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Modelos e Métodos focados no Apoio à Decisão no Contexto de Logística Urbana

Models and Methods to Support Decision Making in Urban Logistics Context

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Tese apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Doutor em Engenharia e Gestão Industrial, realizada sob a orientação científica da Doutora Carina Maria Oliveira Pimentel, Professora Auxiliar do Departamento de Produção e Sistemas da Escola de Engenharia da Universidade do Minho e do Doutor Amaro Fernandes de Sousa, Professor Auxiliar do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro.

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palavras-chave

Logística Urbana; Modelos e Métodos de Otimização Logísticos; Heurísticas, Suporte à Tomada de Decisão; Planeamento Estratégico e Operacional

resumo

Atualmente, existe uma população global em crescimento que vive em áreas centrais e metropolitanas das cidades, juntamente com um aumento nas vendas de comércio eletrónico. Isto enfatiza a necessidade de implementar soluções que melhorem a eficácia da Logística Urbana na entrega de mercadorias nas áreas metropolitanas. Neste contexto, a integração dos fluxos de passageiros e mercadorias nas cidades tem recebido ampla atenção nos últimos anos devido aos potenciais benefícios para a qualidade de vida dos habitantes, como a redução da poluição do ar, do ruído e do congestionamento rodoviário. No entanto, é necessária mais investigação para entender melhor as expectativas e perceções dos stakeholders das cidades sobre a adoção desses tipos de soluções, bem como desenvolver e modelar essas soluções integradas de maneira eficaz.

Esta pesquisa, desenvolvida no âmbito do projeto SOLFI (Sistema de Optimização para a Logística Urbana com Fluxos Integrados de mercadorias e passageiros), aborda uma solução de logística urbana que combina fluxos de mercadorias e passageiros. Esta solução integrada tem como objetivo aproveitar a rede de autocarros da cidade do Porto para transportar pacotes de mercadorias para o centro da cidade, fazendo uso das viagens de passageiros que já ocorrem na cidade. As contribuições desta investigação são divididas em três partes principais.

Primeiro, foi realizada uma avaliação sistemática e abrangente dos modelos e métodos de investigação operacional atuais que investigam a logística urbana, integrando fluxos de mercadorias e passageiros. Isto permitiu entender como outros investigadores abordaram o assunto, destacar lacunas existentes na literatura e delinear as direções de investigação deste trabalho. Em segundo lugar, foi realizado um questionário e três entrevistas semiestruturadas para recolher os requisitos e expectativas dos principais stakeholders em relação à solução logística integrada. Os resultados da aplicação destes instrumentos permitiram desenhar a solução de logística integrada e obter um modelo conceptual para a solução, com base na *Unified Modeling Language* (UML). Por fim, foram desenvolvidos modelos de otimização exata e algoritmos heurísticos e foram aplicados a dois problemas relevantes, dentro do tópico em pesquisa, para apoiar o processo de tomada de decisão: o Problema de Alocação de Fluxo de Rede de Mercadorias (FNFAP) para estudar a alocação de mercadorias ao longo da rede de distribuição, apoiando o planeamento operacional, e o Problema de Planeamento da Rede de autocarros (BNPP) para estudar a dimensão da frota de autocarros necessária, apoiando o planeamento estratégico. Testes computacionais foram realizados para ambos os problemas, utilizando o IBM CPLEX para os modelos de otimização exata e o MATLAB para as abordagens heurísticas, com conjuntos de instâncias geradas.

Esta tese faz várias contribuições para a teoria e para a prática, em particular a proposta de um novo serviço de logística urbana que procura incorporar a sustentabilidade, com a participação dos principais stakeholders. Além disso, os modelos e métodos desenvolvidos para dois problemas mostraram que soluções competitivas podem ser obtidas em curtos períodos de tempo de computação, apoiando eficientemente o processo de tomada de decisão nesta solução logística integrada na cidade do Porto.

keywords

Urban Logistics; City Logistics; Logistic Optimization Models an Methods; Heuristics; Decision Making Support; Strategic and Operational Planning.

abstract

Nowadays, there is an expanding global population living in central and metropolitan areas of cities, as well as an increase in e-commerce sales. This emphasizes the need to implement solutions that improve the Urban Logistics effectiveness in delivering freight into metropolitan areas. In this context, the integration of passenger and freight movements inside cities has received extensive attention in recent years given the potential benefits to inhabitants' quality of life, such as reduced air pollution, noise, and congestion. However, further research is needed to better understand the city stakeholders' expectations and perceptions about the adoption of these types of solutions, as well as how to develop and model these integrated solutions in an effective manner.

This research, developed within the scope of the SOLFI (Sistema de Optimização para a Logística Urbana com Fluxos Integrados de mercadorias e passageiros) project, addresses an urban logistics solution combining freight and passenger flows. This integrated solution is intended to leverage the city of Porto's bus network to transport freight packages into the city center, making use of the passenger journeys that already occur in the city. The contributions of this research are spelt out in three main parts.

First, a systematic and comprehensive evaluation of the current operational research models and methods investigating urban logistics, integrating freight and passenger flows, was done. This allowed to understand how other researchers have addressed the subject, as well as highlight existing literature gaps and describe the research directions of this work. Second, a questionnaire and three semi-structured interviews were conducted to gather the key stakeholders' requirements and expectations for the integrated logistical solution. The results from the application of these instruments allowed to design the integrated logistical solution and obtain a conceptual model for the solution, based on Unified Modeling Language (UML). Lastly, exact optimization models and heuristics algorithms were developed and applied to two relevant problems, within the topic under research, to support the decision-making process: The Freight Network Flow Assignment Problem (FNFAP) to study the assignment of freight along the distribution network, supporting the operational planning, and the Bus Network Planning Problem (BNPP) to study the bus fleet size required, supporting the strategic planning. Computational experiments were conducted for both problems, using IBM CPLEX for the exact optimization models and MATLAB for the heuristic approaches, using sets of generated instances.

This thesis makes several contributions to theory and practice, in particular the proposal for a new urban logistics service that seeks to incorporate sustainability, with the voice of the main stakeholders. Furthermore, the models and methods developed for two relevant associated problems showed that competitive solutions in short computation times can be obtained, efficiently supporting the decision-making process in this integrated logistical solution in the city of Porto.

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Acronym list

(HR-MLHA)- Hybrid Robust Machine Learning-Heuristic Algorithm

ADV- Autonomous Delivery Robots

ALNS- Adaptative Large Neighborhood Search

BEV- Battery Electrical Vehicles

BNPP- Bus Network Planning Problem

BPP- Bin-packing Problem

BTO- Bus Transport Operator

CALMeD SURF- Crowdsourcing Approach for Last Mile Delivery

CL - Crowd Logistics

FNFAP- Freight Network Flow Assignment Problem

GR- Greedy Randomized

GRASP- Greedy Randomized Adaptative Search Procedure

IDSS-Intelligent Decision Support System

ILP - integer linear programming

IoT- Internet of things

ITS- Intelligent Transportation Systems

LMDT- Minimizing the last mile delivery time

LMO- last mile operator

LNS- Large Neighborhood Search

LR - Literature Review

M&S-Modeling and Simulation

MILP- Mixed Integer Linear Programming

MTSDP- Multiple Travelling Salesman Problem with Drones

NBO- Minimizing the number of bus offloads

NBS- Minimizing the number of bus services

NELVs- New Energy Logistic Vehicles

OM- Operations Management

OR- Operational Research

PD- Pickup and Delivery

PDPTW-SLSD- Pickup and Delivery Problem with Time Windows, Scheduled Lines and Stochastic Demands

PRISMA- Preferred Reporting Items for Systematic Review and Meta-Analysis

RBS- Maximizing the robustness to bus service suppressions

RLMF- Maximizing the robustness to last mile failures

RQ – Research Question

SLR- Systematic Literature Review

SOLFI- Optimization System for Urban Logistics with Integrated Freight and Passenger Flows

TSPD- Travelling Salesman Problem with Drones

UL- Urban Logistics

UML- Unified Modeling Language

VRP- Vehicle Routing Problems

1. Introduction

This section provides an overview of the dissertation. It begins with the research motivation. Then, the research objectives, research questions, and research methodology used for this investigation project. It concludes with the thesis structure and the academic contributions.

1.1. Motivation

Urban Logistics (UL) promises to encourage a city's sustainable urban development (Schliwa et al., 2015). This is an issue that affects the entire planet and has gotten worse recently. The most frequently mentioned modern justifications for this issue include the increase in urban population and the growing usage of e-commerce. In more detail:

- According to a recent United Nations report, 68% of the world's population will live in cities by 2050 (Dablanc et al., 2017; Li et al., 2022). In Europe, the percentage arises to 74% (United Nations, 2018).
- E-commerce has further accelerated growth with the COVID 19 pandemic, and it is expected to keep growing (Azcuy et al., 2021; Alves et al., 2023). According to a 2020 global study, 22% of people shopped online weekly (The last mile race challenging Urban Logistics, 2021). Moreover, according to reports by eMarketer (May 2019), annual B2C e-commerce sales reached 3.5 trillion dollars in 2019, 20% more than the previous year, and it is expected to reach 6.5 trillion dollars in 2023.

E-commerce nowadays represents a great convenience for customers. However, for cities, it instantly leads to a rise in the movement of freight. Such movements impact the lives of residents over time, also producing unnecessary congestion and greenhouse gas emissions (Savelsbergh & Van Woensel, 2016).

An increased transportation of goods to consumers' homes rather than traditional retail establishments is observed, resulting in a considerable rise in logistical transport vehicles (Wehbi et al., 2022). As result, the urban traffic and congestion, noise and environmental pollution, as well as potential road accidents, and ultimately, the compromising of the mobility of citizens, are some of the main drawbacks identified in literature (Fatnassi et al., 2015; Masson et al., 2017; Rezgui et al., 2019; Li et al., 2021; El Ouadi et al., 2021, Demir et al., 2015).

At the same time, online retailers are expanding their delivery choices, including same-day delivery, diminishing consolidation opportunities and amplifying the negative externalities of urban delivery operations (Azcuy et al., 2021). Their purpose is to meet the increasing expectation of customers for fast and high-quality delivery services at a low cost (Zhang et al., 2023). As such, a growing number of dedicated vehicles primarily driven by private firms has resulted in an increase in traffic loads on highways, which is one of the biggest hurdles to the successful delivery of products and services to clients.

Since UL is also a key sector of city economies (Strale, 2019), the challenge stands alone, and that motivates the present investigation: establishing an efficient freight transportation within cities while maintaining a quality of life that is appropriate for metropolitan areas.

Generally, the academy introduces UL as the way of finding efficient and effective solutions to transport goods in urban areas in order to avoid all of the aforementioned negative impacts while also providing better and faster delivery (Lagorio et al., 2016; Savelsbergh & Van Woensel, 2016). More recently, Batarlienė & Bazaras (2023) introduce urban logistics as the *"planning on high-quality and fast cargo transportation, with various ecological solutions"*. A primary ambition is, consequently, to find solutions tailored specifically for the people, cities, and planet, with multiple environmental and socio-economic impacts (Strale, 2019).

Hence, a wide range of efficient and effective solutions have been proposed, entailing an equilibrium between individual and social profitability (Bachofner et al, 2022). In some cases, the main focus of urban logistics is on the main carriers operating in the market. However, it is vital to consider a solution for urban logistics that is transversal in the supply chain, making it integrated and sustainable (Piecyk et al., 2015). The integration of networks and infrastructures is one of the interesting alternatives from the standpoint of a logistics system, and it is being addressed in this thesis.

The first hints about this integrated solution were given by the European Commission in 2007 in the European agenda for urban mobility (Mazzarino & Rubini, 2019). Since then, the integration of passenger flows and transportation has been on the agenda in both research and practice. From the academic perspective, optimizing transportation planning and improving the operational efficiency for a sustainable urban freight transportation are becoming more popular (Neghabadi et al., 2019;Zhu et al., 2023)

Combining people and freight flows has the potential to enhance operations by allowing the same transportation needs to be fulfilled with fewer cars while also considerably improving environmental, economic, and social factors (Chang et al., 2021). Customers benefit from faster service solutions, businesses benefit from stock reductions in stores, logistic operators benefit from operational cost minimization and efficient scheduled journeys without jeopardizing service quality, and city authorities are increasingly willing to collaborate and improve operations to avoid externalities (Savelsbergh & Van Woensel, 2016; Melo & Baptista, 2017; Pronello et al., 2017). This integrated people and freight flows approach can maximize the total system rather than individual subsystem performance, (Lagorio et al., 2016; Mourad et al., 2021; Manchella et al., 2021, 2022) but collaboration between customers, enterprises, logistics operators, and local authorities must be managed. Furthermore, carefully planning a UL transportation system aids to reduce actual logistical costs while also improving the robustness of decision-making in real-world cases (Hu et al., 2019).

Therefore, this investigation was designed to study an urban freight logistics solution that combines passenger and freight flows in the city of Porto.

1.2. The SOLFI project

The SOLFI (*Sistema de Otimização para a Logística Urbana com Fluxos Integrados de Mercadorias e Passageiros*; or in English, *Optimization System for Urban Logistics with Integrated Freight and Passenger Flows*) project, with project number 039870, aims to deliver a novel form of freight distribution service based on an intelligent decision support system, using urban passenger transportation networks. Its contribution to the city of Porto, Portugal, is built on two complementary pillars: assisting in the more effective use of available capacities through the integration of the two flows; and improving urban life quality, which is essential to urban logistics and the ultimate objective of any solution in this area. To implement this new service, Project SOLFI must achieve the following three goals:

1. Develop a new business model for urban logistics based on the integration of the bus network of the city and a last mile service to collect and deliver the freight into the city center.

2. Create an Intelligent Decision Support System (IDSS) to manage the freight distribution, in real-time, and help the decision-making process.
3. Incorporate decision support in IDSS to deal with disruptions in the transportation system.

The SOLFI will culminate with a prototype for the solution, which will include carrying out a pilot in the city of Porto involving a number of stakeholders. In this way, the prototype will be tested and validated by project stakeholders such as the bus transport operator, a last mile company, a logistic private company as one potential client of the new service and Porto municipality as the regulator. It should be emphasized that the present investigation contributes to a subset of activities and tasks that contribute to the project's overall purpose. They are the following:

- Development and implementation of customers questionnaire and stakeholders' interviews, that were used to assist the identification of the potential stakeholders' needs and requirements.
- Development of models and algorithms that will be incorporated into the new system that addresses logistical operational and strategic decisions. These models and algorithms will help bus network operators and municipal authorities to make decisions while adopting the combined solution of passenger and freight flows.

The main phases of the SOLFI projects are presented in Figure *1* and the contributions of this research to the project are highlighted in bold.

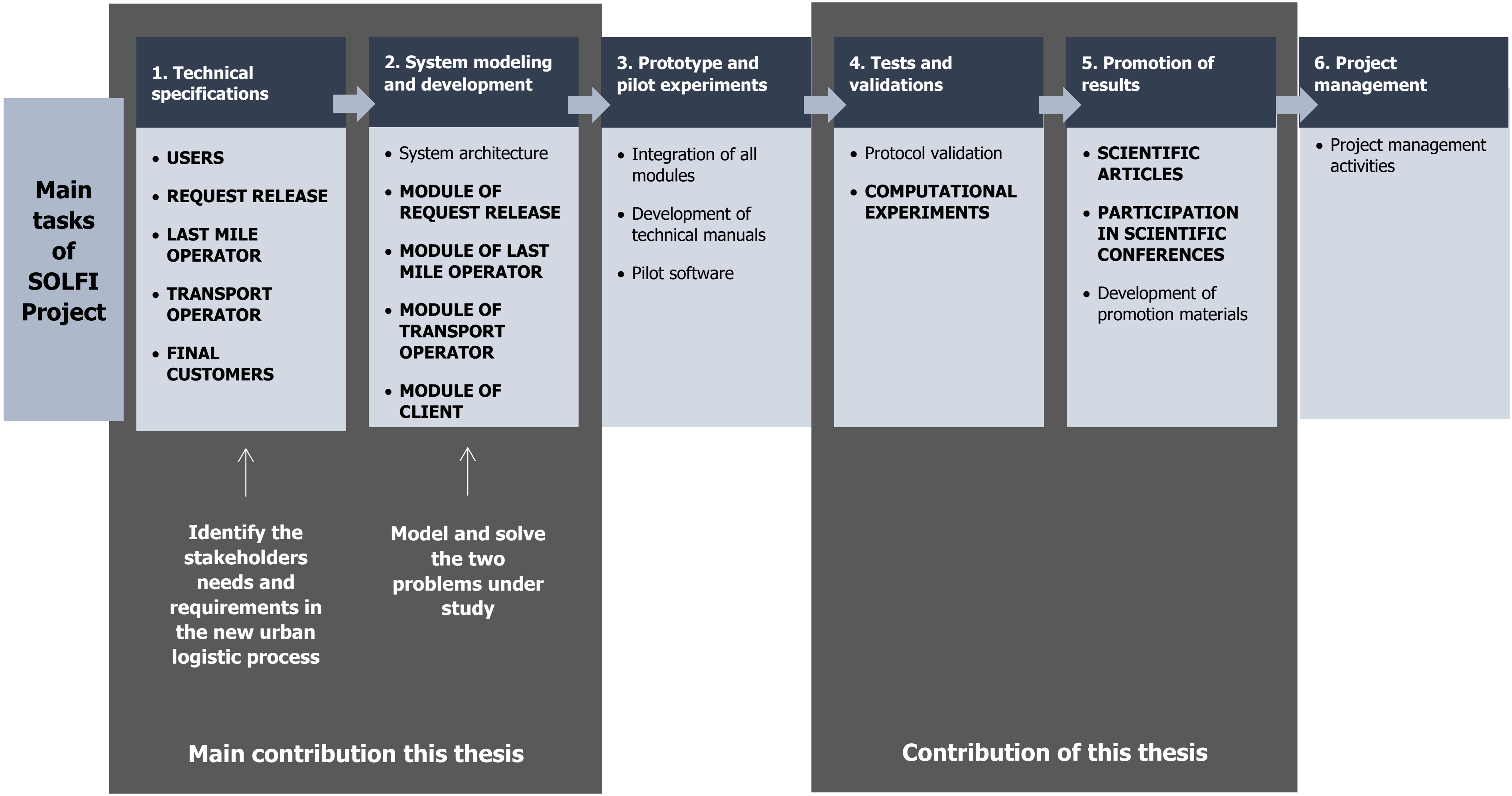

Figure 1 - Scope of this thesis research and contribution to the SOLFI project

The fundamental contribution of this research is built upon the first two phases of the investigation, as seen in Figure *1*. Thus, the contribution is mostly from requirements specification and Operational Research (OR) point of view. Karlsson (2016) characterize OR as “a straightforward extension of the scientific management approach to solving operational process problems”. Mathematical Modeling and Optimization Methods are being the heart of the majority of UL research as recent reviews have noticed. The lack of a mathematical model that can simulate the entire system, or a part of the system, to deal with various aspects of the problem under specific goals and constraints, and in designing exact or heuristic algorithms for computational optimization, is the primary driver of this growing interest. OR represents the main instrument for decision optimization in system analysis. In the context of the SOLFI project, and addressing the UL’ fundamental philosophy according to Neghabadi et al. (2019), the main challenge is to optimally plan, manage and control the freight movements within a logistical network while considering integration and coordination among involved stakeholders. Among the most important transportations planning problems are the Freight Network Flow Assignment Problem (FNFAP) and Bus Network Planning Problem (BNPP), representing both concerns in operational and strategic decision-making levels, respectively. These are the two problems tackled in this investigation. Additionally, another distinctive aspect of the research is how these two problems will be modelled and solved since they are studied in the same context, within the SOLFI project.

Therefore, the main integrated urban logistics process studied in this research considers the transportation of freight parcels from the peripheries into the city center. In this situation, a passenger bus network is used to transport requests to a bus stop located in the city. From there, a last mile operator (LMO) uses a fleet of eco-friendly vehicles to deliver the orders to the final customer. The aim is to reduce the traffic of vans and trucks operating in the city, solely dedicated to the freight transportation, thus contributing to reduce negative effects of urban logistics activities, namely pollution, noise, traffic congestion and accidents.

1.3. Research objectives and questions

This research aims to contribute to the existing literature and practice in UL field through the development and application of questionnaires and interviews to the key stakeholders and through the formulation of novel mathematical programming models and heuristics algorithms for managing an integrated passenger and freight flow urban logistics transportation system, on the operational and strategical layer of the decision-making process.

From a practical perspective, the contributions are twofold. First, this investigation contributes significantly to the SOLFI project, particularly in the first two phases of the project: determining technical specifications of the integrated solution (phase 1), through the development and application of final customers questionnaire and stakeholders’ interviews, which allow to understand and align expectations in the designing phase of the solution. Secondly, this thesis assists in the design and implementation of a new urban logistics service with passenger and freight integration, using the developed models and algorithms (phase 2). In the SOLFI Project, there is a strong need for approaches capable of finding suitable solutions to these complex problems in short computational times. Furthermore, this thesis provides a strong knowledge that can assist decision-makers accelerating planning and examine alternative decision scenarios using models that include many real-world features and subjective influences.

In terms of mathematical models and heuristic algorithms the contributions are tackled from two problems: FNFAP and BNPP. In this context, the goal is building operational and strategic decision levels, which will have practical significance for real-world project SOLFI. Here, single and combined problems, as well as deterministic and stochastic parameters, are addressed to deal with the dynamic and complexity of cities. From an academic aspect, this thesis contributes to the current state-of-the-art literature on this context of integrated passenger and freight flows in an urban logistics context by identifying directions to model and solve two significant problems in these two distinct decision layers.

This thesis is guided by five main research objectives in order to achieve the prior contributions:

(1) Understand how gather all the requirements and expectation from the different stakeholders of the project and how to align them on the integrated logistical solution.

(2) Understand which mathematical programming models contributed to integrated passenger and freight flows in the urban logistics environment, as well as how uncertainty was analyzed and incorporated into such contributions.

(3) Tackle UL planning problems capable of incorporating real-world features.

(4) Formulate novel mathematical programming models, both deterministic and under uncertainty, capable of framing the decision maker's decisions (strategic and operational) regarding the integrated flows.

(5) Develop suitable solution approaches to solve the models efficiently to real-world applications through the SOLFI project.

This investigation is characterized as qualitative, developing and applying semi structured interviews to stakeholders and quantitative, developing a questionnaire and using model-based research employing advanced methods and algorithms to capture (part of) the decision-making problems, that are faced by managers in real-life operational processes (Karlsson, 2016). The research objective (1) and (2) serve as the starting point of the whole investigation by providing the knowledge required to understand: i) the requirements from stakeholders and; ii) the formulations and problem-solving techniques that have been used in the past. Moreover, research objectives (3), (4) and (5) focus on modeling and problem-solving approaches. Each of the specified research objective is associated with four research questions (RQs), which will guide the whole investigation. Figure *2* depicts a visual representation of the research questions that this thesis answers as well as their relationship.

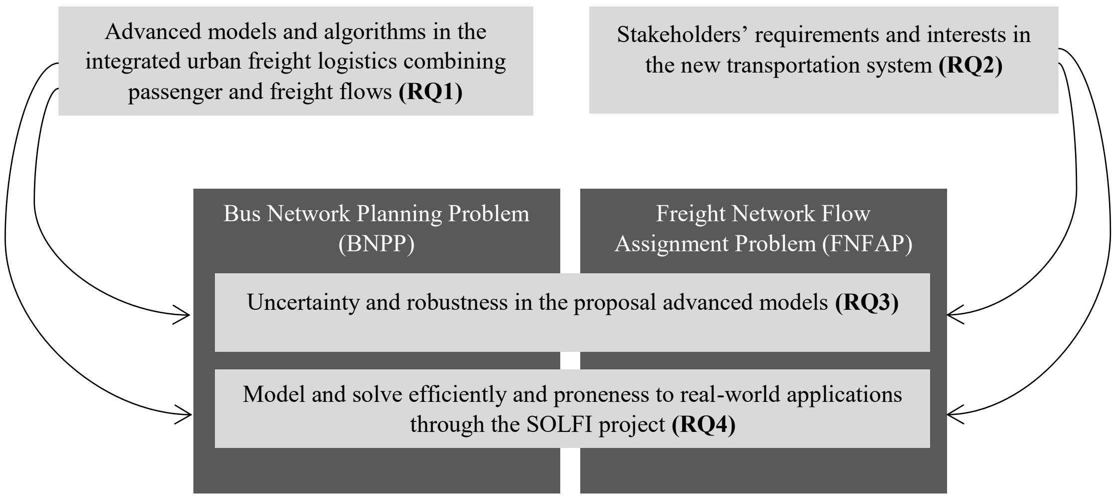

Figure 2 - Research questions framework

Research Question 1:

How have researchers addressed the Urban Logistics integration of passenger and freight flows problem from an operations research perspective?

There have been several problems in the context of integrated passenger and freight flows in urban logistics, each with its own formulation and solution. As a consequence, a detailed overview of previous research on the subject is provided in an effort to get a better understanding of the mathematical modeling methodologies and solutions approaches used. Furthermore, it is investigated how uncertainty has been included and handled. This review, which serves as the basis for this thesis, allows us to reflect on the contributions made to the published data and place this study in reference to them, as well as collect strong foundations to define the action lines taken in the following chapters.

Research Question 2:

How can an urban logistics transportation system that integrates passenger and freight flows be enriched for real world contexts?

Given that the SOLFI project's final output will be used in a real-world context, in the city of Porto, the development of advanced models and algorithms to assist city decision-makers and stakeholders in developing a new integrated urban freight logistics service combining passenger and freight flows must account for a wide range of real-world and subjective influences. The engagement and support of stakeholders is one of the most essential influencing variables of a successful transportation system. The conflict of interests among the numerous stakeholders has been mentioned as a negative affecting element in several contributions. The SOLFI Project is critical in finding and assessing conveniences and features seen in real-world environments in order to integrate them in models. As a result, interviews and a questionnaire were done throughout the conceptualization phase of the mathematical model to guarantee that the stakeholders' requirements are integrated into the models. Their applications have two main goals. A first one with the aim to understand how the final customer accept the adoption of the two conveniences during the last mile deliveries: the first one, the smooth integration of neighbor stores as dropping points where final customers could collect their orders; and the second, the availability of a delivery service based on an automated pick-up point, for example, smart-lockers, and what can affect the acceptation of such conveniences. The second goal lies on the identification of the main features and restrictions that stakeholders value in an integrated transport system for UL. After collecting and analyzing the needs of the many stakeholders and resolving any conflicts of interest, the conceptual solution proposal is established in order to go on in the modeling, solving, and implementation phases.

Research Question 3:

How to address uncertainty and robustness in an urban logistics transportation system that integrates passenger and freight flows?

This research question is motivated by two aspects. The first, which is relevant to the SOLFI project, is the requirement to deal with potential disruptions in the system. Since the Intelligent Decision Support System aims to help the decision maker to make the best decisions, it is a matter of interest to have features which allow the system to deal with potential disruptions that may occur. The feature to deal with robustness was incorporated into the operational level of decision-making process (in FNFAP), allowing the system to build a distribution plan of freight and passengers, through the integrated system, robust enough to deal with the two disruptions most likely to occur.

The second one is the lack of emphasis devoted to incorporating uncertainty in the context of integrated passenger and freight flows transportation problems. Uncertainly is a major factor which should be considered in city logistics problems. As stated before, in this investigation both deterministic and stochastic parameters were studied. The outcome of this research question will be a well-defined model to represent uncertainty in each problem, through the use of stochastic parameters for the FNFAP and a set of scenarios with possible realizations for stochastic parameters for the BNPNP and consequently, different solution methods to solve it.

Research Question 4:

As previously stated, this investigation addresses two major problems connected to two decision-levels: FNFAP for the operational and BNPP for the strategic decision level. Therefore, the aim is to formulate adequate models for specific integrated passenger and freight flow contexts, as well as developing appropriate solution methodologies to efficiently solve each model. Because model formulation has an impact on solving efficiency and solution quality, the two goals of modeling and solving are intimately connected. Thus, a research question is allocated to each decision level, such as research question 4.1 for the operational problem FNFAP and research question 4.2 for the strategic problem BNPP. The answers to both research questions resulted in extending complex knowledge of two transportation problems into mathematical models, with specific goals and constraints and also into heuristic algorithms for both problems.

Research Question 4.1*: How to model and solve the assignment of parcels to bus services in the urban logistic problem of integrated freight and passenger flows?*

From an operational perspective, this investigation aims to study an integrated approach to use spare capacity of the bus network to integrate the freight and passenger flows within the city. This FNAP is modelled by integer linear programming (ILP), studying five objective functions from different perspectives of interest. From the decision-maker point of view, in this case the Bus Transport Operator (BTO) perspective, the number of bus services and robustness to bus service suppressions are studied; concerning the LMO perspective, average last mile delivery time, number of bus offloads, and robustness to last mile failures are addressed. The goal is to provide a distribution plan to the decision-maker for all freight requests to manage the following operations: (i) assign each request to a bus hub where bus services depart from; (ii) assign the request to a bus service starting on the assigned hub; and (iii) assign the request to a bus stop of the assigned bus service, to be offloaded by the LMO and delivered at the final customer destination. Five optimization models are proposed and tested, covering the entire logistics process from the reception of freight delivery requests from clients until the delivery of the freight to the destination address, within city center; and solved using exact and heuristic approaches. Lexicographic optimization models were used to study selected combinations of the five objectives functions mentioned above. To evaluate the proposed models, eighteen instances were generated and solved.

Research Question 4.2*: How to model and solve the adapted bus fleet size needed in the urban logistic problem of integrated freight and passenger flows?*

From a strategic layer perspective, this investigation addresses the BNPP with the aim to help the BTO to estimate the number of buses that must be physically adapted, compared to the buses dedicated only to passenger transportation, to transport goods while also transporting passengers. Considering that this adaptation of the buses to perform freight transportation is expensive, it is a matter of interest to the BTO to optimize the fleet size of these adapted vehicle. The problem is modelled by an integer linear programming (ILP) model and solved using exact and two heuristic approaches, targeting to obtain optimal solutions and assess the efficiency of the heuristics proposed. This study, in addition to contributing to a new approach within BNPP, proposes some new points that represent the study's uniqueness, namely including uncertainty through the development of scenario optimization-based optimization algorithms to support the BTO to deal with it. To evaluate the proposed models, 144 instances were generated and solved.

1.4. Thesis structure and synopsis

This thesis consists in seven chapters. The current chapter introduces the thesis by providing an overview of the investigation, as well as an explanation of the motivation and its goals. Furthermore, it provides an overview of the chapters that compose the thesis.

Chapter 2 provides the fundamental background of UL theory. An initial work was developed with the aim to introduce the concept of urban logistics. This resulted in a book chapter (Machado et al., 2023) that presents the concepts and challenges in UL context:

- *Machado, B., Pimentel, C., Sousa, A., Ramos, A.L., Ferreira, J.V., Teixeira, L.. 2023. A Literature Review of Technological Trends in Urban Logistics: Concepts and Challenges. In: Duffy, V.G., Landry, S.J., Lee, J.D., Stanton, N. (eds) Human-Automation Interaction. Automation, Collaboration, & E-Services, vol 11. Springer, Cham. https://doi.org/10.1007/978-3-031-10784-9_26*

Then, an additional section with a Systematic Literature Review (SLR) is presented with the purpose to answer the research question 1 (RQ1) and ultimately, feeding the decision support models. The aim is to provide a concise overview of how academics at UL have approached the integration of passenger and freight flows from an operations research standpoint. Several literature gaps and research opportunities in existing literature that motivate further research on this topic are highlighted and thereby the contributions in this context. The chapter concludes with a critical view over the literature in this field.

Chapter 3 introduces the research methodology used in this thesis. To address the research question 2 (RQ2), qualitative and quantitative techniques, with the abovementioned interviews and questionnaire, are developed and applied. To address the research questions (RQ3) and (RQ4) Modelling and Simulation is used as methodology. This chapter describes the Modelling and Simulation as research methodology and the research process commonly used in the literature when applying this methodology. The conceptualization, modeling, problem-solving and implementations phases are then described, which supports the study presented in the following chapters.

Chapter 4 studies the stakeholders' expectations and perceptions, tackling the research question 2 (RQ2). This chapter ensures that stakeholders' expectations and needs are met by incorporating this information into the optimization models developed for the SOLFI project's integrated transportation system. A questionnaire was distributed to potential clients of the SOLFI system, to gather their requirements and needs, resulting in 308 respondents. Furthermore, three semi-structured interviews were conducted with three key stakeholders of the SOLFI project, with the aim to gather their requirements for the integrated transportation solution within the scope of SOLFI project. Gathering their requirements allowed us to design and build an integrated solution of passenger and freight flows, incorporating all requirements from all stakeholders of the solution. This incorporation of requirements not only strengthens the link to the real world, but it also helps to close the gap between client expectations and operational performance. The work presented throughout this chapter has resulted in the following conference presentation and article (Machado et al., 2021):

- *Machado, Bruno, Leonor Teixeira, Ana Luísa Ramos, and Carina Pimentel. 2021. "Conceptual Design of an Integrated Solution for Urban Logistics Using Industry 4.0 Principles." Pp. 807–15 in Procedia Computer Science. Vol. 180. Elsevier B.V.*

Chapter 5 addresses the FNFAP and tackles the research question 3 and research question 4.1. In this chapter the FNFAP problem is modelled on the operational layer of the decision-making process, through integer linear programming and heuristic algorithms. The formulation of the problem uses three stochastic parameters, the demand, requests destination, and delivery time window at final customer, tackling the first part of the research question 3 (RQ3). Five objective functions from different perspectives, using different models with specific constraints are studied. Furthermore, several combinations of interest of these five objective functions are studied, using lexicographic optimization for each pair of objective functions. The results allow to conclude the tradeoffs between pairs of objective functions, depending on which objective is prioritized first in the lexicographic optimization. Additionally, the approach to the operational problem FNFAP differs from the current approaches in the literature, since robustness is incorporated into the optimization models, through two different objective functions and constraints: robustness to deal with bus suppressions and robustness to deal with bus offloading failures on the last mile leg of transportation. According to the research analysis of the literature, this study is the first in the literature that explores the problem of incorporating robustness to the operational planning, in the field of integrated flows in UL, in this way. Considering the heuristics approach, two main algorithms for the integrated problem were developed: the request receipt algorithm to accept a new transportation request within short time; and an optimizer algorithm to optimize the distributed plan of all accepted requests for the day. The work presented across this chapter has resulted in the following scientific articles (Machado et al. 2023; Machado et al. 2023) and conference presentations:

- *Bruno Machado, Amaro de Sousa & Carina Pimentel. 2023. "Operational planning of integrated urban freight logistics combining passenger and freight flows through mathematical programming" Journal of Intelligent Transportation Systems, DOI: 10.1080/15472450.2023.2270409*
- *Machado B., Pimentel C., de Sousa A. 2022. "Optimization of last mile logistics process combining passenger and freight flows". Proceedings of International Conference on Quality Innovation and Sustainability 2022, DOI: 10.1007/978-3-031-12914-8_27*
- *Machado B., Pimentel C., de Sousa A., 2022. "Operational planning of integrated urban freight logistics combining passenger and freight flows: A heuristic approach", presentation at Transport Research Arena conference, Lisbon, November 15, 2022 (presentation)*
- *Machado B., Pimentel C., de Sousa A., 2021. "Operational planning of integrated urban freight logistics combining passenger and freight flows through mathematical programming", presentation at the 24th euro working group on transportation meeting, virtually, September 8-10, 2021 (presentation)*

Chapter 6 addresses the BNPP and tackles the research question number 3 and research question 4.2. This chapter models the BNPP at the strategic layer of the decision-making process, through integer linear programming models and heuristic algorithms. The aim of studying this problem is to build decision models to help the BTO to determine, in a strategic planning phase, the minimum number of buses needed to be adapted for the integration of passenger and freight flows. Assuming that the required physical adaptation on the buses is expensive, the minimization of such investment beforehand is a matter of interest for the BTO of the city. To formulate this problem, scenarios of possible realizations of stochastic parameters are used. For each scenario, a possible value is assumed for the stochastic parameters: request demand, requests destination and delivery time window at the final customer. The aim of the optimization models is to find the minimum number of buses needed to cover the transportation needs of 100 scenarios, improving the robustness of the solution, considering the reasonable assumption that if a solution if feasible for a set of 100 possible scenarios, it is a solution with low probability of not being feasible in a future implementation. Moreover, a solution procedure, based on a scenario-based heuristic optimization, that incorporates various transportation scenarios of demand realizations is proposed to solve the problem and get solutions as reliable as possible. To the best of the authors' knowledge, no research is available to this specific strategic problem and characteristics, using realizations of demand to achieve solutions that are closer to reality, in a planning stage of the network design. Concerning the heuristic approach to the problem, Greedy Randomized Adaptative Search Procedure (GRASP) metaheuristic is studied and applied to the BNPP. Two complementary Greedy Randomized (GR) procedures (heuristic H1 and heuristic H2) were researched, with the aim to evaluate the best approach for the problem, in terms of computational runtimes and quality of solutions. The results allow us to conclude what is the best optimization method, ILP formulations, Heuristic 1 or Heuristic 2, to be used for each instances' characteristics of the problem. The work presented throughout this chapter has resulted in the following journal article (Machado, et al. 2023):

- *Machado, Bruno, Carina Pimentel, and Amaro de Sousa. 2023. "Integration Planning of Freight Deliveries into Passenger Bus Networks: Exact and Heuristic Algorithms." Transportation Research Part A: Policy and Practice 171:103645., DOI: 10.1016/j.tra.2023.103645*

Finally, **Chapter 7** concludes with a summary of the main findings and contributions within this thesis and present some limitations to the research. Some future investigation directions are presented as well.

2. Theoretical Background

This chapter sets itself as an overview of the essential theoretical background that underlies the contributions presented throughout this thesis. It begins with an introduction to the UL concept. Following that, three reviews were conducted. The first concerns the main concepts and trends associated with the UL field. The second concerns the operations research models and methods for integrating passenger and freight flows within UL. Specially, this review aims to highlight the existing gaps in the literature, which this research aims to address, using them as a foundation for defining the courses of action taken in the following chapters. A third, as ending the present section, concerns on the most recently published articles, to show how new the research still is.

2.1. Introducing urban logistics

UL is a broad concept that has been employed to seek for new solutions of transporting goods in urban areas, while taking into account the negative effects on congestion, safety, and environment (Savelsbergh & Van Woensel, 2016). Terms like city logistics and urban transportation are often used interchangeably in the literature (Lagorio et al., 2016). For some authors, that clearly distinguishes both concepts, UL can be defined as:

> *"that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and point of consumption in order to meet customers' requirements, as influenced by complex interactions among densely populated social systems and associated infrastructure"* (Rose et al., 2017).

Following the distinction between concepts, according to Na et al. (2022), city logistics represents:

> *"a critical field in urban areas and mainly focuses on stakeholders' interrelationships from the perspective of macro-level logistics."*

Whether it's city logistics or urban logistics, both are essential for improving cities' well-being (Melo & Baptista, 2017). Similarly, the new solutions must be created to accommodate both environmental and demographic challenges, as well as the specific urban logistical challenges that cities confront.

The concept of UL, however, is not new – it dates back to the 1990s (Lagorio et al., 2016). Since then, the world, cities, and science have all evolved. In addition, technological improvements, new business models, and new transportation patterns have evolved, bringing with them a rising development of innovative, integrated urban logistics solutions. The concept's principal scope is inherent in this evolution: UL includes all freight activities in the city, including the assessment, planning, maintenance, and enhancement of logistics activities (Büyüközkan & Ilıcak, 2022).

Much research has been carried out that stems specially in reducing aforementioned challenges, while offering better and faster deliveries (Savelsbergh & Van Woensel, 2016). Further, the increased interest and popularity of UL is reflected in a growth in practitioner publications, conferences, books, PhD thesis, and university courses in the topic (Hu et al., 2019; Neghabadi et al., 2019). In addition, it is also reflected by the different SLRs that have been published in recent years, as well as the increasing number of publications dealing with novel transportation options in the field of urban logistics.

SLRs help to provide a rich picture of the current body of research with methodologically well-defined and rigorous criteria (Thomé et al., 2016). The top 10 most cited literature reviews published in quartile 1 journals is summarized in Table 1. The top 10 was achieved considering a search in Scopus database with the string: “urban logistics" OR "city logistics" OR "urban delivery" OR "last mile delivery" OR "urban freight", considering only review articles published in journals Q1 of the field. The review developed by Pelletier et al., (2014) stands out from the rest due to the number of citations displayed in Table *1*. Moreover, as seen in Table *1*, UL is a topic of interest to a large number of academics and journals worldwide. Specially, journals concerning production and logistic/distribution fields appears as crucial to potentially mitigate the mismatch between supply and demand from an operations research contribution. It is also important to notice the publishing year, which shows the topic's novelty.

Table 1- The 10 most cited reviews in the urban logistics field

R	“Article Name” and (Reference)	Journal	TC
1	“Goods distribution with electric vehicles: Review and research perspectives” (Pelletier et al., 2014)	Transportation Science	206
2	“Consumer-driven e-commerce: A literature review, design framework, and research agenda on last-mile logistics models” (Lim et al., 2018)	International Journal of Physical Distribution and Logistics Management	172
3	“Research in urban logistics: a systematic literature review” (Lagorio et al., 2016)	International Journal of Physical Distribution and Logistics Management	162
4	“Innovative solutions to increase last-mile delivery efficiency in B2C e-commerce: a literature review” (Mangiaracina et al., 2019)	International Journal of Physical Distribution and Logistics Management	144
5	“Impacts of logistics sprawl on the urban environment and logistics: Taxonomy and review of literature” (Aljohani & Thompson, 2016)	Journal of Transport Geography	132
6	“Sustainable urban freight transport in megacities in emerging markets” (Kin et al., 2017)	Sustainable Cities and Society	83
7	*“Crowdsourced delivery: A review of platforms and academic literature” (Alnaggar et al., 2021)*	Omega (United Kingdom)	81
8	“Systematic literature review on city logistics: overview, classification and analysis” (Neghabadi et al., 2019).	International Journal of Production Research	81
9	“Survey Techniques in Urban Freight Transport Studies” (Allen et al., 2012)	Transport Reviews	65
10	“A scientometrics review on city logistics literature: Research trends, advanced theory and practice” (Hu et al., 2019)	Sustainability (Switzerland)	60

Nomenclature: R (Rank); TC (Total of Citations according to the Scopus database and updated to September 2023)

The interest and popularity of UL is also reflected by the numerous solutions dealing with novel transportation options in order to mitigate city logistics complex issues. From a logistics system perspective, the integration of networks and infrastructures is one of the appealing solutions highlighted in the literature. It aims to satisfy adequately current and future urban transportation needs, and this is the goal of the current study. The emergence of sharing transportation practices, in which passengers and freights are part of a joint transportation movement or mixed within the same travel, has been studied based on collaboration between businesses, customers, and the public sector.

According to Bruzzone et al. (2021) an integrated system is defined by passengers and goods sharing vehicles, infrastructures, urban space or more than one of these at the same time, which is addressed in the current study. According to Cavallaro & Nocera (2022), the combination of passenger–freight transport appears to be a research field still in its early phase but with some interesting potentialities.

There are different possibilities for collaboration between businesses, customers, and the public sector. Interested readers are referred to Li et al. (2021), in which the researchers expose three patterns of collaborative urban freight transportation systems, to Romano et al. (2021) who present a simulation-based evaluation for cargo-hitching service using Mobility-on-demand vehicles, and to Van Duin et al. (2019) that study the integration of transportation systems for long-hail transportations. Bus, trains, and taxis are some of the studied collaborative delivery modes.

In recent years, the literature has featured articles exploring the most recent innovations, such as the use of drones by Moadab et al. (2022), the use of Twitter data by Mehlawat et al. (2021), but also the development of new business models (Mazzarino & Rubini, 2019) and user-oriented service concepts (Le Pira et al., 2021). For Muñuzuri et al. (2005) combining solutions is a strategic policy for city logistics. Its strategic advantage stems from new developments in both the literature and practice, with the goal of optimizing the overall system rather than the performance of individual subsystems (Lagorio et al., 2016; Mourad et al., 2021; Manchella et al., 2022), which provide efficiency gains for all transport stakeholders (Ghilas et al., 2016).

Many factors can influence the success of a collaborative freight transportation system, including storage-space sizing (Behiri et al., 2018), logistics information platforms, and the overall structure of the network (Nieto-Isaza et al., 2022), for instance. Among these factors, the Network Design Problem is one of the most difficult transportation problems to deal with (Neghabadi et al., 2019). One reason for UL complexity is the presence of multiple service providers, each of which operating its own independent activity planning, resulting in multiple separate logistics networks within a city (Le Pira et al., 2021; Molenbruch et al., 2021; Moadab et al., 2022). Furthermore, this complexity arises not only from the number of innovative configurations (Li et al., 2022) and the large number of decisions that must also be made in order to reduce the complexity of the City Logistics network, but also from the difficulty in obtaining optimal solutions that are close to reality. The incorporation of uncertainty contributes significantly to this proximity to reality, but it is still also underexplored in this context.

In addition, the management of a new urban logistics system is viewed as complex, with many diverse entities involved: entities having varying goals and purposes that frequently compete with one another. The complexity extends to local and central government, urban planners and residents, all of whom are concerned with city sustainability and quality of life. It also includes customers, suppliers and distribution companies whose focus is to save costs and increase efficiency. Decision-making in city logistics is becoming increasingly difficult in this complicated yet interconnected context (Firdausiyah et al., 2019).

2.2. Technological trends in urban logistics: Concepts and challenges

Accordingly to Lagorio et al. (2016), UL subject is still evolving because of the continuous changes in citizens habits and the unceasing technological evolution enabling new delivery scenarios. Indeed, there exist many challenges specific to the urban logistics that makes difficult the implementation of solutions. One of the challenges for the urban logistics is the creation, implementation and operations management of networks to provide a good service at a low cost with better coordination of the flows of goods, higher consolidation of the freight volumes, and multi-organization cooperation (Savelsbergh & Van Woensel, 2016). On the other hand, focusing on freight transport, increasingly fragmented demand due to the spread of e-commerce and the synchronization and harmonization of the different flows of goods are pointed by Lagorio et al. (2016).

This subsection presents a literature review about the concepts and challenges of UL.

The Literature Review (LR) is selected as the research method for this study due to the nature of the research questions, aiming to understand the trending concepts and technologies supporting urban logistics and how they influence it.

LR was performed in December of 2020, based on the approach presented in Timmins & McCabe (2005) in which the main stages are: (1) identify a topic of interest and spend time identifying keywords, (2) using keywords to conduct a search of relevant literature, (3) review all references sourced and retrieve a copy of relevant references, (4) read all relevant sourced literature and identify new references through citations and, lastly, (5) organize all material in preparation for analysis and integration in the review.

Although the main searching procedure presented above is a 5-step process easy to understand, the steps 1, 2 and 3 have to be further detailed.

Step 1: Identify a topic of interest and spend time identifying keywords

The topic of interest for investigation was urban logistics. The keywords selected for the query were based on the article Lagorio et al. (2016) and they are: "urban logistics", "city logistics", "urban delivery", "last mile delivery" and "urban freight". Since the research objective was to identify the technologies and concepts that support urban logistics and its automation, the terms "concept" and the truncation "technolog*" were added as keywords.

Step 2: Using keywords to conduct a search of relevant literature

After selecting the keywords for the study, some criteria had to be considered to conduct the search of relevant literature. The database Scopus was used to perform the search. As the first filter, only journal articles were considered to do the search. Secondly only Social Sciences, Engineering, Business, Managing, Accounting, Environmental Science, Decision Sciences, Energy, Mathematics, Economics, Econometrics and Finance areas were considered, excluding areas like Medicine, Neuroscience and others. In addition to these two filters, only studies after 2016 were considered. This decision was based on the existence of two LR (Savelsbergh & Van Woensel, 2016) (Lagorio et al., 2016) published on that year and due to the high number of studies on this topic that have been trending, with a rapidly increasement in 2016.

Finally, only studies written in English were considered for this study. As a result of this search, a total of 154 articles were found.

Step 3: Review all references sourced and retrieve a copy of relevant references

To identify a sample of relevant articles, the title, abstract and the article itself was read to ensure that it was related to the objective of this research. At the first stage, each title was read and the article would not be considered only if the title mismatches the research objective. After that, each abstract was also read and the same logic of title criteria was applied. If the title and abstract analysis were not sufficient to reach a conclusion, the article was considered and the full paper was analyzed. During this process, the main mindset for this articles' selection was based on the research questions, always looking for articles that could provide trending concepts and technologies supporting the urban logistics.

