Models and Computational Intelligence Approaches for the Last Mile Delivery Problem in Food Supply Chain

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Declaration of Authorship

I, Hanane EL RAOUI, declare that this thesis titled, "Models and Computational Intelligence Approaches for the Last Mile Delivery Problem in Food Supply Chain" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a PhD degree at these Universities.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Signed: Hanane EL RAOUI

Date: November 9, 2021

Abstract

In cities, the "last mile" is not only a logistical issue, but also a significant urban planning challenge. The final mile in the supply chain involves high-frequency, low-volume, and short-haul distribution of products to end consumers. The last leg of the supply chain is the most crucial, but also the least efficient. Transportation planning is one of the major contributors to the severity of last-mile delivery (LMD) issues in cities. The scope of our thesis is on the transportation planning for perishable food supply chains.

In recent years, the global food market has shown substantial growth. Therefore, posing new challenges, and initiating a drastic change in the last mile logistics. These challenges are mainly related to the high perishability of food product that require specific management approaches to maintain their quality. Additionally, we mention the growing demand from customers for deliveries to be made on time, at a lower cost, and in an environmentally friendly manner. Customers search other alternatives, if the service doesn't meet their expectations. Last mile logistics is essential in developing brand loyalty in this competitive environment, as it allows transporters to deliver fresh and high quality products to consumers, faster and cost-effectively. The aim of this thesis is to propose models and solving approaches that can support decision-making process in food supply chain through addressing concerns about transportation costs, carbon emissions, product quality, service level, etc. Specifically, different decision problems that can be regarded as routing problems, are considered.

We start by modelling a delivery problem with specific temporal customer's requirements as a capacitated vehicle routing problem with soft time windows. The problem is formulated as a Mixed 0-1 non-Linear Program (MINLP). The objective is to minimize the total cost, consisting of transportation costs, food quality degradation costs, and time-windows violation costs. To model the temporal preference of the customers in a most realistic way, we provide another model that represent this preference information as a fuzzy number with respect to the satisfaction of service time. This problem is a Capacitated Vehicle Routing Problem with Fuzzy Time Windows (CVPFTW) and formulated as a fuzzy mixed-integer linear programming model. Both problems are addressed on real road networks where arcs are labelled with multiple attributes, and solved using CPLEX solver. The performance of the proposed models is assessed through computational analyses on several test instances. Some instances are derived from real-life applications, others are randomly generated. The results proved that our approach can help reduce the operational costs of delivery while improving customer service.

To improve customer satisfaction, we propose a many-objective Customer-Centric Perishable Food Distribution Problem. The proposed model focuses on the cost, the quality of the product, and the service level improvement by considering not only time windows but also the customers' target time and their priority. Owing the difficulty of solving such model, we propose a General Variable Neighbourhood Search (GVNS) metaheuristic. By solving a mono-objective sub-problem, such approach enables to generate a set of diverse solutions. These solutions are evaluated over some non-optimized criteria and then ranked using an a posteriori approach that requires minimal information about decision maker preferences. The computational results show: (a) GVNS achieved the same quality solutions as an exact solver (CPLEX) in the sub-problem; (b) GVNS can generate a wide number of candidate solutions, and (c) the use of the a posteriori approach makes easy to generate different decision maker profiles which in turn allows obtaining different rankings of the solutions.

Solving a perishable food distribution problem in a real world setting is a very complex task. This is due to products characteristics, and the requirements of customers.To ensure a safe, quality product with a desired service level, a bunch of specifications should be included during the decision/optimization process. Many times, the computational models necessarily leave out of consideration several characteristics and features of the real world. Thus, trying to obtain the optimum solution can not be enough for a problem-solving point of view. To address this problem, we propose a modelling to generate Alternatives- metaheuristic based approach to generate a set of alternative solutions. The aim is to allow the decision maker to consider different perspectives, and non-modelled criteria.

