	111	65	724	103	52
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	4372.9	1386	5565.8	3920.7	5727.7	3881.6	2102.5	26957.3	3851	1925.5
Distance (Km)	213.1	149.7	362.8	233.5	307.1	213.0	196.2	1675.3	239.3	119.7
Min shift duration (h)	4.1	6.0	3.6	5.1	4.0	4.6	8.2	-	5.1	-
Max shift duration (h)	5.3	-	7.8	6.5	6.0	6.2	-	-	6.3	-
Ratio (Kg/Km)	20.5	9.3	15.3	16.8	18.7	18.2	10.7	-	15.6	-
Vehicles usage rate (%)	99.4	63.0	84.3	89.1	86.8	88.2	95.6	-	86.6	-
Computational time (s)	3065	11	14400	1574	14400	14400	20	47870	6839	-
GAP (%)	0.0	0.0	3.7	0.0	0.2	3.0	0.0	-	1.0	-
Profit (€)	316.5	18.2	311.3	241.3	386.6	257.1	58.4	**1589.3**	**227.0**	**113.5**

3.1.A

KPI	1 2/Apr	7 8/Apr	12 13/Apr	17 18/Apr	24 25/Apr	Total	Average / collection day	Average / route
Number of routes	3	3	3	3	3	15	-	-
Vehicles used	3	3	3	3	3	15	3	-
Attended bins	195	208	199	188	199	989	198	66
Overflowing bins	0	0	0	0	0	0	0	0
Weight (Kg)	6019.2	6047.2	5429.9	5179.9	5050.	27726.1	5545.2	1848.4
Distance (Km)	356.4	399.0	358.1	354.5	363.7	1831.7	366.3	122.1
Min shift duration (h)	5.4	5.3	4.3	3.2	5.2	-	4.7	-
Max shift duration (h)	6.7	7.8	8.8	8.6	7.6	-	7.9	-
Ratio (Kg/Km)	16.9	15.2	15.2	14.6	13.9	-	15.1	-
Vehicles usage rate (%)	91.2	91.6	82.3	78.5	76.5	-	84.0	-
Computational time (s)	14400	14400	14400	14400	14400	72000	14400	-
GAP (%)	2.6	5.0	3.9	6.6	3.5	-	4.3	-
Profit (€)	372.5	333.4	299.4	272.8	247.8	**1525.9**	**305.2**	**101.7**

3.1.R

KPI	1 2/Apr	7 8/Apr	12 13/Apr	17 18/Apr	21 22/Apr	25 26/Apr	28 29/Apr	Total	Average / collection day	Average / route
Number of routes	3	3	3	3	1	2	1	16	-	-
Vehicles used	3	3	3	3	1	2	1	16	2	-
Attended bins	171	190	163	193	96	149	103	1065	152	67
Overflowing bins	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	5737.3	6011.2	4986.5	5804.5	1893.4	3183.7	1957	29573.6	4224.8	1848.4
Distance (Km)	349.1	381.5	314.7	376.1	120.1	246.1	161.5	1949.1	278.4	121.8
Min shift duration (h)	5.1	4.2	3.9	5.5	7.8	6.2	9.2	-	6.0	-
Max shift duration (h)	6.4	8.6	7.1	7.6	-	7.4	-	-	7.4	-
Ratio (Kg/Km)	16.4	15.8	15.8	15.4	15.8	12.9	12.1	-	14.9	-
Vehicles usage rate (%)	86.9	91.1	75.6	87.9	86.1	72.4	89.0	-	84.1	-
Computational time (s)	14400	14400	14400	14400	14400	14400	14400	100800	14400	-
GAP (%)	3.5	4.6	3.2	3.9	1.9	1.9	5.5	-	3.5	-
Profit (€)	345.7	346.5	289.2	326.9	109.1	139.4	75.5	**1632.3**	**233.2**	**102.0**

2.2.M

KPI	1 2/Apr	2 3/Apr	8 9/Apr	9 10/Apr	10 11/Apr	14 15/Apr	15 16/Apr	19 20/Apr	23 24/Apr	27 28/Apr	Total	Average / collection day	Average / route
Number of routes	2	1	2	2	1	2	1	2	1	2	16	-	-
Vehicles used	2	1	2	2	1	2	1	2	1	2	16	2	-
Attended bins	77	24	70	99	28	106	40	114	71	114	743	74	46
Overflowing bins	0	0	0	0	0	0	0	0	0	0	0	0	0
Weight (Kg)	4082.1	884.1	3602.8	4004.5	1075.7	4418.5	1141.8	3829.8	1982.3	3770.4	28792.0	2879.2	1799.5
Distance (Km)	194.3	142.9	241.4	254.2	136.6	211.2	138.5	237.7	126.5	277.6	1960.9	196.1	122.6
Min shift duration (h)	4.3	4.8	4.8	5.7	4.8	5.3	5.5	5.8	6.7	6.3	-	5.4	-
Max shift duration (h)	4.4	-	4.8	5.7	-	5.3	-	5.8	-	6.3	-	5.4	-
Ratio (Kg/Km)	21.0	6.2	14.9	15.8	7.9	20.9	8.2	16.1	15.7	13.6	-	14.0	-
Vehicles usage rate (%)	92.8	40.2	81.9	91.0	48.9	100.4	51.9	87.0	90.1	85.7	-	77.0	-
Computational time (s)	36000	59	36000	36000	124	36000	580	36000	36000	36000	252763	25276	-
GAP (%)	10.6	0.0	65.6	19.2	0.0	18.2	0.0	10.3	6.6	14.2	-	14.5	-
Profit (€)	300.1	-35.9	194.9	230.7	-6.3	323.9	-0.2	226.1	113.6	179.0	**1525.8**	**152.6**	**95.4**