As a result of the LR twenty-five articles, with technological trends, were selected and analyzed in detail, and a summary of the main contributions of this set of articles to this research is explored and analyzed in this section. Thus, in the subsection 2.2.1 the technological trends that are supporting urban logistics, answering to the research question 1 "What are the main topics and technological trends supporting urban logistics", will be identified and examined. Next, in the subsection 2.2.2, a framework with the relationship between the technologies and the topic urban logistics will be presented, allowing to answer the research question 2, i.e. "What are the relationships between these technological trends and concepts and urban logistics' dimensions, namely, regulation & policies, sustainability, operational excellence, collaboration and digitalization".

2.2.1. Technological trends in urban logistics

This subsection details the technologies and trends that are supporting urban logistics that were found on the LR performed. An overview, with the main technologies/concepts, their definition, the respective papers and their goals, is summarized on Table *2,* and then discussed in more detail.

Table 2 - Technological trends found on literature that are supporting urban logistics

Technology or Concept	Description	Goal	Articles
Unmanned aerial vehicles (Drones)	Adoption of drones' technology to perform last mile delivery	- Minimize the operational cost and urban traffic	Agatz et al. (2018); Ha et al. (2018); Kitjacharoenchai et al. (2019); Boysen et al. (2018)
		- Study the market and economic viability of these solutions in Europe	Aurambout et al. (2019)
Sharing economy	Different stakeholders share their resources to perform last mile deliveries	- Determine the sustainability potential of crowd logistics	Rai et al. (2017), Behrend & Meisel (2018); Giret et al. (2018)
		- Provide insights about crowd logistic business models	Frehe et al. (2017)
		- Determine potentials of sharing parking spaces	Melo et al. (2019)
		- Determine potentials of integration of freight and passenger flows	Ozturk & Patrick (2018)
Cargo Bikes	Utilization of cargo-bikes to perform last mile delivery	- Provide recommendations from an extensive empirical survey with experts	Rudolph & Gruber (2017)
		- Study the costs and sustainability impact	Anderluh et al. (2017)
Pick-up points	Secured location where customer can pick-up	- Provide customer insights about pick-up parcel lockers	Vakulenko et al. (2018); Yuen et al. (2019)

	their orders instead of being delivered at home	- Minimize the external and operational costs	Arnold et al. (2018); Orenstein et al. (2019)
		- Optimizes the changing locations to minimize the number of pick-ups	Schwerdfeger & Boysen (2020)
Autonomous delivery robots (ADR)	Autonomous robots that perform the last mile delivery from trucks to city centers	- Presents the factors that influences the acceptance of autonomous robots	Kapser & Abdelrahman (2020)
		- Study the efficiency impact of this concept	Boysen et al. (2018)
Platooning van	Platoons of connected vans performing last mile delivery where the first one is driven and the others are driverless, following the first van instructions	- Models and simulates this platoon solution to decrease the number of vehicles operating	Lupi et al. (2020)
New energy logistics vehicles (NELV)	Usage of battery electric vehicles (BEV) to perform last mile delivery	- Study the adequacy and performance of BEV in urban logistics	Duarte et al. (2016); Jiang & Guo (2020)
Connected cities	Utilization of an open system engaging and interconnecting the actors to perform the last-mile delivery	- Enhance the ecological and societal potential of interconnectivity solution	Mohamed et al. (2017)
Cloud-based order fulfillment	Utilization of a new cloud-based process to plan orders fulfillment	- Improve efficiency of orders planning	Leung et al. (2018)

Unmanned Aerial Vehicles (also known as drones). Using drones for last mile delivery is gaining popularity, since many large companies such Amazon, FedEx, DHL and UPS are currently investigating the effective use of drones for last mile delivery (Boysen et al., 2018). This popularity is due to the potential to decrease delivery costs and elimination of congestions costs leading to less miss-deliveries, since the delay from the dispatch to the delivery is very short when compared to truck based deliveries (Aurambout et al., 2019). The research reported by Aurambout et al. (2019) focuses on the European market and the economic viability of implementing drone solution for last mile delivery. The main goal of their paper is to provide a reality check of this drone delivery concept and investigate the potential optimal location of the distribution centers to accommodate the landing and take-off of the drones. The conclusion of the study points to the viability of the drone delivery based on distribution centers to perform last mile delivery in many European urban areas, confirming the drone delivery as a trending technology for the next years.

On the other hand, Boysen et al. (2018)' study presents an alternative approach to decrease the costs of the network of distribution centers to receive and launch the drones. The authors propose a prototype of a truck-based drone delivery solution, where trucks serve as both a mobile depot, in which the shipments to be delivered are transported, and as a mobile launching platform for one or multiple drones based on the top of the truck. The collaboration of these two types of vehicles is truly important, since the delivery truck moves between different customer locations, performing conventional home deliveries, and the drone simultaneously serves additional near customers, one at a time, returning to the truck after each delivery.

Ha et al. (2018) studied the Travelling Salesman Problem with Drones (TSPD) where a delivery could be performed by a truck or a drone, but the drone had to be launched and rejoin later the same truck at another location. The objective was minimizing the operational cost of the system, including the transportation cost and the waiting penalties when a vehicle has to wait for the other. Similarly, Agatz et al. (2018) report that substantial savings are possible adopting emerging technology (drone) when collaborating with conventional trucks.

Kitjacharoenchai et al. (2019) performed a research on the Multiple Travelling Salesman Problem with Drones (MTSPD). On their study, both trucks and drones can perform deliveries. However, some details are different from the previous studies, resulting on different approaches which are: orders being delivered only by conventional trucks, conventional trucks performing deliveries, simultaneously with drones departing from trucks to deliver additional customer returning to an available truck (not necessarily the same), drones performing deliveries directly from the depot and returning to an available truck or the initial depot. The research goal is to model and seek an optimal delivery route in an urban location with the objective to minimize the total cost of deliveries, which consists in the cost of truck travels, the cost of drone travels and the cost of simultaneous truck and drone travels. Results have shown that using multiple drones and trucks provides shorter delivery times than conventional truck deliveries.

Some benefits of adopting this technology, based on the considered articles are; (i) faster than trucks; (ii) reduction of delivery costs; (iii) shortest delivery time; (iv) elimination of congestion time; and (v) environmentally friendly solution (reduction of air emissions).

Regarding the potential issues adopting this solution, can be pointed out: (i) cargo weight restricted to the weight that drones can carry; (ii) shorter travel range; (iii) drones can only transport one shipment; (iv) drone safety and noise during deliveries; (v) mandatory existence of distribution centers close to the customers location; and (vi) local government policies.

Sharing Economy. The growing interest in shared passenger and freight transportation practices indicates that an important opportunity could be reached in combining both. Crowd Logistics (CL), alternative termed crowdshipping originates from the term crowdsourcing which covers both the word “crowd” or a mass of people and “outsourcing” or the shift of processes, functions and duties to third parties (Mehmann et al., 2015). CL is a promising concept as it encourages passengers to use their spare carrying capacity on cars, bikes, buses and planes to carry packages to other people. CL uses the excess capacity on premeditated trips that already taking place to make deliveries, leading to maximization of logistics efficiency and reduction of emissions and traffic congestions (Arslan et al., 2016). The idea is to encapsulate the physical objects in packets and containers. These containers are then routed as efficient as possible, absorbing spare capacity in transport systems and ensuring that they get to their destination on time (Rai et al., 2017).

Additionally, Frehe et al. (2017) research was performed to evaluate the nature and characteristics of CL business models and propose a four step process that practitioners need to follow to implement a sustainable crowd logistics service.

- Be innovative and try to provide a new added value service for stakeholders;
- Expect a negative return on investment in the long term;
- Be informed about country-specific regulations and restrictions;
- Build up the network as soon as possible.

As an example, Giret et al. (2018) proposes a mobile application called CALMeD SURF (Crowdsourcing Approach for Last Mile Delivery) as a practical approach to implement crowd-logistics in an urban area. This application is accessible for two types of users: those who want to deliver a parcel, and those who wish to serve as occasional deliverers in an urban area. The users register in the system, and CALMeD SURF locates them in the city in real-time. Thus, when there is a delivery request, the app uses the geo-localized temporal deliverers, to compute an optimized path for delivering the parcel to its final destination. It is important to highlight that, when calculating an optimal path, multiple objectives are used such as sustainable means, economic issues, temporal constraints, etc. Also, it is possible that the path may be constructed as a chain of collaborative deliverers, passing the parcel to different deliverers along the way. The main objective of this approach is to minimize new emissions originated by path that deviate the deliverer from his/her daily routes. Their results show that this is a feasible approach and it is a feasible solution for last mile delivery.

The study of Behrend & Meisel (2018) goes further on this topic and presents the integration of CL with item sharing. Item sharing is the term for a relationship among a sharing community where members can rent items from one another. This concept is particularly useful for items that are needed on rare or just temporal occasions and the benefits are that multiple members can sequentially use the same item instead of each buying one such item, individually (Bardhi & Eckhardt, 2012). The research Behrend & Meisel (2018) intends to integrate the CL and item sharing into a single platform that has access to information on supplies and requests of items and on announced trips of crowdshippers for an upcoming planning period. This platform will be based on collecting information over a certain period of time rather than on immediately responding to each single incoming request, resulting in the advantage of the opportunities for fulfilling more demand. Responses in real-time are not needed but a fast, scalable and high-quality decision making is needed for operating the platform. The main objective of the research is showing the potentials of this joined solution, concluding that this integration of concepts is, generally, profitable but it depends on the crowdshippers' flexibility to deviate from their original route and the compensation paid to them.

Other type of sharing economy concept is investigated by Melo et al. (2019). Their paper analyses if a shared parking solution leads to a better environmental, energy and traffic performance. The solution consists of sharing parking spaces previously used exclusively by city logistic vehicles with other users, for example, parents dropping their kids to school. Since these two flows are, typically, not coincident in time, the same reserved spaces can be used by both. Their results reveal that if the municipality would implement the shared usage of the current exclusive places for urban logistics operations, private freights and public transports would experience a decrease in delays and improvements in their speeds, resulting in improvements on environmental, energy and traffic performance.

Lastly, Ozturk & Patrick (2018) proposes an integration of urban freight transport and urban rail flow, using the same infrastructures to perform last mile delivery and passenger transportation. The solution was based on gear trains only with goods with the trains of passenger transportation, departing on the same trip. The research goal is to develop a decision support framework for the optimal transportation of freight by urban rail at an operational level.

Some advantages of sharing economy referred in the analyzed articles are: (i) reduction of delivery cost; (ii) environmentally friendly solution (reduction of air emissions); and (iii) reduction of traffic congestion.

Regarding the potential issues adopting this solution, can be pointed out: (i) hard to monitor the quality and service level; (ii) hard to predict the adherence from the crowd (in case of crowd logistics) to plan delivery services; and (iii) hard to guarantee cargo safety.

Cargo-bikes. Cargo-bikes are recently being used to perform last mile deliveries. Typically, a two-wheeled vehicle, can be as fast or even faster than the conventional vans and trucks performing deliveries within a city. This is because they are less affected by traffic congestion, and because they can often take faster routes where trucks and vans cannot go, such as pedestrian streets or bicycle paths (Decker, 2012).

The study from Rudolph & Gruber (2017) provides some recommendations supporting cargo-bikes use at local level, highlighting that the regulations and policies of municipalities play an important role for the use of cargo-bikes.

A practical example of cargo-bikes utilization is presented on the study of Anderluh et al. (2017) where they suggest the utilization of cargo-bikes to perform last mile deliveries. They study the synchronization of cargo-bikes with vans to perform last mile delivery within an urban area. The study concludes that emissions can be reduced through the substitution of vans by cargo bikes.

Some advantages of utilization of cargo-bikes are: (i) environmentally friendly solution (reduction of air emissions); (ii) faster than vans performing last mile deliveries; (iii) elimination of congestion time; and (iv) low cost of use.

Some disadvantages are related to (i) hard to guarantee cargo safety; (ii) need of decent cycle infrastructure; and (iii) limited load capacity.

Pick-up Points. To deal with the growing volumes of delivered and returned parcels, increasing customer expectations and toughening market competition, retailers and logistics service providers are exploring and implementing innovative tools such as self-service technologies. In last mile deliveries context this technologies are parcel lockers (also named as locker boxes, automated lockers, self-service delivery lockers or intelligent lockers) used as a self-service collection and return of goods purchased online (Vakulenko et al., 2018). The interest by parcel locker networks is increasing and they already represent a significant share of last mile deliveries where the customer plays an active role during the distribution process (Morganti et al., 2014).

The paper of Vakulenko et al. (2018) has studied the customer value and perspective of the adoption of parcel lockers to pick up their products purchased online. They performed a focus group interview with 26 participants that have been purchasing on-line. To ensure that all participants had the same level of experience dealing with parcel lockers, all have collected and returned a parcel using a parcel locker. With insights from the interview they were able to understand how customer look at parcel lockers on last mile delivery. Yuen et al. (2019) perform a similar study identifying that convenience, privacy, security and reliability are important factors to enhance the perceived value of smart lockers by the customers.

A practical example of this solution for last mile delivery is presented by Schwerdfeger & Boysen (2020) through the study of the potential of mobile parcel lockers compared to stationary parcel lockers. According to the authors, mobile parcel lockers have the advantage of flexibility, changing their locations during the day to where the customer concentration is higher, either autonomously or moved by a human driver. Results have shown that mobile parcel lockers can achieve the same service level of stationary lockers with only ¼ of the lockers number.

Orenstein et al. (2019) study the utilization of flexible parcel lockers to identify the potentials of this solution. It is called “flexible” because, on their experiments, each customer can be supplied from different parcel lockers with the same effort rate. The goal is to formulate a problem with flexible parcel lockers and determine the number of vehicles, their routes and assigning parcels to vehicles. Results strengthen the conclusion that exploiting the flexibility of parcels lockers makes the delivery process more efficient.

Arnold et al. (2018) study two different scenarios and compare them with the current situation. The first scenario is the utilization of pick-up points where customer collect their parcels and the second scenario is the utilization of cargo-bikes (a concept mentioned above) to perform the last mile delivery to customer houses. Conclusions are that the adoption of pick-up points reduce the operational costs of companies while the implementation of cargo-bike distribution system decrease the congestion and emissions.

Some advantages of this solution are: (i) flexible pick-up time; (ii) no missed deliveries; and (iii) shorter delivery routes by logistics service providers.

Regarding the disadvantages it is possible to list: (i) increasing number of private cars trips to collect the parcels; and (ii) customer dependency to collect the parcels; and (iii) software/hardware potential errors or flaws.

Autonomous Delivery Robots (ADV). As a response to the current challenges of city logistics, autonomous deliveries are gaining popularity to perform the last mile delivery. Autonomous delivery vehicles are compact robots applied to parcel deliveries moving along the sidewalks till their customer destination (Boysen et al., 2018).

Kapser & Abdelrahman (2020) have studied the factors that determine the acceptance of ADV as a delivery alternative to the conventional ways of last mile delivery. To do that, a survey methodology was employed by using validated scales. The results of their survey show that the price sensitivity was the most impactful factor on the acceptance of ADV from the side of the customers.

Even though autonomous vehicles for last mile deliveries is a recent concept, the study of Boysen et al. (2018) presents a model of truck-based robot solution to schedule the truck route and minimize the truck fleet. On their model, vans and robots are full with parcels to be delivered. Each van leaves the initial depot with robots and follows a route delivering parcels directly to customer locations. During the route there are drop-off points where the robots can leave the van to perform parcels deliveries to customers that are outside of the route, and then returning to the original van. Their results show that the truck fleet can considerably be reduced if autonomous robots support the delivery process.

Some advantages of this solution are: (i) easy integrated with an app to track; (ii) environment friendly solution (reduction of air emissions); (ii) need of a person at home to receive the parcel.

Some disadvantages are: (i) limited to pedestrian speed; (ii) technological interface with customer; (iii) limited load capacity; and (iv) autonomous vehicles can only transport one shipment at a time.

Platooning Van. A solution recently emerging for last mile delivery is the platooning van. Only one paper was found proposing this solution. Lupi et al. (2020) propose a transport system using automatic van platooning to perform deliveries to a city center. According to the authors, van platooning occurs when a series of vans follow automatically behind a leading van. This leading van has a driver and does not transport cargo and the other vans are driverless and contain cargo to be delivered. On their study, they propose a transport system where the van platoon moves from an urban distribution center to a dedicated location close to the city center, so-called "split-up-location", where the platoon is broken and each van of the platoon (apart from the first-one), independently from the others, carries out the last part of its delivery route moving without any driver. After completing the deliveries, all vans return to the same split up location and gather again in a platoon. Here a driven van is added to the platoon and new platoon return to the urban distribution center. They created a model to optimize the deliveries from urban distribution centers to "split-up location" and minimize the number of last mile deliveries. The results show that the total travel time of delivery trips and the total km travelled are much lower in the proposed transport system, than in the conventional transport systems.

Advantages of this solution are: (i) reduction on staff costs; (ii) higher speed than conventional autonomous vans; and (iii) energy saving, since the aerodynamic resistance is lower.

Regarding the disadvantages, can be pointed out: (i) air emissions are the same of conventional systems; and (ii) high investments needed.

New Energy Logistic Vehicles (NELVs). Vehicles that are moved by other energies that are alternatives to the fossil fuels have been gaining attention recently (Jiang & Guo, 2020). The paper of Jiang & Guo (2020) highlights the factors that influence the market penetration of these new energy logistics vehicles. The factors are:

- Policy promotion: Recent incentive polices have promoted the growth of NELVs;
- Improve of the technology level: For example, domestic pure electric technology is gradually approaching the international advanced level;
- Public awareness of environmental protection: With the increasing awareness of environmental protection, the public has increasingly realized the importance of the adoption of "green technologies";
- Market awareness: In terms of market recognition, the right-of-way, cost and social responsibility promote companies to choose NELVs.

An example of NELV application is the study of Duarte et al. (2016) that intends to know how Battery Electrical Vehicles (BEV) contribute to sustainable urban logistics. The research work evaluated the adequacy of BEV in urban logistics in Lisbon, based on a real-world application. Their results show that the adoption of BEV on urban logistics context allows maintaining the same operation patterns, regarding the number of kilometers travelled per day. When comparing the energy consumption, the adoption of BEV allows a reduction of 76% of the consumed energy.

Advantages of this concept are: (i) significant reduction of the air emissions; and (ii) reduction of noise within the cities.

Some disadvantages are related to: (i) high investments needed to changeover the fleet to BEV (or other types of green energy); and (ii) highly dependent of the technological advances.

Connected Cities. This concept was found on just one paper during the review. The study of Mohamed et al. (2017) proposes the last mile delivery process based on the key concept of interconnectivity, which is an open system where a multiple actors can utilize the interconnected urban logistics facilities and usable spaces of the physical internet. These facilities are hubs, warehouses, distribution centers, etc. Also, another key pillar for this interconnected system is the encapsulation of goods in standard modular, smart and reusable containers to be used across the system. The paper model and simulates this concept considering as objective the minimization of the delivery costs, the ecological footprint and the increasing of societal efficiency. Their results have shown that this interconnectivity concept can positively impact these performance indicators for urban logistics.

Some advantages of this concept are: (i) sharing available capacities on the city; (ii) reduction of cartoon packaging; (iii) flexibility on deliveries; and (iv) shorter routes and delivery times.

As disadvantages: (i) investments on the development of containers; and (ii) air emissions are the same of conventional systems.

Cloud-based Order Fulfillment. Leung et al. (2018) developed a cloud-based order fulfillment of the orders to the logistics providers and retailers on the field of urban logistics. According to the authors, this proposed cloud-based order fulfillment process helps retailers and logistics providers when they receive orders from their customers, since they are able to effectively plan for the upcoming internal processing operations of received orders. The proposed cloud-based process consists on consolidating the pending e-orders, using a cloud-database, and then it creates an optimal internal order processing plan, instead of processing the orders one-by-one right after they are received. According to the study, this intelligent process allows warehouse postponement strategy to be adopted, increasing retailers and logistic providers' flexibility and capacity to satisfy their customers. Reduction of processing times is also an important advantage of this concept.

Some advantages of this concept are: (i) lower processing times of the orders; and (ii) higher flexibility and capacity to satisfy the customer expectations.

Some disadvantages are related to: (i) process re-engineering by logistics services providers is needed; and (ii) investments on the cloud database.

2.2.2. Contributions of technologies and innovative concepts on urban logistics

Grounded on the LR performed and considering the results summarized in Table *2*, a framework, which allows to understand the contribution of each technology or concept in urban logistics and in which dimensions it has an impact, is proposed in Figure *3*.

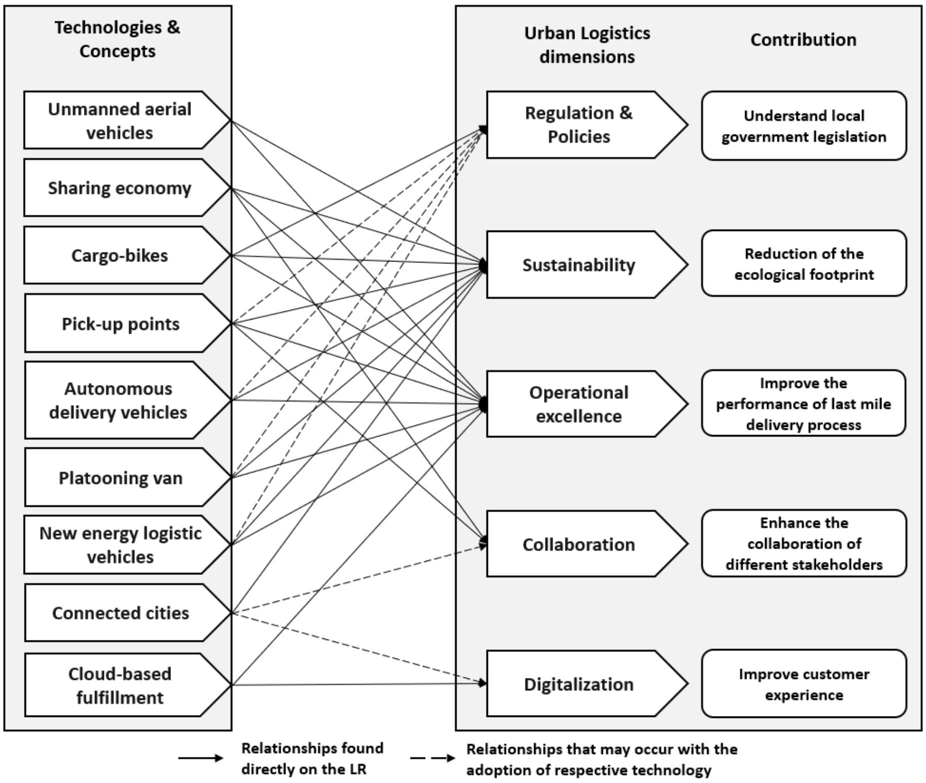

Figure 3 - Framework of contributions of each technology or concept in UL

From the nine technologies and concepts discussed on this study, it is possible to identify contributions on five urban logistics' dimensions. These dimensions are Regulation and Policies, Sustainability, Operational Excellence, Collaboration and Digitalization.

Impacts on Regulation and Policies were found on paper from Rudolph & Gruber (2017) studying the contributions made in the law and policies adopted by the local authorities and municipalities that intend to adopt cargo-bikes technology.

Sustainability is one of the most impacted dimensions by eight of the nine technologies studied. This dimension is related to quality of life and ecological footprint, and can be found impacts on the following analyzed papers: Agatz et al. (2018), Anderluh et al. (2017), Behrend & Meisel (2018), Mohamed et al. (2017), Boysen et al. (2018), Boysen, Schwerdfeger, et al., 2018, Rai et al. (2017), Duarte et al. (2016), Giret et al. (2018), Ha et al. (2018), Kitjacharoenchai et al. (2019); Lupi et al. (2020), Melo et al. (2019) and Schwerdfeger & Boysen (2020).

Operational Excellence dimension is also very contributed from the technologies and concepts presented, since the papers Anderluh et al. (2017), Arnold et al. (2018), Boysen, Schwerdfeger, et al. (2018), Frehe et al. (2017), Ha et al. (2018), Jiang & Guo (2020), Kitjacharoenchai et al. (2019), Lupi et al. (2020), Orenstein et al. (2019), Ozturk & Patrick (2018) and Leung et al. (2018) refer the impact on performance of the urban logistics process, measuring indicators such as operational cost, delivery times, service level etc.

Collaboration is the key relationship of stakeholders of urban logistics that can give advantages in some manner, as mentioned by the studies from Frehe et al. (2017), Vakulenko et al. (2018), and Yuen et al. (2019).

Lastly, and in accordance with the findings described in Leung et al. (2018), Digitalization is represented by process improvements that transform the bureaucratic or manual work in some digital, easier and smarted digital way.

Thus, this framework allows to understand the main contributions of the technological trends for urban logistics and relationships between those technological trends and the urban logistics dimensions that may need further research. Undoubtedly, the main dimensions impacted are Sustainability and Operational excellence, since eight of nine of the technologies and concepts found in the literature have directly mentioned the impact on each one of them. Also, some dashed arrows are represented on the framework that connect technological trends to dimensions of urban logistics. These arrows represent relationships that, even if there were no papers found on the LR studying these impacts, the adoption of respective technological trend has a very high potential to impact the pointed dimension.

2.3. Integration of freight and passenger flows in the field of urban logistics

Aside from recent trends, the majority of integrated flows UL literature contends that considerable gains can only be achieved through a streamlining of distribution activities resulting in less freight vehicles traveling within the city and a better utilization of these vehicles (Manchella et al., 2021, 2022). This streamlining can be obtained through consolidation of loads of different shippers and carriers, and through coordination of operations within the city (Masson et al., 2017). According to Fatnassi et al. (2015) current research on integration of passenger and freight flows is divided into two categories: those researched that develop and improve the service quality of existing transportation modes, and those that develop innovative transportation systems that provide an ecological option to stakeholders in urban areas. The integration allows optimize the overall system rather than the performance of individual subsystems (Lagorio et al., 2016; Mourad et al., 2021; Manchella et al., 2021, 2022), which provides efficiency gains for all transportation stakeholders (Ghilas et al, 2016) in addition to the potential cost reductions and efficiency improvements. Further, passenger's transportation modes have been considered to be one of the huge contributors to greenhouse gas emissions (Fatnassi et al., 2015) and here the environmental issues will apparently be improved.

Some difficulties are addressed to the urban delivery systems planning and management. Among these are the synchronization of diverse flows of goods with different consumer's buying patterns, as well as the rising fragmentation of demand (Lagorio et al. 2016) are issues commonly referenced in the literature. In addition, as business models evolve and consumer expectations for faster service delivery increase (Azcuy et al., 2021) the challenge of designing and managing urban delivery networks increases. Factors such as storage-space sizing (Behiri et al., 2018), logistics information platforms, and the overall structure of the network (Nieto-Isaza et al., 2022) for instance can influence the success of a collaborative freight transportation system. These challenges call for sustainable and efficient solutions to which OR contributes.

In this complex issue of design, planning, managing and operating a new or existing integrated flows transportation system, OR appear as the discipline that provides methodologies to support the logistical operations of cities and assist in process optimization. At the same time, many of the complex problems presented by the UL context also foster the development of new mathematical modeling techniques and algorithms. Modeling and Simulation as a research methodology has been used intensely in the general concept of Urban Logistics. For instance, Lagorio et al. (2016), categorize the articles according to a "Quantitative Modeling" and "Simulation" approach, concluding that "Quantitative Modeling" is the most commonly used research method, while "Simulation" is the least commonly used, accounting for 45% and 1% of the analyzed contributions, respectively. Despite distinguishing between "Mathematical Programming" and "Simulation Modeling", Neghabadi et al. (2019) conclude that they are the two most widely used methods in UL literature. Hu et al. (2019), on the other hand, use the term "Modeling and Simulation" in the same way that this dissertation does, and demonstrate that it is the most widely used approach in the UL field, followed by qualitative analysis and conceptual inquiry. However, these studies generally focus on the concept of urban logistics as a whole, with no difference made for analytical methods developed to help make better decisions specifically in the challenge of integrating passenger and freight flows in the context of urban logistics. It should also be noted that, according to Neghabadi et al. (2019) (mentioned above), the integration of networks and infrastructures to combine freight and passenger transportation remains a big challenge. This thesis arises precisely to mitigate this challenge.

2.4. Operational research models and methods to the integrated passenger and freight transportation problem

A SLR was conducted in July of 2022 to critically evaluate existing operations research models and methods to investigate the integrated passenger and freight transportation problem.

The essence of the SLR is to help establish solid knowledge bases to define the lines of action adopted in subsequent chapters of this thesis. Furthermore, this review allowed to position the contributions of this thesis in the literature and hence exposing the contributions in this context. SLR is particularly helpful to handle with large amounts of information, as well as to minimize the researcher bias and error inherent to the selection of research studies (Thomé et al., 2016).

2.4.1. Methodological approach

The review methodology herein proposed is based on the four steps presented in the “Preferred Reporting Items for Systematic Review and Meta-Analysis” (PRISMA) framework: I. Identification,

II. Screening, III. Eligibility, and IV. Included (Moher et al., 2009; Snyder, 2019), presented in Figure *4*.

Identification: Purposing to collect the most relevant papers to this research, the search process was conducted on Scopus scholarly database under the fields "title, abstract, keywords". The search query considers three levels of keywords. The first level is related with the UL concept, and here, *"urban logistics", "city logistics", "urban delivery", "last mile delivery"* and *"urban freight"* were the keywords used. The terms selection is in line with the Lagorio et al. (2016). Lagorio et al. (2016) conducted an important SLR that consolidates the knowledge on urban logistics and analyses the development of the discipline. Their article counts with 122 citations according to Scopus database. A second level related with the particular problem under study: the integration of passenger and freight flows in Urban Logistic context. For this level the keywords *passenger*, people* and *"public transp*"* are intersected with *goods, cargo, parcels* and *freight* were considered. And, finally, a last level of modeling keywords to characterize OR models and methods, intersecting with the terms *mathematical, algorithm* and *optimiz**. The use of the wildcard character in the search string optimiz* makes it possible to identify papers with the terms optimizing and optimization. This resulted in a total of 313 papers in Scopus.

Screening: The search is limited space to journal papers written in English and excluded conference proceedings, book series, technical reports, and webpages, to help ensure the quality of the pool of identified papers, following Lagorio et al. (2016) approach. Furthermore, only papers written in the latest 12 years UL literature are considered, analyzing the subject's behavior along the January 2010 - July 2022 period. UL is clearly an emerging topic where a lot of exciting research is going on, and the field is developing rapidly. The growth in publications appear in 2011, and the peak appears in 2014 (Lagorio et al., 2016) Employing these two exclusion criteria, the sample set reduced to 92 papers which will serve as the primary data source for the literature analysis.

Eligibility: In order to understand if the selected papers match the present SLR's objective, the 92 papers were subjected to a primary abstract analysis, and further, a full-text analysis, considering:

(a) only papers that integrates passenger and freight flows in a single transportation mode, within city centers;

(b) only papers that presents optimizations algorithms were considered.

(c) only papers that do not consider Vehicle Routing Problems (VRP) as the main problem of study, since the problems addressed on this thesis are not in the same scope of VRP problems.

Included: After these analyses, a final sample of 25 papers was derived. This set of papers formed the basis for the analyses presented hereinafter (see Table *3*).

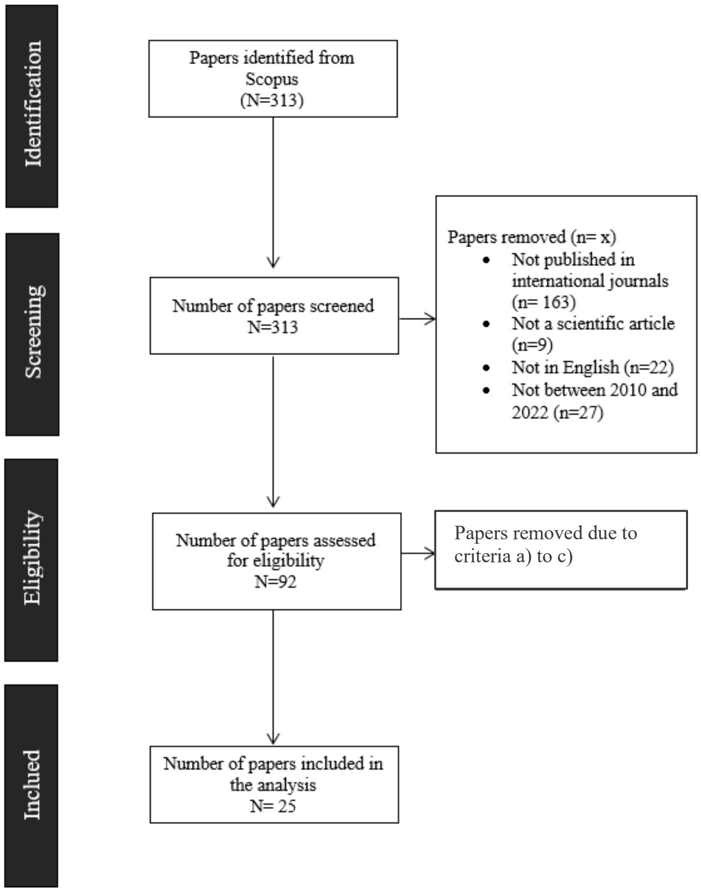

Figure 4 - PRISMA methodology

2.4.2. Descriptive analysis

The selected papers were descriptively characterized according to: the number of publications over time and international journal; Concerning the evolution of the number of published articles from 2010 to 2022, it appears to be significantly increasing in the last five years (see Figure *5*), which means that this research scope is attracting more researchers recently.

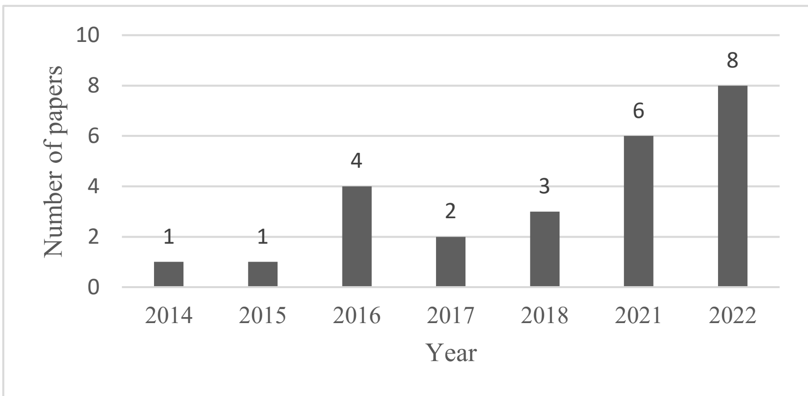

Figure 5 - Papers distribution by year, between 2010 and September of 2022

Concerning the main journals that published the highest number of papers contained in the final sample, the Table 3 presents the results. The international journal of Transportation Research Part B:

Methodological and journal Computers and Operational Research list the maximum number of published articles over the time window considered (4 articles).

Table 3 – Final sample of articles with journal distribution

Journal	**References**
IEEE Transactions on Intelligent Transportation Systems	Manchella et al. (2021) and Manchella et al. (2022)
Scientific Reports	Moadab et al. (2022)
Transportation Research Part B: Methodological	Li et al. (2014), Ghilas et al., (2016), Di et al. (2022) and Nieto-Isaza et al. (2022)
Journal of Advanced Transportation	Ye et al. (2022)
International Journal of Production Research	Mourad et al. (2021) and Li et al. (2022)
The International Journal of Transportation Research	Guimarães et al. (2022)
Transportation Research Part E: Logistics and Transportation Review	Behiri et al. (2018), Azcuy et al. (2021) and Li et al. (2021)
Neural Computing and Applications	Ren et al. (2021)
Expert Systems with Applications	Peng et al. (2021)
Quality and Quantity	El Ouadi et al. (2021)
Transportation Science	Ghilas et al. (2018)
European Journal of Operational Research	Ozturk & Patrick (2018)
Computers and Operations Research	Fatnassi et al. (2015), Li et al. (2016), Ghilas et al. (2016) and Liu & Dessouky (2017)
EURO Journal on Transportation and Logistics	Masson et al. (2017)
Transportation Research Part C: Emerging Technologies	Li et al. (2016a)

2.4.3. Results

In this subsection the results of the SLR are discussed. For the final sample of 25 articles, the general information about the problem under study was analyzed, such as the decisions of the optimization algorithm, the transportation means used for the integrated solution of passenger flows and the decision level of the problem. As in other fields, applications in UL are divided into operational, tactical and strategic decision-making levels. To distinguish between the various decision levels, in addition to their time influence, some authors propose a classification of the same. As an example, at the strategic level, Behiri et al. (2018) placed the storage-space-sizing problem in stations; at the tactical level, decisions on train frequency were made; and at the operational level, train timetabling, goods delivery in the departure station, freight rail transport scheduling or dispatching were systematized. Concerning further details about the problem formulation, it was analyzed how the authors addressed uncertainty on their models and how was the model formulated. Furthermore, the objective functions were also studied to perceive their optimization interests studying their problems. Lastly, the solution approach was also highlighted, with the aim to understand if the authors adopted exact optimization or heuristics approaches. The results of this detailed review of existing problems, their characteristics, and solution approaches are summarized in Table *4.*

Table 4 - Summary of the analysis of the final sample of 25 articles

Authors	Problem under study	Transportation mean	Decisions	Problem Type*	Uncertainty: Type of Uncertainty **	Uncertainty: Source of Uncertainty	Model Formulation***	Objective(s): Nº	Objective(s): Description	Solution approach****
Li et al. (2014)	Share-a-ride-problem	Taxis	Routing, Nº of Taxis	Op	▪	-	MILP	1	Maxime the total profit	E, H
Fatnassi et al. (2015)	Personal and freight rapid transit problem	Rail	Routing	Op	▪	-	MILP	1	Minimize the total cost	E
Li et al. (2016)	Share-a-ride-problem	Taxis	Routing, Nº of Taxis	Op	▪	-	MILP	1	Maxime the total profit	E, H
Li et al. (2016b)	Share-a-ride-problem	Taxis	Routing, Nº of Taxis	Op	S	Travel times, delivery locations	Stochastic programming	1	Maxime the total profit	H
Ghilas et al. (2016a)	Pickup and Delivery Problem	Bus, train, metro	Routing and schedules for both requests and pick-up and deliveries vehicles	Op	▪	-	MILP	1	Minimize the total travel cost of the pick-up and deliveries vehicles	H
Ghilas et al. (2016b)	Pickup and Delivery Problem	Bus, train, metro	Routing and schedules for both requests and pick-up and deliveries vehicles	Op	Sc: 60 scenarios	Demands	MILP	1	Minimize the total travel cost of the pick-up and deliveries vehicles	H
Liu et al. (2017)	Passenger and freight rail scheduling problem	Rail	Timestamps	Op	▪	-	MILP	2	Minimize the total travel times; minimize the total tardiness for the passenger trains	E, H
Masson et al. (2017)	Mixed Urban Transportation Problem	Bus and electric vehicles	Routing of electric vehicles	Op	▪	-	MILP	2	Minimize the number of vehicles, minimize the sum of arcs	E, H

Authors	**Problem under study**	**Transportation mean**	**Decisions**	**Problem Type***	**Uncertainty**		**Model Formulation*****	**Objective(s)**		**Solution approach******
					Type of Uncertainty**	Source of Uncertainty		N o	Description	
Ghilas et al. (2018)	Pickup and Delivery Problem	Bus, train, metro	Routing and schedules for both requests and pick-up and deliveries vehicles	Op	S	Time Windows, service times and pick-up and deliveries vehicles capacity	MILP	1	Minimize the total cost	E
Behiri et al. (2018)	Freight-Rail-Transport-Scheduling Problem	Rail	Assign demands to trains	Op	S	Departure and arrival stations	MILP	1	Minimize the total waiting time of demands	E, H
Ozturk et al. (2018)	Freight transport by rail transportation system	Rail	Scheduling trains	Op	S	Travel time between stations, demand, loading and offloading times, demand release dates	MILP	2	Minimize the inventory levels at departure stations, Minimize the total tardiness of deliveries	E, H
Ren et al. (2021)	Share-a-ride-problem	Car	Routing	Op	▪	-	-	1	Minimize the total cost	H
Peng et al. (2021)	Online bus-pooling problem	Bus	Assign requests to buses	Op	S	Destination of requests and demand	-	2	Maximize the total revenues from passenger and parcel delivery	H
Manchella et al. (2021)	Ride Sharing (Flexpool)	Car	Assign and dispatch vehicles	Op	S	Request rates; Package drop-off locations	-	4	Minimize mismatch, time taken, travel time and the number of vehicles	ML

Authors	Problem under study	Transportation mean	Decisions	Problem Type*	Uncertainty		Model Formulation***	Objective(s)		Solution approach** **
					Type of Uncertainty**	Source of Uncertainty		Nº	Description	
Li et al. (2021)	Train service design problem for collaborative passenger and freight transport	Train	Schedule trains and assignment of freight	Op	▪	-	MILP	1	Maximize the profit	E, H
El Ouadi et al. (2021)	Location problem of Bundling Hubs for joint transportation	Buses	Determine the location of Bundling hubs	St	MLM	Demand	-	3	Minimizes costs, risk and maximizes the demand coverage of the built network	H
Mourad et al. 2021	Pickup and Delivery Problem with Time Windows	Train	Routing of pick-up and delivery robots	Op	Sc: 50 scenarios	Passenger demand	MILP	1	Minimize the total costs	E, H
Moadab et al. (2022)	Drone routing problem model for last mile delivery	Drone and Bus	Assigning requests to drones and delivery sequence	Op	S	Demand	MILP	1	minimize the total energy that drones consumed in delivery operations	E
Di et al. (2022)	Joint optimization problem of train carriage arrangement	Train	Carriage arrangement scheme for each train	Op	▪	-	MILP	1	minimize the weighted sum of the operation cost and total delay time	E
Nieto-Isaza et al. (2022)	Multi-commodity network design problem	Subway	Determines the number and locations of mini-depots, and the flows of goods across the network	St	S	Crowd capacity and demand	MILP	1	minimizes total cost	E

Authors	Problem under study	Transportation mean	Decisions	Problem Type*	Uncertainty		Model Formulation***	Objective(s)		Solution approach****
					Type of Uncertainty**	Source of Uncertainty		Nº	Description	
Ye et al. (2022)	Train schedules and freight distribution plans for joint transportation	Train	Determine train schedule and freight plan	Op	▪	-	MNLP	1	Minimize total cost	H
Li et al. (2022)	Collaborative urban public transport system.	Train	Manage freight transportation	Op	▪	-	MILP	1	Minimize delivery times	E, H
Guimarães et al. (2022)	Multi-commodity network flow problem	Bus	Manage freight flow in a network	Op	▪	-	MILP	2	Minimize total costs and time	H
Azcuy et al. (2021)	Location routing problem	Bus, train	Determine the transfer location to last mile delivery	St	Sc: 10 scenarios	Customer location	MILP	1	Minimize travel distance	H
Manchella et al. (2022)	PassGoodPool for joint transportation	Car	Matching and routing demands	Op	▪	-	-	2	Minimize delivery times and number of vehicles,	H
CHAPTER 5 OF THIS THESIS	Freight network flow assignment problem (FNFAP)	Bus	Assignment of freights to buses lines	Op	S	Demand, Destination address and Deliveries time windows	ILP	5	Minimize delivery times, Minimize the number of bus offloads, minimize the number of buses uses, maximize the robustness to bus suppressions and maximize robustness to offloads mismatches	E, H
CHAPTER 6 OF THIS THESIS	Bus network planning problem (BNPP)	Bus	Determine the minimum number of bus required	St	Sc: 100 scenarios	Demand, Destination address and Deliveries time windows	ILP	1	Minimize the number of bus services needed for all scenarios	E, H

Legend: * Operational level (Op), Strategic level (St); **The authors do not consider uncertainty (▪), Stochastic (S) or Scenario-based (Sc) with the number of scenarios, Machine Learning Models (MLM); *** Integer Linear Programming (ILP), Mixed Integer Linear Programming (MILP), Mixed Integer Non-Linear Programming (MNLP); ****Exact (E), Heuristic (H) or Machine Learning (ML)

As shown in Table *4*, generally, the majority of the published research of the final sample of 25 articles has been concerned with operational level of decision-making process. This level of decision-making entails problems such as routing, scheduling, and assignment issues. From the total sample of twenty-five articles, twenty-two articles tackle operational problems of integrated flows in the contact of UL. The majority of these articles address problems of scheduling, pick-up delivery, and assignment problems. Another finding of the review is that most existing models have ignored some aspects of uncertainty. In some cases, researchers acclaim this opportunity but address it as an avenue of future research. Others, consider pure deterministic data but present possible sources of uncertainty, such as buses capacity, customers demand or possible random events that can occur during the route execution (Masson et al., 2017). Nevertheless, underestimating uncertainty leads to unrealistic planning decisions (Savelsbergh & Van Woensel, 2016; Yanıkoğlu et al. 2019). Only nine articles, of the twenty two that lays on operational level, have addressed uncertainty on their models, mainly by incorporating stochastic parameters into their models. Ozturk & Patrick, (2018) is the work that incorporates the highest number of stochastic parameters to deal with uncertainty: Travel time between stations, demand, loading and offloading times and demand release dates. On the other hand, Ghilas et al. (2016) and Mourad et al. (2021) incorporate uncertainty into their models through a set of 60 and 50 scenarios, respectively. Despite this, both of them only consider one source of uncertainty, i.e. a single stochastic parameter. In Chapter 5 of this thesis, the operational assignment problem FNFAP is addressed, incorporating uncertainty through three stochastic parameters into the models, namely, demand, delivery locations and delivery time windows. The key factors that distinguish the work of studying FNFAP, present in Chapter 5 of this thesis, from the articles presented in Table *4* are the objective functions addressed in the optimization models. Robustness is incorporated to the operational problem of FNFAP to deal with two different possible disruptions of the integrated system of passengers and freight flows: the suppression of a bus that is planned to transport freight and passengers and the failure to offload the freight from the bus stop at the right time and the right stop. The suppression of a bus may have a huge impact in terms of distribution plan because the system can be at the maximum capacity of freight distribution and, therefore, a suppression of a bus leads to undelivered orders to several final customers. The robustness to the offloading the orders at the right stop, may lead to failures respecting the delivery time windows agreed with the final customer. For these reasons, robustness for these two possible disruptions allow the system to act proactively to deal with when they occur. Grounded on this literature analysis, this work is the first in the literature to incorporate robustness to the operational problem of FNFAP, in the context of integration of passenger and freight flows in UL.

Fewer articles of the final sample tackle problems of the strategic level of the decision making. Only three studies - El Ouadi et al. (2021), Azcuy et al. (2021) and Nieto-Isaza et al. (2022) – have specifically investigated strategic issues, and all have addressed network architecture from a location problem point of view. El Ouadi et al. (2021) investigated the strategic location problem of bundling hubs to serve as part of a network design for passenger and freight transportation. The authors propose a Hybrid Robust Machine Learning-Heuristic Algorithm to solve the strategic location problem of Bundling Hubs for joint transportation of passenger and requests, considering varied logistics demand cases and several criteria, such as implementation costs, distribution costs, maximum customer coverage, minimal risk to the population and the urban area. Through a set of computational experiments, the authors present insights in terms of cost minimization and transport demand coverage maximization over the long-term. As further research recommendations the authors suggest that "an interesting issue would be to address the problem of responding to the customer demand using minimum fleet size to efficient urban traffic", which is the focus of Chapter 6 of this thesis. Nieto-Isaza et al. (2022) investigated the problem of strategic mini-depot (such as parcel lockers) location in a last mile system with express deliveries. Their aim is to determine the number and location of the mini-depots and the flow of goods across the subway network, with the objective to minimize the total cost. The authors present a MILP formulation and solve it through benders decomposition algorithm. Their results show that a network of mini-depots is required to accomplish the existing flows of people in the crowd and to support cross-docking activities. Also, their experiments support the use of professional courier services as an alternative to satisfy the demand with a guarantee of service. The authors present future research recommendation to introduce stochasticity and capacity into the system, characteristics of this investigation. Lastly, Azcuy et al. (2021) is the most similar to the present study since they addressed a strategic level network design problem, through the development and implementation of a scenario-based heuristic optimization to solve their location-routing problem, with uncertainty in the customer locations. In their study, the decisions are the location of transfer stations, where the goods are transferred from the public transit vehicle, e.g. bus or tram, to the last mile vehicle to serve the final customers, with the objective of minimizing travelled distance. Their aim is to evaluate the distance impacts resulting from using public transportation capacity to move goods to transfer stations, from which they are moved to their final customer using small vehicles. In their computational experiments, the authors could conclude that a reduction in the total system-wide distance is achieved through the integrated urban delivery system. A decrease in the relative distance savings was observed when higher customer densities exist or when tight delivery deadlines are considered. Furthermore, an increase in savings was observed with the increase in the distance of the depot to the delivery region and when customers are clustered around the public transit line. The authors highlight as future research to consider multiple transfer stations on multiple transit lines, which are features included in the study done in Chapter 6 of this thesis. Furthermore, El Ouadi et al. (2021) aim to reduce costs and risk while maximizing demand coverage of the built network; Nieto-Isaza et al. (2022) attempt to reduce the total expected cost of mini-depot installation and transportation. The study of the Chapter 6 also focuses in a strategic level problem, BNPP, but is distinguished from these studies since the primary goal is to reduce the number of buses required to operate in the network, with the integration of passenger and freight, thus minimizing the investments required in the physical adaptation of the buses. According to List et al. (2003), it is important to incorporate uncertainty into the analysis of fleet sizing decisions, since by ignoring the uncertainty and solving a deterministic problem with expected demands, the decision maker would probably acquire a fleet that is too small, and incur significant penalties for frequently being unable to meet demand. When analyzing the sources of uncertainty included in the models, stochastic parameters are the main source of uncertainty, with demand as the most common parameter with uncertainty, as shown in Table *4*.