Keywords: last mile; routing problem; CVRP; perishable food distribution; many-objectives optimization; real road networks; metaheuristic

Resumen

En las ciudades, la "última milla" no es sólo una cuestión logística, sino también un importante reto de planificación urbana. La última milla de la cadena de suministro implica la distribución de alta frecuencia, bajo volumen y corta distancia de los productos a los consumidores finales. El último tramo de la cadena de suministro es el más crucial, pero también el menos eficiente. La planificación del transporte es uno de los principales factores que contribuyen a la gravedad de los problemas de la última milla (LMD) en las ciudades. En los últimos años, el mercado mundial de la alimentación ha experimentado un crecimiento considerable, lo que ha planteado nuevos retos y ha provocado un cambio drástico en la logística de la última milla. Estos retos están relacionados principalmente con el alto grado de perecederos de los productos alimentarios, que requieren enfoques de gestión específicos para mantener su calidad. Y la creciente demanda de los clientes de que las entregas se realicen a tiempo, con un coste menor y de forma respetuosa con el medio ambiente. La logística de última milla es esencial para desarrollar la lealtad a la marca en este entorno competitivo, ya que permite a los transportistas entregar productos frescos y de alta calidad a los consumidores, de forma más rápida y rentable. El objetivo de esta tesis es proponer modelos y enfoques de resolución que puedan apoyar el proceso de toma de decisiones en la cadena de suministro de alimentos, abordando las preocupaciones sobre los costes de transporte, las emisiones de carbono, la calidad del producto y el nivel de servicio. Comenzamos modelando el problema de las necesidades del cliente para una entrega en un rango de tiempo específico como un problema de enrutamiento de vehículos capacitados con una ventana de tiempo suave, para el que se formula un programa no lineal mixto 0-1 (MINLP). El objetivo es minimizar los costes totales, que consisten en los costes de transporte, los costes de degradación de la calidad de los alimentos y los costes de violación de la ventana de tiempo. Para modelar la preferencia de los clientes en términos de ventana de tiempo muy bien, proporcionamos otro modelo que representa esta información de preferencia como un número difuso con respecto a la satisfacción del tiempo de servicio. Este problema se considera como un problema de enrutamiento de vehículos capacitados con ventanas de tiempo difusas CVPFTW y se formula como un modelo de programación lineal de enteros mixtos. Ambos problemas se abordan en redes de carreteras reales en las que los arcos están etiquetados con múltiples atributos, y se resuelven utilizando algoritmos exactos. El rendimiento de los modelos propuestos se evalúa mediante análisis computacionales adecuados que tienen en cuenta varios conjuntos de instancias de prueba, algunas derivadas de una aplicación real y otras generadas aleatoriamente. Para aumentar la satisfacción del cliente, proponemos un problema de distribución de alimentos perecederos centrado en el cliente que se centra en el coste, la calidad del producto y la mejora del nivel de servicio teniendo en cuenta no sólo las ventanas de tiempo, sino también el tiempo objetivo de los clientes y su prioridad. Reconociendo la dificultad de resolver este modelo, proponemos un enfoque metaheurístico basado en la Búsqueda de Vecindario General (GVNS) que permite resolver eficientemente un subproblema y obtener un conjunto de soluciones. Estas soluciones se evalúan sobre algunos criterios no optimizados xiy luego se clasifican utilizando un enfoque a posteriori que requiere una información mínima sobre las preferencias del decisor. Los resultados computacionales muestran (a) que GVNS logra soluciones de la misma calidad que un solucionador exacto (CPLEX) en el subproblema; (b) que GVNS puede generar un amplio número de soluciones candidatas, y (c) que el uso del enfoque a posteriori facilita la generación de diferentes perfiles de tomadores de decisiones, lo que a su vez permite obtener diferentes clasificaciones de las soluciones.La resolución de un problema de distribución de alimentos perecederos en un entorno real es una tarea muy compleja. Para garantizar un producto seguro y de calidad con el nivel de servicio deseado, es necesario incluir un conjunto de especificaciones durante el proceso de decisión y optimización de las operaciones. Muchas veces, los modelos computacionales no tienen en cuenta varias características y rasgos del mundo real, por lo que intentar obtener la solución óptima puede no ser suficiente desde el punto de vista de la resolución de problemas. Para abordar este problema, proponemos un enfoque basado en la metaheurística Modeling to Generate Alternatives para generar un conjunto de soluciones alternativas. El objetivo es permitir que el responsable de la toma de decisiones considere diferentes perspectivas y criterios no modelados.

Palabras clave: última milla; problema de enrutamiento; CVRP; distribución de alimentos perecederos; optimización multiobjetivo; redes de carreteras reales; metaheurística

List of Publications

1. El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "ABM-GIS simulation for urban freight distribution of perishable food." In MATEC Web of Conferences, vol. 200, p. 00006. EDP Sciences, 2018.

2. El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "Optimization/simulation in the supply chain context: a review." In Proceedings of the International Conference on Learning and Optimization Algorithms: Theory and Applications, pp. 1-7. 2018.