In the studies addressing problems at a strategic level, mentioned before, Nieto-Isaza et al. (2022) assumed a stochastic problem. The authors present a two-stage stochastic network design problem for multi-commodity flows with both stochastic demand and arc capacities. Azcuy et al. (2021) addressed uncertainty in the parameter of customer location. Lastly, El Ouadi et al. (2021) address uncertainty concerning to the requests. Finally, considering the problem-solving approach, most of the studies relied on the application of heuristics (Li et al. 2021) but it is also possible to find exact models and methods (Ghilas et al. 2018) to solve the problems. As illustrated in Table *4*, only six studies propose exact solution approaches (such as MILP formulations) for problems with uncertainty, which are Ghilas et al. (2018), Behiri et al. (2018), Ozturk & Patrick (2018), Mourad et al. (2021), Moadab et al. (2022) and Nieto-Isaza et al. (2022). Concerning to the heuristics, Li et al. (2016) introduce the source of uncertainty in the travel time and delivery locations. Both variants are formulated as a two-stage stochastic programming recursive model. Their solution methodology integrates an Adaptative Large Neighborhood Search (ALNS) heuristic. In the Ghilas et al. (2016) study, the ALNS solution methodology, for the Pickup and Delivery Problem with Time Windows, Scheduled Lines and Stochastic Demands (PDPTW-SLSD), is embedded into a scenario-based heuristic optimization to deal with uncertainty in the demand parameter. Behiri et al. (2018) investigate the problem of Freight-Rail-Transport-Scheduling-Problem and solve it through the implementation of a single-train-based decomposition heuristic. Ozturk & Patrick (2018), present exact formulations for their problem of freight transport by rail transportation network and solve it using a longest path based heuristic method. Peng et al. (2021), investigate the problem of online bus-pooling service for passenger and parcels sharing buses using a Large Neighborhood Search (LNS) heuristic, to assign requests to buses. Manchella et al. (2021) studied the problem of ride-sharing using a distributed model-free deep reinforcement learning algorithm to assign and dispatch vehicles and requests. Mourad et al. (2021) tackled the pickup and delivery problem as a two-stage stochastic problem with the objective of minimizing the overall transportation costs. To solve the stochastic optimization problem, a scenario-based algorithm along with an ALNS algorithm was performed. The authors analyzed the impacts of uncertainty under different settings including passengers demand and scheduled line frequency and capacity. Focusing on the strategic level of the decision-making process, El Ouadi et al. (2021) propose a Hybrid Robust Machine Learning-Heuristic Algorithm (HR-MLHA) to solve the strategic location problem of Bundling Hubs for joint transportation of passenger and requests, minimizing the total costs, risks and the demand coverage of the built network. Nieto-Isaza et al. (2022) investigates the multi-commodity network design problem to determine the number and location of the mini-depots and the flow of goods across the subway network, with the objective to minimize the total cost. As previous said, the authors present a MILP formulation and solve it through benders decomposition algorithm. The work of Azcuy et al. (2021) addresses a strategic level network design problem, through the development and implementation of a scenario-based heuristic optimization to solve their location-routing problem, with uncertainty in the customer locations. In their study, the decisions are the location of transfer stations, where the goods are transferred from the public transit vehicle, e.g. bus or tram, to the last mile vehicle to serve the final customers, with the objective of minimizing travelled distance. Their aim is to understand the impact of such decisions on the operational performance of the system. Besides the similarities, our strategic objective is the minimization of the fleet needed in the network. Ghilas et al. (2018) highlight as future research the minimization of adapted vehicles needed to jointly transport passengers and goods in an efficient network, which is precisely the aim of the work of Chapter 6.

In the urban logistics integrated flows context, new technological and structural solutions are added to the design of the transportations systems in order to improve the customer service, while ensure a better operational efficiency. This can already be seen in the most cited LRs in the UL subject. In the SLR developed in this chapter, these solutions are referred as convenience and their study is essential in our investigation to link the literature and practice in order to suggest and evaluate potential improvements in the SOLFI project process approach.

In the sample, when the focus is last mile delivery, some studies focus on operational research using alternative delivery locations, such as pickup points as stores or parcel lockers. Last mile delivery represents a huge challenge in the near future and must be a focus of transportation and logistics managers according to Fatnassi et al. (2015). Manchella et al. (2021), for instance, suggested by a previous contribution, gas stations and convenience stores to offer storage services to the transportation system to enable such an infrastructure. Nieto-Isaza et al. (2022) addresses the problem of shipping parcels in a last mile system with express deliveries. The authors define a "more flexible setting where a network of strategically located mini-depots, such as parcel lockers that act as automated service points, allow partial order-crowd matching with cross-docking, which makes the (hard) constraint of finding similar origin–destination pairs unnecessary".

At the time of this SLR, the time scope was defined as all publications published up to July 2022. With the evolution of time and given the increased interest in UL in both practice and academic, an additional search was carried out to evaluate the most recent investigations in this field from August of 2022 to September 2023. This additional search used the same keywords and selection criteria about the language and type of paper, as the previous one, with the goal of understanding: on the one hand, the evolution noted in the academic world on the subject under study, and on the other, which new models have supported decision-making in the field of flow integration of passenger and freight. It is crucial to highlight that the articles in Table *5* did not serve as foundation for the construction of the models (described in the next chapters), as the models and algorithms were developed before the date of publication of those articles. It does, however, serve to highlight the originality of the research done in this thesis, to which the literature has yet to give a response after some time.

Between January 2022 and September 2023, 41 papers were published, of which 12 were already included in the initial SLR, as it was prolonged until July 2022, as previously stated. Table *5* lists the title, reference, and journal of the 29 papers that were published at the period.

Table 5 - List of 29 articles found on the literature (with same search criteria), from July 2022 to September 2023

Reference	**Title**	**Year**	**Journal**
Yang et al. (2023)	A crowdsourced co-modality transportation system integrating passenger and freight	2023	Advanced Engineering Informatics
Behiri et al. (2023)	A robust ant colony metaheuristic for urban freight transport scheduling using passenger rail network	2023	Expert Systems with Applications
Sacramento et al. (2019)	An adaptive large neighborhood search metaheuristic for a passenger and parcel share-a-ride problem with drones	2023	Transportation Research Part C
Bosse et al. (2023)	Dynamic priority rules for combining on-demand passenger transportation and transportation of goods	2023	European Journal of Operational Research
Bruzzone et al. (2023)	Feasibility on the integration of passenger and freight transportation in rural areas: A service mode and an optimization model	2023	Research in Transportation Economics
W. Li et al. (2023)	GSOANR-based multi-objective train trajectory optimization	2023	International Journal of Rail Transportation ISSN:
Fehn et al. (2023)	Integrating parcel deliveries into a ride-pooling service—An agent-based simulation study	2023	Transportation Research Part A: Policy and Practice
Machado et al (2023)*	Integration planning of freight deliveries into passenger bus networks: Exact and heuristic algorithms	2023	Transportation Research Part A: Policy and Practice
Hatzenbühler et al. (2023)	Modular vehicle routing for combined passenger and freight transport	2023	Transportation Research Part A: Policy and Practice
Sun et al. (2022)	Multi-objective optimization model for planning metro-based underground logistics system network: nanjing case study	2023	Journal of Industrial and Management Optimization
Zeng & Qu (2023)	Optimization of Electric Bus Scheduling for Mixed Passenger and Freight Flow in an Urban-Rural Transit System	2023	IEEE Transactions on Intelligent Transportation Systems
Boysen et al. (2023)	Optimization of two-echelon last-mile delivery via cargo tunnel and a delivery person	2023	Computers & Operations Research
Hörsting & Cleophas (2023)	Scheduling shared passenger and freight transport on a fixed infrastructure	2023	European Journal of Operational Research

Reference	Title	Year	Journal
Alawad & Kaewunruen (2023)	Unsupervised Machine Learning for Managing Safety Accidents in Railway Stations	2023	IEE Acess
Babaei et al. (2022)	A New Model for Evaluation of the Passenger and Freight Transportation Planning Based on the Sustainability and Safety Dimensions: A Case Study	2022	Process Integration and Optimization for Sustainability
Bhattacharya et al. (2022)	A study on pollution sensitive sponge iron based production transportation model under fuzzy environment	2022	Decision Making: Applications in Management and Engineering
Sahli et al. (2022)	An effective and robust genetic algorithm for urban freight transport scheduling using passenger rail network	2022	Computers & Industrial Engineering
Wang (2023)	An integrated cross entropy methodology for planning scheme evaluation of highway transportation hub with interval-valued intuitionistic fuzzy information	2022	Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology
Begnini & Morita (2023)	Analysis of last-mile operations for mobility and logistics in rural areas	2022	World Review of Intermodal Transportation Research
Muriel et al. (2022)	Assessing the impacts of last mile delivery strategies on delivery vehicles and traffic network performance	2022	Transportation Research Part C: Emerging Technologies
Fatemeh et al. (2022)	Development of a Model to Optimize the Operations of an Intermodal Underground Logistics Transportation	2022	Journal of Pipeline Systems Engineering and Practice
Cerrone & Sciomachen (2022)	VRP in urban areas to optimize costs while mitigating environmental impact,	2022	Soft Computing
Schmidt et al (2023)	Using public transport in a 2-echelon last-mile delivery network	2022	European Journal of Operational Research
Granacher et al. (2022)	Enhancing biomass utilization by combined pulp and fuel production	2022	Frontiers in Energy Research
Chen et al. (2023)	Exploring decision-making mechanisms for the metro-based underground logistics system network expansion: An example of Beijing	2022	Tunnelling and Underground Space Technology
Schwerdfeger & Boysen (2022)	Who moves the locker? A benchmark study of alternative mobile parcel locker concepts	2022	Transportation Research Part C
Huang et al. (2022)	Drone Stations-Aided Beyond-Battery-Lifetime Flight Planning for Parcel Delivery	2022	IEEE Transactions on Automation Science and Engineering
Tsai et al. (2023)	Trajectory feature extraction and multi-criteria k nearest neighbour based job-to-crowd matching for the crowdshipping last mile delivery	2022	IET Control Theory & Applications
Grigoroudis et al. (2022)	Transportation Sustainability and Relevant Ranking of European Countries	2022	Journal of Intelligent & Robotic Systems

Legend: *this is an outcome article of the present research (Chapter 6)

Three observations can be drawn. First, one of the 41 articles is an article that resulted from the research of this thesis, leading to a publication titled "Integration planning of freight deliveries into passenger bus networks: Exact and heuristic algorithms", which was published in the journal Q1 - Transportation Research Part A: Policy and Practice - in 2023. Second, about the evolution noted in the academic world. The integration of diverse modes of transportation, as differentiated across articles, is still being studied. In 2023, electric buses, passenger rail, trains, and metro are among the modes of transportation being researched. Furthermore, there is a need to broaden the scope of research to include rural regions as well as new business models such as ride-sharing services. There are several options for Urban Logistics systems, and the new papers published between August 2022 and September 2023 reinforce this. Lastly, seven articles address the integration of passenger and freight flows in the field of UL from a OR perspective, aiming to develop models to support the decision making on this context. Table *6* presents the summary of the analysis performed on these seven articles found.

Table 6 - Summary of the analysis of the seven articles found in the literature between *August of 2022 to September 2023*

Authors	**Problem under study**	**Transportation mean**	**Decisions**	**Problem Type***	**Uncertainty**		**Model Formulation** ***	**Objective(s)**		**Solution approach** ****
					Type of Uncertainty**	Source of Uncertainty		Nº	Description	
Yang et al. (2023)	Crowdsourced co-modality transportation system	Bus	Parcels assignment to crowdsourced passengers	Op	▪	-	MNLP	1	Minimize total costs of crowdsourcing	E
Behiri et al. (2023)	Freight-Rail-Transport-Scheduling Problem	Rail	Assign demands to trains	Op	S	Demand, Departure and arrival stations	MILP	1	Minimize the total waiting time of demands	E, H
Bosse et al. (2023)	Dynamic pickup and delivery problem with heterogeneous services	Car	Acceptance of requests and routing of the vehicle	Op	S	Request location and revenue	BO	1	Minimize the lost revenue in case customer requests cannot be satisfied	E
Fehn et al. (2023)	Mobility on Demand ride pooling service	Bus	Assignment of freight to vehicles	Op	S	Origin and destination nodes	-	1	Minimize the distance to complete the schedule	H
Zeng & Qu (2023)	Mixed-flow rural-urban transit	Bus	Bus routing	Op	▪	-	MILP	1	Minimize the total operational cost	E
Hörsting & Cleophas (2023)	Schedule rail transport vehicles and cargo allocation	Train	Train schedule and cargo allocation	Op	S	Demand	MILP	2	Minimize waiting passengers and Minimize the delay and number of rejections	E
Schmidt et al. (2023)	Last mile delivery problem with scheduled lines	Bus	Route utilization (first echelon), and routing (second echelon)	Op	S	Stations locations, customer locations	MILP	3	Minimize: the number of last mile operators; the number of last mile trips and the routing cost	E, H

Legend: * Operational level (Op); **The authors do not consider uncertainty (▪), Stochastic (S), ***Mixed Integer Non-Linear Programming (MNLP), Bayesian Optimization (BO); ****Exact (E), Heuristic (H)

The analysis allows to conclude that OR models and methods to support the decision-making process is being strongly researched in the last year, in the field of integrated UL. All the seven articles have their decisions on the operational layer and uncertainty is stochastically addressed, in the majority of the cases. The work of Schmidt et al. (2023) is the most similar to the present investigation, namely the done on Chapter 5, since they address the problem of last mile delivery problem with scheduled lines of buses, using a two-echelon system. Their approach is to use the already existent bus trips that occur in the city center to deliver the parcels (first echelon) and then use an LMO to deliver the parcels from bus stations to the final destination. The main difference to the present investigation is that their focus is on the routing of the LMO, while doing the parcels distribution. Moreover, concerning the scalability of the problem, they study only considers a total set of 150 requests in their instances, while the present investigation considers different sets of instances up to 300 requests. Despite the similarities with the research of the present thesis, none of these seven articles have their decisions on the strategical layer and neither address robustness to deal with the unpredicted failure events.

Considering the above discussion, the present research still shows novelty, both for the academic and for the practical world.

3. Research Methodology

This chapter starts with the justification for using a quantitative-based model research that also uses qualitative instruments to collect and analyze data (examining stakeholders' opinions), that must be included into quantitative models. Following this justification, the chapter proceeds on to a discussion of the research process and ends with the discussion of data collection and analysis procedures used in this dissertation concerning the qualitative instruments.

3.1. Selecting the research methodology

Cities must have higher decision support systems at all decision-making levels in order to manage practice-relevant problems with the complexity and ambiguity inherent of real-world operational procedures. Every decision level, strategic, tactical, or operational, has its own set of challenges and variables. Furthermore, each decision made regarding the new UL transportation system has a significant impact on people's daily lives as well as the long-term profitability of the companies participating in the process. This concern has led to a considerable body of research in the UL field adopting advanced models and algorithms capable of finding satisfying solutions to hard problems in short computational runtimes. For this, long-term and cost-effective solutions are required, which OR can supply. OR deals with advanced analytical methods for decision making. According to the International Federation of Operations Research Societies (IFORS), this scientific field can be described as the "*development and application of a wide range of applied problem-solving methods and techniques in the pursuit of better decision making and efficiency, such as mathematical optimization, simulation, queueing theory and other stochastic models*".

There has been a growth in recent years of the need for quick and precise decision-making, and particularly in the field of UL. UL is rich in terms of modelling the various aspects and details that are considered relevant for the field. This is where Mathematical Modeling and Optimization Methods have been central to the majority of UL's research. They provide to managers and researchers a solution for building models in order to understand, change, manage, and control "(part of) the behavior of real-life operational processes or that can capture (part of) the decision-making problems that are faced by managers in real-life operational processes". The above definition was provided by Bertrand & Fransoo (2002), one of the most cited articles on the Modeling and Simulation (M&S) research methodology. Bertrand & Fransoo (2002) has around 929 citations and their article "*Operations management research methodologies using quantitative modelling*" is included in Karlsson's book (2016) "*Research Methods for Operations Management*" (2016). There are, however, few explanatory studies on this research methodology, and as a consequence, Bertrand & Fransoo (2002) will be the reference article for a full description of the research methodology of this thesis, considering its popularity and importance.

In the field of OR, it must be emphasized, however, that according to Bertrand & Fransoo (2002), the major contribution of OR is not the modeling of operational processes, but the analysis of the mathematical model of the process and the quality of its mathematical solutions as part of the quantitative research in Operations Management (OM). M&S as model-based quantitative research, provide valuable insights into the nature of optimal decisions under specific modeling assumptions (Karlsson, 2016). Furthermore, it has been identified as a powerful problem-solving strategy in the OR field, and importantly, for the analysis of complex systems. This is precisely the main motivation of the present research.

Other designations as Mathematical Programming and Simulation-Optimization can be found in the literature of UL. In this thesis, the definition of Modelling and Simulation as final term for the research approach is heavily influenced by Karlsson (2016).

Bertrand & Fransoo (2002) argue that quantitative (model-based) OM research can be divided into four contributions research types. The authors differentiate between empirical and axiomatic research (classes of quantitative model-driven research), and between descriptive and prescriptive research (research types). A distinction between the various types of research is as follows:

- **Classes of quantitative model-driven research:** while axiomatic quantitative modelling research is primarily driven by the (idealized) model itself, the empirical quantitative modelling research is driven by empirical findings and measurements. More specifically, in an axiomatic research, the researcher's main concern is "to obtain solutions within the defined model and ensure that these solutions provide insights into the structure of the problem as defined within the model," whereas in empirical research, the researcher's main concern is "to ensure that there is a model fit between observations and actions in reality and the model made of that reality". In regard to this classification, this investigation is axiomatic quantitative modeling study. This definition is confirmed by the following sentences from Bertrand & Fransoo's (2002) article, which it is the case of this investigation:
    - *"Axiomatic quantitative OM research starts with a condensed description of the characteristics of the operational process or the operational decision problem that is going to be studied";*
    - *"Axiomatic research produces knowledge about the behavior of certain variables in the model, based on assumptions about the behavior of other variables in the model";*
    - *"It may also produce knowledge about how to manipulate certain variables in the model, assuming desired behavior of other variables in the model, and assuming knowledge about the behavior of still other variables in the model";*
    - *"Researchers look at the operational process or the operational decision problem through the looking glass of the mathematical models that can be analyzed".*

- **Research types:** while prescriptive research is concerned with developing "policies, plans, and actions" to improve over the results available in the existing literature, to find an optimal solution for a newly defined problem or to compare various strategies for addressing a specific problem; descriptive research is concerned with creating a model that adequately describes the causal relationships that may exist in reality. Several of these research types are possible to be combined, as noted by Bertrand & Fransoo (2002). In this way, this research is an axiomatic class that blends axiomatic prescriptive research with axiomatic descriptive research. Furthermore, combining these two types of research allows to ensure that research objectives 3 (formulate novel mathematical programming models under uncertainty capable of framing the decision maker's decisions regarding the integrated flows) and 4 (develop suitable solution approaches to solve the models efficiently and proneness to real-world applications through the SOLFI project) are met. The reason for this is while "*in axiomatic descriptive research, the modelling process is central (...) and researcher typically does not move into the model-solving phase", "in axiomatic prescriptive research, the model-solving process is the central research process reported".* It is for this reason that studying a process can be considered as descriptive, whereas studying a problem may be considered prescriptive according to Bertrand & Fransoo (2002). In this regard, both the process and the problem were examined during investigation.

According to Bertrand & Fransoo (2002), M&S is used as a research method when two types of contributions are expected: the first is related to the study of a "*new variant of the problem, using* *well-known solution techniques*"; and the second is related to the study of a "*problem that has been studied before, but which provides a new, or in some aspects better, solutions to the problem, either by applying new types of solution techniques to the problem, or by achieving better results with accepted solution techniques*". This investigation has a combination of these elements: researching a new variant of the logistical process of integrating passenger and transportation flows in the context of urban logistics, with the goal of providing solutions to the problem through the development of new optimization models and heuristics. Moreover, this study is clearly positioned in the scientific literature according to the above Chapter 2.

3.2. Research process

This thesis applies the model for problem solving proposed by Mitroff et al., (1974) and cited by Bertrand & Fransoo (2002). In his model, the operational research approach consists of four distinct stages, such as 1) conceptualization, 2) modeling, 3) model solving and 4) implementation, as shown in Figure *6*. These four phases are divided between the reality or the real-life problem, conceptual model, the mathematic (scientific) model, and finally the solution approach. Since this research is a combination of axiomatic descriptive and axiomatic prescriptive research, the research cycle includes "conceptual – scientific model - solution" (highlighted in bold in Figure *6*). The first connection is made using axiomatic descriptive research, and the solution is found through axiomatic prescriptive research, as previously mentioned.

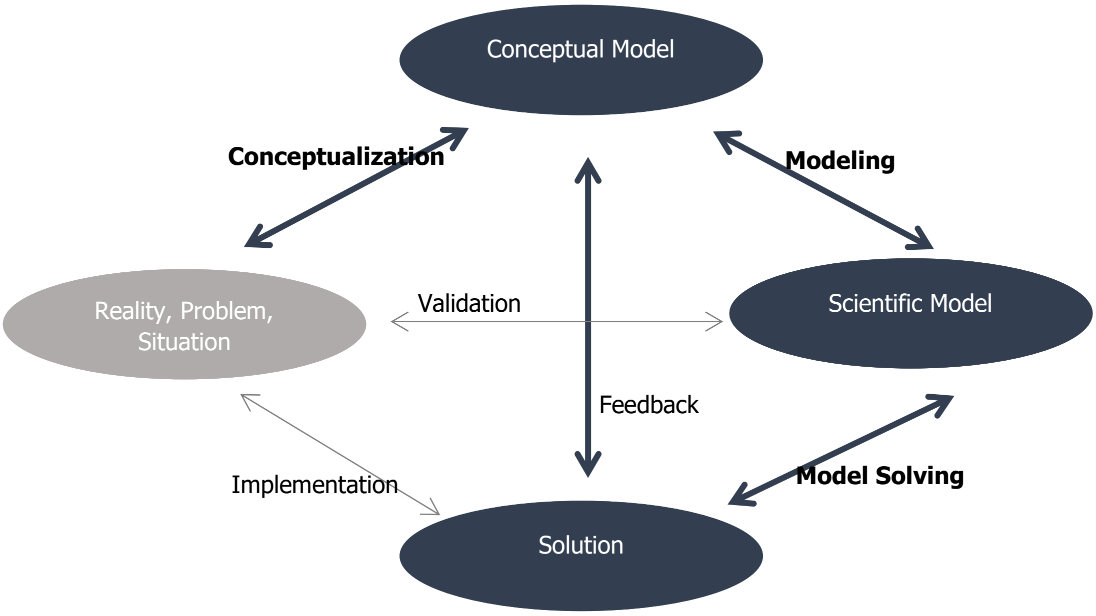

Figure 6 - Research methodology (adapted from Mitroff et al., (1974))

The following is a detailed description of the investigation process, considering each of the three defined stages.

Phase 1) Conceptualization

There are two primary stages in the conceptualization phase. The first phase is to acquire information about the many stakeholders impacted by the new logistics system. Quantitative and qualitative research is used to focus on the major areas of agreement and conflict management between the requirements and demands of each stakeholder. Semi-structured interviews and a questionnaire were applied to compare the two previously indicated aspects. This application of qualitative and quantitative instruments (section 4.2) enables to design a final solution to the proposed logistical process that will be the basis for both operational and strategic problems. The role of the phase is to construct a "plan" (as axiomatic prescriptive research involves) to better explain the existing condition and, as a consequence, to discover an ideal solution for a newly defined problem that seeks to be close to reality. After defining the proposed integration solution for UL, which is one of the outputs of chapter 4, the next step is to create a conceptual model. Here, a condensed description of the characteristics of the operational process or the operational decision problem that is going to be studied is addressed. The conceptual model, presented in section 4.3, is modelled using Unified Modeling Language (UML). Moreover, all assumptions that underlie the conceptual model are described in detail as suggested by Bertrand & Fransoo (2002).

Phase 2) Modelling

The modeling phase started after the collection of all requirements of the stakeholders of the project and the conceptualization phase. Two different type of models were developed: ILP models through mathematical programming and heuristics models through MATLAB language. The properties and characteristics of the real problem are incorporated into these models, through the use of decision variables, stochastic parameters to include uncertainty, objectives and constraints. During this phase, for the FNFAP problem, in terms of exact formulations, five different models were developed, accordingly to the objective function under study for the problem, each one with specific variables and constraints. With the aim to conduct lexicographic optimization between different pairs of objective functions, additional models were created intersecting the optimization constraints of the models. In terms of heuristic, two different approaches were developed accordingly to stakeholders' requirements: request receipt model/algorithm and optimizer algorithm.

For the BNPP problem, in terms of exact formulations, a single model was developed with a single objective of minimizing the fleet needed for transportation. The model is based on a set of scenarios of possible realizations of parameters. Concerning the heuristics, they were modelled following the greedy randomized adaptive search procedure.

Phase 3) Model Solving

To solve the models, instances were generated. For the FNFAP problem, there were two types of instances generated to use and solve the models. The first set of instances is completely fictional, with sets and parameters assuming a fictional value that represent a potential realization of a real case application. On the other hand, pilot instances were also generated with part of the bus network data provided by the BTO of the city, with the goal to test the models with realistic data. Still, data related to the requests forecast (demand, delivery address, delivery time windows) are purely fictional and only the bus network assume real data on these instances. For the BNPP, fictional instances to solve the models were used, including a scenario-based approach to turn the instances as realistic as possible, since the solutions found for a set of 100 scenarios is a potential good solution for a future use-case. The models were solved with commercial solver CPEX and MATLAB software.

4. Integrating Stakeholders’ Expectations Into the Transportation System

This thesis lays a significant emphasis on stakeholders' perspectives. It ensures that stakeholders' expectations and needs are met by incorporating this information into the optimizations models developed within SOLFI project, aimed to propose a new integrated transportation system. This integration not only strengthens the link to the real world, but it also helps to close the gap between client expectations and operational performance. In this way, the chapter is divided into three sections. The first section (Section 4.1) provides theoretical context for this topic, Section 4.2 comprises qualitative and quantitative research through the application of questionnaires and interviews. Section 4.3 introduces conceptual design models of the integrated logistic solution used by SOLFI. Section 4.4 explains the integrated solution of passenger and freight flows to be used on the SOLFI project, and the base of this research. The chapter finishes with a summary of the important findings.

4.1. The significance of investigating stakeholders' expectations

Urban Logistics is characterized by uncertain and dynamic conditions where a wide variety of stakeholders, information, and materials must be managed in order to provide efficient directions for such a complex task. The task gets more challenging due to the highly distributed supply channels and end-use locations with multiple supply methods (Na et al., 2022). Furthermore, in the integration of passenger and freight through the usage of public transit logistics within urban areas both network structure and operational strategies must be updated (He, 2020). A conflict of interest exists, and it is acknowledged in the literature as a factor that must be appropriately anticipated in order to UL be effective in practice (Lagorio et al., 2016). Each city logistics stakeholder involved has its own set of preferences and expectations (Kiba-Janiak et al., 2021) as well as operating characteristics (Lagorio et al., 2016); which must be considered from the early stages of the planning process (Le Pira et al., 2017). Residents, shippers, receivers, freight carriers, transport companies, public transport operators, and regulators are the fundamental stakeholders to be explicitly considered when planning a UL transportation system.

Carvalho et al. (2019) emphasize in their review that successful UL is dependent on stakeholder engagement and interests. It is also noted that UL stakeholders play an important role in both facilitating, but also hindering, the effective implementation and management of an UL transportation system. Lack of support and commitment of stakeholders is another factor contributing to the complexity of UL (Carvalho et al., 2019). As result, several scholars believe that the long-term development of UL will be completely realized if the expectations and collaborative links of the many stakeholders involved are established (Demir et al., 2022). Overlooking the stakeholders' perspective could have serious consequences for the process design, mathematical model development, and, eventually, the realization and interpretation of the findings in a real-world application, where the preceding gains could be compromised.

Several authors, Lagorio et al. (2016), Hu et al. (2019), Carvalho et al. (2019) and Kiba-Janiak et al. (2021) recommend that future research should focus on establishing novel decision-making models and methods that take into consideration the interests and preferences of several stakeholders. One of the most cited reviews in UL, Lagorio et al. (2016) found that "stakeholder involvement" is one of the three essential areas that deserve further exploration. The authors found also a lack of interaction between them. Hu et al. (2019) revealed that stakeholders are rarely included in the design and implementation phases, and that there is also a lack of interation among them. Carvalho et al. (2019) noted a delimitation of specific issues related to UL, namely: project/planning/management of transport and facilities in the urban area with effective participation of stakeholders to formulate sustainable policies. Kiba-Janiak et al. (2021) advocated the need to verify consumer preferences and behaviors in the subjects of sustainable last mile deliveries on e-commerce market. Therefore, there is a substantial gap between recognizing stakeholders' influence on UL challenges and applying it into mathematical models. This is certainly salient when mixing passenger and transportation movements. Following that, this investigation aimed to fill this gap with a qualitative and quantitative research concerning the stakeholders' expectations.

The current challenge in this thesis is to properly grasp the final customer's emotional and practical expectations and then design quantatitive models that also meet those needs. The SOLFI project involves a range of stakeholders, and as a result, multiple interests must be met. Here, qualitative and quantitative research is used through the data collection and analysis of interviews, applied to thee stakeholders and a questionnarire to potential final customers, to help with this concern to supplement the conceptualization phase of new model development. The main goal is to compare perceptions of final customers and logistics operators between the existing and anticipated UL processes, and to determine which requirements for the new transportation systems should be included in the system concept definition and decision support, because they have huge influence on final customer satisfaction and stakeholder engagement. Ultimalty, it will deliver an accurate UL solution with integrated passenger and freight flows to the SOLFI Project.

4.2. Empirical study about stakeholders' expectations

Qualitative research is normally contrasted with quantitative research based on which techniques have been used for data collection and analysis (Karlsson, 2016). Several techiniques can be utilized however, in this investigation, quantitative questionnaires and interviews were chosen as research instruments. While questionnaires yield generalizable results from large sample sizes (which is important for gathering a deep understanding from the potential users), qualitative interview data often yield more in-depth insights on participant attitudes, thoughts, and actions (Harris & Brown, 2010). This last is especially useful to gather the requirements from the SOLFI project's three key stakeholders - the Logistic Operator, the BTO, and the LMO. Hence, using interviews as research instrument ensures that conflicts of interest are managed, as well as the participation and support of several stakeholders in the logistical operations. As previously stated, these two aspects are two of the reasons why an urban logistic system could fail. Stakeholder involvement, particularly in the first phase of the SOLFI project, was crucial throughout the development process.

4.2.1. Final customers questionnaire

The major goals are to define consumers' online shopping preferences and assess the feasibility of implementing additional conveniences for the last mile deliveries of their orders. Concerning the consumers' online shopping requirements: *"what are the preferences that final customers currently assume while purchasing online?"*. Preferences, in this question, pertain to the factors that provide greater final customer satisfaction. Here, the preferred delivery time, the preferred delivery location, and the possibility of receiving goods towards the end of the week, as well as the expected delivery schedule, are being discussed. After that, determine whether final customers are willing to pay more for a more environmentally friendly service, more effort in order collection, or time flexibility in order receipt.

Concerning with the conveniences: "*how customers accept the adoption of new conveniences proposed in the questionnaire? what can affect the acceptation of such conveniences?*". New conveniences are the LMOs' strategies that enable and persuade potential final customers to accept a new transportation system. A review of the literature in chapter 2 helped to define these conveniences. For the questionnaire two main conveniences were studied, mainly considering the final customer requirements to cover the last mile. First, the smooth integration of neighbor stores as dropping points where final customers could collect their orders; and second, the availability of a delivery service based on an automated pick-up point (for example, smart-lockers) where the final customer could pick up the order.

A first version of the questionnaire was designed and pre-tested by a small group of 20 respondents and refined according to the feedback from these test respondents. As indicated in Table *7*, the final questionnaire was divided into three phases, comprising 12 questions. The first phase captures the general information about respondents. The second phase is related to the current behavior and preferences of respondents when they purchase online, and their orders' delivery process. Finally, the third phase of the questionnaire assesses the acceptance and desire of the respondents about new conveniences proposed to the delivering process of their purchased orders. The Table *7* summarizes the twelve questions of questionnaires.

Table 7 - Questions of each phase of questionnaire to the final customers

Phase	**Number and subject of each question**
Phase 1: General Information	1. Genre identification
	2. Age group identification
	3. Profession identification
	4. Online purchasing frequency selection
	5. Products that are typically purchased online definition
Phase 2: Requirements	6. Preferential delivery time window
	7. Acceptance of delivery at the weekend and preferable delivery time during the weekend
	8. Preferential delivery point
	9. Analyze if final customers value and are willing to pay more for delivery speed, less effort to collect goods, or greater flexibility in delivery time.
Phase 3: Conveniences	10. Analyze if the client would benefit from a delivery service based on a network of partner stores. And, if so, what is the impact in terms of time and cost?
	11. Analyze if the client would benefit from a delivery service based on a lockers network. And, if so, what is the impact in terms of time and cost?
	12. Analyze the two presented conveniences to determine which is preferable for the client (stores or lockers network).

The questionnaire was directed to the population of "people, preferably of younger age groups, who purchase on-line". The sample of the study is not aleatory, since the sample collection was based on the following criteria: i) subjective criteria, where groups of people with potential interest on on-line purchasing process was beforehand known such as universities, schools, and private contacts; and ii) convenience criteria, where the potentials groups resultant from the first criteria were selected considering the ease of access, whether due to physical or interpersonal limitations. This second criteria proved to be even more important, since the data collection was performed during Covid-19 pandemic.

A total of 302 replies to the question was obtained. These responses were recorded in a data base, which enabled content analysis and export to the statistical analysis program IBM SPSS. Following variable codification and software feeding preparation work, it was feasible to undertake descriptive statistics research on the topic to better explain the sample in investigation as the first step. In the second stage of the investigation, more complex statistical approaches such as cluster analysis and relationship modeling were used, but it is out of the scope of this thesis since the main conclusions could be obtained from this first stage.

Phase 1: General Information: An overview of the sample revealed a homogeneously in the gender distributions, with 144 females and 158 males. Figure *8* depicts a diagram with sample's gender distribution. In terms of age of the group (Figure *7*), the analysis confirms what the sample's selection criteria had previously indicated: the majority of the individuals in the sample belong to the younger age groups, between 18 and 25 years. According to the their professional situation, Figure *9* shows that around 90% of those who were inquired are either students or employed by a company, commonly situations at the younger ages.

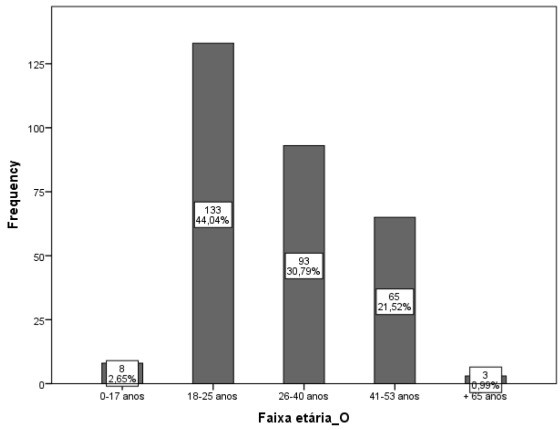

Figure 7 - Sample distribution for age groups

Figure 8 - Sample's gender distribution

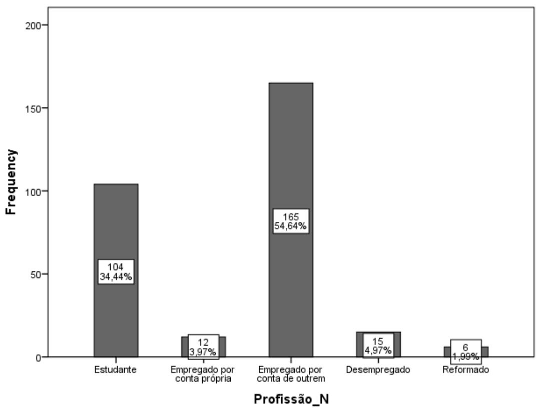

Figure 9 - Professional situation of individuals

Furthermore, continuing the profiling of the sample, the final customers' current purchasing behaviour is examinated. Considering question 4 (online purchasing frequency selection), it was determined that just 16 respondents do not purchase online at all, accounting for about 5% of the sample. Moreover, evaluating the number of online purchases per year, more than 50% of the respondents perform seven or more online purchases per year, as shown in Figure *10*.

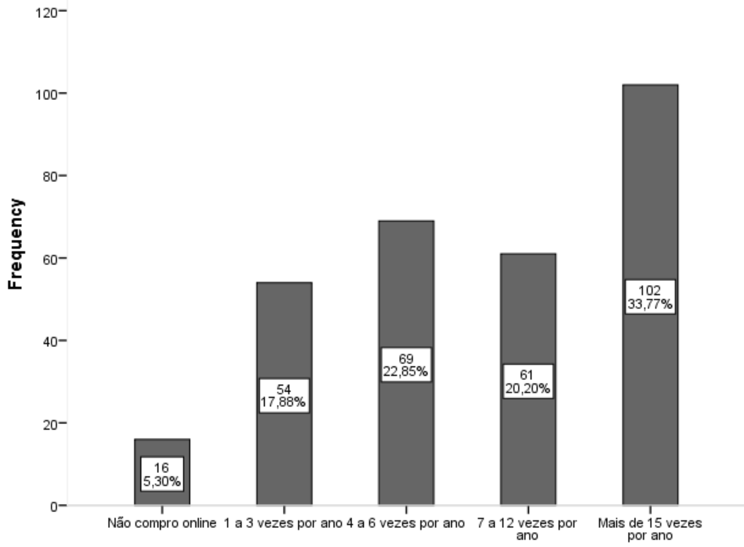

Figure 10 - Online purchasing frequency

Concerning question number 5, the results indicates that 65% of respondents order clothing and footwear as the main category of products purchased online.

Phase 2: Requirements: The aim of question number 6 and 7 is to study the final customer satisfaction with receiving its online orders throughout the weekend and/or in a specific desirable delivery time, since usually deliveries are performed during the week, in accordance with the logistics private companies working hours . The following scenarios were provided to the respondents: receiving orders from 8 a.m. to 13 a.m., 13 a.m. to 18 a.m., and 18 a.m. to 24 a.m. on Saturday, as well as receiving orders from 8 a.m. to 13 a.m. on Sunday. The results indicates that the majority of the respondents (around 60%) consider receiving orders on Saturday morning and afternoon (from 8 a.m. to 18 p.m.) as a plus and a significant advantage to be incorporated into theirs on-line purchasing process. On the other hand, receiving orders on Saturday night (from 18 p.m. to 24 p.m.) and on Sunday is undesirable by the majority of respondentes. Concerning question 8, about 80% of the respondents chose "Domicile" as current preferred location where the final customer prefers to receive his or her online order, and about 15% of the respondents select their job locations as preferered delivery locations for their orders. This finding emphasizes the current importance of the LMO in the logistics distribution plan, whose responsibility it is to complete the last mile delivery process to the final customer preferred location.

In order to determine which aspects final customers value the most during the online purchasing process, the following features were considered: i) the option for delivery speed, ii) the option for reducing their effort and time during orders reception, and iii) the option of increasing the flexibility related to receiving time window of their orders. Results show that all this features are considered valuable from the respondents perspectives, since all the three features are desirable by more than

75% of respondents. Still, the feature iii) related to the flebility to select the receiving time window is the most valued feature by more than 91% of respondents. In terms of willing to pay more for these features, 50% of respondents that value the option for delivery speed are willing to pay more for it. Concerning the others features, only about 30% of respondents who value them are willing to pay more to have them on their orders delivery process.

Phase 3: Conveniences: Lastly, two distinct conveniences for on-line orders delievery were proposed to the respondents: the final customer collects his/her online order at a partner store, or the final customer collects his/her order in a smart-locker placed in a strategic location in the city. The goal of researching final customer acceptance of parcel lockers and stores was to determine if a potential option to use them as delivery points was reasonable (where final customers could pick up their orders), or even as points of delivery if last mile delivery at final customer address fails for some reason. This acceptance was measured in two ways: if respondents accept and value these conveniences in general and whether they were willing to pay more for it (to cover the increase in supply chain costs, motivating them to contribute to the reduction of environmental pollution).

Results indicate that the majority of respondents value and accept these conveniences for order receiving process in the future, with around 93% willing to pick up their order in a store and 90% willing to pick up their order in a smart-locker. Additionally, for both conveniences, the 80% of respondents who value them are willing to be charged and pay more to have them.

Finally, through the question 12, which aims to determine the respondents preference between these two conveniences during on-line order delivery process (collect the order on a partner store of the city vs collect the order on a smart locker), results show that the preference is for order collection at a partner store, but only by three percentage points as shown in Figure *11*. Consequently, it was concluded that the adoption of these these conveniences is valued by 90% of respondents, as a potential feature to be incorpored in the order delivery process.

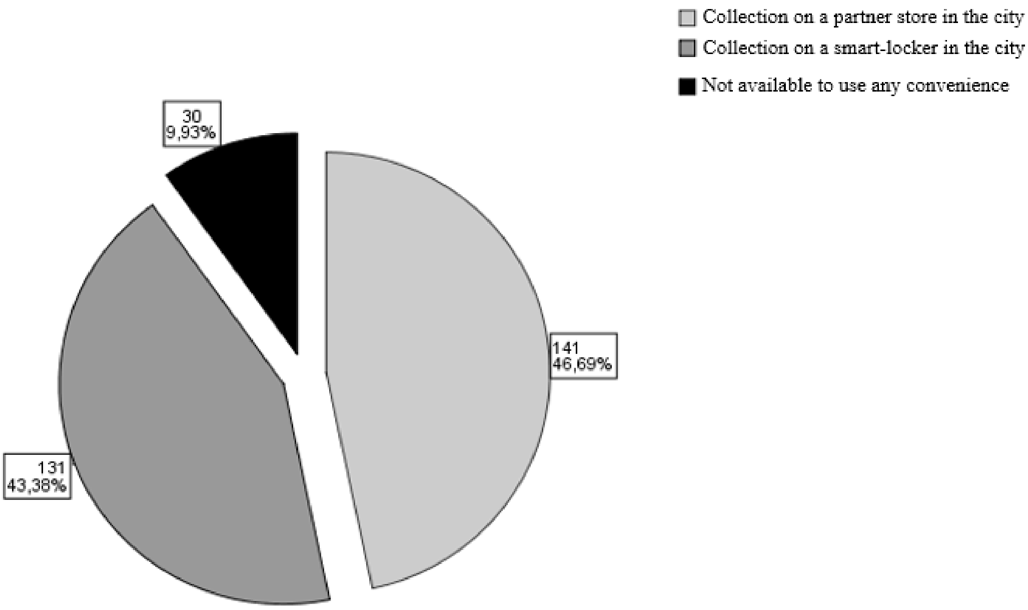

Figure 11 - Respondents preference between both conveniences

4.2.2. Stakeholders' semi-structured interviews

In the urban logistics field, stakeholders play a crucial rule for an effective UL transportation system. Understanding how the different stakeholders perceive the new UL solution and find what are their requirements to be incorporated in the solution were the main goals of the qualitative research. For this qualitative research, semi structured interviews were used to provide useful conceptual insights to understand the problem under study, and also to know how to mathematically model the problem, especially for the context of SOLFI Project. Three different stakeholders, partners of the project, were interviewed: a private logistics company which is seen as one of the biggest clients of the SOLFI platform, to use the integrated passenger and freight flows transportation SOLFI solution; the BTO of the city who manages the network of the city, and the LMO working on the city, to perform the last mile delivery to the final customer houses or collection points. For each interview, an interview protocol (in *Appendix*) with the guidelines for the interview was pre-elaborated, even though there was flexibility in terms of questions order and scope. The next subsections detail the interviews to each stakeholder.

4.2.2.1 Interview to the private logistic operator

Logistic companies are the main entities that perform deliveries within the cities. These entities are potential clients for the SOLFI project. When these logistic companies have small volume deliveries to be transported from the outskirt of the city into the city center, they can use SOLFI platform to request for the delivery. Firstly, it is crucial to understand what type of market these companies operate with and its characteristics. The response is aligned with the SOLFI project characteristics, since they often work with business to consumer market delivering small orders to different residents within the city. The type of products fits the project limitation of small and light boxes.

> *"Currently we are facing a significant increasement of B2C market mainly derived by the e-commerce boom in recent years. This market is characterized by orders with very small volume that we collect from our client, sort and distribute them to the final customer within the city. This market would be a perfect fit for the scope of SOLFI project, considering its characteristics. The main type of products are Clothing & footwear and Technology."*

The communication between the SOLFI platform with the company is managed by internet platforms to do the request releases, where the logistic company releases the transportation order and SOLFI receives this order.

> *"We have an integrated platform where our clients perform their request release of orders to be dispatched. We can integrate this platform with SOLFI platform to automatically inform/confirm a new order transportation, considering the SOLFI capacity, during the client request release."*

In terms of operations, the logistic company notify and access the capacity of SOLFI platform when they have a request release by their client to be transported by SOLFI solution. After this notification the SOLFI platform evaluates the current capacity and determines if it possible to accept the request to be transported by SOLFI or not. This notification is done on the previous days, until the day before the transportation day required by the client.

> *"For the scope of the SOFI project, we are able to inform on the days before what are our planned orders to be delivered into the city center. For a certain day, we close the acceptance window for new orders till 19h of the day before. After this time, we do not accept any other requests for the next day."*

The clients of SOLFI solution, in this case the logistic company, are responsible for the first mile of the delivery, meaning that they need to drop the order volumes at specific locations defined by SOLFI platform. During the request release, the logistic company has to select what are the drop points, from a list in the SOLFI platform, that they are available to drop their orders.

> *“Integrating our operations with this project would result on drop points selected by you, where our drivers could drop the orders destined for the city core. Moreover, we are responsible for the first leg of the distribution, collecting at our client locations and dropping them at your dropping points. Importantly, we must indicate first what drop points we are available to drop orders from your list. I think it is feasible to operate like this.”*

At this drop points it is necessary to have a human resource to receive the bus driver and collect all the order volumes.

> *“Additionally, a human resource is needed at these drop points to receive the orders from our drivers and then load them into the bus. We cannot do this loading operation.”*

In terms of capacity limits, the typical orders from this logistic company are small and light boxes, and each order can have more than one box. The SOLFI system does not partitions the different boxes from the same order in different flows.

> *“One order can have more than one box/volume to be transported, and they cannot be separated in terms of transportation flows."*

The capacity of the system is determined for all steps of the transportation flow of the SOLFI project and it is related to the request demand of the orders. Thus, the demand of each order is characterized by the number of small orders that respect the limit of weight and volume. These limits guarantee that all boxes can be handled by all transport entities of the SOLFI project.

> *“We anticipate that orders demand is determined by the number of boxes of the order. Also, we have a limit in terms of weight and volume for each box to be able to be transported by the infrastructures of all SOLFI project’s transport entities. To operate this, we need to know these limits, but I believe this would not be an issue, since the e-commerce market is characterized by very small and light boxes.”*

4.2.2.2 Interview to the BTO of the city

The BTO of the city is the entity that manages the bus network of the city. This network will be responsible for a portion of the distribution plan of the orders distributed by SOLFI project. A distribution plan is an official information with the identification each bus hub, bus service route, and bus service stop where the request is assigned and respective times for transportation. Firstly, is key to understand how the communication should be performed between the SOLFI system and the BTO of the city and its drivers. The response indicates that voice communication is the main channel of communication between the drivers and the central office of the BTO of the city. Buses are equipped with technology to allow the communication between drivers and the central office. The communication between the SOLFI system and the BTO has to be done through the central office.