3. El Raoui, Hanane, Mustapha Oudani, David Pelta, Ahmed El Hilali Alaoui, and Abdelali El Aroudi. "Vehicle routing problem on a road-network with fuzzy time windows for perishable food." In 2019 IEEE International Smart Cities Conference (ISC2), pp. 492-497. IEEE, 2019.

4. El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "Coupling Soft Computing, Simulation and Optimization in Supply Chain Applications: Review and Taxonomy." IEEE Access 8 (2020): 31710-31732.

5. El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "Perishable food distribution in urban area based on real-road network graph." In 2020 5th International Conference on Logistics Operations Management (GOL), pp. 1-6. IEEE, 2020.

6. El Raoui, Hanane, Mustapha Oudani, David A. Pelta, and Ahmed El Hilali Alaoui. "A Metaheuristic Based Approach for the Customer-Centric Perishable Food Distribution Problem." Electronics 10, no. 16 (2021): 2018.

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Finally, a special thanks to you – yes, you! – for picking up a copy of my thesis. I hope you find it interesting!

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List of Abbreviations

ABM	**A**gent **B**ased **M**odel
ABS	**A**gent **B**ased **S**ystem
ANN	**A**rtificial **N**eural **N**etwork
ACO	**A**nt **C**olony **O**ptimization
B2B	**B**usiness **T**o **B**usiness
BVNS	**B**asic **V**ariable **N**eighborhood **S**earch
CVPFTW	**C**apacitated **V**ehicle **R**outing **P**roblem **W**ith **F**uzzy **T**ime **W**indows
CVRP	**C**apacitated **V**ehicle **R**outing **P**roblem
CE	**C**ross-**E**ntropy **M**ethod
DARP	**D**ial-**A**-**R**ide **P**roblem
DSS	**D**ecision **S**upport **S**ystem
DM	**D**ecision **M**aker
DC	**D**istribution **C**enter
EDA	**E**stimation **of** **D**istribution **A**lgorithms
ES	**E**volution **S**trategies
FSC	**F**ood **S**upply **C**hain
FTL	**F**ull **T**ruckload
FLM	**F**ood **L**ogistics **M**anagement
FPA	**F**inite **P**erturbation **A**nalysis
FDM	**F**requency **D**omain **M**ethod
FD	**F**inite **D**ifference
GM	**G**radient-Based **M**ethods
GE	**G**radient **E**volution
GA	**G**enetic **A**lgorithm
GSM	**G**radient **S**urface **M**ethod
GVNS	**G**eneral **V**ariable **N**eighborhood **S**earch
GIS	**G**eographic **I**nformation **S**ystems
HA	**H**armonic **A**nalysis
ILP	**I**nteger **L**inear **P**rogramming
IPA	**I**nfinitesimal **P**erturbation **A**nalysis
JIT	**J**ust **I**n **T**ime
KPI	**K**ey **P**erformance **I**ndicators
KM	**K**riging **M**odels
LMD	**L**ast-Mile **D**elivery
LML	**L**ast **M**ile **L**ogistics
LM	**L**ast **M**ile
LTL	**L**ess **T**han **T**ruckload
LR	**L**ikelihood **R**atio
LP	**L**inear **P**rogramming

MILP	**M**ixed **I**nteger **L**inear **P**rogramming
MINLP	**M**ixed **I**nteger **N**on-Linear **P**rogram
MO	**M**ulti-**O**bjective
MOMIP	**M**ulti-**O**bjective **M**ixed **I**nteger **P**rogramming
MGA	**M**odeling **T**o **G**enerate **A**lternatives
MH	**M**etaheuristics
MCA	**A**ll **p**air **w**ise **M**ultiple **C**omparisons
MCB	**M**ultiple **C**omparisons **w**ith **t**he **B**est
MCC	**M**ultiple **C**omparisons **w**ith **a** **C**ontrol
NLP	**N**on-**L**inear **P**rogramming
NGM	**N**on **G**radient **M**ethods
NP	**N**ested **P**artitions
OSM	**O**pen **S**treet **M**ap
OO	**O**rdinal **O**ptimization
PA	**P**erturbation **A**nalysis
RVRP	**R**ich **V**ehicle **R**outing **P**roblem
RS	**R**andom **S**earch
RSM	**R**esponse **S**urface **M**ethodology
R&S	**R**anking **A**nd **S**election
RVNS	**R**educed **V**ariable **N**eighborhood **S**earch
SFLM	**S**ustainable **F**ood **L**ogistics **M**anagement
SS	**S**catter **S**earch
SA	**S**imulated **A**nnealing
SPO	**S**ample **P**ath **O**ptimization
TS	**T**abu **S**earch
TSP	**T**raveling **S**alesman **P**roblem
VRP	**V**ehicle **R**outing **P**roblems
VRPTW	**V**ehicle **R**outing **P**roblem **W**ith **T**ime **W**indow
VHT	**V**ehicle **H**ours **T**ravelled
VKT	**V**ehicle **K**ilometers **T**ravelled
VNS	**V**ariable **N**eighborhood **S**earch
VND	**V**ariable **N**eighborhood **D**escent