> *“We have a centralized communication system between the central office of the company and the drives of the buses. We mainly use technology incorporated in buses for the voice communication, or even mobile phones for the case of any problem with the main system. The communication between our company and the SOLFI platform has to be done through our central office.”*

Aiming for a smooth integration of freight and passenger flows, it is important to perceive if there were significant peak hours during a day, in terms of passenger adherence. The response is that during the early hours of the morning and at the end of the day, there are more passengers in the buses and so these bus lines have to be avoided for this integrated solution of SOLFI project.

> *"We recognize that the early hours of the morning and latest hours of the noon are the most demanding bus lines in terms of passenger affluence. These lines are harder to be converted into a combined passenger and freight flows, so we must avoid these critical lines."*

The interviewed was asked, how would the receiving process of orders' volumes and their loading on the bus services could be performed, to model these operations accordingly. The response indicates that the orders must be dropped by the clients of the SOLFI system at the bus hubs where bus routes depart from and, ideally, they must be ready at the bus hub at the beginning of the day, so the BTO has time to sort, prepare and load the orders into buses.

> *"The best approach would be to have the volumes to be transported available at bus hubs on the beginning of the day. Thus, we have time to sort and prepare these volumes according to bus schedules."*

These operations are handled by a dedicated human resource to receive the orders into a dedicated area for their preparation. For the pilot stage of the project, the dedicated area is large enough to cover all the order volumes for a day.

> *"It is feasible to have a human resource at the bus hubs responsible to receive, prepare and load the order into the buses, accordingly to the distribution plan. These preparation process would be done at a dedicated room, large enough to receive the all the orders for a certain day, at least at the pilot stage of the project".*

To understand what would be the network points for loading and offloading the buses within the city, the BTO provided a network to be used for the SOLFI project, so they can select buses and stops that are less used for passenger transportation, avoiding the most critical lines and routes.

> *"Our network is large enough to cover all the important points of the city. We have bus hubs, where different bus routes depart from, in every corner of the city to use them to connect to the city core. We will select these points and share them with you. Also, we can select the bus stops that are less used by passengers and use them as offloading points of the cargo, aiming for the less impact as possible to the passenger experience."*

Additionally, it is important to understand what are the requirements to transport the order on the buses of the city. The answer indicates that the buses need to be adapted to include a sealed and secured area, with restricted access, to put the request boxes and transport them on the bus at the same time of passengers. As limit capacity, the BTO indicates that it has to be in number of standard boxes that a bus can transport in a route. Also, for the offloading process of orders from the buses, there must be a limit of number of boxes that can be offloaded at each time that the bus stops at a certain bus stop.

> *"Currently, some buses have a shelve structure where passengers can put their bags during their transport on the bus. For the orders transportation within the buses, some adaptations will be needed to guarantee a sealed and secured area dedicated to the orders transportation to transport a limit number of boxes. Additionally, this sealed area must only be accessible for the entity that collects the orders from the buses, through a code or a key. For the*

offloading process of orders from the buses, there has to be a limit number of boxes to be offloaded at each time a bus stops at a certain stop, to not jeopardize the passenger experience."

In case of the LMO is not ready on time, at the bus stop, to offload the orders, the orders can be offloaded at the next stop of the route, or return to the bus hub where they departed from.

"If the entity that collects the orders from the buses cannot be at the bus stop on time, for some reason, the orders can return to the bus hubs where they departed from. Alternatively, they can collect the orders at the next stop of the bus route."

4.2.2.3 Interview to an LMO of the city

This subsection presents the key findings of the interview to the LMO in the city of Porto.

The LMO, which will be part of the distribution process of the SOLFI project, aims to provide a logistic service that collects and delivers all the orders from their clients, within the same day. This feature fits the main objective of SOLFI project, as the goal is to deliver the requests to the final customer during the same day, and not on the day after the collection. Next is a transcription from the interview about the aim of the company:

"Our main goal is to provide a local last mile logistic service to people who need to deliver their orders within the same day, not retaining the order for the next day."

The company provides this service with an environmentally friendly fleet of electric bikes and electric motorcycles, contributing for the sustainability and the quality of life of the city, which is the main goal of the SOLFI project. The interviewed said:

"We use electric bikes and motorcycles to perform our deliveries and, for the electric vehicles, we have substitutes batteries to change after a battery goes down to ensure we can fulfill the orders deliveries."

To ensure that the last mile drivers of the company have the IT tools to receive the pick-up requests by the SOLFI system/platform, understanding about what technologies do they use on their daily business is significant. Their response fulfills the SOLFI project goal to maintain the contact with the drivers of the last mile drivers through internet technology:

"Our drivers use mobile devices with access to internet so they can receive updates in real time about potential urgent orders to be delivered or how they need to proceed in case of any disruption occurs."

To understand how the last mile company intends to receive the SOLFI order delivery request on their system, the interviewed was asked how is their process to build their distribution plan. Their response allowed us to conclude that they want to receive the delivery request from SOLFI at the beginning of the day, (or even on the day before), so they can include the requests on their "standard deliveries" to plan the day according to the delivery constraints of the order:

"We have standard deliveries during a day that we know beforehand and which are the basis for our route planning. However, in case a client asks for an urgent delivery we have flexibility to accept and deliver this urgent order, reorganizing our routes based on priority. For this project, the best scenario is to know the deliveries beforehand and include them as standard deliveries and we manage our routes according to the delivery constraints."

How much time do they need, typically, to deliver their orders within the city was also asked. This question aims to understand how much time the driver needs to deliver the order at a destination address after collection. The response of the interviewed clarified that it depends on the zones and how much zones/localities they have to cross in the city to deliver the orders. It was clear that if the order is to be collected and delivered to a final customer within the same zone/locality, it took them about 30 minutes to deliver the orders. However, if they have to cross three or more zones/localities it takes about one hour. This plays an important role on the decision-making tool to account this time as delivery time. They have stated the following:

> *"We have defined a maximum delivery time of 1 hour for any order. Still, in case the order is collected in the same zone of the destination, we can deliver it in 30 minutes maximum. For orders we have to cross 2 zones the delivery time is between 30 and 60 minutes, depending in many factors."*

Other important factors were to understand the type of products this company works with and what capacity do they have in terms of volume or weight. Their answer was that they typically transport very small orders, that can be handled manually, from categories of Sports clothing, Technology and Stationery. They also stated that they can collect more than one order at a time and the weight has to be less than 10 Kg. These requirements are aligned with the type of products to be transported within the scope of SOLFI project:

> *"Each bike/motorcycle that we use allows to transport many orders at the same time, with the maximum weight of 10 Kg for bikes and 30 KG for motorcycles, for cargo. The typical orders are boxes/volumes with small volume to be able to transport manually, without any device to handle them". "Our main categories of products are Sports clothing and footwear, technology components and stationery material, as books and paper, which typically respect our constraints of capacity."*

As an output from the questionnaire to the potential final customers, previously presented in Section 4.2.1, domicile delivery is the current preference of final customers to receive their orders. Nevertheless, they perceive the use of smart-lockers and stores attractive to the delivery process of their orders. This interview allowed to understand how the LMO experience dealing with this stores and smart-lockers. The answer allowed us to conclude that they are available to deliver the orders to a specific location that is worth trusty to the final customer, since they have done it before sporadically.

> *"Occasionally, we had cases where if we could not deliver the orders to the client destination due to any reason, we could deliver them to a neighbor or a store that is trustworthy for the client. It is possible to use it in these terms, from our side."*

Table *8* summarizes the main findings from the interviews to the stakeholders and the questionnaire to the final customers.

Table 8 - Main results and contributions from the interviews and questionnaire

Contribution	Theme	Stakeholder	Managerial implication	How it was addressed in this research
Parameters incorporated in the models	Request Demand	Logistic Operator	It was defined that the request's demand should represent the number of boxes, with limited weight and volumes, of each request and the capacity of the system should act accordingly	Demand parameter in the mathematical models as an integer representing the number of volumes /boxes for each request
	Last mile delivery time window	Final customers (questionnaire)	It was inferred that final customers value the time window flexibility, selecting a day and a delivery time window they want to receive the order	The request is transported on the day of preference to the final customer; A parameter is incorporated in the models to fulfil the delivery time window selected by the final customer;
	Service Time	BTO	It was determined that a dedicated area in the bus hubs would exist to receive and prepare all the. It was also defined that it would be needed a preparation time for each request	Assuming the availability of a dedicated resource, no bus hub capacity to receive requests has been incorporated in the models. Additionally, a service time parameter was included to prepare the requests before transport
	Bus service capacity	BTO	Bus capacity: It was determined that a bus service would have a dedicated sealed area to transport requests and the capacity of the bus would mean the maximum number of boxes each bus service could transport during each trip	Bus service capacity parameter in the models as an integer representing the number of volumes /boxes each bus service can transport
	Bus stop capacity	BTO	Offloading limit: It was determined that there is a maximum number of boxes to be offloaded from the bus at each bus stop, to not jeopardize and significantly impact the passenger experience	Bus stop capacity parameter in the models as an integer representing the maximum number of volumes /boxes that can be offloaded from each bus at each bus stop
	Maximum delivery time	LMO	It was determined a maximum delivery time to deliver any request from the bus stop (after offload) to any address within the city	A parameter the maximum delivery time was incorporated into the models.

Contribution	Theme	Stakeholder	Managerial implication	How it was addressed in this research
Assumptions in the models	Last mile delivery	Final customers (questionnaire)	It was inferred that, currently, potential final customers prefer to receive their orders at their home address. Stores and smart lockers are very good options with a high potential to be used on the scope of this project as well, since final customers would foresee these conveniences as good options for their deliveries	The final destination of each request is considered the location within the city where the LMO delivers the requests and ends the distribution process. This location can be the final customer home address or a preselected store/smart locker by the final customer.
	Requests are delivered to the starting routes points (bus hubs)	Logistic Operator	It was agreed that the logistic company must be responsible for the first mile of the requests, meaning that it has to deliver the requests to the location where the bus service routes depart from. The logistic operator has to previously inform what are the dropping points it is available to drop the orders	The models assume that the requests are delivered to the starting routes points of the bus services
	Requests transportation	Logistic Operator	It was determined that the volumes/boxes of each request must be transported by the same bus service (no partitioning is allowed)	Incorporated in the models indirectly by the requests demand, since the demand has to be fully transported by the bus service
	Avoid bus services in the peak hours	BTO	Possibility to not use the most critical bus services in terms of passenger attendance to the integrated passenger and freight solution, avoiding the bus services in the peak hours	The models only use the bus service schedules provided by the BTO beforehand.
	Maximum delivery time	LMO	It was determined to split the city in different destinations zones and determine a maximum delivery time to each zone and between zones	The parameter for maximum delivery time depends on each zone the request is destined to
	Requests offloaded	LMO	It was determined that the volumes/boxes of each requests must be completely offloaded from the bus (no partial offloading's should occur)	Incorporated in the model indirectly by the requests demand, since the demand has to be fully offloaded
Contributions to the problem-solving approaches	Possible Disruptions	BTO	Possible disruptions in the process: main disruptions are (1) the suppression of the bus service by an unexpected event during the day (e.g. driver absence); and (2) a new bus services schedule of a day that is reformulated with requests already accepted for that day. (3) The driver cannot wait for the offloading entity to be on time at the bus stop. In case the LMO cannot be on time at the bus stop, the orders return to the bus hub or can be offloaded ate the next bus stop	(1) Objective function incorporating robustness to the system to deal with bus services suppressions; and (2) Algorithm to check if the total set of accepted requests can still be accepted for the new bus service schedules (3) Objective function incorporating robustness to the system to deal with bus stops mismatches
	Algorithm for orders receipt	BTO	The time response to the client from the algorithm during a request release has to be no more than 10 seconds. After this time, the client has to know if its order is accepted or not by the system.	Development of two different algorithms to build a distribution plan: (1) Requests receipt algorithm to accept or not a new request in 10 seconds; (2) optimizer algorithm of the distributing plan for the list of accepted orders.
	Instances	BTO	Pilot network information for the Pilot Instances with 220 bus services; 2 hubs; 7 bus stops; 3 destination zones throughout the city	Information used to build the Pilot Instances.
	Time Windows	LMO	Two standard time windows durations are considered, based on the LMO experience: the time windows duration of to 4 hours and the time window duration of 2 hours. The final customers can select intervals of 4 hours or 2 hours to receive their orders.	All instances are based in time windows of 4 hours and 2 hours, according the selection by the final customer.

4.3. Conceptual design of an integrated solution for urban logistics

This co-modality, the combination of passenger traffic and freight transport, is one of the major dimensions of City Logistics 4.0, along with others such as integrated platforms based on advanced Intelligent Transportation Systems (ITS), Internet of things (IoT) and artificial Intelligence systems, and public-private partnerships involving participation of all stakeholders (government, shippers, freight carriers, administrators, residents) for balancing economic growth and environmental friendliness (Gonzalez-Feliu, 2018; Taniguchi et al., 2020).

In the recent literature several advanced technologies are being proposed to support urban logistics activities and reduce its negative impacts. As an example, Kim et al. (2020) propose a drone-based parcel delivery using rooftops of city buildings. Faugère & Montreuil (2020) approach an urban logistics system grounded in networks of smart locker banks as pickup and delivery points in the inner city. Also, He et al. (2020) introduce the Joint Distribution urban logistics concept, which is an intelligent platform to provide efficient, reliable, high-quality, low-cost and personalized logistics services for the whole process of delivery, using IoT, Internet, cloud computing and RFID. To conclude, Li et al. (2020) use a Cyber Physical System to dispatch urban logistics vehicles.

This subchapter describes the integrated passenger and freight flow through UML models (Booch, 2005; Jeffrey L. Whitten, 2016). The UML models provide information about static structure and dynamic behavior of the system through diagrams that are windows or views unto UML models. The UML diagrams can be divided in two main categories: structural and behavioral. The structural group describes the components of the system and their relationships such as package diagrams, component diagrams or class diagrams and the behavioral category describes the behavior of the system over time, for example, activity diagrams or use case diagrams. The next subsections present the UML use case diagram to illustrate the functional requirements of the system and its representation from the user's point of view and also the UML class diagram as a data model to represent the main information objects and relationships, to accomplish the functional requirements.

4.3.1. Functional requirements of the solution

The high-level use case diagram illustrates the main functional requirements of the system, the use cases as ellipses and the actors in the system as human figures. Figure *12* shows a use-case diagram illustrating the main functionalities and actors of the future SOLFI system.

This model starts with the client/sender performing a use case which is "request order quotation". Then the system calculates the final quotation and performs planning, using algorithms and optimization models, to transport the respective order and returns the information to the client who requested the quotation. Note that the use cases that are performed by the system are represented in blue, in order to distinguish them from the use cases performed by the other actors. The client is also notified by the system of the distribution plan for his/her order. After receiving notifications from the system with the final quote and the order distribution plan, the client decides whether to register the order or not. In case the client proceeds with the order placement, it is necessary to confirm the order, which will authorize the system to create notifications and send them to all actors involved in the order distribution process. These notifications include the distribution plan with details for each of the actors who will interact with the order such as the estimated time when the order arrives to each part in the delivery process. Thus, the client is notified of the location and times that the order must be dropped off at the hub and then the order is checked-in on the respective urban transport, notifying the LMO this check-in was successful.

The urban transport driver is responsible for transporting the order along its route and communicating any disruptions in transport, such as traffic accidents, breakdowns, etc. When the bus arrives at the stop where the order has to be offloaded, an LMO must be present to make the transfer between the bus for his/her vehicle. In order to minimize the stopping time for urban passenger transport, the

LMO performs the check-out of the order from the bus and automatically the check-in in his/her last mile vehicle. When the check-in of the LMO is carried out, a notification is sent to the final customer informing the status of the order as well as the estimated delivery time at the destination address. When the order is delivered to the destination address, the LMO checks out the order from the last mile transport. The final customer also has a use case that confirms receipt of the order.

This model is a high-level model that illustrates the macro operation of the system as well as its requirements, step by step, throughout the order distribution process, in a scenario where everything goes well.

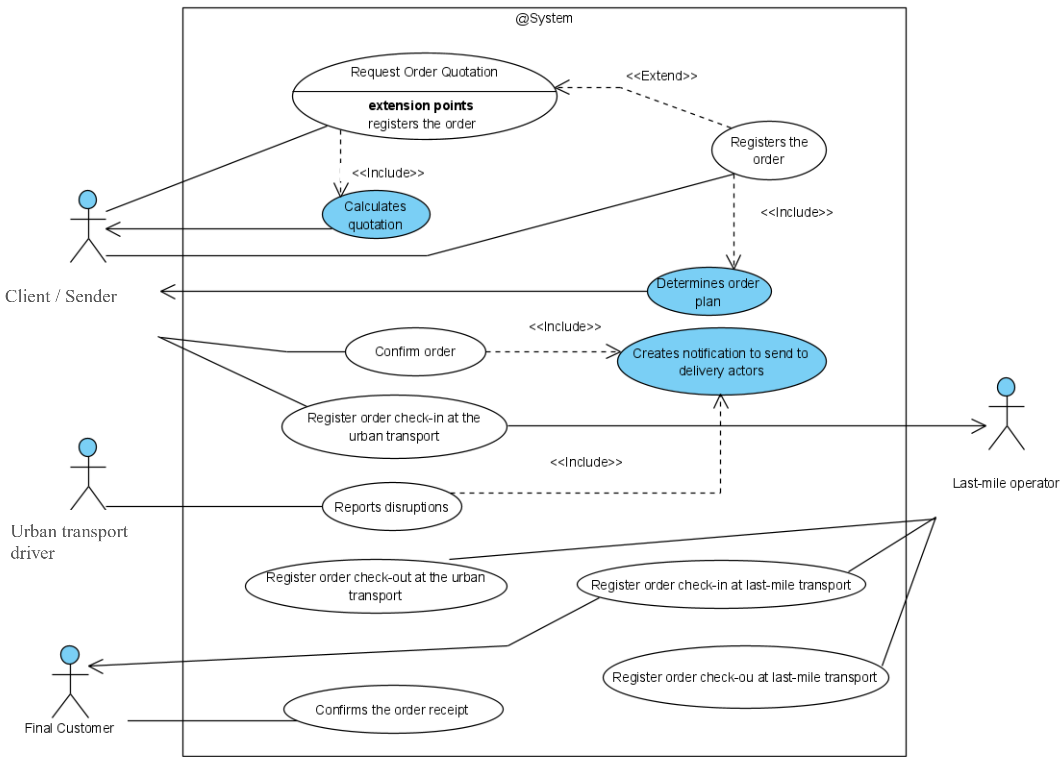

Figure 12 - Use-case diagram representing the main functionalities and actors of the SOLFI system

4.3.2. Data model of the solution

The UML class diagram is a representation of the structure and relationships between classes as well as their attributes. This type of diagram allows to represent in a simple and graphical way the functioning of the system. A class is represented by a square divided into 2 sections: the upper section represents the name of the class, the lower section its attributes. Between classes there are relationships that are represented by a line. The Figure *13* illustrates the general class diagram of the system.

This diagram represents the general structure of the SOLFI solution as well as the main relationships between the key elements. The diagram starts with a sender who wants to send an order. These two classes, with their respective attributes, are related in a way that each sender can have one or more orders to send and each order can only be sent by one, and only one, sender. Then the final customer class is presented, ensuring that each order has one and only one final customer and that each final customer can have one or more orders. The order class is related to the urban transport class in which the relationship is many to many. This relationship results in the transport, which represents loading of the order to urban passenger transportation vehicle and its transportation, characterized by the date and start and arrival time. This transport is related to one and only one bus, and it can have one or more transports. The bus can have one or more weekly routes, and vice versa. Each route is associated with one and only one Hub. Each order is associated with one, and only one, bus stop for offloading. This relationship results in transshipment which represents the offloading of the order from the bus order to one, and only one, vehicle of the LMO. Each LMO is associated with one or more transshipment and one or more bus stops also, each LMO is associated with one and only one vehicle type, but each vehicle type can be used by one or more operators.

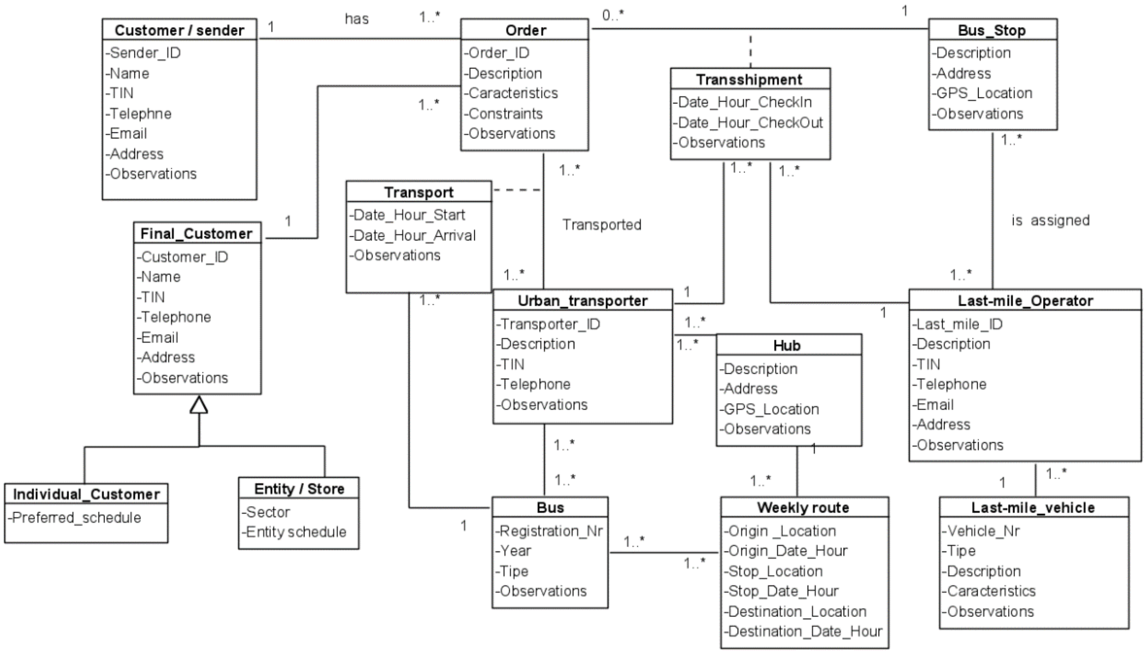

Figure 13 - General UML class diagram for SOLFI

4.3.3. Intelligent process of check-in and check-out using Industry 4.0 technologies

This subsection presents a use-case diagram developed to represent the interface between the order and the bus. The aim is to develop an automatic method to perform the check-in and check-out of the order volumes form/to the bus automatically, through the usage of specific tools such as sensors, authentication cards or other type of technology. This method will require some adjustments on the bus structure to perform check-in and check-out automatically and on real time. This automatic approach to update the order status on the system delivers some advantages, once the human interface with the system itself is minimized, avoiding potential errors or delays during the process. These delays are even more important on the step previously named as "transshipment", where the bus stops to offload the goods to the LMO, and has to be quick to be possible to continue its route and accomplish its schedule. Figure *14* represents a use case diagram focused on this automatic method.

As can be seen from the interactions represented in the Figure *14* it starts when the urban transport driver enters his credentials in the system through the scanning of his personal identification card or even his/her fingerprints, assuring a fast and reliable log-in process when compared to a manual method for the same goal. The system, then, analyzes the credentials and performs the authentications for the respective user. Once again, the use-cases that are performed by the system are represented in blue. After this log-in is performed successfully, the urban transporter driver puts the order into an available slot of a dedicated shelve present on the bus. This shelve has to be equipped with technology that can identify the presence of the order into the respective slot to confirm the check-in. After this, the system will notify the LMO about the check-in status with information about the bus and slot where the order is stored. When the bus arrives to the offloading bus stop, the LMO enters on the bus and inserts his/her credentials in the system, through the same method used previously by the urban transport driver. The system will then perform the authentication and only allows the LMO to access and open the slots that were assigned to him to avoid wrong order pick-ups from the bus. When the LMO picks the order from the slot, the system will automatically perform the check-out of the order and update its status on the system. When the LMO closes the trunk of the bus, the system registers the check-in, in the last mile phase of the transportation, and at the same time notifies the final customer with information about the state of the order and respective location. The system instantly updates the slot status to “empty” so it can receive and store more orders on the next iteration.

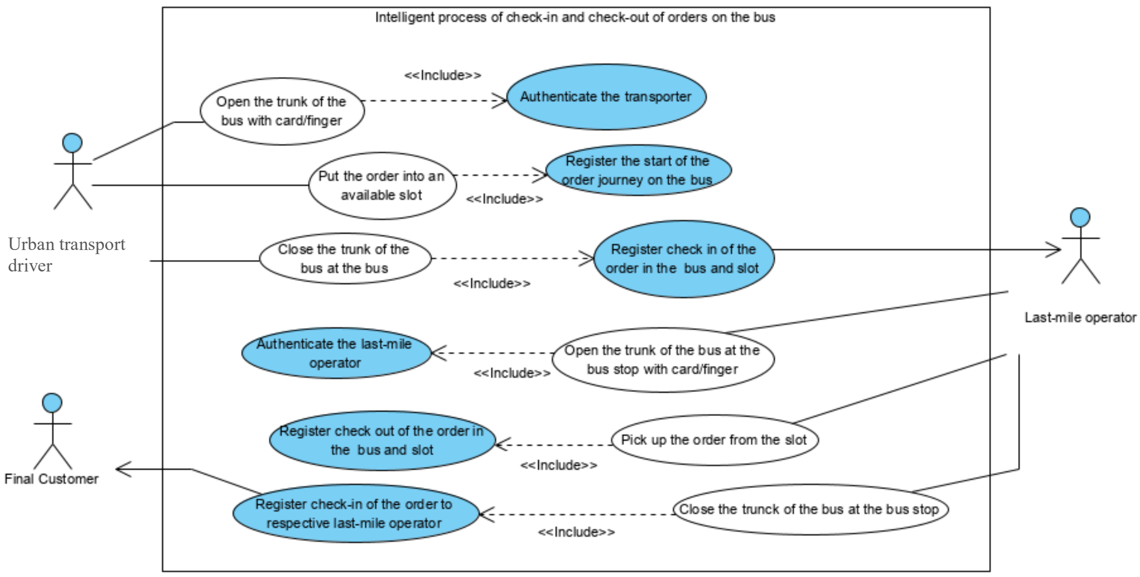

Figure 14 - Use-case diagram reporting automatic process of check-in and check-out of the orders

These models helped to understand how the integrated solution of passenger and freight flows would work together with the different actors (stakeholders) and their requirements.

4.4. Integrated freight and passenger proposed solution for urban logistics

As a result of gathering the requirements of the stakeholders and of the conceptual design of the system, this subsection details the problem description accounting these requirements. The problem under study in this thesis considers the transportation of freight parcels from the peripheries into the city center using an integrated solution of passenger and freight transportation. For this purpose, a passenger bus network is used to transport requests to a bus stop located in the city. From there, the requests are delivered to the final customer through a fleet of environmentally friendly vehicles used by an LMO. The aim is to reduce the traffic of vans and trucks operating in the city, solely dedicated to the freight transportation, thus contributing to reduce negative effects of urban logistics activities, namely pollution, noise, traffic congestion and accidents.

Bearing in mind the output from the project's stakeholders' interviews, present in Table *8*, the problem under study is characterized as follows. Consider a set of bus hubs, located on the outskirts of the city, and a set of bus services, departing from each hub, performing a predetermined route known beforehand, through the city center, and stopping at respective bus stops of their route to offload either passengers or freight requests. Consider a set of requests of freight to be delivered to the city center. Finally, consider an LMO that performs the last mile delivery of the requests from the offloading bus stops to the requests' destination addresses. Thus, the main entities of the integrated solution are Clients, Bus hubs, Bus services, Bus stop, LMO and Final customer. Each of these entities are described in the next paragraphs.

4.4.1. Clients

Clients are the entity that triggers a request release to transport freight towards the city center. From now on, clients will be used for this entity to distinguish with the final customer who receives the order at home. These clients are, typically, individuals or private logistic companies which intend to send parcels to their customers (the same individual can act as client and final customer simultaneously). To perform a request release, the client has to access the SOLFI platform indicates the desired day for transportation and the request demand, which is the number of boxes/volumes of his/her request. The client also has to indicate destination address of the request within the city center and the time window agreed to deliver the request at his/her address. Moreover, the platform informs the client about the list of Bus Hubs, in the city periphery defined to receive parcel requests, i.e. which bus hubs are part of the integrated solution for freight and passenger transportations. Subsequently, the client must indicate which are the Bus Hubs that he/she is available to drop the request. After the SOLFI platform defines the distribution plan, the client has to drop their request at the bus hub indicated by the platform.

4.4.2. Bus hubs

Bus hubs are centers where bus routes start, located in the periphery of the city, and defined to receive parcel requests, within this integrated flow system. Thus, requests dropped by the clients are received and logistically prepared, by a dedicated operator, to be loaded into bus services. At bus hubs, three operations occur: (i) reception of the requests dropped by clients, (ii) sort and package of requests on standard packaging containers and (iii) load of standard containers into bus services. It is assumed that each hub is characterized by a logistic service time to perform the three operations. Moreover, it is assumed that each hub has enough capacity to store early dropped requests until the moment they need to be packaged in containers, since it is expected to have a dedicated area for request preparation. Finally, transshipments of requests between different bus hubs are not allowed, which means that a request cannot be transported from the original hub to another hub to be transported again towards its final bus stop.

4.4.3. Bus services

Bus services represent the transportation service performed by the buses. The schedule and route of each bus service that can transport both passengers and freight is predetermined in advance by the BTO. This predetermination can possibly avoid bus services planned for peak hours in terms of passenger flows. The capacity of each bus to transport requests is limited, in number of boxes/volumes a bus can transport in each trip, and can vary from one bus to another depending on the dimensions of the bus. To guarantee the safety of the requests during transportation, a specific and sealed area within the buses will be dedicated to requests. Figure *15* illustrates the potential initial dedicated area for the requests, even though there is the need for some physical adaptations to be a sealed and secured area for requests transportation. Some technological adaptation would be necessary to achieve a smart and automatic check-in and check-out of orders from the buses, as describes on previous subsection 4.3.3.

Figure 15 - Potential dedicated area for requests transportation

Thus, each bus service can transport more than one request, stop in several bus stops of its route, to possibly offload passengers and/or requests. Additionally, transshipments of requests between different bus services are not allowed, which means that a request cannot be transported by more than one bus service from its hub towards its final bus stop.

4.4.4. Bus stops

Predetermined bus stops are selected by the BTO to be part of the systems as offloading points, where buses can stop to offload requests in addition to the usual passengers' dropping process. These bus stops are part of the bus routes and are located within the city core. In order to guarantee the smoothest experience to the passengers, there each bus has to respect the limit of number of boxes/volumes that can be offloaded at each bus stop, to not significantly deteriorate the passenger's service and to limit the passengers' waiting times during offloads, thus impacting as less as possible the normal flow of the public transportation. To maintain a fast and smooth freight offloading from the bus an automated process is used (Machado et al., 2021). The offload operations are conducted by the LMO which involves synchronizing buses and the LMO to be at the right bus stop at the right time.

4.4.5. Last mile delivery

The last mile delivery is performed by the LMO. The LMO is notified to be at the bus stop at the right time to offload the requests and deliver them to the destination address, within the time window defined during the request release. To guarantee that the deliver to the final customer is within the time window, the LMO partitions the city center in different zones and defines a maximum delivery time to deliver any request from each bus stop to each zone. The LMO routes are managed by itself providing flexibility to integrate this operation with its daily operations.

4.4.6. Final customer

Represents the entity that receives the request at the destination address, within the agreed time window.

Figure *16* entails all the steps of the integrated distribution system.

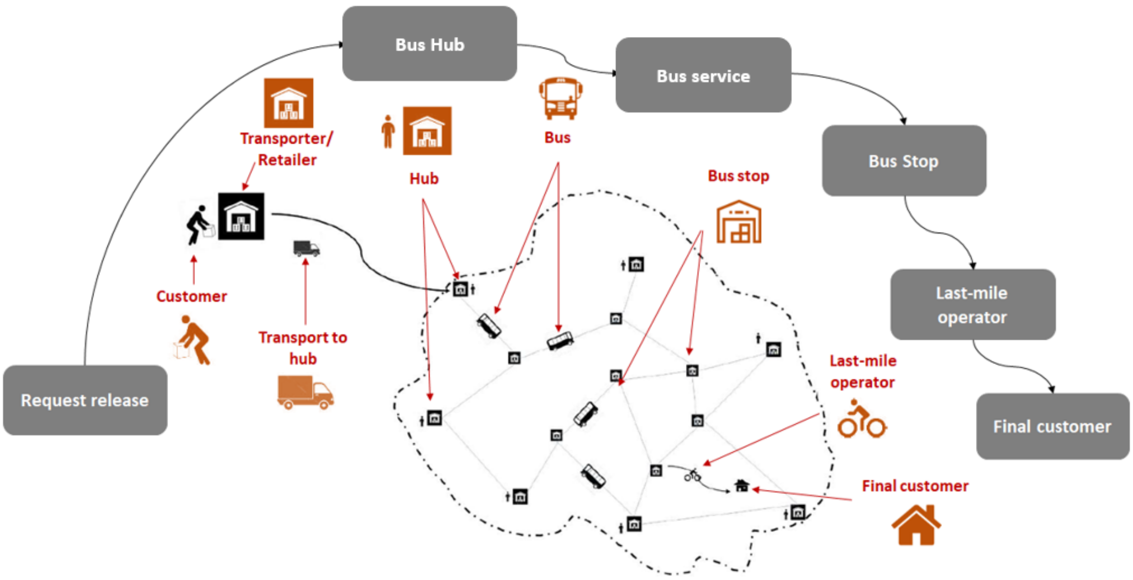

Figure 16 - Steps of SOLFI integrated distribution system

5. Operational approach for the Freight Network Flow Assignment Problem (FNFAP)

This chapter addresses the operational problem FNFAP to study the integration of passenger and freight flows within the city, proposing a new UL concept for distribution. Although other authors have studied the integration of freight and passenger flows on an operational level, the research presented on this chapter is a novel contribution, through the application of robustness to deal with unexpected disruptions. The robustness issue is addressed by the use of objective functions to maximize the back-up plan of distribution, in case of disruption occurrences. Exact formulations and heuristic algorithms are proposed to tackle this problem. The chapter provides computational experiments and conclusions for both types of models.

5.1. Motivation

The problem under study falls in the operational layer of the decision-making process, where the goal is to determine the distribution plan for freight requests to be delivered into a city center, using part of a bus network installed and running in the city, adopting an integrated solution of passenger and freight flows. Finally, to deliver the freight orders from the bus stops to their destination a fleet of green vehicles are considered, such as electrical scooters or bikes, conducting the last mile of the distribution.

For the scope of this integrated solution, a set of bus hubs, located on the outskirts of the city, and a set of bus services, departing from each hub, performing a predetermined route through the city center, and stopping at bus stops of their route have to be selected to offload passengers and/or freight requests. These sets of bus hubs, bus services and bus stops are part of a larger and more complex bus network running in the city. Moreover, it is assumed that these sets are strategically selected beforehand, to be part of an integrated solution to deliver freight into the city center. The reasons for selecting each bus hub, bus service, or bus stop among all existing alternatives may be related with their location, covered area, less busy time of day for passengers or logistical considerations. As a result, a densely populated metropolitan area would have a limited number of hubs, buses and stops, strategically selected and distributed throughout the city, that will be used by this integrated logistics service.

In terms of demand characterization, only small orders with the city center as their destination can be distributed using this integrated solution. Thus, this integrated solution's goal is not to replace the current day-to-day flows of goods within cities, but rather to give logistics operators an alternative option when they need to deliver smaller goods to cities, that typically have their destination within the city center. This alternative option is even more appealing when the logistics provider has to deliver the orders during peak hours and deal with traffic jams, or when they are unable to handle isolated requests for small orders to be delivered to different destinations within the city center within the same time span. For these cases, the integrated solution is a very competitive alternative for transportation, since it allows them to transport different orders at the same time, using different buses in different routes.

The integration of flows addressed in this solution provides several benefits for the citizens who live in cities, including the ability to reduce the number of vans/trucks that are brought into the city, solely for the transportation of goods. Instead, this solution uses the pre-selected sets of bus services that already take place in the city, to transport goods. The advantages of this vehicle reduction include minimization of the air pollution, traffic jams, and noise pollution that would be caused by the standard transportation means. Considering these benefits, the adoption of these alternative and greener logistic solutions within the cities may end up being mandated by the cities' local governments due to the significant environmental and quality-of-life benefits for the citizens, even if it is more financially advantageous, for the logistical operators, to distribute goods directly to the consumer.

Even if the integrated solution is more expensive in the perspective of the client that needs to deliver goods to city center destinations, it does not explicitly quantify the environmental and quality of life benefits to the cities that are equally important for an urban logistics solution, leaving a path for future research. However, analyzing previous contributions from different authors, it is possible to deduce some findings. A first one, based on Crainic et al. (2009), the authors emphasize that the reduction of freight traffic also contributes to the reduction of the belief that "cities are not safe". Here, the environmental factor is covered. Moreover, an integrated solution also implies global benefits across the value chain, rather than isolated benefits (Molenbruch et al., 2021), since, typically, each city logistics stakeholder has its own preferences and expectations (Kiba-Janiak et al., 2021). According to Bachofner et al. (2022), logistics practices that increase profitability for shippers or receivers are generally those that generate the worst impacts on society and on the environment. Finally, a reduction in the number of vehicles in the city allows to offer a freight transport service that can be used as a UL solution to also reduce CO2 emission and noise (Azcuy et al., 2021), in addition to the known mobility and congestion reduction benefits. Note that cities governments play a crucial role in promoting public private understanding, collaboration, and innovative partnerships towards a more sustainable, and integrated transportation system in cities (Crainic et al., 2009; Kiba-Janiak et al., 2021; Lauenstein & Schank, 2022).

According to Crainic et al. (2009), ITS are a promising research direction in the UL field, as they generally refer to the planning, operation, and control methods to be used for the transportation of people and freight, aiming for a better use of the transportation system, infrastructure, and services. Furthermore, the adoption of intelligent freight-transportation systems into UL problems, especially in the field of OR, has recently gained considerable attention in the literature (Manchella et al., 2021b). OR methods have the potential to assist decision makers, and particularly in the field of UL, to allow for more coordinated, safer, and successful freight management (Lagorio et al., 2016), and ITS is acknowledged as a fundamental component and an enabling factor to achieve it (Crainic et al., 2009). So, the optimization planning of the logistics activities of the integrated UL system proposed in this chapter aims to leverage the implementation of ITS, when integrated in an information and decision support platform.

The optimization models proposed to tackle this problem have to manage the following operations: (i) Assign each request to a bus hub where bus services depart from; (ii) Assign the request to a bus service starting on the assigned hub; and (iii) Assign the request to a bus stop of the assigned bus service, to be offloaded by the LMO and delivered at final customer destination. Moreover, different constraints must be met: (a) the freight requests assigned to a given bus service must be upper bounded by its capacity for freight transportation, (b) the freight requests offloaded on a given stop must be upper bounded to a given value so that the expected stopping time of the bus at the stop is not jeopardized, and (c) the arrival time at the bus stop must guarantee that the LMO can deliver the offloaded freight requests at their destination addresses within their delivery time windows. Thus, an operational solution is to indicate, for each accepted request, what is the bus hub, bus service and bus stop assigned to him in the distribution plan.

This operational problem is addressed from different perspectives, since 5 different objective functions of interest are studied: the minimization of the number of bus services and the maximization of the robustness to bus service suppressions, from the BTO perspective; and the minimization of the last mile delivery time, the minimization of the number of bus offloads, and the maximization of the robustness to last mile failures, from the LMO perspective.

Considering the output from the BTO and LMO interviews, a critical point of the system is its robustness to deal with unpredictable events. The two main events with most severe impact on the system performance were identified in the interviews. The first one is bus driver's nonappearance resulting in bus service suppressions, since all requests assigned to such bus services would not be transported as initially planned. The second one is the LMO desynchronization at the bus stop to be ready to offload the requests from the bus, and therefore the requests cannot be delivered in time to the final customer. As seen in the SLR section, this feature of robustness applied to the field of integration of passenger and freight flow in UL is inexistent. Thus, one of the main research contributions is the incorporation of robustness to the operational layer of this problem under study.

This chapter is organized as follows: the current Section 5.1 details the motivation to study this problem and its novelty; Section 5.2 describes the problem formulation using the exact methods, presenting the different ILP models for optimization; Section 5.3 details the datasets used to solve the models suggested and the rationale used for the dataset generation; Section 5.4 presents and discusses the results of the computational experiments with the exact methods; Section 5.5 explains the problem formulation with heuristic methods; Section 5.6 presents and discusses the results of the computational experiments with heuristic methods. Lastly, Section 5.7 summarizes the chapter with the main conclusions of the experiments performed.

5.2. Problem formulation using exact methods

The optimization models proposed in this section are aimed to support the operational planning decision making of the UL service under study, through the development of a distribution plan. They are the core of an intelligent decision support system that allows the management of freight transportation operations in a coordinated manner, in time and space. This coordination plays a major role in the loading/offloading/transfer of freight. In addition, this system also ensures the preplanning of transport operations, to respond to some failure events (described below).

The optimization models presented in this section are aimed to support the operational decision-making process of FNFAP, through the use of ILP models.

Consider a bus network with a set of hubs T (where requests can be dropped by clients), a set of bus stops S (where the requests can be offloaded by the LMO) and a set of bus services P (where requests can be transported from bus hubs to bus stops). Each hub $t \in T$ is characterized by a logistic service time F_t (the maximum time interval required to prepare the freight to be loaded into the bus service) and has an associated set of bus services $P(t) \subset P$. Each bus service $p \in P(t)$ has an associated load capacity U_{tp} (i.e., the maximum number of boxes that can be transported), a departing time H_{tp} from hub t and a set of bus stops $S(p) \subset S$. Finally, each bus stop $s \in S(p)$ of bus service $p \in P(t)$ has an associated arrival time H_{tps} (according to the route of the bus service) and an offload capacity U_{tps} (i.e., the maximum number of boxes that can be offloaded).

Consider a set of requests K. Each request $\mathrm{k} \in \mathrm{K}$ has an associated demand $\mathrm{D_k}$ (number of boxes), a destination address within the city $\mathrm{B_k}$ and a delivery time window $[\mathrm{E_k}, \mathrm{L_k}]$ defining the earliest $\mathrm{E_k}$ and the latest $\mathrm{L_k}$ delivery time instants of the request at its destination address. Moreover, the hubs at which the client of request $\mathrm{k} \in \mathrm{K}$ can drop it are modelled by the binary parameters $\mathrm{A_{kt}}$ that are equal to 1 if request $\mathrm{k} \in \mathrm{K}$ can be dropped by the client in hub $\mathrm{t} \in \mathrm{T}$ or equal to 0, otherwise. Consider an LMO whose service is characterized by the maximum time $\mathrm{T_{ks}}$ to deliver request $\mathrm{k} \in \mathrm{K}$ from bus stop $s \in S$ to the request destination address B_k. All sets and parameters are summarized in Table *9* and Table *10*.

Table 9 - Sets of the models

Set	Description
K	Set of requests k
T	Set of bus hubs t
S	Set of bus stops s
P	Set of all bus services p
$P(t) \subset P$	Set of bus services departing from hub $t \in T$
$S(p) \subset S$	Set of bus stops s of bus service $p \in P$

Table 10 - Parameters of the models

Parameter	Description
F_t	Maximum time on hub t to prepare any incoming request to load into any bus service
H_{tp}	Departing time of bus service $p \in P(t)$
H_{tps}	Arrival time of bus service $p \in P(t)$ to bus stop $s \in S(p)$
U_{tp}	Capacity of bus service $p \in P(t)$
U_{tps}	Capacity of bus service $p \in P(t)$ to offload requests in bus stop $s \in S(p)$
D_k	Demand of request k
B_k	Destination address of request k
E_k	Earliest delivery time of request k at its destination address
L_k	Latest delivery time of request k at its destination address
A_{kt}	Binary parameter indicating if request k can be dropped in hub t
T_{ks}	Maximum delivery time of request k from bus stop s to the destination address of k

All optimization models described next consider the following additional binary parameters, h_{ktps}, that are computed beforehand. The binary parameter h_{ktps} is set to 1 if, for request $k \in K$, hub $t \in T$ is one of the possible hubs for the request (i.e., A_{kt} is equal to 1) and it is possible to meet the delivery time window $[E_k, L_k]$ of the request when it is dropped at hub $t \in T$ in time to be logistically prepared, loaded in bus service $p \in P(t)$ and offloaded in bus stop $s \in S(p)$. This can be mathematically formulated as follows:

$$h_{ktps} = \begin{cases} 1 & , A_{kt} = 1 \ \wedge \ E_k \leq H_{tps} + T_{ks} \leq L_k \\ 0 & , \text{otherwise} \end{cases}$$

All optimization models described next consider the basic binary decision variables, z_{ktps}. A given solution such that variable z_{ktps} is equal to 1 defines that request $k \in K$ must be dropped in hub $t \in T$ no later than time instant $H_{tp} - F_t$ to be loaded in bus service $p \in P(t)$ whose departing time is H_{tp} and offloaded (by the LMO) in bus stop $s \in S(p)$ at time instant H_{tps}. This decision variable can be defined as:

z_{ktps} – binary variable that is equal to 1 if request $k \in K$ is dropped in hub $t \in T$, loaded in bus service $p \in P(t)$ and offloaded in bus stop $s \in S(p)$; and is equal to 0, otherwise.

A feasible solution is modelled by the following set of ILP constraints:

$$\sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} h_{ktps} z_{ktps} = 1 \qquad , \forall\, k \in K \tag{1}$$

$$\sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} (1 - h_{ktps}) z_{ktps} = 0 \qquad , \forall\, k \in K \tag{2}$$

$$\sum\nolimits_{k \in K} \sum\nolimits_{s \in S(p)} D_k z_{ktps} \leq U_{tp} \qquad , \forall\, t \in T, \forall\, p \in P(t) \tag{3}$$

$$\sum\nolimits_{k \in K} D_k z_{tkps} \leq U_{tps} \qquad , \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{4}$$

$$z_{ktps} \in \{0,1\} \qquad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{5}$$

Constraints (1) guarantee that the assigned bus service and bus stop to each request $k \in K$ starts in one of the possible hubs for each request, is ready on time to be loaded into the bus (considering the Logistic service time of that hub) and meets with its delivery time window (i.e., the associated parameter h_{ktps} is equal to one). These constraints guarantee this because the variable z_{ktps} is multiplied by parameter h_{ktps} (that is equal to 1 if all previous conditions are met). Constraints (2) guarantee that each request $k \in K$ cannot be assigned with one bus service $p \in P(t)$ in one hub $t \in T$ to be offload in one bus stop $s \in S(p)$ such that the associated parameter h_{ktps} is zero. Constraints (2) are not necessary to obtain feasible solutions, since constraints (1) alone guarantee that variable z_{ktps} contains a feasible solution. However, constraints (2) are valuable because, although they increase the number of constraints of the model, they allow the solution to eliminate the variables z_{ktps} for all the combination of requests, bus hubs, bus services and bus stops that are not possible to be selected. So, for all the combinations where the h_{ktps} is equal to zero, the corresponding variable z_{ktps} is set to 0. Some experiments were done with and without constraints (2) showing that, in general, the solver could achieve the solutions faster with these constraints, improving the performance. Constraints (3) guarantee that the requests loaded on each bus service $p \in P(t)$ of each hub $t \in T$ are within the bus service capacity U_{tp}. This is guaranteed because constraints sum the demands of all requests assigned to a bus service and ensure that this sum has to be equal or lower than the capacity of the bus service itself. Constraints (4) guarantee that the requests offloaded on each bus stop $s \in S(p)$ of each bus service $p \in P(t)$ of each hub $t \in T$ are within the bus stop capacity U_{tps}. This is guaranteed because these constraints sum the demand of all requests offloaded in a bus stop and ensure that this sum has to be equal or lower than the capacity of the bus stop itself. Finally, constraints (5) are the domain constraints of the basic variables.