Dedicated to my familly

Chapter 1

Introduction

This chapter introduces the research topic and provides the justification for this study. The chapter is organized into six sections. Following the general context, Section 1.2 provides the problem statement, which highlights the last mile delivery challenges in food supply chains. Section 1.3 presents the rationale of the research, while Section 1.4 describes the scope of the study. The research objectives are presented in Section 1.5. Section 1.6 outlines the thesis structure.

1.1 General context

Increased online retail transactions, as well as fluctuations in demand for global items in local and international markets due to complex and dynamic population and demand changes, are likely to drive up the last mile delivery. The last mile delivery refers to the very last step of the delivery process when a parcel is moved from a transportation hub to a customer, which is usually a personal residence or retail store as shown in Fig.1.1. In general, retailers and manufacturers outsource the delivery process to specialized logistics providers with a big fleet of vehicles to deliver the goods efficiently. The last mile delivery makes part of a larger logistic process. Therefore, logistics provider need to manage efficiently their logistics systems to provide an efficient delivery service and maintain customer satisfaction.

Nowadays, companies in several sectors are struggling to enhance the performance of their logistics systems. Moreover, they have to deal with the issues that sustainability brings to their business as a result of the movement towards being more sustainable. The sustainability, in this sense, is concerned with not only the economic aspect, but also the environmental and social issues related to the movement of goods through the supply chain.

Transportation activity is a major source of air pollution that has a negative impact on human health and emits greenhouse gases that cause global warming (Wang et al., 2011). From the point of food supply chain, food transportation is growing up with the increasing demand, and distances between production and consumption. Thus, its is a significant source of carbon emission. These issues have raised awareness of the need to optimize transportation energy consumption and reduce carbon emissions, which are Key Performance Indicators (KPIs) for evaluating logistics systems sustainability.

The growing global population, combined with the expansion of international food trade, necessitates a focus on preventable product waste in Food Supply Chains (FSCs) (Jedermann et al., 2014). According to a study of (Gustavsson et al., 2011), the developed world wastes more food per capita than poor countries. The per capita food waste in Europe and North America is 95-115 kg per year, whereas in Sub-Saharan Africa and South/Southeast Asia, it is 6-11 kg per year. (Gustavsson et al., 2011), (Garnett, 2011) define wasted food as a waste of resources, as well as emissions generated during the production and distribution process. Correspondingly, addressing the food waste problem can help in improving the sustainability. In fact, it will not only improve economic performance, but also help to prevent the potential environmental and social impact.

To summarize, food supply chain have recently faced challenges such as the food waste reduction, the minimization of energy consumption, and the carbon footprint of the transportation process.To face these challenges, efficient logistics systems that can balance between three aspects: the economic, environmental, and social, are needed. As a response, in this research, we propose models to help the decision maker in incorporating environmental and social factors besides costs when making logistics decisions.

1.2 Problem statement

The final leg in the supply chain known as the last-mile delivery is regarded as the most inefficient, expensive, and time-consuming component of the entire supply chain.

Freight flows in urban areas has a continuous upward tendency. The main driving forces behind this expansion are population growth, urbanization, densification, globalization, online retailing, and urban economic development. As a result of globalization, goods production facilities are dispersed throughout broad regions or countries. This in turn has increased the distances, and the transport related problems such as carbon emissions, congestion, air and noise pollution, traffic accidents. In terms of urbanization, the economic activities and the increasing development are leading to a rising flows. The requirement for last-mile delivery will grow as the city's population grows, as seen above. As a result, urban planners must think about how to improve and optimize the last-mile. From the point of food supply chain, the logistics systems have evolved over the previous two decades, from classical Logistics Management to Food Logistics Management (FLM), and then to Sustainable Food Logistics Management (SFLM). The traditional Last Mile (LM) system coordinates and optimize the logistics activities by taking decisions at different levels such as the delivery quantities and schedules, the routes to deliver, the transportation mode, etc. These decisions are taken with a mean focus on the cost reduction, and responsiveness. However, this situation is changing as people become more concerned about food safety and sustainability.