In order to address the different perspectives of the major stakeholders in an integrated logistic system, it is crucial to include their needs and concerns during the operations of a logistical service as well as to analyse possible trade-offs among their needs. Thus, the operational problem under study is addressed with 5 different optimization aims. From the BTO point of view, two optimization objectives are addressed: the minimization of the number of bus services needed to transport freight requests, and the robustness optimization of the solutions to bus service suppressions. From the LMO perspective, three optimization objectives are addressed: the minimization of the last mile delivery average time, the minimization of the number of bus offloads, and the robustness optimization of the solutions to last mile failures.

To study the influence of the simultaneous consideration of the BTO and the LMO needs, five optimization problems through lexicographic optimization are also investigated. Each optimization problem considers the combination of a pair of objective functions, such that the first objective function is considered to be more important/crucial than the second one.

In the next subsections, it is presented the different optimizations problems of interest under study, explaining the motivation to study them and how they are modelled.

5.2.1. Minimizing the last mile delivery time (LMDT)

In this optimization problem, the focus is on optimizing the last mile delivery process to ease the integration of requests collection by the LMO into their daily operations and routes. This can be achieved by selecting the bus stops (where requests are offloaded by the LMO) closer to the requests' destination addresses. Recall that the last mile service is characterized by a maximum delivery time T_{ks} (from bus stop s to the destination address B_k of request k). Assuming that the maximum delivery times are correlated with the distance between stops and destinations addresses, if the maximum delivery time T_{ks} is higher the LMO needs to cover higher distances to deliver the requests from the stop s to the destination B_k. From the LMO's perspective, it may be interesting to minimize this last mile delivery time, so they can travel less distance and deliver the requests faster to their destination, and after that continue their daily operations as usual. To accomplish this aim, the objective function of interest is the minimization of the average of the maximum delivery times among all requests.

The LMDT model is defined by the following ILP formulation:

Minimize $$\frac{1}{|K|}\sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} T_{ks}z_{ktps} \qquad (6)$$

Subject to:

(1) – (5)

The objective function (6) is the minimization of the average delivery time of all requests. In this objective function, the maximum last mile delivery time (B_k) for all requests are summed and divided by the total number of requests. Constraints (1) to (5) are the same constraints presented before to model a feasible solution.

5.2.2. Minimizing the number of bus offloads (NBO)

In this optimization problem, the focus is again on the last mile delivery of the requests aiming at minimizing the number of bus offloads of requests. As previously indicated, the LMO must arrive at the offloading bus stop at the same time as the bus (or just a few minutes before). For this reason, the LMO may be interested in minimizing the total number of times that he needs to go to bus stops to pick up freight requests. By minimizing the number of bus offloads, the LMO needs to go to bus stops a fewer number of times and collect a higher number of requests each time he picks up the freight requests at bus stops, to facilitate integration of requests collection by the LMO into their daily operations and routes.

To define this optimization problem, the following additional binary variables are considered to count the number of bus offloads/number of times that the LMO needs to pick up freight from bus stations (one or more requests for pick up):

y_{tps} – binary variable that is equal to 1 if at least one request is dropped in hub $t \in T$, loaded in bus service $p \in P(p)$ and offloaded in bus stop $s \in S(p)$; and is equal to 0, otherwise.

With these additional variables, the NBO model is defined by the following ILP formulation:

$$\text{Minimize} \quad \sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} y_{tps} \tag{7}$$

Subject to:

(1) – (5)

$$z_{ktps} \leq y_{tps} \quad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{8}$$

$$y_{tps} \in \{0,1\} \quad , \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{9}$$

The objective function (7) is the minimization of the number of bus offloads and, subsequently, the number of times the LMO needs to offload requests at bus stops. Constraints (1) to (5) are the same constraints presented before to model a feasible solution. Constraints (8) guarantee that an offload is accounted when at least one request is delivered in hub $t \in T$, loaded in bus service $p \in P(t)$ and offloaded in bus stop $s \in S(p)$. This is guaranteed because when assigning a request to a new combination of bus hubs, bus services and stops ($z_{ktps} = 1$), the variable y_{tps} is set to 1 as well for that same combination of bus hub, service and stop, to fulfil constraints (8). Note that if all variables z_{ktps} associated to a given bus stop of a bus service are set to 0, the corresponding variable y_{tps} is also set to 0 (although it can be assigned with 1 by constraints (8)) due to the minimization of the objective function (7) where variables y_{tps} have associated positive parameters. Constraints (9) are the variable domain constraints of the additional variables.

5.2.3. Minimizing the number of bus services (NBS)

In this optimization problem, the focus is on the management of the bus network impact, assuming that the bus vehicles available for freight transportation are limited, and the adaptations of such buses are expensive. For this reason, the BTO may be interested in minimizing the total number of such bus vehicles that need to be physically adapted. From the BTO's perspective, it can lead to a smaller investment on the adaptation of the bus fleet and also with less impact on the normal flow of passenger transportation, since less bus services are used for the mixed transportation of freight and passengers.

Thus, in this case, the aim is to minimize the number of bus services used for transportation of requests. To define this optimization problem, the following additional variables are introduced:

y'_{tp} – binary variable that is equal to 1 if at least one request is dropped in hub $t \in T$ and loaded in bus service $p \in P(p)$; and is equal to 0, otherwise.

Then, the NBS model is defined by the following ILP formulation:

$$\text{Minimize} \quad \sum_{t \in T} \sum_{p \in P(t)} y'_{tp} \tag{10}$$

Subject to:

(1) – (5)

$$z_{ktps} \leq y'_{tp} \qquad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{11}$$

$$y'_{tp} \in \{0,1\} \qquad , \forall\, t \in T, \forall\, p \in P(t) \tag{12}$$

The objective function (10) is the minimization of the number of bus services used for all requests. Constraints (1) to (5) are the same constraints presented before to model a feasible solution. Constraints (11) guarantee that a bus service is accounted when at least one request is delivered in hub $t \in T$ and loaded in bus service $p \in P(t)$. This is guaranteed because when assigning a request to a new combination of bus hubs, bus services and stops ($z_{ktps} = 1$), the variables y'_{tp} are equal to one as well for that same combination of bus hub and bus service, to fulfil constraints (11). Note that if all variables z_{ktps} associated to a given bus service are set to 0, the corresponding variable y'_{tp} is also set to 0 (although it can be assigned with 1 by constraints (11) due to the minimization of the objective function (10) where variables y'_{tp} have associated positive parameters. Constraints (12) are the variable domain constraints of the additional variables.

5.2.4. Maximizing the robustness to bus service suppressions (RBS)

In this optimization problem, the focus is on considering possible failures in the bus network causing bus service suppressions, i.e., a bus service might be unexpectedly suppressed by driver non-appearance or by a bus vehicle failure (still within the bus hub) that is replaced by another without the logistical adaptation for freight transportation (in the latter case, the bus service is suppressed only for freight transportation). The aim of this problem is to incorporate robustness to deal with these unexpected events that can suppress a bus service which, accordingly the BTO, are very likely to occur.

To achieve a robust solution to bus service suppressions, each request is assigned with a main bus service (modelled by the previously defined z_{ktps} basic variables) and, if possible, with an alternative bus service starting in the same bus hub of the main bus service and also fulfilling the delivery time window of the request. Then, the aim is to maximize the number of requests assigned with an alternative bus service, trying to have the highest number of requests with an alternative bus service assigned to it. Thus, a robust solution is one that maximizes the number of requests that can be assigned with an alternative bus service. This robust solution provides intelligence to the operations informing the BTO of how to react in case of a bus service suppression occur, acting as an alternative transportation plan for all requests that were previously assigned to the suppressed bus service. To define this optimization problem, the following additional binary variables are considered, modelling the assignment of alternative bus services:

x_{ktps} – binary variable that is equal to 1 if the alternative bus service of request $k \in K$ is bus service $p \in P(t)$ starting on hub $t \in T$ and bus stop $s \in S(p)$; and is equal to 0, otherwise.

With these additional variables, the RBS model is defined by the following ILP formulation:

$$\text{Maximize} \quad \sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x_{ktps} \tag{13}$$

Subject to:

(1) – (2), (5)

$$\sum_{k\in K}\sum_{s\in S(p)} D_k\left(z_{ktps} + x_{ktps}\right) \le U_{tp} \qquad ,\forall\, t \in T, \forall\, p \in P(t) \tag{3'}$$

$$\sum_{k\in K} D_k\left(z_{ktps} + x_{ktps}\right) \le U_{tps} \qquad ,\forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{4'}$$

$$\sum_{p\in P(t)}\sum_{s\in S(p)} h_{ktps}x_{ktps} \le \sum_{p\in P(t)}\sum_{s\in S(p)} h_{ktps}z_{ktps} \qquad ,\forall\, k \in K, \forall\, t \in T \tag{14}$$

$$\sum_{s\in S(p)} \left(h_{ktps}z_{ktps} + h_{ktps}x_{ktps}\right) \le 1 \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t) \tag{15}$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} (1 - h_{ktps})x_{ktps} = 0 \qquad ,\forall\, k \in K \tag{16}$$

$$x_{ktps} \in \{0,1\} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{17}$$

The objective function (13) is the maximization of the number of requests with assigned alternative bus services. Constraints (3') and (4') replace the previous constraints (3) and (4) and guarantee that the requests loaded on each bus service $p \in P(t)$, in constraints (3'), and offloaded on each bus stop $s \in S(p)$, in constraints (4'), are within the bus service and bus stop capacities, respectively, even if the requests are transported in their alternative bus services. This is guaranteed because these constraints sum the demand of all requests assigned for each combination of bus hub, bus service, and ensure it is not higher than the bus capacity (constraints (3')) and bus stop capacity (constraints (4')). The reason to sum the two variables z_{ktps} and x_{ktps} is to sum the demand assigned to a specific bus that acts as main bus for some requests and alternative bus for other requests simultaneous, always guaranteeing capacity for all requests assigned to it.

Constraints (14) guarantee that the alternative bus service to each request, when possible, starts in the same hub of the main bus service. Note that constraints (1) and (2) guarantee that the right-hand expression of constraints (14) is 1 for one of the hubs and 0 for all other hubs. So, constraints (14) together with constraints (1) and (2) guarantee that each request is assigned with at most one alternative bus service from the same hub of the main bus service. On the other hand, constraints (15) guarantee that the main and the alternative bus services cannot be the same bus service, since the constraints ensure that the same combination of bus hub, service, stop cannot be assigned simultaneous as a main bus and alternative bus (the sum of z_{ktps} and x_{ktps} has to be equal or less than 1).

Constraints (16) are similar to constraints (2) but now applied to the additional variables, i.e., they guarantee that each request $k \in K$ cannot be assigned with one alternative bus service $p \in P(t)$ in one hub $t \in T$ to be offload in one bus stop $s \in S(p)$ such that the associated parameter h_{ktps} is zero. Finally, constraints (17) are the variable domain constraints of the additional variables.

Note that, for each request such that one of the variables x_{ktps} is equal to 1 in the solution of the optimization problem, the above formulation does not guarantee that the alternative bus service assigned to a request departs later than the main bus service of that same request, since the formulation does not guarantee that the select bus service defined by variable x_{ktps} departs later than the main bus service defined by variable z_{ktps}. For the requests such that this condition is not met, the final solution is defined by switching the role of the two bus services, i.e., considering the bus service defined by x_{ktps} as the main bus service and the bus service defined by z_{ktps} as the alternative bus service. In this way, it is always guaranteed that the main service assigned to a request will depart first from the bus hub and an alternative later bus service is also assigned to the request to act as an alternative solution in case the main bus service is suppressed.

One alternative to potentially strength the proposed formulation is to break the symmetry between variables z_{ktps} and x_{ktps} by defining constraints that guarantee the time relation between the main and the alternative bus services. Symmetry occurs when two different mathematic solutions correspond to the same real solution and it is known that symmetry can negatively impact the performance of branch-and-bound algorithms. According to Margot, (2010) an ILP is symmetric if its variables can be permuted without changing the structure of the problem, which is precisely what occurs in this formulation.

This can be done by replacing the previous constraints (15) by the following constraints:

$$\sum_{s \in S(p)} h_{ktps} z_{ktps} + \sum_{a \in A(p)} \sum_{s \in S(a)} h_{ktas} x_{ktas} \leq 1 \quad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t) \qquad (15')$$

In these constraints, set $A(p)$ is a set of bus services composed by bus service p plus all bus services departing from the same hub of bus service p whose departing time from the hub is before the departing time of bus service p. Thus, with these constraints, for each request the alternative bus service to be assigned to it must be after the main bus service. This is guaranteed because in the second part of this inequality, the subset $A(p)$ considers all the bus services departing from the same bus service of p (including) and all the services that departure before the service p, and the sum of variables z_{ktps} and x_{ktps} can be at most 1, meaning that no bus service prior to the service p can be selected as alternative bus service.

5.2.5. Maximizing the robustness to last mile failures (RLMF)

In this optimization problem, the focus is on considering possible failures in the last mile process, when the LMO cannot arrive on time to a given bus stop of a given bus service for the planned offload of requests. This desynchronization of bus service and LMO can be caused by different unexpected events, such as traffic congestions or even a vehicle failure. By default, when a request is not collected at bus service, it returns to the Bus Hub of bus service to be integrated into the next day deliveries. Nevertheless, consider the case when the LMO is still able to offload the requests in one of the next stops of the same bus service, acting as an alternative bus stop where the requests can be offloaded. In this case, to incorporate robustness to deal with these events, the aim of this problem is to maximize the number of requests that can be assigned with an alternative bus stop still fulfilling the delivery time windows of the requests. Again, this robust solution provides intelligence to the process informing the BTO and LMO, beforehand, of how to react in case of a last mile offload failure. To define this optimization problem, the following additional binary variables are considered:

x'_{ktps} – binary variable that is equal to 1 if the alternative bus stop of request $k \in K$ is bus stop $s \in S(p)$ of bus service $p \in P(t)$ starting on hub $t \in T$; and is equal to 0, otherwise.

With these additional variables, the RLMF model is defined by the following ILP formulation:

$$\text{Maximize} \quad \sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x'_{ktps} \tag{18}$$

Subject to:

(1) – (3), (5)

$$\sum_{k\in K} D_k\left(z_{ktps} + x'_{ktps}\right) \leq U_{tps} \qquad ,\forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{4''}$$

$$\sum_{s\in S(p)} h_{ktps}x'_{ktps} \leq \sum_{s\in S(p)} h_{ktps}z_{ktps} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t) \tag{19}$$

$$h_{ktps}z_{ktps} + h_{ktps}x'_{ktps} \leq 1 \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), s \in S(p) \tag{20}$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} (1 - h_{ktps})x'_{ktps} = 0 \qquad ,\forall\, k \in K \tag{21}$$

$$x'_{ktps} \in \{0,1\} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{22}$$

The objective function (18) is the maximization of the number of requests with assigned alternative bus stops. Constraints (4'') replace the previous constraints (4) and now guarantee that the requests offloaded on each bus stop are within the bus stop capacities even if the requests are offloaded in their alternative bus stops. This is guaranteed because these constraints sum the demand of all requests assigned for each combination of bus hub, bus service, and ensure it is lower than the bus stop capacity, independently if the bus stop acts as a main bus stop or an alternative bus stop for the request.

Constraints (19) guarantee that the alternative bus stop assigned to each request, when possible, is in the same bus service of the main stop. Note that constraints (1) and (2) guarantee that the right-hand expression of constraints (19) is 1 for one of the bus services and 0 for all other bus services. So, constraints (19) together with constraints (1) and (2) guarantee that each request is assigned with at most one alternative bus stop. On the other hand, constraints (20) guarantee that the main and the alternative bus stops cannot be the same.

Constraints (21) are similar to constraints (2) but now applied to the additional variables, i.e., they guarantee that each request $k \in K$ cannot be assigned with one alternative bus stop $s \in S(p)$ on a bus service $p \in P(t)$ of a hub $t \in T$ such that the associated parameter h_{ktps} is zero. Finally, constraints (22) are the variable domain constraints of the additional variables.

Note that, similarly to the previous optimization problem, for each request such that one of the variables x'_{ktps} is equal to 1 in the solution of the optimization problem, the above formulation does not guarantee that the bus stop defined by variable x'_{ktps} is subsequent on the route of the bus than the bus stop defined by variable z_{ktps}. For such requests, the final solution is defined by switching the role of the two bus stops, i.e., considering the bus stop defined by x'_{ktps} as the main bus stop and the bus stop defined by z_{ktps} as the alternative bus stop.

Again, one alternative to potentially strength the proposed formulation is to break the symmetry between variables z_{ktps} and x'_{ktps} by defining constraints that guarantee the time relation between the main and the alternative bus services. This can be done by replacing the previous constraints (20) by the following constraints:

$$h_{ktps} z_{ktps} + \sum_{b \in A(s,p)} h_{ktpb} x'_{ktpb} \leq 1 \qquad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), s \in S(p) \qquad (20')$$

In these constraints, set $A(s,p)$ is the set of bus stops of bus service p composed by the bus stop s plus all bus stops whose arrival time is before the arrival time of bus stop s. Thus, with these constraints, for each request the alternative bus stop to be assigned to it must be subsequent to the main bus stop of the bus service route.

5.2.6. Lexicographic optimization of two planning objectives

Several times, when aiming to optimize a given planning objective, multiple solutions with the same optimal value can be obtained. To select one of such solutions, a second planning objective of interest can be used. Overall, the aim is the lexicographic optimization of two objectives where the first objective is the most important to be optimized while the second objective is the second most important.

When the optimization problem of each objective can be defined with an ILP model, an optimal solution for the lexicographic optimization of two objectives is computed as follows. First, the ILP model of the first objective is solved, and its optimal value is registered. Then, the ILP model of the second objective is augmented with: (i) one constraint guaranteeing the registered optimal value of the first objective, and (ii) all constraints of the first ILP model that are not in the second ILP model. Then, the augmented ILP model is solved.

In the computational results, five operational planning cases of practical interest, which will be explained later, are considered where pairs of two of the previous objectives are lexicographically optimized.

Next, it is illustrated an example of how the lexicographic optimization is conducted for the combination of the objective functions of models NBO and RLMF.

Consider that the planning objective is first to minimize the number of bus offloads (NBO) and then to maximize the robustness to last mile failures (RLMF). With this aim, the NBO model presented in Section Minimizing the number of bus offloads (NBO) is solved individually, providing a solution with the objective function value v. Then, the second model is now solved, ensuring that this value is kept. To do so, the second model is augmented as follows:

$$\text{Maximize} \quad \sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x'_{ktps} \tag{18}$$

Subject to:

(1)–(3), (4''), (5) , (8)–(9), (19)–(22)

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} y_{tps} \leq v \tag{7'}$$

The objective function (18) is the one of the RMLF model. Constraint (7') is added to guarantee that the value of the NBO objective is not worse than v and all other constraints are the constraints of the RLMF model plus the constraints of the NBO model that are not in the RLMF model. Note that the constraint that guarantees the value obtained in the first optimization, in this example constraint (7'), is defined as an inequality because even though the value v is known after the first optimization, preliminary computational tests suggested that inequalities, using $\leq or \; \geq$ instead on = (depending on if the first model is a Maximization or Minimization problem), would help the solver performance when solving the augmented model.

Finally, this augmented model is solved, and its solution minimizes the RLMF objective (18) guaranteeing that the NBO objective value is v.

Later in this chapter, in section 5.4 and 5.6, along with the outcome of each individual optimization problem, motivation and discussed results are presented for the study of the lexicographic optimization.

5.3. Instances dataset generation

This section presents the dataset generated to be used in computational experiments. The goal is to detail all the information and parameters used in the optimization's methods. Two main groups of instances were generated: Fictional instances and Pilot instances.

5.3.1. Fictional instances

To evaluate the proposed optimization models, six fictional instances were generated to test the models' performance and scalability. These instances are divided in two sets, they are based on two different fictional bus networks: a small bus network and a large bus network.

5.3.1.1 Small bus network instances

In this set of fictional instances, four of the instances (Instances 1 to 4) have been created. These instances use a bus network based on a fictional city center partitioned in 4 different zones (labelled from 1 to 4) simulating the LMO partitioning process, which contain a total of 8 bus stops (labelled from 2 to 9). The timespan considered in all instances is from 8 a.m. to 10 p.m. and the time unit is in minutes, which means that the instant 0 minutes is referring to 8:00 a.m. The bus network for the instance 1, 2, 3 and 4 is shown in Figure *17*.

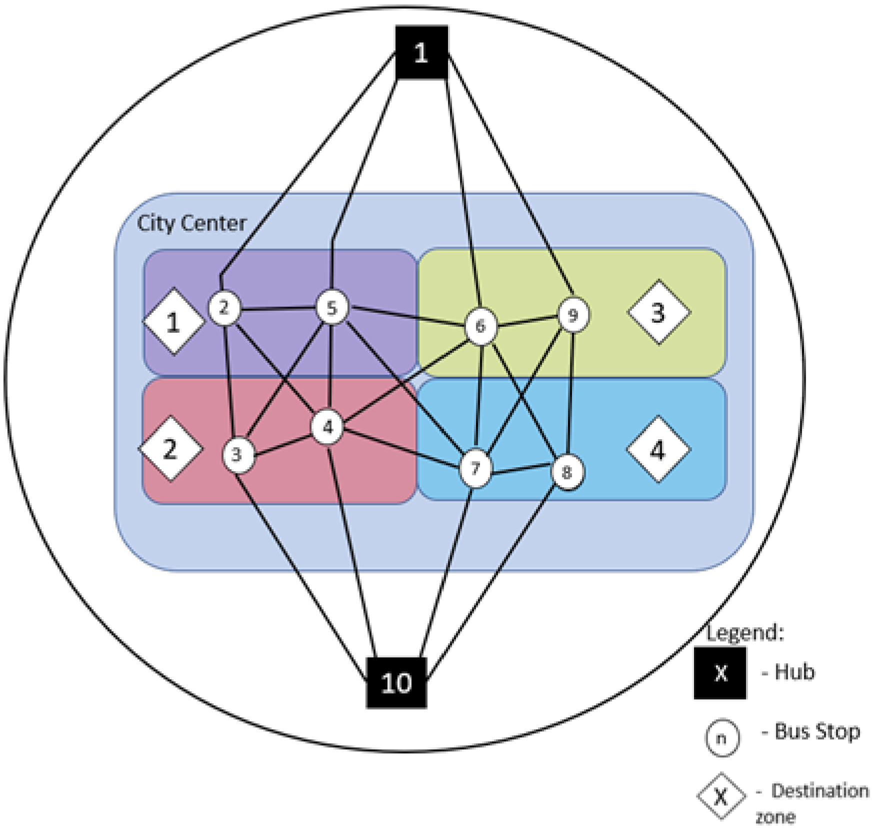

Figure 17 - Bus network and city center destination zones of Instances 1, 2, 3 and 4

The network illustrated in Figure *17* has 2 hubs and 24 bus services: the first twelve services departing from hub 1 and the other twelve services departing from hub 10. To complete the information about the network, the maximum service time to load a request into a bus service, for both bus hubs 1 and 10, is 10 minutes, the capacity of bus stops is 80 for each offload and the bus travel time between consecutive bus stops is 10 minutes.

From each hub, the bus services include three different routes which are used four times during the day (routes of each bus service shown in Table *11*).

Table 11 - Bus schedule for each bus hub

Departure bus hub	Bus service	Bus capacity	Departure time (min)	Nr of bus stops	Route (Hub-Stops-Hub)
1	1	100	20	4	1-2-3-4-5-1
	2	120	80	6	1-2-3-4-7-8-9-1
	3	100	140	4	1-9-8-7-6-1
	4	120	200	4	1-2-3-4-5-1
	5	100	260	6	1-2-3-4-7-8-9-1
	6	120	320	4	1-9-8-7-6-1
	7	120	380	4	1-2-3-4-5-1
	8	100	440	6	1-2-3-4-7-8-9-1
	9	120	500	4	1-9-8-7-6-1
	10	100	560	4	1-2-3-4-5-1
	11	120	620	6	1-2-3-4-7-8-9-1
	12	100	680	4	1-9-8-7-6-1
10	13	120	20	4	10-3-2-5-4-10
	14	100	80	6	10-3-2-5-6-9-8-10
	15	120	140	4	10-8-9-6-7-10
	16	100	200	4	10-3-2-5-4-10
	17	120	260	6	10-3-2-5-6-9-8-10
	18	100	320	4	10-8-9-6-7-10
	19	120	380	4	10-3-2-5-4-10
	20	100	440	6	10-3-2-5-6-9-8-10
	21	120	500	4	10-8-9-6-7-10
	22	100	560	4	10-3-2-5-4-10
	23	120	620	6	10-3-2-5-6-9-8-10
	24	100	680	4	10-8-9-6-7-10

Table *11* details the 24 bus services used in these instances, where 12 depart from bus hub 1 and 12 depart from bus hub 2. The bus services have a pattern, since there are only 3 routes that repeat over the day, each 3 hours. For example, bus service 1, 4, 7, and 10 are different services that perform the same route but in different times of the day. This table also shows the bus services capacity.

Instance 1 is used as the reference instance for the three subsequent instances. These subsequent instances are based on the first one, only changing one parameter at a time, so it is possible to evaluate the impact of changing each parameter in the results.

For all the four instances of this set, the maximum LMO travel time between each bus stop and each destination zone is characterized in the following Table *12*. For example, the first row of the table defines that a request collected by the LMO at bus stop 2 takes a maximum of 30, 45, 45 and 60 minutes to be delivered to an address within destination zone 1, 2, 3 and 4, respectively.

Table 12 - Maximum delivery time (in minutes) of the LMO from each bus stop to each destination zone

Bus stop ID	Destination zone			
	1	2	3	4
2	30	45	45	60
3	45	30	60	45
4	45	30	60	45
5	30	45	45	60
6	45	60	30	45
7	60	45	45	30
8	60	45	45	30
9	45	60	30	45

Concerning the data related to the requests, Instance 1 considers a set of 36 requests with delivery a time window duration of 4 hours and with random demand values between 1 and 100 each. The delivery time windows were equally distributed throughout the time span of a day. The destination zone of the requests was randomly generated with equal probability to all four destination zones. Also, all the requests are available in both bus hubs at the beginning of the time span.

Table *13* presents the details of Instance 1 with "Req. ID" indicating the request ID, "Dest. Zone" indicating the destination zone of each request, "Demand" indicating the demand and "Earliest del. time - Latest del. Time" indicating the delivery time window at the destination address of each request.

Table 13 - Demand detailed data of instance 1

Req. ID	Dest. zone	Demand	Earliest del. time - Latest del. time
1	4	14	60-300
2	1	10	60-300
3	2	50	60-300
4	1	17	60-300
5	3	40	120-360
6	4	30	120-360
7	2	52	120-360
8	1	20	120-360
9	2	50	180-420
10	3	45	180-420
11	4	60	180-420
12	1	17	180-420
13	3	12	240-480
14	2	50	240-480

Req. ID	Dest. zone	Demand	Earliest del. time - Latest del. time
19	1	36	300-540
20	3	41	300-540
21	3	38	360-600
22	2	24	360-600
23	4	17	360-600
24	1	25	420-660
25	3	45	420-660
26	3	35	420-660
27	1	70	480-720
28	4	20	480-720
29	2	15	480-720
30	3	45	480-720
31	3	30	540-780
32	2	20	540-780

15	1	23	240-480	**33**	4	12	540-780
16	4	41	240-480	**34**	1	43	540-780
17	4	25	300-540	**35**	4	10	600-840
18	2	14	300-540	**36**	2	25	600-840

As mentioned previously, Instances 2, 3 and 4 were computed based on Instance 1 changing one single parameter at each instance.

Instance 2 considers all requests with a delivery time window duration of 2 hours, increasing 1 hour to the earliest time and reducing 1 hour to the latest time of the interval. The aim is to evaluate the impact on the results of different delivery time window durations.

Instance 3 is similar to Instance 1 but considers zone 1 as the destination zone for all requests. The goal is to study the impact of concentrating the delivery addresses of all requests in the same zone of the city. In this case, capacity constraints of bus stops within destination zone 1 may push the offloads to a different zone of the requests' destination, leading to a higher delivery time by LMO, in general.

Instance 4 is similar to Instance 1 but considers that all requests can be dropped only in bus hub 1 by their clients. The purpose is to assess the impact of all requests departing from only 1 hub. In this case, it is expected a significant impact on the results and performance, since reducing the number of bus hubs available, also limits the number of bus services available to transport the requests, since only twelve bus services depart from each bus hub (recall that transshipments between bus hubs are not allowed).

Table *14* summarizes the characteristics and differences between the four instances. Instances' ID are "F1" to "F4" to indicate that they belong to the group of fictional instances. For each instance, "Nr Req." indicates the number of requests, "Nr bus services" indicates the number of bus services, "Nr Bus stops" indicates the number of bus stops, and "TWD" indicates the time window duration.

Table 14 - Characteristics and differences between the four instances F1 – F4

Instance ID	**Nr Req.**	**Nr bus services**	**Nr Bus stops**	**TWD**	**Changes compared to instance F1**	**Rule to conduct the change compared to instance F1**
F1	36	24	8	4h	-	-
F2	36	24	8	2h	2h of time window	Increasing 60 minutes to the lower limit and decreasing 60 minutes to the upper limit.
F3	36	24	8	4h	Only one destination zone to deliver requests	All the requests have destination 1 as destination.
F4	36	24	8	4h	Only one bus hub is considered	All the requests can only be transported from bus hub 1.

5.3.1.2 Large instances

In order to increase the size of the problem (and consequently its complexity), and evaluate the performance of the model in such conditions, two more instances, F5 and F6, were generated. Each of these instances are based on a larger bus network and consider a higher number of requests.

The larger network of these two instances has 2 hubs and 36 bus services: the first eighteen services departing from hub 1 and the other eighteen services departing from hub 24. The network considers a city center partitioned in 9 destination zones and contains 22 bus stops (labelled from 2 to 23), as shown in Figure *18*.

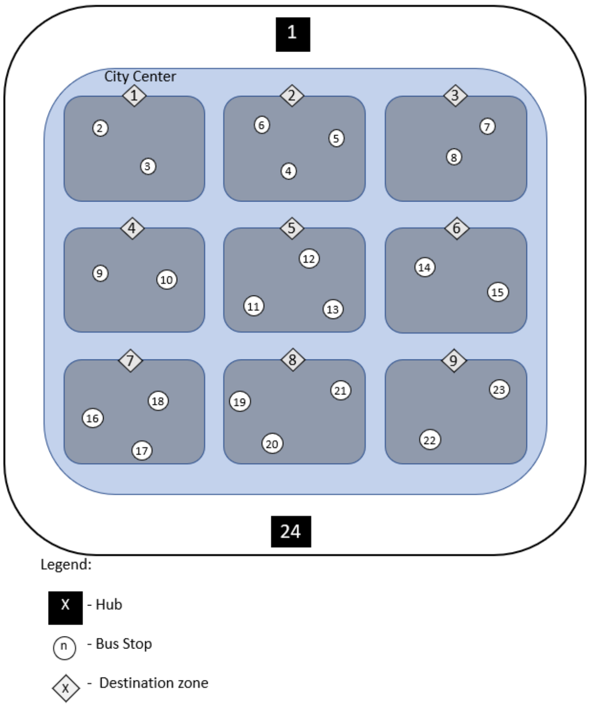

Figure 18 - Bus network for larger instances

From each hub, the bus services include three major routes which are used six times during one day. To complete the information about these instances, the maximum service time to load a request into a bus service, for both bus hub 1 and 24, is 10 minutes, the capacity of bus stops is 80 for each offload and the bus travel time between consecutive bus stops is 10 minutes. Table *15* and Table *16* present all the information concerning the bus routes departing from each bus hub, for both instances.

Table 15 - Bus schedule information of buses departing from bus hub 1

Departure bus hub	Bus service	Bus capacity	Departure time (min)	Nr of bus stops	Route (Hub-Stops-Hub)
1	1	100	20	6	1-2-3-4-5-8-7-1
	2	120	60	8	1-2-9-10-11-13-14-15-8-1
	3	120	100	10	1-3-10-16-17-19-20-22-23-15-7-1
	4	100	140	6	1-2-3-4-5-8-7-1
	5	120	180	8	1-2-9-10-11-13-14-15-8-1
	6	120	220	10	1-3-10-16-17-19-20-22-23-15-7-1
	7	100	260	6	1-2-3-4-5-8-7-1
	8	120	300	8	1-2-9-10-11-13-14-15-8-1
	9	120	340	10	1-3-10-16-17-19-20-22-23-15-7-1
	10	100	380	6	1-2-3-4-5-8-7-1
	11	120	420	8	1-2-9-10-11-13-14-15-8-1
	12	120	460	10	1-3-10-16-17-19-20-22-23-15-7-1
	13	100	500	6	1-2-3-4-5-8-7-1
	14	120	540	8	1-2-9-10-11-13-14-15-8-1
	15	120	580	10	1-3-10-16-17-19-20-22-23-15-7-1
	16	100	620	6	1-2-3-4-5-8-7-1
	17	120	660	8	1-2-9-10-11-13-14-15-8-1
	18	120	700	10	1-3-10-16-17-19-20-22-23-15-7-1

Table 16 - Bus schedule information of buses departing from bus hub 24

Departure bus hub	Bus service	Bus capacity	Departure time (min)	Nr of bus stops	Route (Hub-Stops-Hub)
24	19	100	20	6	24-22-23-21-19-18-16-24
	20	120	60	8	24-22-15-14-12-11-10-9-17-24
	21	120	100	10	24-23-14-7-8-5-6-3-2-9-18-24
	22	100	140	6	24-22-23-21-19-18-16-24
	23	120	180	8	24-22-15-14-12-11-10-9-17-24
	24	120	220	10	24-23-14-7-8-5-6-3-2-9-18-24
	25	100	260	6	24-22-23-21-19-18-16-24
	26	120	300	8	24-22-15-14-12-11-10-9-17-24
	27	120	340	10	24-23-14-7-8-5-6-3-2-9-18-24
	28	100	380	6	24-22-23-21-19-18-16-24
	29	120	420	8	24-22-15-14-12-11-10-9-17-24
	30	120	460	10	24-23-14-7-8-5-6-3-2-9-18-24
	31	100	500	6	24-22-23-21-19-18-16-24
	32	120	540	8	24-22-15-14-12-11-10-9-17-24
	33	120	580	10	24-23-14-7-8-5-6-3-2-9-18-24
	34	100	620	6	24-22-23-21-19-18-16-24
	35	120	660	8	24-22-15-14-12-11-10-9-17-24
	36	120	700	10	24-23-14-7-8-5-6-3-2-9-18-24

To generate instance F5, 64 more requests were added, performing a total of 100 requests, since the data of the 36 requests of Instance 1 were maintained. The delivery time windows of these added requests were generated and distributed randomly through the timespan of the instance, but maintaining the original length of four hours. Table *17* details the demand data of the new set of 64 requests of instance F5. Again, “Req. ID” indicates the request ID, “Dest. Zone” indicates the destination zone of each request, “Demand” indicates the demand and “Earliest del. time - Latest del. Time” indicates the delivery time window at the destination address of each request.

Table 17 - Demand detailed data of the new set of 64 requests of instances

Req. ID	Dest. zone	Demand	Earliest del. time - Latest del. time	Req. ID	Dest. zone	Demand	Earliest del. time - Latest del. time
37	5	17	120-360	**69**	9	13	410-650
38	6	22	60-300	**70**	6	24	440-680
39	7	15	70-310	**71**	7	26	100-340
40	8	10	110-350	**72**	5	51	110-350
41	9	5	115-355	**73**	6	38	160-400
42	7	35	220-460	**74**	5	47	115-355
43	8	49	210-450	**75**	7	49	225-465
44	5	50	230-470	**76**	9	10	355-595
45	6	23	340-580	**77**	8	13	455-695
46	7	21	250-490	**78**	8	15	145-385
47	8	9	190-430	**79**	7	8	165-405
48	9	15	180-420	**80**	9	9	565-805
49	9	1	210-450	**81**	6	25	615-855
50	6	9	155-395	**82**	5	26	425-665
51	8	25	90-330	**83**	5	22	585-825
52	7	36	85-325	**84**	6	21	495-735
53	5	27	450-690	**85**	8	11	695-935
54	5	55	520-760	**86**	7	13	635-875
55	9	46	680-920	**87**	9	17	605-845
56	8	29	700-940	**88**	6	8	205-445
57	7	12	650-890	**89**	5	10	505-745
58	6	26	580-820	**90**	8	71	405-645
59	5	24	490-730	**91**	9	78	105-345
60	9	20	430-670	**92**	7	66	115-355
61	6	19	350-590	**93**	6	65	215-455
62	5	36	320-560	**94**	5	50	275-515
63	5	49	640-880	**95**	9	45	475-715
64	6	55	660-900	**96**	8	55	375-615
65	7	23	500-740	**97**	7	20	305-545
66	8	8	400-640	**98**	7	21	295-535
67	9	18	300-540	**99**	6	30	195-435
68	8	54	310-550	**100**	8	10	95-335

All the requests can be dropped at both bus hubs of the network. Lastly, the maximum LMO delivery time between each bus stop and each destination zone is characterized in the following Table *18*. “Bs.ID” indicates the bus stop ID where the requests may be offloaded.

Table 18 - Maximum last mile delivery time (in minutes) by the LMO, for each bus stop to each destination zone of new network

Bs ID	Destination zone									Bs ID	Destination zone								
	1	2	3	4	5	6	7	8	9		1	2	3	4	5	6	7	8	9
1	30	45	60	45	45	60	60	60	60	**12**	45	45	45	45	30	45	45	45	45
2	30	45	60	45	45	60	60	60	60	**13**	60	45	45	60	45	30	60	45	45
3	45	30	45	45	45	45	60	60	60	**14**	60	45	45	60	45	30	60	45	45
4	45	30	45	45	45	45	60	60	60	**15**	60	60	60	45	45	60	30	45	60
5	45	30	45	45	45	45	60	60	60	**16**	60	60	60	45	45	60	30	45	60
6	60	45	30	60	45	45	60	60	60	**17**	60	60	60	45	45	60	30	45	60
7	60	45	30	60	45	45	60	60	60	**18**	60	60	60	45	45	45	45	30	45
8	45	45	60	30	45	60	45	45	60	**19**	60	60	60	45	45	45	45	30	45
9	45	45	60	30	45	60	45	45	60	**20**	60	60	60	45	45	45	45	30	45
10	45	45	45	45	30	45	45	45	45	**21**	60	60	60	60	45	45	60	45	30
11	45	45	45	45	30	45	45	45	45	**22**	60	60	60	60	45	45	60	45	30

The next Table *19* summarizes the differences between the instance F5 and instance F6.

Table 19 - Characteristics and differences between instance F5 and F6

Instance ID	Nr Req.	Nr bus services	Nr Bus stops	TWD	Changes compared to instance F5	Rule to conduct the change compared to instance F5
F5	100	36	22	4h	-	-
F6	100	36	22	2h	2h of time window	Increasing 60 minutes to the lower limit and decreasing 60 minutes to the upper limit.

5.3.2. SOLFI project pilot instances

All problem instances presented in this subsection are based in a real bus network dataset in the city of Porto, Portugal, defined and provided in SOLFI project. As part of the project, a pilot was planned to run in Porto and this dataset was the initial plan for the pilot, defined by the main project contractor company and based on the bus network of the BTO in Porto. The goal of these instances is to evaluate the feasibility and scalability of the proposed methods. These instances are entitled as “Pilot” due to the fact that they are built under a real bus network of Porto city, accounting the real routes and schedules for the bus services of the city, which were provided by the BTO for the pilot test. On the other hand, all data related to the requests, such as demand and time windows are fictional. The considered bus network is based on four bus hubs of the city (with IDs 34, 42, 107 and 305) strategically selected by the BTO among the ones with high connectivity from outside the city, and seven bus stops (labelled from 1 to 7) strategically selected nearby the areas with higher concentration of potential final customers, see Figure *19*. For these instances, the BTO has selected a total of 220 bus services that can be used for freight and passenger transportation: 66 services departing from hub 34, 54 services departing from hub 42, 12 services departing from hub 107 and 86 services departing from hub 305. Albeit bus hub 305 is located within the city center, the bus BTO considers this bus hub as essential to be part of the network as a departing point for buses and requests.

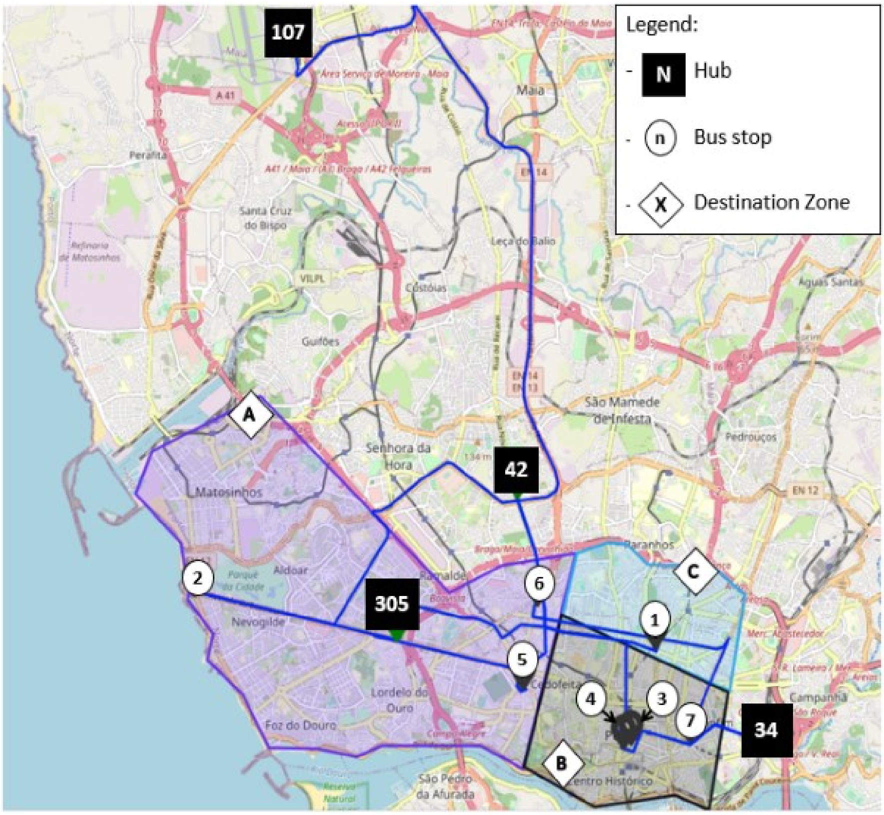

Figure 19 - Real bus network preselected for SOLFI project of the city of Porto

Concerning the LMO, the city is partitioned in three destination zones (highlighted in Figure *19* with different colors). Then, the maximum delivery time of each request is computed considering the zone of the request destination address and the zone of each bus stop location using the values shown in Table *20*.

Table 20 - Maximum delivery time (in minutes) from each bus stop to each destination zone

Bus stop	**Destination zone of request**		
	A	**B**	**C**
1	60	45	30
2	30	45	60
3	60	30	45
4	60	30	45
5	30	45	60
6	30	45	60
7	60	30	45

For these Pilot instances, two sets of 6 problem instances each are considered. The first set is composed by instances 1 to 6 and consider (i) all requests with a fixed demand value of 1, (ii) all bus services with a load capacity of 7 and (iii) all bus stops (of all bus services) with an offload capacity of 5. The second set is composed by instances 7 to 12 and consider (i) the request demand values randomly generated between 1, 2 and 3, with equal probability, (ii) all bus services with a load capacity of 14 and (iii) all bus stops (of all bus services) with an offload capacity of 10. In both sets, all requests can be dropped in any hub and their destination zone is randomly generated considering all zones with equal probability.
Concerning the number of requests of these instances, three values on each set of instances were considered: 100, 200 and 300 requests. Finally, for each of the three values, it was considered two problem instances: one instance where the delivery time windows are with a duration of 4 hours around a central time instant (randomly generated with a uniform distribution) and another instance where the previous delivery time windows are shortened to a duration of 2 hours by increasing in one hour the earliest delivery time and decreasing in one hour the latest delivering time. All problem instances were generated ensuring that the optimization problem is feasible. In Table *21*, 'Inst' indicates the instance ID starting with "P" (Pilot), '$|K|$' indicates the number of requests, "Dem." indicates the requests demand, 'Bus Cap' indicates the bus service capacity, 'Stop Cap' indicates the bus stop capacity, 'W' indicates the delivery time window duration.

Table 21 - Summary of all 12 Pilot instances

Inst.	$\|K\|$	Dem.	Bus Cap	Stop Cap	W	Inst.	$\|K\|$	Dem.	Bus Cap	Stop Cap	W
P1	100	1	7	5	4 hours	*P7*	100	1,2 or 3	14	10	4 hours
P2	100	1	7	5	2 hours	*P8*	100	1,2 or 3	14	10	2 hours
P3	200	1	7	5	4 hours	*P9*	200	1,2 or 3	14	10	4 hours
P4	200	1	7	5	2 hours	*P10*	200	1,2 or 3	14	10	2 hours
P5	300	1	7	5	4 hours	*P11*	300	1,2 or 3	14	10	4 hours
P6	300	1	7	5	2 hours	*P12*	300	1,2 or 3	14	10	2 hours

5.4. Computational experiments with exact methods

The computational results with exact methods were obtained with CPLEX Studio IDE 12.10 running on an ASUS VivoBook, intel core i7 processor 1.80 GHz and 16 Gb of RAM and considering a runtime limit of 1800 seconds (30 minutes).

5.4.1. Fictional instances

Table *22* presents the results (optimal/best value and runtime) of each model for each Fictional Instance, resulting from the optimization of each model. The results with '[a-b]' show the solution found and the lower/upper bound, meaning that a provable optimal solution was not found within the runtime limit, and the obtained gap (maximum difference between the obtained value and the optimal value) is presented in percentage.

Table 22 - Results of all optimization models for all instances

Inst	**LMDT (minutes)**	**NBO (no. offloads)**	**NBS (no. used buses)**	**RBS (no. requests)**	**RLMF (no. requests)**	**Runtime of each model (seconds)**
F1	30	15	10	36	36	0.02 | 2.15 | 0.38 | 0.16 | 0.11
F2	30	15	10	[35-36] (2.86%)	36	0.03 | 0.48 | 0.22 | 1800 | 0.06
F3	30	15	10	36	36	0.03 | 1.03 | 0.36 | 0.28 | 0.13
F4	30	[17-16] (5.8%)	11	12	36	0.03 | 1800 | 0.13 | 3.91 | 0.13
F5	30	[39-37] (5.12%)	25	[63-64] (1.59%)	100	0.31 | 1800 | 2.70 | 1800 | 1.11
F6	30	[41-37] (9.75%)	25	[60-61] (1.67%)	100	0.25 | 1800 | 275.2 | 1800 | 0.88

When aiming to minimize the last mile delivery time, model LMDT is very easy to solve in all instances, including the largest ones (whose running times are well below 1 second). The maximum delivery time of the LMO to deliver a request when the bus stop is in the same zone as the destination address was considered to be 30 minutes, for all zones. When solving model (LMDT), the solver always obtained the optimal value of 30 minutes meaning that in all cases the network has enough capacity to enable all requests to be offloaded in bus stops located in the same zone of their destination address.

When aiming to minimize the number of bus offloads, NBO cannot find provable optimal solutions neither for the largest instances (F5 and F6) nor for Instance F4, suggesting that the model is hard to solve with high number of requests and large network, and also when all requests depart from the same bus hub. The optimal solutions in Instances F1, F2 and F3 show that the 36 requests can be offloaded in the same 15 bus offloads both when shorter delivery time window are considered and when all requests are destined to one single destination zone. On the other hand, if all requests are dropped only in one hub (Instance F4), the minimum number of bus offloads increases from 15 to 17. In this latter case, the number of bus services that can be used to transport requests departing from 1 hub is reduced to half, since Instance F4 only considers the use of bus hub 1 and its corresponding network. Consequently, considering the same demand for just one hub and corresponding bus fleet that departs from the hub, the model is solved only using half of the network that are used for the base Instance 1. In this case, the solver could not obtain a provable optimal value for the model NBO, obtaining a feasible solution of 17 offloads in 30 minutes (two more offloads compared to Instance 1). Additionally, the solver found a lower bound of 16 offloads, which means that the optimal value for this instance F4 is either 16 or 17 offloads, (maximum gap to the optimal solution of 5.8 %).

For instances F5 and F6 (larger instances with a large network and more demand), the solver could not obtain a provable optimal solution for the model NBO. Nevertheless, the solver obtained a feasible solution, during the runtime, of 39 and 41 offloads, for instance P5 and P6 respectively. This increase of offloads is expected since there is a higher number of requests distributed to a higher number of destination zones.

Additionally, the obtained lower bounds mean that a maximum gap between the solution found and the potential optimal solution can be calculated for both instances, which is 5.12% and 9.75% for F5 and F6, respectively. Thus, these results have shown that to solve NBO model with an instance with increasing number of demand requests and a larger network turns the problem significantly harder to solve and to prove the optimality of the obtained solutions.

When aiming to minimize the number of bus services, NBS is easy to solve in the smaller instances and becomes harder to solve in the larger instances although obtaining the optimal solutions below the runtime limit (Instance F5 in 2.7 seconds and Instance F6 in 275.2 seconds). The optimal solutions in Instances F1, F2 and F3 show that the 36 requests can be assigned to a minimum of 10 bus services both when shorter delivery time windows are considered and when all requests are destined to one single destination zone. On the other hand, if all requests are dropped only in one hub (Instance F4), the minimum number of required bus services suffers a slight increase from 10 to 11 (of the total 12 bus services allowed in this instance) showing that using only one possible bus hub, forces the utilization of almost all bus services departing from that hub. For the largest instances, the 100 requests have been assigned to a minimum of 25 bus services out of 36 in both instances, showing again that the delivery time window duration does not have any impact on this optimal value, since the value is the same when comparing the F1 and F2 instances and comparing F5 and F6, where only the time window width is changed between the pair of instances.

When aiming to maximize the robustness to bus service suppressions, RBS is very easy to solve for Instances F1 and F3. Instance F4 was solved in 3.91 seconds and the remaining instances ended by runtime limit although with small gaps (below 3%) in all cases. The obtained solutions in Instances F1, F2 and F3 show that all (or almost all) of the 36 requests can be assigned with an alternative bus service, both when shorter delivery time windows are considered and when all requests are destined to one single destination zone. On the other hand, if all requests are dropped only in one bus hub (Instance F4), the reduction to half of the bus services that can be assigned to requests makes the robustness of the solution to be significantly reduced as only one third (12 out of 36) of the requests can be assigned with one alternative bus service. This is an expected behavior since only buses from the same hub can be assigned to requests as alternative bus and for this instance F4 only 12 buses depart from each bus hub. For Instances F5 and F6, the optimality was not reached, obtaining values with small gaps to the optimal value of less than 2%. Moreover, the number of requests assigned with an alternative bus is significantly lower than the total number of requests (100 requests), with the value of 63 and 60 respectively, showing that, for these instances, the set of available bus services is not enough to reach full robustness to bus service suppressions.

When aiming to maximize the robustness to last mile failures, RLMF is very easy to solve in all instances, including the largest ones (whose running times are around 1 second). Moreover, a fully robust solution was obtained in all cases as all requests were assigned with an alternative bus stop. These results highlight the importance of a careful planning of the bus network and associated destination zones: by considering at least two bus stops in each destination zone, as considered of both bus networks (Figure *17* and Figure *18*), the possibility of obtaining robust solutions is only constrained by the bus stop capacities since it allows requests to be offloaded in the second bus stop of the same destination zone if a last mile failure occurs in the first bus stop.

Table *23* presents the results of the same instances for models RBS and RLMF, considering symmetry breaking constraints (15') instead of (15) of RBS model, and (20') instead of (20) of RLMF model. The goal of these experiments is to assess if the models are easier to solve with them or not.

Table 23 - Results of RBS and RLMF models for all instances with symmetry breaking constraints

	With symmetry breaking constraints		
Instance	**RBS (no. requests)**	**RLMF (no. requests)**	**Runtime of each model (seconds)**
F1	36	36	0.22+0.08
F2	35	36	9.97+0.09
F3	36	36	0.38+0.09
F4	12	36	0.56 + 0.23
F5	[62-64] (3.12%)	100	1800+ 1.22
F6	[60-61] (1.67%)	100	1800 + 0.89

The results show that incorporating symmetry breaking constraints allow to prove the optimality of 35 requests in 9.97 seconds for F2 in the RBS model (this solution was found with no symmetry breaking constraints but the optimality was not proven (Table *22*). On the other hand, the lower bound obtained for F5 in the same RBS model with the symmetries breaking constraints has decreased from 63 to 62 requests, increasing the gap to the potential optimal solution. Finally, among the other instances, the running times of the two alternatives (with or without symmetry breaking constraints) are not substantially different. These results show that, in these models, the two modeling alternatives are equivalent in the efficiency of the solvers to compute their solutions.

Note that, as explained before on Section *Lexicographic optimization of* **two planning objectives**, when aiming to optimize a given objective, it is possible to have multiple solutions with the same optimal value. To select one of such solutions, a second objective might be used. This approach requires to solve two ILP models in sequence (see Section Lexicographic optimization of **two**

planning objectives). In the next subsections, the results of the lexicographical optimization for different pairs of previous models are presented.

5.4.1.1 LMDT-NBO

This combination of objective functions focuses entirely in the last mile delivery process, since both individual objectives functions are focused on the last mile process. This combination allows us to obtain the solution with the lowest average delivery time for all the requests and, then, the lowest number of bus offloads to guarantee the previous average delivery time, fully facilitating the integration of last mile operation in the LMO daily business. Since the optimization of the LMO daily operation is not in scope of this thesis, the aim is to find a solution that facilitates the incorporation of the request's transportation on the LMO daily transportation routes.

In this combination, the focus is on optimizing the last mile delivery by first minimizing the last mile delivery time (LMDT) and, then, minimizing the number of bus offloads (NBO), to obtain the minimum number of bus offloads guaranteeing that all requests are offloaded as close as possible to their destination.

This combination of objective functions results in an augmented model LMDT-NBO. This model is similar with the model NBO itself, simply adding the constraint with the value *v* obtained for model LMDT – constraint (6') below. The augmented model LMDT-NBO is defined by the following ILP formulation:

$$\text{Minimize} \quad \sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} y_{tps} \tag{7}$$

Subject to:

(1) – (5)

$$\frac{1}{|K|} \sum_{k \in K} \sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} T_{ks} z_{ktps} \leq v \tag{6'}$$

$$z_{ktps} \leq y_{tps} \qquad , \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{8}$$

$$y_{tps} \in \{0,1\} \qquad , \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{9}$$

Table *24* presents the obtained results for fictional instances of the combined model LMDT-NBO.

Table 24 - Results of LMDT-NBO

Instance	LMDT - NBO		
	LMDT (minutes)	NBO (no. offloads)	Runtime (seconds)
F1	30	18	0.02+0.23
F2	30	22	0.03+0.08
F3	30	15	0.03+0.44
F4	30	20	0.03+0.45
F5	30	47	0.31+4.55
F6	30	55	0.25+0.58

These results show that minimizing the number of offloads, minimizing first the last mile delivery time leads to more offloads, on average, than minimizing solely the number of bus offloads. The number of offloads increases from 15 to 18 in Instance F1. Reducing the delivery time window from 4 hours to 2 hours increases the number of offloads from 15 to 22, since with 2 hours of time -window duration there is less margin for a bus stop to act as offloading point for different requests at the same time (Instance F2). When all requests are destined to one single destination zone (Instance F3), the number of offloads remain the same value of 15 because the destination of all requests is closer between each other, and only bus stops capacities force the increase of offloads. If all requests are dropped only in one hub (Instance F4), the number of bus offloads increases from 17 to 20 because the number of bus services that can be used is reduced to half, and key bus services that have the possibility to transport more requests may be unavailable. For larger instances (F5 and F6), it was possible to get the optimal value of 47 offloads for F5 and 55 offloads for F6, showing again an increase of the number due to shortening the delivery time window. On average, the number of bus offloads increases 24% over all instances, when minimizing first the last mile delivery time, and then the number of offloads keeping the last mile delivery time.

5.4.1.2 NBO-LMDT

Like in the previous combination, the focus is on optimizing the last mile delivery, but now prioritizing the number of offloads to be done by the LMO. The motivation to study this combination of objectives, NBO-LMDT, is to compare this approach with the last one, when the focus is on the last mile delivery process. As said in the previous combination of objectives, the goal is to assess the system when the focus is on the last mile delivery process to facilitate the integration of this distribution tasks by the LMO on its daily tasks/routes.

In this combination, the focus is on minimizing the number of bus offloads (NBO), and then minimizing the last mile delivery time. Thus, the procedure is first to minimize the NBO model to obtain the minimum number of offloads possible, and then to minimize the last mile delivery time (LMDT), while guaranteeing the minimum number of offloads obtained before.

This combination of objective functions results in an augmented model NBO-LMDT. This model is similar with the model LMDT itself, simply adding the constraint with the value v obtained with model NBO – constraint (7’) below, and the new constraints (8) and (9) that are part of the model NBO as well. The augmented model NBO-LMDT is defined by the following ILP formulation:

$$\text{Minimize} \quad \frac{1}{|K|}\sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} T_{ks}z_{ktps} \tag{6}$$

Subject to:

(1) – (5)

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} y_{tps} \leq v \tag{7'}$$

$$z_{ktps} \leq y_{tps} \quad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{8}$$

$$y_{tps} \in \{0,1\} \quad ,\forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{9}$$

Table *25* presents the obtained results for fictional instances.

Table 25 - Results of NBO-LMDT

Instance	NBO – LMDT		
	NBO (no. offloads)	LMDT (minutes)	Runtime (seconds)
F1	15	32.5	2.15 + 4.75
F2	15	35	0.48 + 0.78
F3	15	30	1.3 + 1.41
F4	17	32.5	1800 + 167.17
F5	39	[39.6-31.36] (20.79%)	1800 + 1800
F6	41	[41.25-35.29] (20.99%)	1800 + 1800

These results show that minimizing the last mile delivery time guaranteeing the minimum number of bus offloads leads to longer last mile delivery times, on average, than minimizing solely the last mile delivery time. For instances F5 and F6, the optimality was not reached, finding solutions with gaps of, around, 21%, showing that these models are very hard to be solved for larger problem instances.

The average increase in the last mile delivery time is 17.1% over all instances, when optimizing the number of offloads first and then optimizing the delivery time window keeping the number of offloads. Since both combinations (this and the previous one) are focused on optimizing the last mile delivery (and assuming that both objectives are equally important in the integration of these deliveries in the daily operations of the LMO), it is concluded that this second combination is the best trade-off between the two objectives as the average increase of the last mile delivery time in this combination is much smaller than the average increase in the number of bus offloads obtained with the first combination (which is 24%). This may be the best scenario for the LMO, since it leads to the minimum number of offloads and travelling as less as possible to deliver the requests, with the greater benefits.

5.4.1.3 NBO-RLMF

For this pair of objectives, the focus is once more on the last mile delivery process because the number of offloads/times the LMO needs to collect freight requests from the buses are minimized, and also providing an alternative bus stop to collect freight requests in case any disruption occurs during the day. It is expected that when the number of bus offloads is minimized, the average number of requests to be offloaded by the LMO per bus increases. Therefore, the negative impact of a potential last mile failure becomes higher since, in case LMO is not available to collect the requests at a given bus stop, a higher number of requests are not offloaded and delivered to final customers. This is the reason to combine the objective function NBO with the objective function RLMF: when minimizing the number of offloads from the buses that the LMO has to perform, the easiest is the process for them to collect and manage with daily activities/route but it also increases the negative impact of a potential failure to collect requests at a bus stop. This impact would be significantly higher since more requests would not be offloaded from the bus and, consequently, not delivered to the final customer/destination. Hence, the robustness to deal with a last mile offload failure is incorporated on this combination of objectives, trying to, whenever feasible, assign an alternative bus stop to all requests. If all requests have an alternative bus stop to be offloaded from the bus to act as alternative plan in case the LMO fails to offload them in the main bus stop, the LMO can still offload and collect the requests on respective alternative bus stops.

In this combination, the focus is on minimizing the number of offloads (NBO), and then maximizing the robustness of last mile failures (RLMF), The procedure is first to solve model NBO to obtain the minimum number of offloads possible, and then solve model RLMF, while guaranteeing the minimum number of offloads obtained before.

This combination of objective functions results in an augmented model NBO-RLMF. This model is similar with the model RLMF itself, adding the constraint with the value *v* obtained for model NBO – constraint (7’) below, and the constraints (8) and (9) that are part of the model NBO as well. Note that constraints (4) are not needed to be added from NBO to the augmented model NBO-RLMF because they are mathematically guaranteed by constraints (4’’) of model RLMF. The augmented model NBO-RLMF is defined by the following ILP formulation:

$$\text{Maximize} \quad \sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x'_{ktps} \tag{18}$$

Subject to:

(1) – (3), (5)

$$\sum\nolimits_{k\in K} D_k\left(z_{ktps} + x'_{ktps}\right) \leq U_{tps} \qquad ,\forall\, t\in T, \forall\, p\in P(t), \forall\, s\in S(p) \tag{4''}$$

$$\sum_{s\in S(p)} h_{ktps}x'_{ktps} \leq \sum_{s\in S(p)} h_{ktps}z_{ktps} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t) \tag{19}$$

$$h_{ktps}z_{ktps} + h_{ktps}x'_{ktps} \leq 1 \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), s \in S(p) \tag{20}$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} (1 - h_{ktps})x'_{ktps} = 0 \qquad ,\forall\, k \in K \tag{21}$$

$$x'_{ktps} \in \{0,1\} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{22}$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} y_{tps} \leq v \tag{7'}$$

$$z_{ktps} \leq y_{tps} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{8}$$

$$y_{tps} \in \{0,1\} \qquad ,\forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{9}$$

Table *26* presents the obtained results for this combination NBO-RLMF

Table 26 - Results of NBO-RLMF

Instance	NBO-RLMF		
	NBO (no. offloads)	**RLMF (no. requests)**	**Runtime (seconds)**
F1	15	36	2.15+1.09
F2	15	36	0.48+4.08
F3	15	36	1.3+1.03
F4	17	36	1800+5.03
F5	39	100	1800+589.56
F6	41	[99-100] (1.01%)	1800+1800

These results show that, for the smaller instances F1-F4, it was possible to obtain fully robust solutions in all cases (all 36 requests were assigned with an alternative bus stop to be offloaded in case any unexpected event occurs) while guaranteeing the minimum number of bus offloads. For largest instances F5 it was possible to obtain a fully robust solution with all requests with an alternative bus stop after 590 seconds, approximately. For Instance F6, the solver could not solve this model within the runtime to obtain the optimal solution but found a feasible solution with 99 requests with an alternative bus stop assigned, where only one requests cannot get an alternative bus stop (gap of 1%). Again, these results highlight the importance of a careful transportation network plan, considering at least two bus stops in each destination zone and route. In this case, probability to assign an alternative bus stop that still fulfils the delivery time window of the requests is increased.

Table *27* presents the results to the same instances for this augmented model NBO-RLMF, considering the symmetry breaking constraints (20') instead of constraints (20) of model RLMF.

Recall that these constraints force the model to select, for each request, an alternative bus stop that is subsequent to the main bus stop assigned to it.

Table 27 - Results of NBO-RLMF with symmetry breaking constraints

Instance	NBO-RLMF: With symmetry breaking constraints		
	NBO (no. offloads)	**RLMF (no. requests)**	**Runtime (seconds)**
F1	15	36	2.15+1.39
F2	15	36	0.48+3.00
F3	15	36	1.3+1.67
F4	17	36	1800+6.09
F5	39	100	1800+239.56
F6	41	NSOL (Lim=100)	1800+1800

The results of this table show that, despite the fact that the runtime of NBO-RLMF has decreased for instance F5 on about 250 seconds, no solution was found for instance F6 during the runtime of 30 minutes (as it is a maximization problem, an upper bound of 100 was returned, which is the total number of requests). Moreover, in the other instances, the running times are of the same order as the ones with constraints (20). Thus, these results suggest that none of the alternatives is better than the other since with the original constraints it was possible to find a solution of value 99 for instance F6.

5.4.1.4 NBS-RLMF

This combination of objective functions mixes the interests of the two perspectives: BTO and the LMO, although giving more importance to the first one. It is expected that when the number of bus services that are used for this joint transportation is minimized, the average number of requests assigned per bus service also increases. If the buses are transporting more requests on average, it means also that the average number of requests to be collected by the LMO in each offload is also higher on average, or it may lead to more offloads at different stops along the same bus route. These consequences may place strain on the LMO and may increase the probability of offload failures, as it may be harder to fulfill the schedule or be on time at the different bus stops. Again, the negative impact of a potential last mile failure becomes higher since a higher number of requests not offloaded results in a higher number of requests that fail to be delivered to the final customer. In summary, the goal of this combination of objectives is to incorporate robustness to deal with strain on last mile delivery process, now created by reducing the number of bus services used for freight transportation.

This combination of objective functions results in an augmented model NBS-RLMF. This is a combination of objectives similar to the previous one but optimizing first the number of bus services instead of the number of bus offloads. Thus, the resulting augmented model NBS-RLMF is similar with the model RLMF itself, simply adding the constraint with the value v obtained for model NBS – constraint (10’) below, and the new needed constraints (11) and (12) that are part of the NBS model as well. Again, constraints (4) are not needed to be added from NBS to the augmented model NBS-RLMF as they are guaranteed by constraints (4’’). The augmented model NBS-RLMF is defined by the following ILP formulation:

Maximize $\sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x'_{ktps}$ (18)

Subject to:

(1) – (3), (5)

$$\sum\nolimits_{k\in K} D_k\big(z_{ktps}+x'_{ktps}\big) \le U_{tps} \qquad ,\forall\, t\in T, \forall\, p\in P(t), \forall\, s\in S(p) \qquad (4'')$$

$$\sum_{s\in S(p)} h_{ktps}x'_{ktps} \le \sum_{s\in S(p)} h_{ktps}z_{ktps} \qquad ,\forall\, k\in K, \forall\, t\in T, \forall\, p\in P(t) \qquad (19)$$

$$h_{ktps}z_{ktps} + h_{ktps}x'_{ktps} \le 1 \qquad ,\forall\, k\in K, \forall\, t\in T, \forall\, p\in P(t), s\in S(p) \qquad (20)$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} (1-h_{ktps})x'_{ktps} = 0 \qquad ,\forall\, k\in K \qquad (21)$$

$$x'_{ktps} \in \{0,1\} \qquad ,\forall\, k\in K, \forall\, t\in T, \forall\, p\in P(t), \forall\, s\in S(p) \qquad (22)$$

$$\sum_{t\in T}\sum_{p\in P(t)} y'_{tp} \le v \qquad (10')$$

$$z_{ktps} \le y'_{tp} \qquad ,\forall\, k\in K, \forall\, t\in T, \forall\, p\in P(t), \forall\, s\in S(p) \qquad (11)$$

$$y'_{tp} \in \{0,1\} \qquad ,\forall\, t\in T, \forall\, p\in P(t) \qquad (12)$$

Table *28* presents the obtained results for this combination NBS-RLMF

Table 28 - Results of NBS–RLMF

Instance	**NBS–RLMF**		
	NBS (no. buses)	**RLMF (no. requests)**	**Time (seconds)**
F1	10	36	0.38+1.77
F2	10	35	0.22+77.95
F3	10	36	0.36+3.30
F4	11	36	0.13+0.20
F5	25	NSOL (Lim=100)	2.70+1800
F6	25	NSOL (Lim=100)	275.2+1800

Again, these results show that, for the smaller instances (F1-F4) it was possible to obtain fully (or almost fully) robust solutions in all cases while guaranteeing the minimum number of bus services (only F2 has a request with no alternative bus stop). For the larger instances F5 and F6, no solution was found during the runtime of 30 minutes, again returning the upper bound of 100 (the total number of requests in these instances). These results suggest that for instances with larger number of requests, the performance of the solver when running model RLMF after NBS is much worse than after NBO. It is an expected behavior because when minimizing the number of bus services first, and forcing this minimum number of bus services on the model RMLF, the model has significantly less bus services to search for alternatives to select bus services that have in their route bus stops that can be used as alternative bus stops for a higher set of requests. Example of these buses are buses that pass through the central zones of the city, and therefore may have subsequent bus stops that still can be used to offload requests within the time window (zone 4, 5 or 6 of larger instances F5 and F6).

Table *29* presents the results to the same instances for this combination, considering the symmetry breaking constraints (20') instead of constraints (20) of model RLMF. Recall that these constraints force the model to select, for each request, an alternative bus stop that is subsequent to the primary bus stop assigned to it.

Table 29 - Results of NBS-RLMF with symmetry breaking constraints

Instance	NBS–RLMF: With symmetry breaking constraints		
	NBS (no. buses)	RLMF (no. requests)	Time (seconds)
F1	10	36	0.38+4.14
F2	10	[35-36] (2.86%)	0.22+1800
F3	10	36	0.36+2.03
F4	11	36	0.13+0.20
F5	25	NSOL (Lim=100)	2.70+1800
F6	25	NSOL (Lim=100)	275.2+1800

The results of this table show that using constrains (20') instead of the original constrains (20) jeopardize the overall performance of the RLMF model, since the only significant variation is the solution found for F2 of 35 requests with alternative bus stops to be offloaded. With constraints (20'), the model could not prove the optimality of the solution found within the runtime of 1800 seconds. Nevertheless, from results of

Table *28*, 35 is the optimal value of requests with alternative bus stop.

5.4.1.5 RBS-NBS

In this combination, the focus is entirely on the decision-making process of the BTO of the city. This combination of objectives is primarily concerned to incorporate robustness to the system to deal with unexpected events that lead to buses suppressions (model RBS). For this reason, it is very important to have a backup plan and assign alternative bus services to all requests, whenever it is possible. On the other hand, when the robustness to bus service suppressions is maximized, the total number of bus services (acting either as main or as alternative bus services) might become significantly larger than the minimum number required. This is an expected behavior when optimizing solely RBS, as the model does not optimize the number of services used on the solution. Thus, it is important to combine the RBS objective function with the NBS, with the aim to incorporate the maximum robustness for buses suppressions, and afterwards minimize the number of bus services needed to guarantee this level of robustness in the system.

This combination of objective functions results in an augmented model RBS-NBS, first optimizing the robustness to bus service suppressions (RBS) and afterwards optimizing the number of bus services used (NBS). The resulting augmented model RBS-NBS is similar with the model NBS itself, simply adding the constraint with the value *v* obtained for model RBS – constraint (13') below, and the constraints (3'), (4'), (14), (15), (16) and (17) that are part of the RBS model as well. Again, constraints (4) are not needed in the augmented model RBS-NBS as they are guaranteed by constraints (4'). Note that constraints (11) of model NBS have to be changed to include the second term x_{ktps}, resulting in constraints (11'). This change in constraints (11) is required because these constraints ensure that a bus service is accounted when at least one item is delivered in hub $t \in T$ and loaded in bus service $p \in P(t)$, and summing the x_{ktps} to the first part of the inequality ensures that alternative bus services are also considered to the total number of bus services. The augmented model NBS-RLMF is defined by the following ILP formulation:

$$\text{Minimize} \quad \sum_{t\in T}\sum_{p\in P(t)} y'_{tp} \tag{10}$$

Subject to:

(1) – (2), (5)

$$z_{ktps} + x_{ktps} \leq y'_{tp} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{11'}$$

$$y'_{tp} \in \{0,1\} \qquad ,\forall\, t \in T, \forall\, p \in P(t) \tag{12}$$

$$\sum_{k\in K}\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} x_{ktps} \tag{13'}$$

$$\sum\nolimits_{k\in K}\sum\nolimits_{s\in S(p)} D_k\big(z_{ktps} + x_{ktps}\big) \leq U_{tp} \qquad ,\forall\, t \in T, \forall\, p \in P(t) \tag{3'}$$

$$\sum\nolimits_{k\in K} D_k\big(z_{ktps} + x_{ktps}\big) \leq U_{tps} \qquad ,\forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{4'}$$

$$\sum_{p\in P(t)}\sum_{s\in S(p)} h_{ktps}x_{ktps} \leq \sum_{p\in P(t)}\sum_{s\in S(p)} h_{ktps}z_{ktps} \quad ,\forall\, k \in K, \forall\, t \in T \tag{14}$$

$$\sum_{s\in S(p)} \big(h_{ktps}z_{ktps} + h_{ktps}x_{ktps}\big) \leq 1 \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t) \tag{15}$$

$$\sum_{t\in T}\sum_{p\in P(t)}\sum_{s\in S(p)} (1 - h_{ktps})x_{ktps} = 0 \qquad ,\forall\, k \in K \tag{16}$$

$$x_{ktps} \in \{0,1\} \qquad ,\forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{17}$$

Table *30* presents the obtained results for this combination of models.

Table 30 - Results of RBS-NBS

Instance	RBS-NBS		
	RBS (no. requests)	NBS (no. buses)	Time (seconds)
F1	36	21	0.16+10.73
F2	35	[21-20] (5%)	1800+1800
F3	36	21	0.28+8.36
F4	12	12	3.91+0.47
F5	63	NSOL (Lim=36)	1800+1800
F6	60	NSOL (Lim=36)	1800+1800

These results show that to obtain the maximum robustness to bus service suppressions, most of the bus services are used: 21 out of 24 bus services in Instances F1, F2 and F3; and 12 out of 12 bus services in Instance F4 (the instance where all requests are dropped only in one hub and, therefore, where the number of bus services that can be assigned is reduced to half). In practice, this means that, for the smaller instances (F1-F4) full robustness to bus service suppressions is only possible if all (or almost all) bus services are available for freight transportation.

For F5 and F6, the total set of 36 bus services of these instances only allow to 63 and 60 requests with an alternative bus service. The difference between them is explained with the reduced delivery time window of two hours, since less bus services are used to deliver the requests and respect the delivery time window of 2 hours, when compared to 4 hours. The results also prove that it is hard to optimize the number of services used after maximizing the robustness to bus service suppressions (the augmented model RBS-NBS), since after the runtime limit is reached, no feasible solution was found and the upper bound did not decrease (the upper bound equals the total number of 36 bus services)

Table *31* presents the results to the same instances for this combination, considering the symmetry breaking constraints (15’) instead of constraints (15) of model RBS. Recall that these constraints force the model to select, for each request, an alternative bus service that departs after the primary bus service assigned to it.

Table 31 - Results of RBS-NBS with symmetry breaking constraints

Instance	RBS-NBS: With symmetry breaking constraints		
	RBS (no. requests)	NBS (no. buses)	Time (seconds)
F1	36	21	0.16+21.73
F2	35	[22-21] (4.5%)	9.97+1800
F3	36	21	0.28+11.8
F4	12	12	3.91+0.50
F5	62	NSOL (Lim=36)	1800+1800
F6	60	NSOL (Lim=35)	1800+1800

The results of this table show that including constraints (15’) instead of the original constraints (15) jeopardize the overall performance when solving NBS model, since the only significant variation is the solution found for F2 of 22 bus services needed, one more than the solution provided with constraints (15). Despite constraints (15') allowed to prove the optimality of the solution with value 35 of the first model RBS (already seen in Table *23*), it increased 1 more bus service needed in the solution of RBS-NBS.

With these constraints (15'), the solver could not prove the optimality of the solution found within the runtime of 1800 seconds, for instance F2. Nevertheless, combining these results with the ones of the previous Table *30*, it can be concluded that 21 is the optimal value of requests with alternative bus stop, since the feasible solution found for F2 in Table *30* is the lower bound found for F2 in Table *31*.

Analyzing the overall results, it is clear that using symmetry breaking constraints do not systematically improve the performance when solving the models. Consequently, adopting the strategy of switching the role between primary and alternative bus service/stop is preferable.

5.4.2. SOLFI project pilot instances

With the aim of testing the optimization models within the scope of the pilot of SOLFI project, the combinations LMDT-NBO and NBO-LMDT were tested using the pilot instances, presented before. These combinations were selected from the BTO to be run for the pilot tests, as they optimize two metrics/objectives that the BTO of the city values the most.

5.4.2.1 LMDT-NBO solved for pilot instances

Table *32* presents the results of the implementation of LMDT-NBO for the pilot tests, where 'Inst' indicates the instance ID, '$|K|$' indicates the number of requests, 'W' indicates the delivery time window duration, "LMDT" and "NBO' indicate the value of the solution for each model, "LMDT-NBO" indicates the two values of the solution found for the combination of objectives, 'Runtime' indicates the runtime (in seconds) to obtain the solution for "LMDT-NBO" and 'DZ' indicates the number of requests, in the solution of combination "LMDT-NBO", that are offloaded in a bus stop located in a zone different from the request destination zone. The results highlighted with [a-b] mean that an optimal solution was not found within the runtime limit, *a* is the value of the obtained solution and *b* is the obtained lower bound. However, the gap to the optimal value is 4.7%, at maximum.

Table 32- Results of LMDT-NBO for pilot instances

Inst.	|*K*|	*W*	Values of single Optimization: *LMDT* (min)	Values of single Optimization: *NBO* (*offloads*)	LMDT - NBO: *LMDT* (mins)	LMDT - NBO: *NBO (offloads)* [solution found-lower bound]	LMDT - NBO: *Runt*ime (sec.)	LMDT - NBO: DZ
P1	100	4 h	30	20	30	[22-21] (4.5%)	0.67+1800	0
P2	100	2 h	30	20	30	22	0.55+ 5.64	0
P3	200	4 h	30	40	30	[42-41] (2.4%)	1.31+1800	0
P4	200	2 h	30.60	40	30.60	[43-41] (4.7%)	1.08+1800	8
P5	300	4 h	30.20	60	30.20	[63-62] (1.5%)	1.76+1800	4
P6	300	2 h	31.95	63	31.95	64	1.84 + 48.9	30
P7	100	4 h	30	19	30	20	0.69 + 12.8	0
P8	100	2 h	30	19	30	22	0.59 + 2.5	0
P9	200	4 h	30	39	30	40	1.42 + 24.7	0
P10	200	2 h	30.53	39	30.53	41	1.41 + 120	0
P11	300	4 h	30.15	59	30.15	62	2.17 + 432	3
P12	300	2 h	31.70	62	31.70	63	2.13 + 53.8	25

These results show that the first 6 instances, in which all requests have fixed demand of 1 are harder to solve compared to the ones where the requests have a random value between 1, 2 or 3 since optimality was not reach for instance P1, P3, P4 and P5 within 1800 seconds. On the other hand, for the instances with random demand, the model could obtain the optimal solution in all cases.

The results also show that minimizing the number of offloads after minimizing the last mile delivery time (LMDT–NBO) leads to more offloads, on average, than minimizing solely the number of bus offloads (NBO). On average, the number of bus offloads increases 5.3% over all twelve instances, when minimizing first the last mile delivery time. All instances with 100 requests have an optimal value of 30 minutes, which means that the bus network capacity is enough to offload all requests in a bus stop located in the requests' destination zones. For larger number of requests, this is not the case as bus service and bus stop capacities become a constraint. In the instances with 200 requests, the delivery time window of 4 hours still allows all requests to be offloaded in a bus stop located in the request destination zone but with the delivery time window of 2 hours, 8 out of 200 requests (i.e., 4% of the requests) are offloaded in zones different from the request destination zone (for instance 10 all requests are offloaded in the same zone). Moreover, in instances with 300 requests, there are always some requests offloaded in zones different from the request destination zones and this number is always higher for the instances with the shortest delivery time window duration.

5.4.2.2 NBO-LMDT solved for pilot instances

Table *33* presents the results of the implementation of NBO-LMDT for the pilot tests (the meaning of each column is similar to the previous table). In these cases, the gap to the optimal value is 1.95%, at maximum.

Table 33 - Results of NBO-LMDT for pilot instances

Inst.	|*K*|	*W*	Values of single Optimization		NBO – LMDT (exact optimization)			
			NBO **(*offloads*)**	***LMDT*** **(min)**	***NBO*** **(*offloads*)**	***LMDT*** **(min) [solution found-lower bound]**	***Run*time (sec.)**	***DZ***
P1	100	4 h	20	30	20	[30.75-30.15] (1.95%)	59.19+1800	0
P2	100	2 h	20	30	20	[30.9-30.75] (0.49%)	15.47+1800	0
P3	200	4 h	40	30	40	[30.3-30.15] (0.5%)	74.91+1800	0
P4	200	2 h	40	30.60	40	[31.725-31.425] (0.95%)	67.34+1800	11
P5	300	4 h	60	30.20	60	[30.55-30.40] (0.49%)	191.73+1800	16
P6	300	2 h	63	31.95	63	[32.05-31.95] (0.31%)	193.74+1800	39
P7	100	4 h	19	30	19	[30.3-30.15] (0.49%)	67.00+1800	0
P8	100	2 h	19	30	19	[31.2-30.95] (0.76%)	19.26+1800	0
P9	200	4 h	39	30	39	30.15	72.70+257.50	0
P10	200	2 h	39	30.53	39	31.2	65.73+151.75	0
P11	300	4 h	59	30.15	59	[30.3-30.22] (0.27%)	172.44+1800	14
P12	300	2 h	62	31.70	62	31.75	467.97+244.5	28

The results show that this combination NBO-LMDT is harder to solve compared to the previous combination LMDT-NBO, since the solutions found, within 1800 seconds, for all instances with fixed demand of 1 are not optimal. Nevertheless, the solutions of this combination NBO – LMDT have potential gaps to the optimal value of 0.69% on average, which are very small.

The results also show that minimizing the last mile delivery time after minimizing the number of offloads after (NBO-LMDT) leads to higher delivery time, on average, than minimizing solely the last mile delivery time (LMDT), and this number increases as the number of requests also increases.

This combination is the combination selected by the BTO of the city to be incorporated into the decision models of the pilot platform, and the results suggest that despite the optimal solutions could only be obtained solving three of twelve instances, the gaps to the optimal value are very small and reasonable accepted in terms of transportation engineering. Nevertheless, heuristics approaches for this combination were also studied (described in the next subsection) to be included in the SOLFI platform.

5.5. Problem formulation with heuristic methods

As a deliverable of the project, heuristic algorithms were developed to be integrated into the SOLFI platform. The reason for the development of heuristics are three: (1) the BTO does not have access to the CPLEX solver to run and solve the exact models, since the license is expensive; (2) The BTO of the city has selected the objective function NBO-LMDT to use at the pilot stage of the project, facilitating the integration of requests collection by the LMO (the results of solving NBO-LMDT for fictional and pilot instances show that increasing the number of requests make the integer linear programming models hard to solve, and heuristics are needed to solve these instances in reasonable time); (3) the BTO aims to operate based on a platform that receives the requests release by clients one by one and, for these reason, the BTO demands an algorithm that provides a fast acceptance feedback to the client upon each request release. When the platform does not accept more requests by the client to be delivered, a more efficient and time-consuming algorithm is required to provide the best solution possible, performing this optimization task during the night before the day of operation.

Considering the interview to the bus BTO, the platform must run based on two different algorithms. The first algorithm runs in each request release by a client and aims to decide as quickly as possible if a request can be accepted or not for transportation on the desired day. Thus, an efficient and fast request receipt algorithm has to run during the request release by the client, to determine, if its request can be transported or not, on the desired day requested by the client. The second algorithm is an optimizer to be run when the time window of acceptance of new requests is closed for a certain day (typically on the day before). This optimization algorithm considers all the accepted requests and determine the best distributed plan for the whole set of requests.

This subsection describes the two heuristics, to solve each of these two algorithms, developed and tested with MATLAB software.

As previously mentioned, the aim of these optimization algorithms is the lexicographical optimization of two objectives NBO-LMDT: first, to minimize the number of bus offloads (minimizing the number of times the LMO needs to go to bus stops to collect requests) and then, to minimize the average last mile delivery time (selecting the bus stops that are closer, on average, to the requests' destinations), guaranteeing the minimum number of offloads.

5.5.1. Requests receipt algorithm, based on Greedy Randomized

The Request receipt algorithm is run when a new freight request is triggered by one client for a certain day in the future. For each day, there is an acceptance time window to receive requests release by the Client (for example, the 7 previous days). During the request release by the Client for a certain day, this algorithm evaluate the system capacity to verify if the new requests can be accepted or not accepted, considering the already accepted requests for the same day. Although this algorithm requires the computation of an operational planning solution, this algorithm is built to finish as soon as it computes a feasible solution that accommodates the new request. The aim of this algorithm is to give an acceptance response to the requests release within 10 seconds, as the BTO considers this the "acceptable" time for response of a request release. For this reason, the optimality is not a requirement in this algorithm (the feasible solution found may not be the optimal one), but it guarantees that requests can be accepted to be transported on the intended day. In case of no system capacity to accept the new request release, the client is informed and he/she can request the transportation for another day.

5.5.1.1 Greedy randomized

This subsection explained the GR used as the base for the request receipt algorithm.

An operational planning solution is a list with a selected option for each request defined by a combination of the bus hub, the bus service used to transport the request and the bus stop used for offloading it. All options for each request are computed in advance guaranteeing that the bus hub of the option is one of the bus hubs where the client of the request can drop the request and the arrival time at the bus stop enables the LMO to deliver the request at its destination within the delivery time window of the request. Thus, whenever an option is mentioned, it is referred as a singular combination of bus hub, bus service and bus stop.

This algorithm makes use of the GR algorithm (shown at the end of this paragraph) which takes as input a set K_{in} of requests and computes an operational planning solution from the scratch. The algorithm starts by setting an empty solution *Sol* and an empty set K_{out} of requests with selected options (line 1). In line 2, the set K' of all inputted requests $k \in K_{in}$ ordered by decreasing order of their demand value is determined. This decreasing order of demand, proved to be best strategy for the greedy randomized in preliminary tests. This can be explained by the fact that since following this decreasing order, the requests with more demand are fitted into the system first, using the larger capacity of it first. Thus, requests with lower demand are left to the end of the order, when it is potentially easier to fit them into already used bus services to transport the largest requests. Then, the 'For' cycle (lines 3 to 8) considers each request by the previous order. On each cycle, the algorithm tries to select in line 4 an option $i = 1,2,\dots,|I_k|$ for each request k that can be accommodated in the partial solution *Sol* given by all previous selected options. If such option exists (line 5), the algorithm updates solution *Sol* with the selected option and adds the request to the set K_{out} (line 6). After the cycle, the algorithm computes in line 9 the two objective values of the final solution Sol: the number of bus offloads (*nBO*) and the average last mile delivery time (*aLMDT*). At the end, the algorithm outputs the set K_{out} of requests with selected options (i.e., the accepted requests), together with solution *Sol* and its objective values. So, if the outputted K_{out} is equal to K_{in}, it means that the algorithm was able to accommodate all requests in solution *Sol*.

GR (Greedy Randomized) Algorithm:

Input: K_{in}

1. $Sol \leftarrow \{\}$, $K_{out} \leftarrow \{\}$
2. $K' \leftarrow$ order($k \in K_{in}$)
3. **For** $k = K'$ **do**
4. $i \leftarrow$ SelectOption(Sol, I_k)
5.   **If** $i \geq 1$ **do**
6. $Sol \leftarrow Sol + \{i\}$, $K_{out} \leftarrow K_{out} + \{k\}$
7.   **EndIf**
8. **EndFor**
9. (*nBO, aLMDT*) $\leftarrow$ Compute(*Sol*)

Output: K_{out}, *Sol, nBO, aLMDT*

The strategy used for selection of an option for request k in line 4 of the GR algorithm is as follows. First, the subset of options using an already selected bus stop that can still accommodate the request for transportation (i.e., neither the available capacity of the stop nor the available capacity of its bus service is lower than the request's demand) whose LMO delivery time is minimum is computed. If this subset is not empty (i.e., it is possible to accommodate the request without increasing the number of bus offloads), one of its options is randomly selected. If the subset is empty, it means that a new bus stop must be used. Therefore, the subset of options using a bus stop not yet selected that can still accommodate the request and whose LMO delivery time is minimum is computed. If this new set is not empty, one of its options is randomly selected. Otherwise, i is returned with 0 (a valid option is when $1 \leq i \leq | I_k |$), indicating that the request cannot be assigned with a transportation option by the system.

5.5.1.2 Request receipt

As mentioned, requests receipt algorithm is run when a new request is triggered by a client to decide in the shortest possible runtime if the new request is or is not accepted. This algorithm is as follows:

REQUESTS RECEIPT algorithm

Input: K, *Sol, nBO, aLMDT,* k', *DecisionTime*

```
return ← FALSE
i ← SelectOption(Sol, I_k')
If i ≥ 1 do
    K_out ← K + {k'} ,  Sol ← Sol + {i}
    (nBO, aLMDT) ← Compute(Sol)
    return ← TRUE
Else
    K_in ← K + {k'}
    While return = FALSE and Runtime < DecisionTime do
        (K_out, Sol_aux, nBO_aux, aLMDT_aux) ← GR(K_in)
        If K_out = K_in do
            Sol ← Sol_aux ,  nBO ← nBO_aux ,  aLMDT ← aLMDT_aux
            return ← TRUE
        EndIf
    EndWhile
EndIf
```

Output: K_{out}, *Sol, nBO, aLMDT, return*

The Requests receipt algorithm takes as input the set of already accepted requests K, the solution *Sol* obtained when the last request of K was accepted (together with its two objective values *nBO* and *aLMDT*), the new request k' and a maximum decision time *DecisionTime*. At the end, the algorithm outputs a Boolean variable *return* as TRUE if the new request is accepted or as FALSE, otherwise. Depending on this decision, the algorithm returns either the new solution (that includes the new request) or the initial inputted solution not including the new request.

The Boolean variable $return$ is initially set to FALSE (line 1). To speed up the decision time, first, the algorithm tries to select in line 2 an option $i = 1,2, \dots, |I_{k'}|$ for the new request k' that can be accommodated in the inputted solution *Sol*. If such option exists (line 3), the algorithm computes set K_{out} with all requests, updates solution *Sol* and its objective values with the selected option (lines 4 and 5) and sets $return$ with TRUE. Otherwise (line 7), a 'While' cycle is run (lines 9 to 15) until either a solution is found for all requests or the runtime reaches the *DecisionTime* value (line 9). In each cycle, a greedy randomized solution is first computed with the GR algorithm (line 10). Then, if the solution includes all requests (line 11), solution *Sol* (and its objective values) are updated (line 12) and variable $return$ is set to TRUE. If the 'While' cycle ends without finding a solution that includes all requests, the variable $return$ remains as FALSE and the outputted solution *Sol* remains the same as the inputted solution *Sol*, not accepting the new request and maintaining the inputted solution for the already accepted requests.

An example of the Request receipt algorithm is shown on the *Table 34*.

Table 34 - Example of the Requests Receipt algorithm

Request ID	Bus Hub ID	Bus Service ID	Bus stop ID	Number of offloads
R01	3	122	5	1
R02	1	1	7	2
R03	3	122	5	2
R04	1	1	7	2
R05	2	79	4	3
R06	2	68	4	4
R07	2	68	4	4
R08	2	79	4	4
R09	1	19	2	5
R10	1	17	2	6
R11	1	17	2	6
R12	1	23	5	7
R13	1	23	5	7
R14	1	19	2	7
R15	1	25	8	8
R16	1	31	5	9
R17	1	31	5	9
R18	1	33	2	10
R19	1	33	2	10
R20	1	1	7	10

This table shows the final solution of the request receipt algorithm to give response to 20 separated requests. Those requests were triggered by clients one by one, following the order in the table (i.e., first the algorithm received the R01 then R02 and so on). For each request receipt, the Request receipt algorithm is run for a total runtime limit of 10 seconds, stopping whenever an option is found, according to the strategy already explained above. As mentioned, an option is a combination of bus hub, bus service and bus stop that fulfil the system capacity and the delivery time of request. As example, in the final solution of the table, the R01 is assigned to the option composed by: bus hub 3, bus service 122 and bus stop 5; while the R02 is assigned to the option bus hub 1, bus service 1 and bus stop 7, etc.

Each time a new request is received, the algorithm tries first to fit the request in an option that already is used by previous accepted requests, meaning that when running the algorithm tries first to minimize the get the solution as faster as possible. This behaviour is observed on the table for the R03, and R04, where the algorithm found a way to accept the request on the same option already selected for R01 and R02, respectively. That is why the total number of offloads remains 2 after the four first requests. Thus, whenever an already used option can be found, the new incoming request is assigned to it.

After the acceptance of the request R20, the final solution illustrated on *Table 34* has a total number of 10 bus offloads, since every different option means a different offload and there is a total of 10 different options used to transport all the R20 requests.

5.5.2. Optimizer algorithm

The Optimizer algorithm is run when the deadline of the acceptance time window for a certain day is reached, typically, at the end of the day before. The aim of this algorithm is to compute the best possible solution during a predetermined decision time duration, obtaining the final operational planning solution for all the accepted requests for the day. An operational planning solution is a transportation plan, containing an option for all accepted requests that optimizes the objective function, in this case, NBO-LMDT.

The Optimizer algorithm is based on a GRASP metaheuristic approach which uses two basic algorithms: the previously described GR algorithm and a Local Search (LS) algorithm. The LS algorithm is as follows:

LS (Local Search) Algorithm:

Input: *Sol, nBO, aLMDT*

```
Sol_final ← Sol , nBO_final ← nBO , aLMDT_final ← aLMDT
continue ← TRUE
While continue = TRUE do
    (Sol, nBO, aLMDT) ← BestNeighbor(Sol_final)
    If nBO < nBO_final or (nBO = nBO_final and aLMDT < aLMDT_final) do
        Sol_final ← Sol
        nBO_final ← nBO
        aLMDT_final ← aLMDT
    Else
        continue ← FALSE
    EndIf
EndWhile
```

Output: *Sol_final, nBO_final, aLMDT_final*

The LS algorithm takes as input a given solution *Sol* and its two objective values (*nBO* and *aLMDT*) and starts by setting the final solution *Sol_final* with the inputted solution (line 1). Then, the 'While' cycle (lines 3 to 12) is run until the boolean variable *continue* becomes FALSE (this variable is initialized as TRUE in line 2). On each cycle, the best solution *Sol* which is neighbor to *Sol_final* is first computed in line 4 (with its objective values). Then, if the neighbor solution *Sol* is better than the current final solution *Sol_final* (line 5), the final solution is updated (line 6) together with its two objective values (lines 7 and 8) and the cycle is repeated: *Sol* is better than *Sol_final* if its number of bus offloads is lower or if its number of bus offloads is equal and the average last mile delivery time is lower (line 5). If the neighbor solution *Sol* is not better than the current *Sol_final* (line 9), the variable *continue* is set with FALSE (line 10) to end the cycle (i.e., the final solution *Sol_final* is a local optimum solution, which means that there is no neighbor solution that can improve the optimization objectives NBO-LMDT). At the end, the algorithm outputs solution *Sol_final* and its objective values.

The selection of the best neighbor solution of the LS algorithm (line 4) is as follows. For a given solution *Sol_final*, a neighbor solution is a solution that is different from *Sol_final* on the selected option of a single request. The algorithm computes all possible individual option swaps and returns the neighbor solution *Sol* (together with its two objective values) with the lowest number of bus offloads and, if multiple solutions exist with the same minimum number of bus offloads, the one with the minimum value of the average last mile delivery time.

The Optimizer algorithm runs a GRASP metaheuristic when the deadline time for requests release of a certain day is reached, to compute the final operational planning solution for all previous accepted requests for that day. Optimizer algorithm (shown at the end of this paragraph) takes as input the set of accepted requests K, the solution *Sol* previously obtained by the Request receipt algorithm for the set K (together with its two objective values *nBO* and *aLMDT*) and a maximum decision time *DecisionTime*. The final solution *Sol_final* is first set with the local optimum solution obtained by giving the inputted solution *Sol* to the LS algorithm (line 1). Then, a 'While' cycle is run (lines 2 to 10) until the runtime reaches the *DecisionTime* value. On each cycle, a new local optimal solution *Sol* is first computed by generating first a solution with the GR algorithm (line 3) and giving it as input to the LS algorithm (line 4). Then, if the new solution is better than the previous solution *Sol_final* (line 5), solution *Sol_final* is updated together with its objective values (lines 6 to 8). At the end, the algorithm outputs *Sol_final* (and its two objective values) which is the best solution computed in all cycles.

Optimizer Algorithm

Input: K, *Sol, nBO, aLMDT, DecisionTime*

1. (*Sol_final*, *nBO_final, aLMDT_final*) ← LS(*Sol*, *nBO, aLMDT*)
2. **While** *Runtime* < *DecisionTime* **do**
3.   (*Sol*, *nBO, aLMDT*) ← GR()
4.   (*Sol*, *nBO, aLMDT*) ← LS(*Sol*, *nBO, aLMDT*)
5.   **If** *nBO* < *nBO_final* **or** (*nBO* = *nBO_final* **and** *aLMDT* < *aLMDT_final*) **do**
6.   *Sol_final* ← *Sol*
7.   *nBO_final* ← *nBO*
8.   *aLMDT_final* ← *aLMDT*

9. **EndIf**

10. **EndWhile**

Output: *Sol_final*, *nBO_final, aLMDT_final*

Table *35* shows the results of the Optimizer algorithm for the same example before with a set of 20 requests, for a decision time of 10 minutes.

Table 35 - Example of Optimizer algorithm for 20 requests example

Request ID	Bus Hub ID	Bus Service ID	Bus stop ID	Number of offloads
R01	3	127	8	1
R02	1	5	3	2
R03	3	127	8	2
R04	1	5	3	2
R05	1	17	8	3
R06	1	7	5	4
R07	1	7	5	4
R08	1	17	8	4
R09	1	27	2	5
R10	1	22	2	6
R11	1	22	2	6
R12	1	27	2	6
R13	1	34	5	7
R14	1	27	2	7
R15	1	28	3	8
R16	1	34	5	8
R17	1	36	8	9
R18	1	28	3	9
R19	1	36	8	9
R20	1	5	3	9

The interpretation of Table *35* is similar to *Table 34*.

The Optimizer algorithm could, within a decision time period of 10 minutes, improve the solution found by the Request receipt algorithm, since this solution only contains 9 bus offloads instead of 10, which is the primary objective to optimize (minimization).

5.6. Computational experiments with heuristic methods

Table *36* presents the results of computational experiments of Pilot instances solved by the Requests receipt and Optimizer algorithms. The "NBO – LMDT (exact optimization)" section presents the results obtained using exact optimization through CPLEX for comparison, and "Heuristic" section presents the results of Request receipt Algorithm run with a maximum runtime of 10 seconds and Optimizer algorithm with a runtime of 30 minutes (1800 seconds). Recall that these algorithms are based on NBO – LMDT combination of objective functions, which means that first minimizes the number of offloads and then the average delivery time.

Table 36 - Results of NBO-LMDT using Request receipt algorithm and Optimizer algorithms solving pilot instances

			NBO – LMDT (exact optimization)			**Heuristic**			
						Request Receipt Algorithm		**Optimizer Algorithm**	
Inst.	**|*K*|**	***W***	***NBO* (*unloads*)**	***LMDT* (min)**	***Run*time (sec.)**	**NBO**	**LMDT (min)**	**NBO**	**LMDT (min)**
P1	100	4 h	20	[30.75-30.15] (1.95%)	59.19++1800	23	38.55	22	34.5
P2	100	2 h	20	[30.9-30.75] (0.49%)	15.47+1800	27	37.5	22	36.3
P3	200	4 h	40	[30.3-30.15] (0.5%)	74.91+1800	45	40.8	44	37.425
P4	200	2 h	40	[31.725-31.425] (0.95%)	67.34+1800	46	39	44	34.425
P5	300	4 h	60	[30.55-30.40] (0.49%)	191.73+1800	71	40.75	65	38.5
P6	300	2 h	63	[32.05-31.95] (0.31%)	193.74+1800	NS	NS	NS	NS
P7	100	4 h	19	[30.3-30.15]	67.00+1800	23	40.35	21	34.05
P8	100	2 h	19	[31.2-30.95] (0.76%)	19.26+1800	23	41.25	22	33.45
P9	200	4 h	39	30.15	72.70+257.50	44	40.05	42	36.375
P10	200	2 h	39	31.2	65.73+151.75	46	38.03	45	34.43
P11	300	4 h	59	[30.3-30.22] (0.27%)	172.44+1800	70	39.4	68	34.3
P12	300	2 h	62	31.75	467.97+244.5	NS	NS	NS	NS

The results show the advantages of the Optimizer algorithm run with a larger runtime limit of 1800 seconds, since compared to the Requests receipt algorithm, with runtime limit of 10 seconds, it reduces the number of offloads, on average, by 3 offloads for the first 6 instances and by 1,6 offloads for the last 6 instances. Recall that the request receipt algorithm is run during the request release and stops as soon as it founds a feasible solution. For this reason, the results of Request receipt algorithm are not optimized and the solution values are significantly higher than the solution values, found for NBO-LMDT through exact optimization, which are optimal values or close to the optimal value (gaps less than 2%). On the other hand, the results of Optimizer algorithm are significantly closer to the results found for NBO-LMDT through exact optimization.

For instances with 300 requests and delivery time windows of 2 hours, P6 and P12, the scalability point is reached at receipt #255 with the Request receipt algorithm, i.e. it can accept the request #254 but the algorithm cannot accept the new request #255 in 10 seconds. As previously mentioned, the Request receipt algorithm is based on a GR first using the previous solution for n-1 requests, and trying to fit the last request into the same solution. When the request cannot fit the previous solution, the GR runs considering the set of all requests accepted so far to build a solution. The results show that the algorithm can accept the request #254 fitting it in the previous solution found for request #253 but cannot accept the request #255 fitting it into the solution of #254. Moreover, when the GR is run considering the entire set of requests, no solution is found for P6 and P12, during the runtime limit of 10 seconds. For these cases, it was tested to run the Requests receipt algorithm for 1800 seconds and still no feasible solutions were found. On the other hand, for instances with 300 requests with 4 hours of delivery time window, P5 and P11, it was possible to accept all 300 requests. This is explained by the fact that when the delivery time window is 4 hours, there are much more options ($|I_k|$) for a request to be transported, and therefore the GR has more flexibility to select an option that can be used for a higher number of requests.

The Optimizer algorithm is built based on a Greedy Randomized with Adaptive Search Procedure and therefore, it requires an initial feasible solution to use as a starting point of the adaptive search procedure. Since for instances P6 and P12 no initial feasible was found the Optimizer could not be run to improve this initial solution found.

Nevertheless, the scalability point on request #254 was considered as an acceptable number of requests for a day during the pilot test of the project. Additionally, the results of the optimizer algorithm after 1800 seconds were relatively close to the results obtained with exact optimization during 1800 seconds for all instances up to 200 requests. This allows to conclude that these algorithms are efficient to be used for the pilot phase of the project, since their results are acceptable compared to the optimal solutions.

5.7. Chapter resume and conclusion

In this chapter the problem FNFAP was introduced and addressed with exact optimization models and heuristic optimization models. To run the optimization models fictional and pilot instances were generated, to be used by the models in the computational experiments. The results of these experiments were detailed and gave helpful insights of the performance of the optimization models proposed in this chapter.

After gathering all the results from the experiments, some conclusions can be highlighted:

1. Decrease the time window of requests delivery from 4h to 2h can lead to more offloads than compared to the time window of 4 hours.
2. In the fictional instances, the second combination NBO-LMDT has the best trade-off between the two objectives compared to LMDT-NBO. The lexicographic optimization of combination NBO-LMDT leads to an average increase of 24% over all instances on the last mile delivery time, while the combination LMDT-NBO leads to an average increase of 17% on the number of offloads, over all instances.
3. On the other hand, the NBO-LMDT is much harder to solve, since the runtimes are higher and no optimality was reach for the largest instances (F5-F6). The NBO-LMDT was the combination selected to be solved using heuristics optimization methods (section *5.5*), since the problem is harder to solve using exact optimization but the global benefits are higher.
4. The symmetry in the problems under study has not a significant impact on the solvers performance while solving the optimization models. The experiments allowed to conclude that including the symmetry breaking constraints into the robustness models (symmetry only occurs when optimizing models RBS and RLMF) do not improve consistently the performance of solving those models. Thus, the best strategy to deal with the symmetry is to switch the role between alternative and main bus services and bus stops, whenever the symmetry occurs.

5. The results have also shown that to achieve robustness to deal with last mile failures (i.e. failure to offload the request in a specific bus stop), it is truly important that each delivery zone of the city has a minimum of two bus stops to be used for the mixed freight and passenger transportation solution. Thus, having more bus stops in the same area will maximize the probability of request being assigned with an alternative bus stop to be offloaded in case of a failure offloading in the main bus stop.
6. Reducing the number of services to be used for freight and passenger transportation can potentially remove the probability of robustness of the system to deal with last mile delivery failures, because reducing bus services can lead to not using key buses that pass through central zones of the city. The BTO has to be careful when reducing the number of bus services beforehand, and should try to keep the bus services that give more flexibility to the system, i.e., key services that passes through the central area of the city and, consequently, can be used by several requests as an option to be transported.
7. Robustness to bus services suppressions is significantly impacted by the delivery time window duration of the requests. Thus, the larger is the delivery time window, the higher is the number of requests that can have an alternative bus service assigned to it, to be used in case of the main bus service is suppressed.
8. The scalability tests to heuristic algorithms done in section *5.6* help to conclude that, for the pilot instances, the Request receipt algorithm and the Optimizer algorithm can deal efficiently with a total of 200 requests with 4 hours of delivery time window.

6. Strategic approach for the Bus Network Planning Problem (BNPP)

This chapter addressed the strategic layer problem BNPP, applied to the field of UL with integrated passenger and freight flows. The problem is new in the literature as it is focused on the strategic layer of the problem, to help the decision-making process of the LMO of the city to decide what should be the set of bus services to use on the integrated solution of passenger and freight flow. Exact formulations and heuristic algorithms are proposed to tackle this problem, providing computational experiments and conclusions for both types of algorithms. The problems are based on a set of scenarios of possible realizations for certain parameters to model uncertainty to the parameters and robustness to the found solution, which is also a novel feature when addressing this problem.

6.1. Motivation for the strategic approach to the problem

The base problem under study in this chapter is the one presented on the section 4.4, but now the decision-making lays on the strategic layer of the problem.

The work on this chapter contributes to the literature by addressing a strategic planning problem - the BNPP. The distinct feature addressed in this well-known problem results from the integration of the freight delivery process into the decision of sizing a bus fleet to perform both passenger and freight transportation for short-distance trips in an urban environment. The aim is to determine the subset of bus services whose buses should be physically adapted for passenger and freight transportation, from an installed bus network solely prepared for passengers' transportation. On the previous problem FNFAP, the pilot instances were based on a pilot network of 220 bus services, which is a considerable number of bus services allocated to the integrated passenger and freight flow addressed on the SOLFI project. Thus, this BNPP problem is worth of being investigated as the main motivation for such urban logistic solution is to use the current bus networks (in particular, during the periods when the number of passengers using the network is lower) to transport freight requests of small size to the city centers instead of using dedicated vehicles to transport them.

To the best of current knowledge, only three researches - Azcuy et al. (2021), El Ouadi et al. (2021) and Nieto-Isaza et al. (2022) - have specifically investigated strategic problems in the context of integrated passenger and freight flows in UL. Location analysis and network design have emerged as two major research areas for these three studies. This work, on the other hand, contributes to the literature by investigating fleet optimization from a strategic planning level, where the BTO aims to minimize the number of bus services required to support urban logistics activities, because, typically, they need to be physically adapted to be able to transport goods and passengers. The bus adaptation to transport goods is expensive and so the goal is to select the minimum number of adapted buses while covering a wide range of future demand scenarios, ensuring that all transportation requests are met. According to Lei et al. (2016), the fleet sizing of Pickup and Delivery (PD) vehicles "is one of the most important decisions as it is a major fixed investment for starting any business". Ghilas et al. (2018) highlight as future research the minimization of adapted vehicles needed to jointly transport passengers and goods in an efficient network, which is precisely the aim of this work.

This work, in addition to contributing to a new approach within the BNPP, includes some new perspectives, namely the consideration of uncertainty, through the incorporation of stochastic parameters, and the development of a scenario-based optimization heuristic algorithm to support the BTO to deal with the problem. Azcuy et al. (2021) also uses a scenario-based heuristic for their strategic problem but the focus is on the location routing problem to determine the transfer station location to demand transfer. As a result, this study of BNPP can be used as a starting point for future research incorporating uncertainty, with stochastic parameters, such as demand, delivery time windows and destination address of the requests, while considering a scenario-based heuristic algorithm, with the aim to minimize the bus resources needed for the UL process using a network of passengers' city buses to also move freight.

The aim is to plan the fleet size of a given workday that is robust to uncertainty in terms of the requests that are expected for that day. To simulate the demand of a certain workday, a set of scenarios is used as a set of possible realizations of requests for that workday being planned. In this problem, it is considered a set of 100 scenarios of possible realizations of requests with stochastic parameters for the demand, destination zone and delivery time window of each request. The goal is to find a minimum number of bus services to be adapted, guaranteeing that all requests are fulfilled for all the scenarios. The same number of scenarios used by in their work was selected for this study, and therefore it is considered that 100 scenarios is reasonable and large enough to find good solutions for the future realization that can occur. This problem can be formulated as a generalization of the classic bin-packing problem (BPP) which is defined as the placement of a set of different-sized items into identical bins such that the number of used bins is minimized. In the BNPP problem, a set of requests (items), with different demands, must be assigned to a minimum set of bus services (bins). Considering the particular case when all requests can be assigned to any bus service (i.e., can be delivered to the final customer at any time during the day), all requests transported on each bus service can be offloaded at any bus stop and the demand uncertainty modelled by a single request scenario, BNPP problem is formulated as a classic BPP. Following Munien & Ezugwu (2021), the BPP is an age-old NP-hard combinatorial optimization problem and so is this problem. Therefore, besides proposing an ILP model that can be solved to compute the optimal solutions of relatively small problem instances, two heuristic algorithms are also proposed to get solutions for larger problem instances (i.e., with larger number of uncertainty scenarios and number of requests).

Although this problem is a design problem that must be solved at a strategic planning level where there is no time pressure, heuristics are needed to address larger instances within realistic computation time and affordable hardware configuration. Next, the ILP model is described in the first subsection. Then, the two proposed heuristic algorithms (Heuristic 1 and Heuristic 2) are described.

6.2. Problem formulation based on exact methods

The exact method is based on an ILP formulation that is solved by a standard commercial solver.

Consider a bus network with a set of hubs T (where requests can be dropped by clients), a set of bus stops S (where requests can be offloaded by the LMO) and a set of bus services P (with routes from hubs to stops). Each hub $t \in T$ has an associated set of bus services $P(t) \subset P$ that depart from t. Each bus service $p \in P(t)$ has an associated set of bus stops $S(p) \subset S$. Finally, each bus stop $s \in S(p)$ of bus service $p \in P(t)$ has an associated arrival time H_{tps} (according to the route of the bus service p).

Consider the demand uncertainty modelled by a set of demand scenarios U, with scenario $u \in U$ defined by a set of requests K_u whose characteristics are randomly generated with the probability distributions assumed for the demand uncertainty. Each request $k \in K_u$ of each scenario $u \in U$ is characterized by a demand D_{uk} (in number of freight parcels), a destination address B_{uk} and a delivery time window $[E_{uk}, L_{uk}]$ defining the earliest E_{uk} and the latest L_{uk} delivery time instant of the request at its destination address B_{uk}. Moreover, the hubs at which the client of request $k \in K_u$ can be dropped are modelled by the binary parameters A_{ukt} that are equal to 1 if request $k \in K_u$ can be dropped in hub $t \in T$ or are equal to 0, otherwise.

Consider an LMO whose service is characterized by the maximum time T_{uks} to deliver request $k \in K_u$ from each bus stop $s \in S$ to the request destination address B_{uk}.

The bus network planning problem aims to select a minimum subset of bus services, from the global bus network operating in the city, that need to have the physical logistic means for freight transportation. A bus service $p \in P(t)$ with such means is characterized by a load capacity C_{tp} (the maximum number of freight parcels that can be transported) and each of its bus stops $s \in S(p)$ is characterized by an offload capacity C_{tps} (the maximum number of freight parcels that can be offloaded by the LMO which bounds the maximum waiting times of passengers during offloads).

Table *37* summarizes all notations of the problem.

Table 37 - All notations of the problem

Notation	Type	Description
T		Set of bus hubs $t \in T$
P		Set of bus services $p \in P$
S		Set of bus stops $s \in S$
$P(t) \subset P$	Set	Set of bus services p departing from hub $t \in T$
$S(p) \subset S$		Set of bus stops s of bus service $p \in P$
U		Set of demand scenarios $u \in U$
K_u		Set of requests $k \in K_u$
H_{tps}		Arrival time of bus service $p \in P(t)$ to bus stop $s \in S(p)$
C_{tp}		Load capacity of bus service $p \in P(t)$
C_{tps}		Offload capacity of bus service $p \in P(t)$ in bus stop $s \in S(p)$
D_{uk}		Demand of request $k \in K_u$
B_{uk}		Destination address of request $k \in K_u$
E_{uk}		Earliest delivery time of request $k \in K_u$ at its destination address
L_{uk}	Parameter	Latest delivery time of request $k \in K_u$ at its destination address
A_{ukt}		Binary parameter indicating if request $k \in K_u$ can be dropped in hub $t \in T$
T_{uks}		Maximum delivery time of request $k \in K_u$ from bus stop $s \in S$ to its destination address
h_{uktps}		Binary parameter indicating if hub $t \in T$ is one of the hubs where the request $k \in K_u$ of scenario $u \in U$ can be dropped by the client and if the arrival time of the bus service $p \in P(t)$ on bus stop $s \in S(p)$ plus the maximum delivery time of the LMO from bus stop s to the request's final destination is within the delivery time window $[E_k, L_k]$
z_{uktps}	Decision variable	Binary variable indicating if request $k \in K_u$ is dropped in hub $t \in T$, loaded in bus service $p \in P(t)$ and offloaded in bus stop $s \in S(p)$
y_{tp}		Binary variable indicating if at least one request $k \in K_u$ of any scenario $u \in U$ is dropped in hub $t \in T$ and loaded in bus service $p \in P(t)$

To model the optimization problem, first consider the following additional parameters. For request $k \in K_u$ of scenario $u \in U$, the binary parameter h_{uktps} is defined as:

$$h_{uktps} = \begin{cases} 1 & , A_{ukt} = 1 \ \wedge \ E_{uk} \leq H_{tps} + T_{uks} \leq L_{uk} \\ 0 & , \text{otherwise} \end{cases}$$

i.e., h_{uktps} is equal to 1 if hub $t \in T$ is one of the hubs where the request $k \in K_u$ of scenario $u \in U$ can be dropped by the client and if the arrival time of the bus service $p \in P(t)$ on bus stop $s \in S(p)$ plus the maximum delivery time of the LMO from bus stop s to the request's final destination is within the delivery time window $[E_k, L_k]$. These parameters are computed beforehand and then, are used in the ILP formulation.

Then, the following decision variables are considered:

z_{uktps} – binary variable that is equal to 1 if request $k \in K_u$ is dropped in hub $t \in T$, loaded in bus service $p \in P(t)$ and offloaded in bus stop $s \in S(p)$; and is equal to 0, otherwise.

y_{tp} – binary variable that is equal to 1 if at least one request $k \in K_u$ of any scenario $u \in U$ is dropped in hub $t \in T$ and loaded in bus service $p \in P(t)$; and is equal to 0, otherwise.

Finally, the optimization problem is modelled by the following ILP formulation:

$$\text{Minimize} \quad \sum_{t \in T} \sum_{p \in P(t)} y_{tp} \tag{1}$$

Subject to:

$$\sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} h_{uktps} z_{uktps} = 1 \qquad , \forall\, u \in U, \forall\, k \in K_u \tag{2}$$

$$\sum_{t \in T} \sum_{p \in P(t)} \sum_{s \in S(p)} (1 - h_{uktps}) z_{uktps} = 0 \qquad , \forall\, u \in U, \forall\, k \in K_u \tag{3}$$

$$\sum_{k \in K_u} \sum_{s \in S(p)} D_{uk} z_{uktps} \leq C_{tp} y_{tp} \qquad , \forall\, u \in U, \forall\, t \in T, \forall\, p \in P(t) \tag{4}$$

$$\sum_{k \in K_u} D_{uk} z_{uktps} \leq C_{tps} y_{tp} \qquad , \forall\, u \in U, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{5}$$

$$z_{uktps} \in \{0,1\} \qquad , \forall\, u \in U, \forall\, k \in K, \forall\, t \in T, \forall\, p \in P(t), \forall\, s \in S(p) \tag{6}$$

$$y_{tp} \in \{0,1\} \qquad , \forall\, t \in T, \forall\, p \in P(t) \tag{7}$$

The objective function (1) is the minimization of the number of bus services that can transport all requests of all demand scenarios.

Constraints (2) guarantee that for each scenario $u \in U$, the assigned bus service and bus stop to each request $k \in K_u$ starts in one of the possible hubs for each request (considering the Logistic service time of that hub) and meets with its delivery time window (i.e., the associated parameter h_{ktps} is equal to one). These constraints guarantee this because the variable z_{uktps} is multiplied by a predetermined parameter h_{uktps} (that is equal to one if all mentioned conditions are fulfilled) and the constraints force the result to be 1, i.e., to select one combination of assignment of request to bus hub, bus service and bus stop.

Constraints (3) guarantee that for each scenario $u \in U$, each request $k \in K_u$ cannot be assigned with one bus service $p \in P(t)$ in one hub $t \in T$ to be offload in one bus stop $s \in S(p)$ such that the associated parameter h_{uktps} is zero. Constraints (3) are not necessary to obtain feasible solutions since constraints (2) alone guarantee that variable z_{uktps} contains a feasible solution. However, constraints (3) are valuable because, although they increase the number of constraints of the model, they allow the solver to eliminate from the model the variables z_{uktps} for all the combination of requests, bus hubs, bus services and bus stops that are not feasible. Some preliminary experiments were conducted with and without constraints (3), and the solver could, generally, achieve the solutions faster with these constraints, improving the performance. Note that constraints (3) can be eliminated from the model if the involved variables are eliminated from the set of the variables of the model, obtaining in this way a more compact model (i.e., with a smaller number of variables and constraints). In fact, the results reported in this chapter were obtained with this more compact model but the ILP model is described as above for clarity.

Constraints (4) guarantee that for each demand scenario $u \in U$, the total demand of the requests loaded on each bus service $p \in P(t)$ of each hub $t \in T$ is not higher than the bus capacity C_{tp} if the bus service p is in the solution (i.e., if y_{tp} is one) or is zero if the bus service p is not in the solution (i.e., if y_{tp} is zero). Similarly, constraints (5) guarantee that for each demand scenario $u \in U$, the total demand of the requests offloaded on each bus stop $s \in S(p)$ of each bus service $p \in P(t)$ of each hub $t \in T$ is not higher than the bus stop offload capacity C_{tps} if the bus service p is in the solution (i.e., if y_{tp} is one) or is zero if the bus service p is not in the solution (i.e., if y_{tp} is zero).

Finally, constraints (6) and (7) are the domain constraints of the variables.

6.3. Problem resolution with heuristic algorithms

Heuristic algorithms are procedures that try to find a good solution in reasonable running time but without any guarantee that the best solution found at the end is the optimal one. To model a solution of BNPP, the set of all possible options for each request of each scenario that fulfil their delivery time window constraints is first computed. The set of options for request $k \in K_u$ of scenario $u \in U$ is identified as I_{uk} and each option $i = 1, 2, \dots, |I_{uk}|$ is defined as a 3-tuple in the form (t_i, p_i, s_i) indicating the hub t_i,, the bus service p_i and the bus stop s_i of the option. An option (t_i, p_i, s_i) is in set I_{uk} if:

$$A_{kt} = 1 \ \wedge \ E_k \leq H_{tps} + T_{ks} \leq L_k, \qquad , t = t_i \, , p = p_i \, , s = s_i$$

i.e., if hub t_i is one of the hubs where the request can be dropped by the client and if the arrival time of the bus service p_i on bus stop s_i plus the maximum delivery time of the LMO from bus stop s_i to the request's destination is within the delivery time window $[E_k, L_k]$. So, an operational planning solution is obtained by selecting one of the options in I_{uk} for each request $k \in K_u$ of each scenario $u \in U$ such that the capacities of all selected bus services and stops are met at each scenario.

In this section, two heuristic algorithms are proposed (Heuristic 1 and Heuristic 2), both based on GRASP, a metaheuristic first introduced in Feo & Resende (1989) and successfully applied to many optimization problems since then. A GRASP metaheuristic includes two basic procedures: a greedy randomized procedure that computes a random solution from scratch and an adaptive search procedure that tries to improve a given input solution to a better one.

The two algorithms proposed in this chapter use the same adaptive search procedure but are different in their greedy randomized procedure. The next subsections describe first the greedy randomized procedure used on each of the two algorithms; then the adaptive search procedure used in both algorithms and, finally, the two algorithms are described.

6.3.1. Greedy randomized procedure of Heuristic 1

The core idea of the greedy randomized procedure used in Heuristic 1 is to build a planning solution by iterating over all scenarios and, for each scenario, selecting one option to each request of the scenario giving preference to the options of the bus services previously selected both on the current scenario and on all previous scenarios. The procedure is as follows:

Heuristic 1 – Greedy Randomized Procedure

1. $Sol \leftarrow \{\}$
2. $SelectedBS \leftarrow \{\}$
3. **For** $p \in P$ **do**
4. n_p ← number of options that include bus service p in all sets I_{uk}
5. **EndFor**
6. **For** u = random($u \in U$) **do**
7.   **For** k = order($k \in K_u$) **do**
8.   (Sol, $SelectedBS$) ← BestOption(Sol, $SelectedBS$, I_{uk}, $\{n_p, p \in P\}$)
9.   **EndFor**
10. **EndFor**

Output(*Sol, SelectedBS*)

The procedure starts by considering an empty solution *Sol* (line 1) and an empty set of selected bus services *SelectedBS* (line 2). Then, parameter n_p is computed for each bus service $p \in P$ (lines 3–5) with the number of options that include bus service p in all sets I_{uk}. Note that a bus service with a higher value of n_p can potentially be assigned to more requests and, therefore, these values are used when a new bus service is to be selected. Then, the nested 'For' cycle (lines 6–10) iterates over all scenarios (line 6) and over all requests of each scenario (line 7) to select one option for each request (line 8).

The BestOption() procedure in line 8 is the key component of this greedy randomized procedure. It considers as input the current solution *Sol*, the current selected set of bus services *SelectedBS*, the set of options I_{uk} for the current request and the set of parameters n_p. If the current request can be assigned to multiple bus services in *SelectedBS*, it selects one option using the bus service in *SelectedBS* with the current lowest load (the load of a bus service is the sum of the demands of all requests assigned to it). The aim is to maintain as much free capacity as possible in all already selected bus services to maximize the probability of the requests not yet assigned to fit on one of them. Otherwise, it selects an option on the bus service p not in *SelectedBS* (i.e., not yet selected) with the highest value of n_p among the bus services included in the set of options I_{uk}. At the end, the procedure outputs solution *Sol* and its set of selected bus services *SelectedBS*.

In order to generate different solutions on each run of the procedure, the order by which the scenarios are iterated (line 6) is randomly selected. On the other hand, the order by which the requests of each scenario are iterated (line 7) has an impact on the algorithm efficiency. In general, the efficiency improves (i.e., either generates better solutions in the same running time or generates similar solutions in shorter running time) if the order is from the requests which are the hardest to be assigned to the requests which are the easiest to be assigned. There are two possible criteria. One criterion is to consider the requests ordered from the ones with the highest demand value (i.e., highest D_{uk} value) to the ones with the lowest demand value, as the requests with high demand are harder to fit in the already selected bus services. Another criterion is to consider the requests from the ones with the lowest number of options (i.e., lowest $|I_{uk}|$ value) to the ones with the highest number of options, as the requests with the lowest number of options have a lower probability to be assigned to the already selected bus services. The three following orders were tested:

(a) Order requests from the highest to the lowest demand value and, for the requests with the same demand value, order from the lowest to the highest number of options.

(b) Order requests from the lowest to the highest number of options and, for the requests with the same number of options, from the highest to the lowest demand values.

(c) Random order of the requests.

The preliminary computational tests have shown that case (b) provides the best efficiency on average and, therefore, the results reported in the computational results for Heuristic 1 only consider this case.

6.3.2. Greedy randomized procedure of Heuristic 2

The key idea of the greedy randomized procedure used in Heuristic 2 is to build a planning solution by selecting one bus service at a time and, for each selected bus service, assigning as much requests as possible in all scenarios until all requests of all scenarios have been assigned with one option each. The procedure is as follows:

Heuristic 2 – Greedy Randomized Procedure

Input(r)

1. $Sol \leftarrow \{\}$
2. $SelectedBS \leftarrow \{\}$
3. $tRequests \leftarrow$ total number of requests on sets K_u of all scenarios $u \in U$
4. **For** $u \in U$ **do**
5. $\widetilde{K}_u \leftarrow K_u$
6.   **For** $k = K_u$ **do**
7. $\tilde{I}_{uk} \leftarrow I_{uk}$
8.   **EndFor**
9. **EndFor**
10. **While** *Sol* is not complete **do**

11. $P' \leftarrow P \backslash SelectedBS$
12. **For** $p \in P'$ **do**
13. $n_p \leftarrow$ number of options that include bus service p in all sets $\tilde{I}_{uk}$
14. **EndFor**
15. $nRequests \leftarrow$ total number of requests on sets $\widetilde{K}_u$ of all scenarios $u \in U$
16. $r' \leftarrow \left\lceil r \times \frac{nRequests}{tRequests} \right\rceil$
17. $p \leftarrow$ random selection among the r' bus services in P' with the highest values of n_p
18. **For** $u \in U$ **do**
19. **For** $k =$ order($k \in \widetilde{K}_u$) **do**
20. (*Sol*, *Out*) $\leftarrow$ Assign(*Sol*, $\tilde{I}_{uk}$, p)
21. **If** *Out* = TRUE **do**
22. $\widetilde{K}_u \leftarrow \widetilde{K}_u \backslash \{k\}$
23. $\tilde{I}_{uk} \leftarrow \{\}$
24. **Else**
25. $\tilde{I}_{uk} \leftarrow$ eliminate from $\tilde{I}_{uk}$ the options using bus service p
26. **EndIf**
27. **EndFor**
28. **EndFor**
29. *SelectedBS* $\leftarrow$ *SelectedBS* $\cup \{p\}$
30. **EndWhile**

Output(*Sol, SelectedBS*)

The procedure has an input integer parameter r which is used to control the randomness of the generated solution when the procedure is run multiple times.

The procedure starts by considering an empty solution *Sol* (line 1) and an empty set of selected bus services *SelectedBS* (line 2). The variable *tRequests* is set with the total number of requests of all scenarios (line 3). Set $\widetilde{K}_u$ represents at any step of the algorithm the set of requests of each scenario that still do not have a selected option and set $\tilde{I}_{uk}$ represents at any step of the algorithm the available options of each request on each scenario. So, at the beginning (lines 4–9), the set $\widetilde{K}_u$ of each scenario is initialized with K_u and the set $\tilde{I}_{uk}$ of each request at each scenario is initialized with I_{uk}. Then, a 'While' cycle (lines 10–30) is run until solution *Sol* is complete (i.e., until *Sol* has one option selected to each request of each scenario).

Each 'While' cycle starts by computing set P' with all not yet selected bus services (line 11) and by computing a parameter n_p for each bus service in P' with the number of options that include bus service p in all sets $\tilde{I}_{uk}$ (lines 12–14). As in the case of heuristic 1, a bus service with a higher value of n_p can potentially be assigned to more requests and, therefore, these values are used next to select each new bus service. Then, an integer parameter r' is computed (line 16) as r (the input parameter) multiplied by the fraction of the requests that still do not have a selected option (computed in line 15 as variable *nRequests*) divided by the total number of requests *tRequests* and the resulting value rounded to the nearest integer greater than or equal to it. Then, a bus service p is randomly selected (line 17) among the r' bus services in P' (i.e., the bus services still not selected) with the highest values of n_p. Then , for each scenario $u \in U$ (line 18) and each request of $\widetilde{K}_u$ (line 19), the algorithm tries to assign one of the options in $\tilde{I}_{uk}$ using the selected bus p (line 20): the solution *Sol* is either updated with the selection of an option for the current request and the Boolean variable *Out* is returned as TRUE or solution *Sol* is returned unchanged and the variable *Out* is returned as FALSE. If *Out* is returned as TRUE (line 21), the current request k of the current scenario u is eliminated from $\widetilde{K}_u$ (line 22) and its set of options $\tilde{I}_{uk}$ becomes empty (line 23). Otherwise (line 24), all options in $\tilde{I}_{uk}$ using the selected bus service p are eliminated from $\tilde{I}_{uk}$ (line 25). Lastly, the selected bus service p is added to the set of already selected bus services *SelectedBS* (line 29). At the end, the procedure outputs solution *Sol* and its set of selected bus services *SelectedBS*.

The Assign() procedure in line 20 assigns the first option in $\tilde{I}_{uk}$ among the ones using bus service p such that neither the bus service capacity nor the bus stop capacity is violated and returns solution *Sol* updated with the selected option (together with the variable *Out* set as TRUE) or returns the input solution *Sol* unchanged (together with the variable *Out* set as FALSE) if either there is no option in $\tilde{I}_{uk}$ using bus service p or if none of the options can be selected without violating the bus service and bus stop capacities.

Note that, at the end of each 'While' cycle, the set of requests $\widetilde{K}_u$ of each scenario $u \in U$ only contains the requests that still not have a selected option (the other requests were eliminated in line 22). Moreover, the set of options $\tilde{I}_{uk}$ is either empty if the request k of scenario u has already one selected option (line 23) or it contains only options using not yet selected bus services (the other options were eliminated in line 25). So, in the next cycle, the computation of the parameters n_p with the number of options that include each bus service in P' (lines 12–14) takes into consideration only the options of the requests that still not have a selected option.

Similar to the greedy randomized procedure used in Heuristic 1, the order by which the requests of each scenario are iterated (line 19) has again an impact on the overall algorithm efficiency (recall the discussion in the previous algorithm). The conducted preliminary tests have confirmed for this procedure the same conclusions that have been previously described in the case of Heuristic 1: the best efficiency is obtained by considering, for each scenario, the requests ordered from the ones with the lowest number of options to the ones with the highest number of options and, for the requests with the same number of options, from the ones with the highest demand value to the ones with the lowest demand values. So, the results reported in the computational results for Heuristic 2 only consider this ordering case.

Finally, as already explained, the randomness of the solutions generated by the greedy randomized procedure is given by the parameter *r'* when selecting a new bus service (line 17) which is equal to the input value *r* in the first 'While' cycle and then decreases proportionally to the number of requests with selected options in the subsequent cycles. On standard GRASP approaches, though, a simpler strategy is usually used, which is to consider a fixed value of *r* in all cycles. The preliminary results have shown that the proposed approach is more efficient as using a large value of *r'* at the first cycles improves the diversity of the solutions provided by different runs of the procedure but in the last cycles of the procedure (when only a small portion of the requests still do not have selected options) it is important to select the next bus service among the very few ones with the best values of n_p.

6.3.3. Adaptive search procedure for both algorithms

In general, the adaptive search procedure of GRASP takes an input solution and tries to improve it, step by step, until no further improvement can be obtained. In BNPP, the aim is to obtain a solution that minimizes the number of selected bus services. So, the aim of the adaptive search procedure is to try to eliminate each bus service of the input solution, one by one, by changing the selected options using it to options using other bus services of the solution. This proposed Adaptive Search Procedure is significantly different from the standard approaches which usually apply local search methods (a multiple step algorithm where at each step the best among all neighbor solutions of a current solution is first computed and the current solution is replaced by the best neighbor solution if it is better moving to the next step, or the current solution is a local optimum solution and the algorithm stops). In BNPP, a neighbor is a solution where a current selected bus service can be eliminated. In this case, if it cannot be eliminated at the initial step, there is no need to compute again such neighbor solution, whatever the current solution is in the next steps. Moreover, all neighbor solutions that allow the elimination of one bus service represent the same objective value improvement and, therefore, the current solution is replaced as soon as a better neighbor solution is found. As a consequence, the proposed Adaptive Search Procedure runs much quicker than the traditional approach.

The procedure is as follows:

Adaptive Search Procedure

Input(*Sol, SelectedBS*)

Sol_final ← *Sol*

SelectedBS_final ← *SelectedBS*

For p = order(p ∈ *SelectedBS*) **do**

    Out ← TRUE

    For $u \in U$ **do**

        K_{pu} ← all requests of K_u whose selected option in *Sol* uses bus service p

        For $k \in K_{pu}$ **do**

            (*Sol*, *Out*) ← Eliminate(k, *Sol*, *SelectedBS*, $\tilde{I}_{uk}$, p)

            If *Out* = FALSE **do**

                Break

            EndIf

        EndFor

        If *Out* = FALSE **do**

            Break

        EndIf

    EndFor

    If *Out* = TRUE **do**

        Sol_final ← *Sol*

        SelectedBS_final ← *SelectedBS_final*\\{p}

    EndIf

EndFor

Output(*Sol_final, SelectedBS_final*)

The algorithm takes as input a given solution *Sol* and its set of selected bus services *SelectedBS* and starts by initializing the final solution *Sol_final* and its set of selected bus services *SelectedBS_final* with the input solution (lines 1–2). Then, a 'For' cycle iterates over all bus services p in *SelectedBS* (lines 3–21) by an order (line 3) which is discussed later.

In each 'For' cycle (lines 3–21), the Boolean variable *Out* is used to determine if bus service p can or cannot be eliminated and this variable is initially set with TRUE (line 4). Then, an inner 'For' cycle (lines 5–16) iterates over all scenarios (line 5) where the set of requests of the scenario using bus service p is first computed as set K_{pu} (line 6) and the options of the requests in K_{pu} are tried to be swapped with options using one of the other bus services in the solution (lines 7–12). The procedure Eliminate() in line 8 assigns the first option in $\tilde{I}_{uk}$ of request k among the ones using a bus service in *SelectedBS*$\setminus\{p\}$ such that neither the bus service capacity nor the bus stop capacity is violated and returns solution *Sol* updated with the swapped option (together with the variable *Out* set as TRUE) or returns the input solution *Sol* unchanged (together with the variable *Out* set as FALSE) if either there is no option in $\tilde{I}_{uk}$ using one of the bus services in *SelectedBS*$\setminus\{p\}$ or if none of the options can be selected without violating the bus service and bus stop capacities. So, at the end of the inner 'For' cycle (lines 5–16), the variable *Out* is either TRUE if bus service p was eliminated in all scenarios or FALSE, otherwise. Then, if *Out* is TRUE (line 17), the final solution *Sol_final* is updated with solution *Sol* and bus service p is eliminated from the final set of selected bus services (line 19). At the end, the procedure outputs solution *Sol_final* and its set of selected bus services *SelectedBS_final*.

Note that when the Eliminate() procedure returns *Out* as FALSE, there is no need to keep trying to eliminate the current bus service p in the remaining requests of the current scenario or in the remaining scenarios. In this case, the 'For' cycle of lines 7–12 is immediately terminated (lines 9–11) and the 'For' cycle of lines 5–16 is also immediately terminated (lines 13–15).

The order by which the bus services $p \in$ *SelectedBS* are iterated (line 3) influence the final solution obtained by the adaptive search procedure. The three following orders were tested: (i) from the bus service with the highest load to the bus service with the lowest load in the input solution *Sol*, (ii) from the bus service with the lowest load to the bus service with the highest load in the input solution *Sol* and (iii) selecting a random order. None of the three alternatives was the best in the preliminary tests since there were always a significant percentage of cases where each of the three alternatives was better than the other two. Moreover, the tests have shown that the running time of the adaptive search procedure is at most 2% of the running time of any of the two previously described greedy randomized procedures. So, in both algorithms (described next), when a solution is to be improved, instead of running a single adaptive search procedure, the adaptive search procedure is run 6 times: the first time with the first order, the second time with the second order and the 4 additional times with a random order.

6.3.4. Algorithm of Heuristic 1 and Heuristic 2

The general GRASP algorithm used in both proposed algorithms (Heuristic 1 and Heuristic 2) is as follows:

GRASP algorithm of Heuristic 1 and Heuristic 2

Input(*MaxTime*)

1. $b \leftarrow |S|$

2. **While** ruuning time < *MaxTime* **do**
3.   (*Sol, SelectedBS)* ← GreedyRandomizedProcedure()
4.   **For** *i* = 1, 2, 3, …, 6 **do**
5.   (*Sol_aux*, *SelectedBS_aux*) ← AdaptiveSearchProcedure(*Sol, SelectedBS*)
6.   *aux* ← | *SelectedBS_aux* |
7.   **If** *aux* < *b* **do**
8.   *Sol_best* ← *Sol_aux*
9.   *SelectedBS_best* ← *SelectedBS_aux*
10.   *b* ← *aux*
11.   **EndIf**
12.   **EndFor**
13. **EndWhile**
Output(*Sol_best*, *SelectedBS_best, b*)

The algorithm takes as input the maximum decision time *MaxTime*. The integer variable *b* is used to compute the number of selected bus services of the best solution and, therefore, is initialized with the total number of bus services (line 1). Then, the 'While' cycle (lines 2–13) runs while the running time does not reach *MaxTime* (line 2). On each cycle, a solution *Sol* (and its set of selected bus services *SelectedBS*) is first computed by the greedy randomized procedure (line 3). Then, the adaptive search procedure is run 6 times (lines 4–12) with the same input solution *Sol* (line 5) – recall the discussion at the end of the previous section. The number of selected bus services of each *Sol_aux* outputted by each run of the adaptive search procedure (line 5) is computed in variable *aux* (line 6). If value of *aux* is lower than the number of selected bus services of the best solution found so far (line 7), the best solution *Sol_best* is updated (line 8), together with its set of selected bus services *SelectedBS_best* (line 9) and its number of selected bus services *b* (line 10). At the end, the algorithm outputs the best-found solutions *Sol_best*, its set of selected bus services *SelectedBS_best* and its number of selected bus services *b*.

The Heuristic 1 algorithm is obtained by using in line 3 of the GRASP algorithm the Greedy Randomized procedure previously described for Heuristic 1. The Heuristic 2 algorithm is obtained by using the Greedy Randomized procedure previously described for Heuristic 2, which, in this case, requires the input parameter *r* that controls the randomness of the generated solutions.

6.4. Instances dataset generation

Recall that the last mile delivery process is performed by the LMO, which is responsible to offload the requests at the bus stops and deliver them to the final customer destination addresses, within the time window of each request. The considered problem instances assume that the LMO partitions the city center in different destination zones and defines a maximum delivery time to deliver any request from each bus stop to each zone. All problem instances consider the city center geometry with 9 destination zones shown in Figure *20*. Moreover, there are 22 bus stops labelled from 2 to 23 (their location within each zone is also show in Figure 1) and 2 bus hubs located outside the city center labelled as 1 and 24.

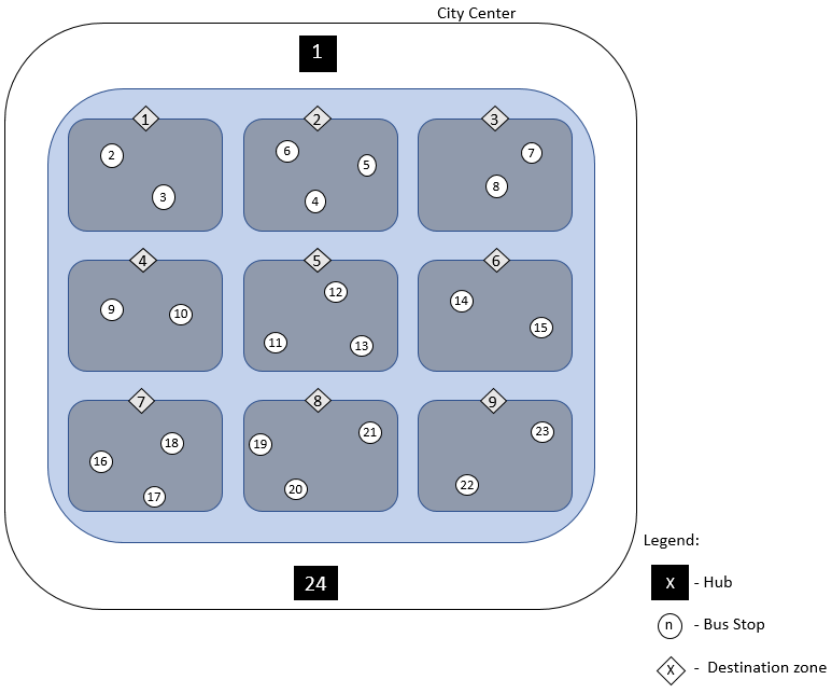

Figure 20 - Bus hubs, bus stops and city center destination zones of BNPP

Depending on the type of vehicles used by the LMO (bicycles vs. motorcycles vs. vans), the mobility constraints in the city center (one-way streets, pedestrian streets) and/or the geographical area of the zones, the existing LMO might impose different delivery constraints on its delivery service. In order to assess the impact of different LMO constraints, three possible cases were considered:

1. The LMO accepts to offload requests only from bus stops located in the same destination zone of the requests' destination addresses.
2. The LMO accepts to offload requests only from bus stops located either in the destination zone of the requests' destination addresses or in one of the neighboring zones. Consider the following three examples in Figure *20*: a request offloaded on bus stops 2 or 3 can only be to a destination address in zones 1, 2, 4 or 5; a request offloaded on bus stops 9 or 10 can only be to a destination address of the zones 1, 2, 4, 5, 7 or 8; finally, a request offloaded on bus stops 11, 12 or 13 can be to any destination address as in this case the neighbor zones of zone 5 are all other zones.
3. The LMO accepts to offload requests from any bus stop to any destination address.

In all cases, the LMO maximum delivery time is 30 minutes from any bus stop to any address located in the same zone of the stop of the offload. In case 2 and case 3, the LMO maximum delivery time is 45 minutes from any bus stop to an address of a neighbor zone of the stop. In case 3, the LMO maximum delivery time is 60 minutes from any stop to an address of a zone that is neither the zone of the stop nor one of its neighbor zones. Neighbor zones are pairs of zones that are adjacent (on Figure *20*, zone 1 is neighbor of zone 2, 4 and 5, for example).

In general, the LMO defines a daily activity period and imposes its constraints concerning the delivery time windows they can accept for their last mile delivery process. First, all problem instances consider a daily activity period of 12 hours starting at 8:00 and ending at 20:00 where the delivery time window $[E_{uk}, L_{uk}]$ imposed by the LMO for any request of any scenario must have a duration of 3 hours (i.e., $L_{uk} - E_{uk} = 3$ hours). As a consequence, the earliest and latest delivery windows that can be accepted for any request are [8:00 11:00] and [17:00-20:00]. The problem instances considering these constraints are referred to as having a 'random' time window type since the requested windows can be freely selected between these time window limits. Moreover, for internal organization of the daily deliveries, the LMO can have an additional requirement imposing the delivery time windows to be only one of a possible set of disjoint time windows. To access the impact of this additional LMO constraint, it is considered the case where the delivery time window imposed by the LMO for any request must be only one of the four possible options: [8:00-11:00], [11:00-14:00], [14:00-17:00] [17:00-20:00] and the problem instances considering these constraints are referred to as having a 'clustered' time window type.

The bus network used for all instances has 96 bus services: 48 services departing from bus hub 1 and 48 services departing from hub 24. From each hub, the bus services include three different routes which are used sixteen times in one day, with an interval of 45 minutes for each route. For consecutive routes, the time difference of departure time is 15 minutes. Table *38* details the three different routes departing from each bus hub. In all bus services, the time difference between the bus departure from the hub and the instant of arriving to the first stop is 30 minutes and the time difference between arrivals on consecutive stops is 10 minutes.

Table 38- Bus service routes departing from each bus hub of the city

Hub	**Bus route**	**Departure time**	**Route description**	**Hub**	**Bus route**	**Departure time**	**Route description**
1	1	06:30	1-2-3-4-5-8-7-1	24	1	06:30	24-22-23-21-19-18-16-24
1	2	06:45	1-2-9-10-11-13-14-15-8-1	24	2	06:45	24-22-15-14-12-11-10-9-17-24
1	3	07:00	1-3-10-16-17-19-20-22-23-15-7-1	24	3	07:00	24-23-14-7-8-5-6-3-2-9-18-24

The freight capacity of all bus services prepared for the combined transportation of passengers and freight is 12 parcels, and the offload capacity of all stops is 6 parcels.

On each problem instance, the demand uncertainty is modelled by a set of scenarios U where the set of requests K_u of each scenario $u \in U$ are computed in the following way:

1. The demand of each request is randomly generated as 1, 2 or 3 parcels, with probabilities 0.5, 0.3 and 0.2, respectively. The motivation to select these probabilities is the fact that, for this type of business and integrated flow, it is expected more requests of single parcels and less requests of multiple parcels.
2. The destination zone of each request is randomly generated as an integer between 1 and 9 with given probabilities p_i, with $1 \leq i \leq 9$. Different sets of probability values are presented as Cases in Table *39*. In case A, all requests have their destination zone equally distributed in the city. In cases B and C, most of the requests are for the central zone 5 of the city (recall Figure *20*). In cases D and E, most of the requests are for the corner zone 1 of the city center. In cases F and G, there are much more requests for zones 1, 2 4 and 5 when compared to the remaining zones. The aim is to assess the impact of different distributions of the destination addresses among the different destination zones in the solutions of the planning problem.
3. The delivery time window of each request is randomly generated with a fixed width of 3 hours. First, in the instances considering 'random' time windows, the time window is randomly generated with a uniform distribution between [8:00 11:00] and [17:00-20:00].

Then, for each of these instances, an instance considering 'clustered' time windows is generated by shitting the previous randomly generated delivery time window to the nearest option among the 4 possible ones: [8:00-11:00], [11:00-14:00], [14:00-17:00] [17:00-20:00].

Table 39 – Requests' zone probabilities for each case

Cases	Destination Zones								
	1	2	3	4	5	6	7	8	9
A	11,1%	11,1%	11,1%	11,1%	11,1%	11,1%	11,1%	11,1%	11,1%
B	10,0%	10,0%	10,0%	10,0%	20,0%	10,0%	10,0%	10,0%	10,0%
C	7,5%	7,5%	7,5%	7,5%	40,0%	7,5%	7,5%	7,5%	7,5%
D	20,0%	10,0%	10,0%	10,0%	10,0%	10,0%	10,0%	10,0%	10,0%
E	40,0%	7,5%	7,5%	7,5%	7,5%	7,5%	7,5%	7,5%	7,5%
F	15,0%	15,0%	8,0%	15,0%	15,0%	8,0%	8,0%	8,0%	8,0%
G	20,0%	20,0%	4,0%	20,0%	20,0%	4,0%	4,0%	4,0%	4,0%

6.5. Computational experiments

Concerning the computational experiments for the exact methods, the ILP model was solved by CPLEX Studio IDE 12.0 with a runtime limit of 1 hour (3600 seconds). Like many other solvers, CPLEX includes a default pre-processing phase that analyses the input problem and adds symmetry breaking constraints in order to improve its resolution time of the resulting model. After some preliminary tests with the symmetry detection option of CPLEX turned on, in some cases the solver took more than 1600 seconds in the pre-processing phase. The same tests without the symmetry breaking detection option showed that, in the hardest problem instances, the performance of the solver becomes worst with this option (i.e., either it takes longer times to find the optimal solution or it ends with a worse solution when the runtime limit is reached). For this reason, all the results for the ILP model presented next do not consider the symmetry breaking detection option.

For the heuristic algorithms, Heuristic 1 (H1) and Heuristic 2 (H2) were run with a runtime limit of 10 minutes (600 seconds) and H2 was run with parameter r = 10, since in the preliminary tests the best results were obtained when r is around 10% of the total number of buses (96 buses). In the results presented next, time values associated to the heuristics are the runtime instants when the best solution was found by the respective heuristic.

A first evaluation of the results obtained by the three methods (the exact method and the two heuristics) is presented based on problem instances where the demand uncertainty considers a set of $|U|$=10 scenarios (small enough to guarantee that the exact method always finds the optimal solution). This first evaluation considers only instances where the destination addresses of the requests are equally distributed among all 9 zones (case A in *Table 39*) and the number of requests per scenario is 50, 100 or 150. Table *40* presents the results for the instances with 'random' time windows while Table *41* presents the results for the instances with 'clustered' time window. In these tables, "ILP" indicates the solution value (i.e., the number of selected bus services) found by the solver, "H1" indicates the solution value found by the Heuristic 1 and "H2" indicates the solution value found by Heuristic 2. Moreover, column "U" indicates the number of demand scenarios, column "K" indicates the number of requests per scenario, column "LMO" indicates the type of LMO delivery process and column "TW" indicates the type of delivery time windows. For each instance, the best among the two heuristic methods (H1 or H2) is highlighted in bold, where the best means that the method that has obtained either the best solution value or a solution with the same value found in a shorter runtime.

Table 40 - Computational results of the three optimization methods with random time windows

Case	U	K	LMO	TW	ILP	Time (s)	H1	Time (s)	H2	Time(s)
A	10	50	1	Random	17	1.5	20	3.1	**18**	**93.6**
A	10	50	2	Random	10	71.8	11	11.8	**11**	**4.3**
A	10	50	3	Random	10	12.6	**10**	**2.5**	10	21.6
A	10	100	1	Random	20	44.4	**23**	**3.2**	24	1.92
A	10	100	2	Random	17	33.3	17	54.1	**17**	**17.5**
A	10	100	3	Random	17	20.9	17	38.6	**17**	**1.3**
A	10	150	1	Random	24	407.1	**28**	**347.0**	29	293.3
A	10	150	2	Random	24	123.8	**25**	**4.2**	25	6.8
A	10	150	3	Random	24	84.1	**24**	**82.6**	24	84.4

Table 41 - Computational results of the three optimization methods with “clustered” time windows

Case	U	K	LMO	TW	ILP	Time (s)	H1	Time (s)	H2	Time(s)
A	10	50	1	Clustered	20	1.1	**20**	**1.2**	21	95.9
A	10	50	2	Clustered	10	12.9	**11**	**2.8**	11	3.6
A	10	50	3	Clustered	10	6.9	**10**	**15.6**	10	574.4
A	10	100	1	Clustered	21	8.3	**22**	**5.2**	24	13.4
A	10	100	2	Clustered	17	110.1	**17**	**90.0**	18	45.6
A	10	100	3	Clustered	17	30.1	**17**	**13.9**	17	16.2
A	10	150	1	Clustered	24	358.2	**27**	**2.8**	29	2.1
A	10	150	2	Clustered	24	27.0	25	168.6	**25**	**7.6**
A	10	150	3	Clustered	24	239.9	**24**	**20.6**	24	365.3

In these instances, the exact method obtained the optimal solution of all instances with the hardest cases solved under 7 minutes. The results of H1 and H2 suggest that the heuristic methods are efficient for the instances with the LMO processes 2 or 3, since they either obtain the optimal value provided by the exact method (in number of buses needed to transport all requests) or one more bus than the optimal value, requiring in general less runtime than the exact method to find their solutions.

On the other hand, for the instances with the LMO process 1, the results suggest that the heuristics methods are not efficient, since in some cases the best found solution has a gap of 20% to the optimal value obtained by the ILP. These observations are justified as follows. In the LMO process 1, the number of bus services and bus stops that can be assigned to each request is very limited, which makes the ILP model to be more efficiently solved by CPLEX (as it contains a smaller number of variables), while it makes harder the heuristic methods to find good solutions. In the LMO processes 2 and 3, the number of variables of the ILP model grows significantly making its resolution harder (although in these instances, all ILP models were solved to optimality) while the number of possible services and bus stops that can be assigned to the requests becomes larger enabling the heuristic methods to find optimal or near optimal solutions.

In general, the larger the number of scenarios is, the more robust the solution becomes (to demand uncertainty) but there is a limit beyond which the optimal solution value does not change. After preliminary tests, it was concluded that such limit is 100 scenarios for the BNPP. The next tables present the results of the three methods for the same cases as the previous tables but with problem instances where the demand uncertainty considers a set of $|U|$=100 scenarios. First, Table *42* and Table *43* present the computational results only for LMO process 1 (the meaning of each column is the same as in the previous tables). In these tables (and next ones), when the ILP model was not solved to the optimality within the time limit, the results are shown as [LB UB], where LB is a Lower Bound of the optimal number of bus services (based on the lower bound provided by CPLEX at the end of its execution) and UB is the number of the bus services of the best solution found by CPLEX (which is by definition an Upper Bound of the optimal value).

Table 42 - Results of instances only for LMO process 1 and random time windows, for each optimization method

Case	U	K	LMO	TW	ILP	Time (s)	H1	Time (s)	H2	Time(s)
A	100	50	1	Rand	22	25.7	24	3.8	**23**	**80.5**
A	100	100	1	Rand	22	129.2	**25**	**302.8**	27	137.9
A	100	150	1	Rand	[25-44]	3600	**30**	**432.9**	31	177.6
A	100	150	1	Rand	[25-26]	14400	**30**	**432.9**	31	177.6

Table 43 - Results of instances only for LMO process 1 and "clustered time windows, for each optimization method

Case	U	K	LMO	TW	ILP	Time (s)	H1	Time (s)	H2	Time(s)
A	100	50	1	Clustered	20	38.8	**20**	**12.8**	21	220.7
A	100	100	1	Clustered	[23-24]	3600	27	13.0	**26**	**136.4**
A	100	150	1	Clustered	[24-33]	3600	**31**	**29.0**	31	144.0
A	100	150	1	Clustered	25	14201	**31**	**29.0**	31	144.0

In these instances, with 100 scenarios, the results show that the exact method obtains the optimal solution for the problem instances with 50 requests per scenario and at least near optimal solutions for 100 requests per scenario. However, for 150 requests per scenario, the gaps between the LB and the UB are very high. As an attempt to reduce these gaps, these instances were solved a second time with a runtime limit of 4 hours (14400 seconds), whose results are also shown in these tables highlighted in grey. The results obtained in this second run reduce the gap from 76% to 4% in the case of 'random' time windows and from a gap of 37.5% to the optimal solution in the case of 'clustered' time windows. Moreover, these results confirm the previous results that the heuristic methods (both H1 and H2) are not efficient to solve the instances with LMO process 1 (the difference to the solution values found using exact methods is still high). Thus, the exact method is the more efficient method to solve instances with LMO process type 1.

Note that the heuristic methods H1 and H2 are randomized methods that can find different solutions in different runs. Therefore, to obtain the next results, each heuristic method was run 10 times. The results obtained by the three methods on the instances with 100 scenarios and LMO process 2 and 3 are presented in Table *44* (for the instances with 'random' time windows) and Table *45* (for the instances with 'clustered' time windows). In these tables, the results of the heuristics are the best value (in number of bus services) among the 10 runs, the average of the 10 solution values, the standard deviation of the 10 solution values and the average running time to find the 10 solutions. On each case, the best average value between heuristic H1 and heuristic H2 is highlighted in bold.

The results of Table *44* show that H2 is the best method for the instances with 'random' time windows since the average values found for the 10 runs are always lower than the results of H1. Moreover, the average values found by H2 are very close to the lower bounds provided by the exact method. On the other hand, the results of Table *45* show that H1 is the best method to solve the instances with 'clustered' time windows since the average values are always better than the results of H2. Moreover, the average values found by H1 are very close to the lower bounds provided by the exact method. Finally, both heuristics perform better than the exact method since their average values are lower than the value of the exact method in almost all cases with much shorter running times.

Table 44 - Results for instances of Case A with 100 scenarios and LMO process 2 and 3 for random time windows

K	LMO	ILP		H1				H2			
		ILP	Runtime (s)	Best Value	Avg. Value	Std. Dev	Avg. Runtime	Best Value	Avg. Value	Std. Dev	Avg. Runtime
50	2	[10-13]	3600	12	12	0	39.79	11	**11.5**	0.53	163.71
50	3	[10-12]	3600	11	11	0	22.45	10	**10.9**	0.31	66.162
100	2	[17-29]	3600	18	18.5	0.53	162.28	18	**18.1**	0.32	163.20
100	3	[17-18]	3600	18	18	0	218.191	17	**17.2**	0.42	221.20
150	2	[24-56]	3600	25	25.8	0.42	207.70	25	**25.5**	0.53	127.12
150	3	[24-31]	3600	25	25.6	0.52	161.06	25	**25**	0	79.96

Table 45 - Results for instances of Case A with 100 scenarios and LMO process 2 and 3 for clustered time windows

K	LMO	ILP		H1				H2			
		ILP	Runtime (s)	Best Value	Avg. Value	Std. Dev	Avg. Runtime	Best Value	Avg. Value	Std. Dev	Avg. Runtime
50	2	10	2784	11	**11**	0	39.79	11	11.9	0.32	123.71
50	3	10	3552	11	**11.1**	0.32	22.45	11	11.4	0.52	189.17
100	2	[17-21]	3600	18	**18.3**	0.48	162.28	19	19.6	0.52	139.76
100	3	[17-19]	3600	18	**18**	0	218.191	18	18.7	0.67	224.68
150	2	[24-32]	3600	26	**26.4**	0.52	207.70	27	27.1	0.32	245.68
150	3	[24-29]	3600	25	**25**	0	161.06	26	26.1	0.32	261.27

To determine if there are significant statistical differences between the results of heuristic H1 and heuristic H2 (in terms of average solution values and average runtimes), a Paired sample T-test was conducted (Kent State University Libraries, 2022). First, the data was tested in SPSS and the results have shown that the data is normally distributed, random, and similar spread between variables and the variables of interest are continuous, which are the assumptions required for the validity of the Paired sample T-test.

Concerning the results related to the 'random' time windows instances (Table *44*), the results of paired samples T-Test indicate that the average solution values obtained by H1 and H2 are statistically different from each other (since in Table *46* the *P1* value is lower than 0.05), while there are no significant differences between the two heuristics concerning the average running times (*P2* value is higher than 0.05 in Table *46*). Moreover, because of the small dimension of the samples, the non-parametric Wilcoxon test (matched samples) was also used with this data. Results agreed with the T-Test, namely rejecting the equality of the medians (p1-value = 0,028) between the average solution values obtained by H1 and H2, and not rejecting the equality of medians (p2-value = 0,753) between the average running times of H1 and H2. These results indicate that H2 computes statistically better solutions than H1 in similar running times.

Concerning the results related to the ‘clustered’ time windows instances (Table *45*), the results of paired samples T-Test indicate that the average solution values obtained by H1 and H2 are also statistically different from each other (since in

Table 47 the *P1* value is lower than 0.05) and, again, there are no significant differences between the average running times of the two heuristics (*P2* value is higher than 0.05 in

Table 47). These results indicate that H1 computes statistically better solutions than H2 in similar running times.

Next, the computational results of all cases (defined in Table *39*) are presented in Table *48* (where the previous results obtained for Case A are repeated for comparison reasons). In these results, the previous conclusions were used to select the best method for each problem instance as indicated in column “Method” of Table *48*. Columns “Case A”, “Case B”, …, “Case F” and “Case G” indicates the value of the solution obtained for each problem instance in number bus services needed to transport all requests of all 100 scenarios.

Table 46 - Paired samples T-Test for average solution values between H1 and H2, for random time windows

K	LMO	H1	H2	H1	H2
		Average Solution Value for 10 runs	Average Solution Value for 10 runs	Average runtime for 10 runs	Average runtime for 10 runs
50	2	12,00	11,50	39,79	163,61
50	3	11,00	10,90	22,45	66,16
100	2	18,50	18,10	162,28	163,20
100	3	18,00	17,20	218,19	221,20
150	2	25,80	25,50	207,70	127,12
150	3	25,60	25,00	161,06	79,96
p value			P1=0.006		P2=0.961

Table 47 - Paired samples T-Test for average solution values between H1 and H2, for clustered time windows

K	LMO	H1	H2	H1	H2
		Average Solution Value for 10 runs (buses)	Average Solution Value for 10 runs (buses)	Average runtime for 10 runs (seconds)	Average runtime for 10 runs (seconds)
50	2	11,00	11,90	14,01	123,71
50	3	11,10	11,40	82,50	189,17
100	2	18,30	19,60	207,90	139,76
100	3	18,00	18,70	44,20	224,68
150	2	26,40	27,10	177,16	245,68
150	3	25,00	26,10	197,54	261,27

p value	P1=0.002		P2=0.071

Table 48 - Results of the all instances solved by the best method for each instance type

U	K	LMO	TW	Method	Case A	Case B	Case C	Case D	Case E	Case F	Case G
100	50	1	Rand	ILP	22	22	22	22	21	22	22
100	50	2	Rand	H2	12	11	11	11	11	11	11
100	50	3	Rand	H2	11	10	10	10	10	10	10
100	100	1	Rand	ILP	22	22	24	22	22	22	22
100	100	2	Rand	H2	18	19	19	18	18	18	18
100	100	3	Rand	H2	18	18	18	17	17	17	17
100	150	1	Rand	ILP	[25-26]	[24-26]	27	24	[25-26]	[24-26]	[24-27]
100	150	2	Rand	H2	26	25	25	25	25	25	25
100	150	3	Rand	H2	25	25	25	25	24	25	25
100	50	1	Clust	ILP	20	20	23	20	21	21	20
100	50	2	Clust	H1	11	11	11	11	10	10	11
100	50	3	Clust	H1	10	10	10	10	10	9	9
100	100	1	Clust	ILP	[23-24]	22	28	23	[22-23]	22	23
100	100	2	Clust	H1	18	18	18	18	18	18	18
100	100	3	Clust	H1	18	18	19	17	18	18	18
100	150	1	Clust	ILP	25	[25-27]	33	25	29	[25-27]	26
100	150	2	Clust	H1	26	26	26	27	27	27	26
100	150	3	Clust	H1	25	26	26	25	25	25	26

The results show that for the instances with 50 requests, the LMO process significantly impacts the number of required bus services needed to transport requests, since on average, there is a reduction around 50% on the number of required bus services changing the LMO process from 1 to 3. For the instances with 100 requests, the LMO process still impacts the number of required bus services, but the reduction when LMO process is changed from 1 to 3 is significantly lower (around 20%). For the instances of 150 requests, the impact of the different LMO processes is negligible, since the reduction of required bus services changing the LMO process from 1 to 3 is around 4% for instances with 'random' time windows and is around 6%, and 9% for instances with 'clustered' time windows.

There are some cases, highlighted in grey in the Table *48*, where the value of the solution found for an instance with the LMO process 2 is higher than the value of the solution for the equivalent instance with the LMO process 1 (this can happen as these results are obtained with heuristics which do not guarantee that the found solutions are optimal). In these cases, the first value can be replaced with the second value, since a solution for an instance using the LMO process 1 is also a valid solution for the instance using the LMO process 2. The same replacement can be applied between the instances using the LMO process 3 when compared to the equivalent instances using LMO process 2.

Recall that Case A considers that all 9 zones have the same probability of being the destination zones of the request. On the other hand, the cases C, E and G are the cases where the probabilities between the 9 zones are more unbalanced. Comparing Case C (where the requests have a probability of 40% to be destinated to the central zone 5) with Case A, for the instances with 50 requests and 'random' time windows, the number of required bus services in Case C is either the same or even one bus less than the required number of bus services in Case A. For the equivalent instances with 100 or 150 requests, the number of required bus services start to increase (except in the instance with 100 requests and the LMO process 2, with one bus less). For instances based on Case C, with 'clustered' time windows, the number of required bus services is always higher when the LMO process is 1 and the same or one more bus to the LMO process 2 and process 3. Note that for Case C, as 40% of requests have the central destination zone as their destination, for these requests the LMO process 2 is equivalent to LMO process 3 (as all other zones are neighbor zones of the central zone 5), and therefore the results are expected to be similar.

Comparing the instances of Case E (where requests have a probability of 40% to be destinated to a zone located in a corner of the city center), for 'random' time windows, with the equivalent instances based on Case A, the results show that the number of required bus services for Case E is always lower or the same value of the number of required bus services on the equivalent instances of Case A. For the equivalent instances with 'clustered' time windows, the results show that for a large set of requests and using LMO process 1 and 2, the number of required bus services is increased compared to the instances of Case A.

Regarding the instances of Case G, where requests have more probability to go to a subset of zones in the city center, the results show that for instances of 150 requests using the LMO process 1, the obtained value of required buses is one more when compared to case A. Additionally, compared to case A, one less bus is required for the instances with 'random' time windows using the LMO process 2 and the number of required buses is the same for instances with the LMO process 3. For the equivalent instances with 'clustered' time windows, one additional bus is required for all LMO processes when compared with the number of required buses in the equivalent instances of Case A.

6.6. Chapter resume and conclusion

This chapter contributes to the literature with a new approach to the integration of passenger and freight flows in the field of UL, studying the strategic BNPP. The study of Azcuy et al. (2021), is the most similar comparing to BNPP problem, since they address a strategic problem in the field of UL with uncertainty in the customer locations and use a scenario based approach to solve it. Nevertheless, the present study goes a step further, since in the test instances, a network with two depots and three transit lines is considered, while their study considers a stylized system for a single depot and a single transit line. Moreover, uncertainty widely addressed, by incorporating it in more parameters, and also consider a higher number of scenarios. While Azcuy et al. (2021) consider the uncertainty in customer locations, the work of this chapter addresses uncertainty in final customer locations, demands and delivery time windows, and uses 100 scenario realizations instead of only 10 in their work. Combining all these aspects, the findings of this work bring novelty to the UL field. In the overall, the main findings of the obtained results and their analysis are:

- All proposed optimization methods (the exact method and the two heuristics H1 and H2) are of interest in practice to solve the addressed Bus Network Planning optimization problem since it was clearly identified the type of instances characteristics for which each method is more efficient.
- The LMO constraints concerning the delivery between different destination zones have a huge impact on the required number of buses in the early stages of the integrated passenger and freight flows service: when the number of requests is 50 per day, the LMO process 1 (the most constraining case) requires much more bus services than the LMO process 3 (the least constraining case) and the difference between the two LMO processes becomes small for 100 requests per day and negligible for 150 requests per day.
- The LMO constraints concerning delivery time windows do not have a significant impact on the required number of bus services, as the differences between the instances with ‘random’ time windows and with ‘clustered’ time windows are small for all cases.
- Different distributions of destination addresses among the different destination zones (modelled by Case A, Case B, …) also do not have a significant impact on the required number of bus services as the differences between the instances of the different cases are small.

7. Conclusion

This chapter closes the present dissertation. It begins with an overview about the Urban Logistics concept under research. Then, the research contributions for each chapter are discussed. Lastly, limitations and future research are outlined.

7.1. Thesis overview

In conclusion, this PhD dissertation underscores the importance of efficient urban logistics solutions in addressing the contemporary challenges posed by the ever-expanding urban environments. In a world where urbanization continues to surge, the integrated flow of goods into city centers has become an imperative for sustaining economic growth, reducing environmental impacts, and enhancing the overall quality of urban life. Thus, one groundbreaking approach that has emerged is the integration of passenger and freight flows within urban areas. In a society increasingly driven by interconnectedness, it is only fitting to harness this synergy to revolutionize the way goods are transported into city centers. The research presented has demonstrated that by optimizing the utilization of existing resources, particularly the spare capacity of buses, it is possible to alleviate the burden placed upon city centers by the abundant presence of vans and trucks.

The concept of utilizing public transportation networks for freight transport not only minimizes the congestion and pollution typically associated with goods delivery but also promises to enhance the overall efficiency of urban logistics operations. Embracing this integrated approach can unlock the full potential of urban transportation systems, making them more sustainable and environmentally friendly.

This thesis proposes "Models and methods to support decision making in urban logistics context", studying the integration of passenger flows to propose a new urban logistics solution to transport goods to city centers. The research was done in the scope of the SOLFI project, with the main contributions outlined in the next section.

7.2. Summary of contributions

In what follows, it is presented a summary of the contributions throughout the Chapters *2, 4, 5, 6*.

7.2.1. Systematic literature review on urban logistics problems addressing integrated flows

In Section *2.4* of Chapter *2*, a SLR was conducted to gather and discuss the existing literature that uses Operational Research models and methods in the field of Urban Logistics, particularly addressing integrated passenger and freight flows.

The results of this review contributed to the understanding of the research gap in the literature and how the researchers are addressing this topic. Thus, an analysis of the review results was performed to respond to the RQ1:

How have researchers addressed the Urban Logistics integration of passenger and freight flows problem from an operational research perspective?

Even though there are several researches in the field of Urban Logistics, the integration of passenger and freight flows is a relatively new topic under investigation, as the results suggested. Table *4* presented in section *2.4,* summarized the characteristics of the main relevant researches on this topic. Regarding to RQ1, the following conclusions could be made about the state-of-the-art:

1. Researches about the integration of passenger and freight flows, using OR models and methods is relatively scarce, but trending in recent years;
2. The majority of the research addresses the topic from the operational planning point of view, such as tackling the routing of the transport vehicles and assigning the demand to the vehicles;
3. Few researchers address uncertainty on their problems to model the problem data and parameters;
4. None robust approach was found in the operational layer of integrating passenger and freight flows, which is one of the main contributions in the present research for the FNFAP problem.

By performing this review, an overview of how these problems is being tackled in the literature could be obtained, as well as the gaps to be filled could be identified.

7.2.2. Integrating stakeholders' expectations into the integrated transportation system

In Chapter 4, qualitative and quantitative research methodologies were utilized to analyze the stakeholders' requirements for the integrated transportation system. The research done on this thesis was based on the SOLFI project, which included a variety of stakeholders with varying viewpoints and needs for such an integrated transportation system. Therefore, the primary purpose of Chapter 4 was to collect all of the needs and anticipate potential conflicts while designing and developing the integrated transportation system, guaranteeing that the adoption of the integrated solution by stakeholders would be facilitated.

Firstly, a questionnaire was developed and shared with potential final customers of the integrated transportation solution, resulting in a total of 302 respondents. The main results obtained from this questionnaire are threefold: i) the majority of the material purchased online, nowadays, by the respondents is clothes and footwear, which can be transported by the SOLFI system (small orders with low volume and weight); ii) currently, the respondents' preference is to receive their orders at their domicile residence; iii) nevertheless, respondents are willing to accept the use of new conveniences on their delivery process when purchasing online, such as collecting their packages at a neighbor store or smart lockers, even if the price of the delivery increases. These three main conclusions were considered on the problems addressed as requirements/expectations of the final customers.

Secondly, three semi-structured interviews were conducted with three key stakeholders of the SOLFI project: a logistic company, the bus BTO and the LMO. The goal for these interviews was to understand their requirements and constraints to use the integrated transportation system, to build a flexible solution appropriate in those stakeholders' operations. The interviews were different, however with similar questions to understand the different perspectives about the same constraint of the problem.

With the research done on this chapter, it was possible to answer the RQ2:

How can an urban logistics transport system that integrates passenger and freight flows be enriched for real world contexts?

Analyzing the results of the responses for the questionnaire and interviews, allowed to understand the realistic constraints and demands of the different stakeholders, translating them into the assumptions and parameters for the problems formulations, and the structure of data needed for the instances to solve the developed models. These findings are summarized on the Table *8* of this thesis.

7.2.3. Operational approach for the Freight Network Flow Assignment Problem (FNFAP)

The operational approach for the FNFAP was studied in Chapter 5. The main goal of this problem was developing models to obtain operational solutions for the integrated passenger and freight transportation. An operational solution is achieved when three decisions are made: (i) Assign each request to a bus hub where bus services depart from; (ii) Assign the request to a bus service starting on the assigned hub; and (iii) Assign the request to a bus stop of the assigned bus service, to be offloaded by the LMO and delivered at final customer destination.

Different models are proposed according to the objective function of interest to be optimized on each model. One of the key novel points of the research on the scope of FNFAP problem, is the incorporation of robustness to deal with disruptions that can occur on real world application. Two disruptions were considered: i) when a bus service is planned to transport passengers and requests and it is suppressed in short notice; ii) When the last mile offload of a request at the bus stop is not conducted by the LMO, and the requests are not collected from the buses. Therefore, RQ3 was fulfilled with the research done in this chapter:

How to address uncertainty and robustness in an urban logistics transport system that integrates of passenger and freight flows?

By addressing the robustness to deal with the mentioned disruptions. Lexicographic optimization is also addressed to study combination of objectives, resulting in "augmented" models. Heuristic algorithms were also proposed for the FNFAP problem. The importance of heuristic algorithms to solve this problem is enhanced by the fact that in a real-world scenario, the operational decision has to be made in a very short period, and so be incorporated on the SOLFI platform. Thus, when the client on the SOLFI platform performs a request release, the decision of the platform is as fast as possible. Both exact and heuristic proposed formulations are solved using generated datasets, and results are obtained when solving the models. Therefore, RQ4.1 was fulfilled in this chapter:

How to model and solve the assignment of parcels to into city centers in the urban logistic problem of integrated freight and passenger flows?

The main results are present on section *5.7* of this thesis.

7.2.4. Strategic approach for the Bus Network Planning Problem (BNPP)

The strategic approach for the BNPP was studied in Chapter 6. The main goal for studying this problem is to achieve, in a strategic layer, the minimum fleet size of buses needed to be part of the integrated transportation solution. Part of the role of the BTO of the city is to make decisions and manage the fleet and routes of buses running in the city. Considering the integrated transportation solution, a decision has to be made and known, beforehand, how many buses would need to be part of the integrated solution, and therefore, physically adapted to guarantee the safety of the passengers and freight. To help this decision of the BTO, Chapter 5 presents the problem formulation using exact models and heuristic algorithms, using a scenario-based approach of stochastic parameter realizations. The scenario approach for parameter realizations is specifically important to model uncertainty into the models, allowing to achieve solutions that represent the uncertainty of the real-world. This approach allowed to respond to the RQ3: "*How to address uncertainty and robustness in an urban logistics transport system that integrates of passenger and freight flows?"* since the uncertainty was guaranteed by the scenario approach of realizations of stochastic parameters for the problem BNPP.

The exact formulation using ILP and the heuristic algorithms based on GRASP allowed to model the problem BNPP, which was solved using generated instances. Proposing these model formulations and solving them allowed to respond to the RQ4.2:

How to model and solve the adapted bus fleet size needed in the urban logistic problem of integrated freight and passenger flows?

The main conclusions for the research of BNPP problem in Chapter *6* can be stated in two main domains:

From a macro perspective, this is a new approach to a problem that is critical for the BTO of the city and municipalities to make efficient decisions regarding future resources needed and to evaluate the system feasibility. So, the solution approaches developed tackle an important decision problem at the strategic planning level, estimating the required number of buses that must be adapted to transport goods while also transporting passengers, considering a set of future demand scenarios. To the best of the author's knowledge, no research is available to this specific strategic problem and characteristics, using realizations of demand to achieve solutions that are closer to reality, in the planning stage of the network design.

The results provide also important insights to practice. For the stakeholders involved in the network strategic network design problem such as, policy makers, BTO, logistics companies, LMOs, passengers and residents, solution approaches provide valuable insights as they incorporate uncertainty to get solutions as closest to the reality as possible. Additionally, the results allow stakeholders to anticipate the impact of their operational decisions in an integrated passenger and freight network, at a planning stage. For example, results suggest that delivering requests scattered across all the area of the city, and having a clustered time windows to deliver them, do not have a huge impact on the number of bus required.

7.3. Limitations and future research

A number of research future paths can be followed in order to continue the work presented in this thesis. In what follows, some interesting future research directions are outlined.

Data collection: In Chapter *4* questionnaires and semi-structured interviews were conducted. Concerning the semi-structured interviews, the sample of stakeholders interviewed is limited to just one stakeholder of each type (Logistic Operator, Bus Transport Operator, Last Mile Operator). As future research, other stakeholders could also be interviewed to gather requirements and derive assumptions based on different inputs, avoiding the bias caused by the small sample size. Concerning the questionnaire to the final customers, all respondents are geographical limited to city of Porto, and other target groups and regions of the country could be considered in the future.

Applicability: In Chapters *5* and *6*, it were used fictional generated instances to be used to solve the models. Pilot instances were generated as well, where only the bus network data was realistic, based on the bus network of Porto city. Evidently, extending the computational experiments with some instances that reflect other city bus networks would be beneficial to the conclusions that can arise from the computational experiments. Furthermore, the demand data utilized in all instances is purely fictitious, attempting to model a prospective demand behavior. This is less important for the BNPP problem since using scenarios with various realizations broadens the range of parameter values utilized on the instances. As future research, historical data for demand characterization could also improve the confidence level for the decision making in the scope of these problems.

Problems formulation: In Chapters 5 and 6 the two problems FNFAP and BNPP were formulated based on the stakeholders' inputs, researchers experience and knowledge on OR and logistics/ transportation fields. Nevertheless, even though a significant set of models with different optimization algorithms were addressed, other formulations and methods can be used to extend the scope of the work done on this thesis. Transportation costs, supply chain costs, and environmental factors from an integrated passenger and freight system might be some optimization goals that expand the current work.

Scalability: This study was conducted as part of the SOLFI project. The first practical stage in this project is a pilot test, in which some of the algorithms suggested in this research are tested in a real-world setting. Although this study was developed to meet the demands of a pilot setting, some scaling experiments with realistic data would be a future research route that would infer the performance of the suggested models in a realistic and fast-paced context.

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Appendix

Appendix A: Customer questionnaire.

Questionário clientes particulares on-line

1. Género:

☐ Masculino ☐ Feminino

2. Faixa etária:

☐ 0 – 17 anos ☐ 18 – 25 anos ☐ 26 – 40 anos ☐ 41 – 65 anos ☐ + 65 anos

3. Profissão / Situação profissional:

☐ Estudante ☐ Empregado por conta própria ☐ Empregado p/ conta de outrem ☐ Desempregado ☐ Reformado

4. Com que frequência realiza compras on-line?

☐ Não compro on-line ☐ 1 a 3 vezes por ano ☐ 4 a 6 vezes por ano ☐ 7 a 12 vezes por ano ☐ Mais de 12 vezes por ano

5. **Que tipos de produtos costuma comprar on-line?** *(assinale com um X o(s) tipo(s) de produto(s) que costuma comprar)*

☐ Peças de roupa/calçado/acessórios ☐ Produtos eletrónicos

☐ Produtos alimentares e bebidas ☐ Produtos de saúde/cosmética/perfumaria

☐ Produtos de papelaria ☐ Artigos para o lar

☐ Produtos desportivos e outros produtos de lazer/entretenimento ☐ Outros: ____________________

6. Quando compra on-line, em que horários prefere receber a respetiva encomenda?

☐ Manhã (8h-13h) ☐ Tarde (13h-18h) ☐ Noite (18h-24h)

7. Usando a escala que se segue, assinale <u>o quanto gostaria de receber uma encomenda ao fim de semana</u> *(Pinte o círculo da posição que melhor corresponde à sua apreciação)*

	Não gostaria			Gostaria muito	
	1	2	3	4	5
7.1 Receber uma encomenda ao Sábado das 8h às13h	○	○	○	○	○
7.2 Receber uma encomenda ao Sábado das 13h às 18h	○	○	○	○	○
7.3 Receber uma encomenda ao Sábado das 18h às 24h	○	○	○	○	○
7.4 Receber uma encomenda ao Domingo das 8h às13h	○	○	○	○	○
7.5 Receber uma encomenda ao Domingo das 13h às 18h	○	○	○	○	○
7.6 Receber uma encomenda ao Domingo das 18h às 24h	○	○	○	○	○

8. Qual o seu local de preferência para a receção das suas compras on-line?

☐ Domicílio ☐ Emprego ☐ Loja do retalhista ☐ Loja de recolha (ponto de entrega)

9. Para os serviços abaixo listados assinale com um X aquele(s) que mais valoriza em relação ao local de recolha das suas compras on-line? Estaria disposto a ter um custo adicional para ter esse serviço incluído nas suas compras on-line?

Serviço	**Disposto(a) a pagar?**	**Se respondeu sim, quanto?**
Permitir que eu receba a encomenda mais rápido. ☐	☐ Sim ☐ Não	☐ Até 2,5 euros ☐ De 2,5 a 5 euros ☐ De 5 a 10 euros ☐ Até ________
Permitir reduzir o tempo/esforço que eu gasto na recolha da encomenda. ☐	☐ Sim ☐ Não	☐ Até 2,5 euros ☐ De 2,5 a 5 euros ☐ De 5 a 10 euros ☐ Até ________
Dar-me liberdade/flexibilidade em relação ao horário de entrega ☐	☐ Sim ☐ Não	☐ Até 2,5 euros ☐ De 2,5 a 5 euros ☐ De 5 a 10 euros ☐ Até ________

10. Imagine a existência de um serviço de entregas baseado numa rede de lojas de recolha, com o mesmo horário de funcionamento da respetiva loja, onde recolheria a sua encomenda com impacto positivo na pegada ecológica uma vez que vai reduzir o número de veículos a assegurar a atividade de logística urbana na cidade.

10.1 Estaria disposto a utilizar este serviço, dado o seu impacto ambiental e a sua flexibilidade na recolha?

☐ Sim ☐ Não. Porquê? ___________________________________

10.2 Se respondeu sim, qual o tempo, em minutos, que estaria disposto a caminhar para recolher a sua mercadoria? Considere o tempo de ida e volta.

☐ até 5 minutos ☐ De 5 a 10 Minutos ☐ De 10 a 15 Minutos

10.3 Quanto estaria disposto a pagar por esse serviço? Para efeitos do valor a pagar considere como referência uma encomenda até 32 Kg.

☐ Nada, pois prefiro manter a opção atual ☐ Até 2,5 euros ☐ De 2,5 a 5 euros

☐ De 5 a 10 euros ☐ Até ________

☐ Não importa o valor, pois prefiro sempre optar por este serviço amigo do ambiente

11. Imagine a existência de um serviço de entregas baseado numa rede de pontos de recolha automática (por exemplo cacifos) onde recolheria a sua encomenda com impacto positivo na pegada ecológica uma vez que vai reduzir o número de veículos a assegurar a atividade de logística urbana na cidade.

11.1 Estaria disposto a utilizar este serviço, dado o seu impacto ambiental e a sua flexibilidade na recolha?

☐ Sim ☐Não. Porquê? ___________________________________

11.2 Se respondeu sim, qual o tempo, em minutos, que estaria disposto a caminhar para recolher a sua mercadoria? Considere o tempo de ida e volta.

☐ até 5 minutos ☐ De 5 a 10 Minutos ☐ De 10 a 15 Minutos

11.3 Quanto estaria disposto a pagar por esse serviço? Para efeitos do valor a pagar considere como referência uma encomenda até 32 Kg.

☐ Nada, pois prefiro manter a opção atual ☐ Até 2,5 euros ☐ De 2,5 a 5 euros

☐ De 5 a 10 euros ☐ Até ________

☐ Não importa o valor, pois prefiro sempre optar por este serviço amigo do ambiente

12. Imagine a existência destes dois serviços: entregas em rede de lojas e entregas automáticas em rede de cacifos pela cidade. Qual dos serviços utilizaria como preferencial?

☐ Entregas numa rede de lojas como ponto de recolha ☐ Entregas numa rede de cacifos como ponto de recolha

☐ Nenhuma, prefiro utilizar a opção atual

Appendix B: Interview protocol to private logistic operator.

GUIÃO DE ENTREVISTA A OPERADORES LOGÍSTICOS

- **Dados gerais:**

1. O principal negócio da Rangel Distribuição (Express) é B2B ou B2C?
1. Tipos de serviço que executam (recolhas, entregas, etc)?
2. Qual a viabilidade do funcionamento do SOLFI nos moldes em que estamos a considerar? Que requisitos e necessidades antecipa que seriam necessários assegurar no âmbito do serviço de logística urbana, proposto pelo projeto SOLFI, para que a Rangel pudesse ser parceira deste serviço?
3. Tipo de equipamento/tecnologias/software usados para o planeamento e gestão das encomendas a entregar pela Rangel? Fazem atualização em tempo real do estado das encomendas?
4. Qual a forma recomendada de comunicação da informação da/para a solução SOLFI de/para a Rangel?
5. Considera adequada uma abordagem em que o SOLFI negoceia com a Rangel um instante ou uma janela temporal para entrega da encomenda/tipologias de encomenda no hub de autocarros ou seria na sua ótica mais adequada outra abordagem e nesse caso qual?
6. Tendo em consideração a etapa do processo de entrega de encomendas no hub de autocarros por parte da Rangel, faria mais sentido optar por um período diário, fixo ou variável (nesse caso o que pode fazer depender), para este serviço? Estaríamos a falar de um período em que ordem de grandeza?
7. Considera adequada a abordagem em que o SOLFI realiza o planeamento das encomendas no dia anterior? Qual seria o horizonte temporal para lidar com as entregas planeadas? e em casos de entregas urgentes?

- **Sobre a distribuição na cidade do porto**

8. Existe sazonalidade em relação ao número de encomendas a entregar na cidade do Porto?
9. Que períodos do dia são os mais críticos em relação ao número de encomendas a entregar na cidade do Porto?
10. Número médio de encomendas para o centro da cidade do Porto que entregam por dia? Número médio de viagens por dia?
11. Existe entreposto de suporte operacional dentro da cidade do Porto? Onde?

12. Têm rotas estabelecidas para a distribuição das encomendas? Se sim, como são organizadas? *(em caso de não existir rotas estabelecidas, avançar para pergunta 13)*
    a. As rotas são fixas ou dinâmicas?
    b. Há horários estabelecidos para cada rota? Qual é a duração média para percorrer uma rota?
    c. Quantas paragens por rota/ Quantas encomendas transportam em média em cada rota?
13. Atualmente a partir de que pontos pode ser enviada a mercadoria – apenas Alfena ou também de outros pontos? Quais? Principais vias de acesso utilizadas para as entregas? Zonas que entregam encomendas com mais frequência?
14. Equipamentos utilizados para efetuar a descarga/carga de encomendas?
15. Antecipa que seja estritamente necessário a presença de uma pessoa para receber a encomenda no destino? Neste caso no hub de autocarros? Ou acha que seria viável avançar para um processo automático de confirmação da entrega da encomenda no hub de autocarros, sem interação com qualquer outra pessoa?
16. Cada encomenda corresponde apenas a um só destino? E é entregue de uma só vez?
17. Qual é a entidade responsável pela mercadoria em caso de acidentes, perdas ou danos da mesma durante o seu transporte?
18. Qual é a entidade responsável pela segurança e integridade da mercadoria durante o seu trajeto no SOLFI? Qual a melhor abordagem a adotar? A rangel tem algum sistema de verificação da mercadoria que transporta?
19. Qual a abordagem que aconselharia para lidar com uma falha na entrega por parte da Rangel e/ou por parte do SOLFI?

- **Sobre a frota**

20. Tipos e dimensões (capacidade) dos veículos que operam no Porto? Que tipos são amigos do ambiente (emissões de CO2)? Há a afetação de tipos de veículos por áreas/zonas urbanas de atuação?

- **Sobre os produtos**

21. Tipos de produtos que transportam que considera que poderiam ser entregues via SOLFI?
22. É normal lidarem com produtos que necessitam de cuidados especiais? (temperatura controlada, fragilidade do produto etc.). Seria vantajoso incluir este tipo de produtos no âmbito da solução SOLFI?
23. Pesos e dimensões médios e máximos dos volumes que transportam? É necessário saber as três dimensões da encomenda? Volumes organizados por encomenda? Como vai agregada

(embalada) a encomenda? Seria viável usarmos contentores com algumas dimensões padrão alternativas?

24. Existem outros dados que caracterizam uma encomenda?
25. Utilizam embalagens retornáveis na entrega dos seus produtos?

Appendix C: Interview protocol to bus transport operator.

GUIÃO DE ENTREVISTA À STCP

- **Dados gerais:**

2. Qual a viabilidade do funcionamento do SOLFI nos moldes em que estamos a considerar? Que requisitos e necessidades antecipa que seriam necessários assegurar no âmbito do serviço de logística urbana proposto pelo projeto SOLFI para que a STCP pudesse ser parceira deste serviço?
3. Qual a forma recomendada de comunicação da informação da/para a solução SOLFI da/para a STCP
4. Para o tracking dos veículos que equipamento/tecnologia/software é usado?
5. Sabendo que existe sazonalidade ao longo do ano em relação ao número de utentes de transportes públicos, esta é relevante?
6. Que períodos do dia são os mais críticos em relação à utilização da capacidade disponível? E quais os períodos com maior folga? Qual a taxa de ocupação média do autocarro em cada uma destas alturas?
7. Tendo em consideração toda a etapa do processo sob a responsabilidade da STCP, faria mais sentido optar por uma janela temporal diária para este serviço fixa ou variável (nesse caso o que pode fazer depender)? Estaríamos a falar de um tempo em que ordem de grandeza?
8. Com que antecedência necessitaria a STCP de saber que tem uma dada encomenda para transportar?
9. Relativamente ao custo/receita associados à prestação do serviço por parte da STCP ao SOLFI, que abordagem lhes parece adequada para a relação entre a STCP e a solução SOLFI?

- **Sobre a distribuição na cidade do Porto**

10. Quantos Interfaces/centros de autocarros na cidade do Porto suportam a STCP nas suas operações e sua localização? Seria viável usarmos estes pontos como pontos de receção da mercadoria proveniente do exterior da cidade? Numa situação de funcionamento pleno do serviço, seria exequível a afetação de um recurso humano nestes pontos para assegurar a gestão das encomendas? Existem, nestes locais, condições físicas para a armazenagem de mercadoria?
11. Principais vias de acesso utilizadas? Zonas com mais rotas associadas?
12. O que carateriza uma paragem de autocarro (espaço, características da via, etc) e que condições devem ser asseguradas nestas para que possam funcionar como pontos de

transbordo da mercadoria no âmbito do SOLFI? Qual a estimativa do tempo máximo que poderia ser gasto na retirada da mercadoria do autocarro para não comprometer a qualidade do serviço a passageiros?

13. Tempo médio de espera em cada paragem?
14. Como lidar com uma situação de exceção quando a mercadoria não é recolhida na paragem?

- **Sobre a frota**

15. Tipos e dimensões dos veículos que operam no Porto? Que tipos são amigos do ambiente (emissões de CO2)?
16. Existem na frota veículos com capacidade de armazenagem de mercadoria? Se não existem, em que condições considera que seria possível o transporte de mercadoria no autocarro e quais os requisitos em termos de infraestruturas físicas de apoio à atividade logística? Se existem, qual é a capacidade de transporte de bagagens/encomendas para cada tipo de autocarro que operam na cidade do Porto?
17. Há a afetação de tipos de veículos por áreas/zonas urbanas de atuação?
18. Parece-lhe viável no futuro a existência de um serviço de transporte de mercadorias em autocarro, com a separação física das mercadorias dos passageiros, com recurso a tecnologias avançadas em que o check-in e check-out da mercadoria possa ser assegurado com segurança com o mínimo de intervenção humana, recorrendo por exemplo à tecnologia RFID, com controlo de acessos à mercadoria?
19. Quais as condições/restrições a considerar na utilização da frota que devam ser incorporadas no SOLFI? Será importante considerar um limite de capacidade em relação ao peso/volume de encomendas a serem transportadas via STCP?

Appendix D: Interview protocol to last mile operator of the city.

GUIÃO DE ENTREVISTA À CONTRA-RELÓGIO

- **Sobre a empresa:**

20. Há quanto tempo opera a empresa na cidade do Porto.
21. Qual é a missão, visão e objetivos da empresa?

- **Dados gerais:**

22. O principal negócio é B2B ou B2C?
23. Tipos de serviço que executam (recolhas, entregas, etc)?
24. Tipo de equipamento/tecnologias/software usados para o planeamento e gestão das encomendas da Contra Relógio? Qual a forma recomendada de comunicação da informação da/para a solução SOLFI da/para a Contra Relógio?
25. Fazem tracking dos veículos? Se sim, tipo de equipamento/tecnologia/software usados?
26. Fazem atualização em tempo real do estado das encomendas? Se não, quanto é o *delay*?
27. Considera adequada uma abordagem em que a Contra Relógio negoceia um tempo de serviço/custo para a entrega da encomenda/tipologias de encomenda entre a paragem de autocarro e o cliente final ou seria na sua ótica mais adequada outra abordagem e nesse caso qual?

- **Sobre a distribuição na cidade do porto**

28. Têm rotas estabelecidas para a distribuição das encomendas? Se sim, como são organizadas? *(em caso de não existir rotas estabelecidas, avançar para pergunta 10)*
    a. As rotas são fixas ou dinâmicas?
    b. Há horários estabelecidos para cada rota? Qual é a duração média para percorrer uma rota?
    c. Quantas paragens por rota/ Quantas encomendas transportam em média em cada rota?
29. Principais vias de acesso utilizadas? Zonas mais frequentemente utilizadas?
30. Equipamentos utilizados para efetuar a descarga/carga de encomendas?
31. É estritamente necessário a presença de uma pessoa para receber a encomenda no destino? Conferir o material?
32. Se sim, como procedem se o destinatário não se encontra no local?
33. Número médio de volumes por dia? Quais são as horas mais críticas ao longo do dia?
34. Existe sazonalidade relevante ao longo do ano? Em que alturas são as mais críticas e qual a variação de volumes?

35. Existe entreposto de suporte operacional na cidade do Porto? Onde?
36. Existe alguma restrição em relação ao local de entrega que dependa das condições da área urbana onde deverá ser realizada a entrega, ou basicamente, dentro da cidade do Porto, conseguem entregar em qualquer local?

- **Sobre os produtos**

37. Tipos de produtos que transportam? Representatividade do transporte de volumes e de documentos?
38. Conseguem responder à necessidade de lidar com os produtos de forma especial? (temperatura controlada, fragilidade do produto etc.). Quais as restrições em relação ao tipo de artigos que podem transportar?
39. Pesos e dimensões médios e máximos dos volumes que transportam?
40. Embalagens utilizadas para o transporte de encomendas?

- **Sobre a frota**

41. Quantidade, tipos e dimensões (capacidade) dos veículos que operam no Porto? Que tipos são amigos do ambiente (emissões de CO_2)? Há a afetação de tipos de veículos por áreas/zonas urbanas de atuação?
42. A frota utilizada é própria ou subcontratada? Há uma frota estável e base estável de motoristas?
43. Quais as condições/restrições a considerar na utilização da frota que devam ser incorporadas no SOLFI? Será importante considerar um limite de capacidade em relação ao volume de encomendas a serem entregues via Contra Relógio?