Food supply chains are associated to additional challenges compared to other sectors. These challenges are mainly related to the high perishability of

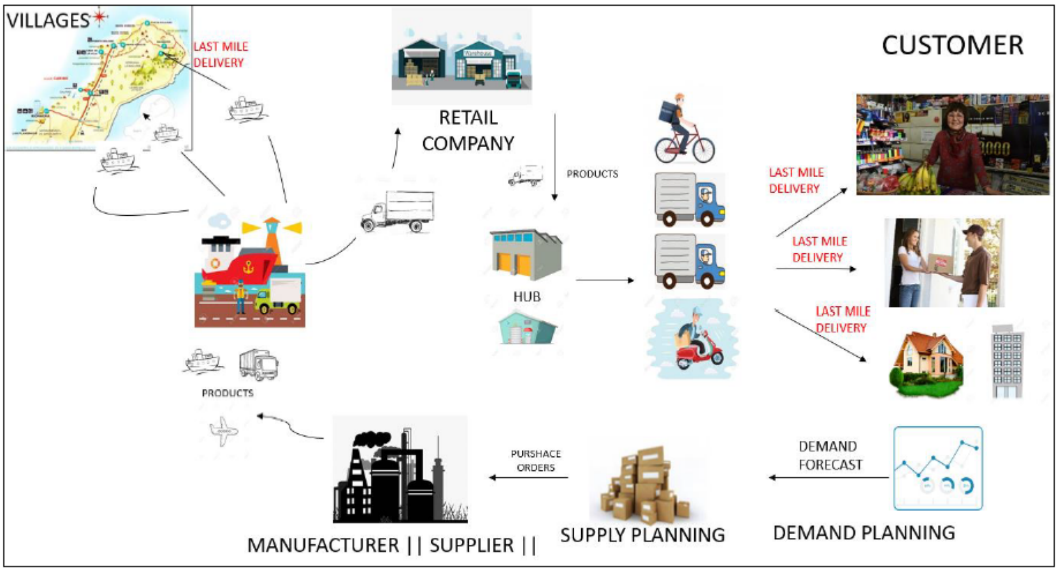


FIGURE 1.1: Last mile part in the supply Chain (Gutierrez Franco, 2019)

food product that require specific management approaches to maintain their quality.

Last mile logistics will continue to grow due to the rising demand, drive up by population concentrations in important nodes of economic vitality. Furthermore, customers continue to request a wide range of perishable food, and they are becoming more exigent. Customers want items to arrive right on time and, in most situations, on a more frequent basis. As a result, last mile delivery has continued to grow in terms of volume and distance travelled, and subsequent fuel consumption, and carbon footprint. These changes, combined with the requirement for flexible, and just-in-time logistics, have resulted in an increase in last-mile delivery issues. The aforementioned challenges have pushed companies towards a sustainable food supply chain that broaden the traditional logistics management by adding of new key logistics issues, to mitigate negative environmental and social impacts and maintain their profitability.

The rising challenge in sustainable food supply chains, is to determine how to include the key performance indicators of sustainability into the decision-making process. In fact, considering sustainability objectives, alongside with cost optimization objectives, combined with the perishability characteristics, makes the decision-making more challenging for food supply chains. Therefore, there is a need for advanced decision support models which can capture the economic, social, and environmental aspects of sustainability.

1.3 Research rationale

The attention to the last mile delivery is growing due to several trends that are affecting the cities. The latter were explicitly highlighted in the problem statement. In this section, we refer to these trends and discuss their impact on the last mile delivery to provide a justification of our study.

- Population growth and urbanization

The worldwide population is rapidly increasing, particularly in developing economies. Globally, the proportion of people who require last-mile delivery has risen to about 54.5%. The requirement for extra last-mile delivery will continue to grow as the population grows. By 2040, demand for last-mile deliveries is expected to increase (Harrington, 2015). The impact of population growth on last-mile delivery needs around the world is depicted in Fig. 1.2. This urbanization growth has raised several challenges for the last mile. In fact, this growth will result in an increasing number of delivery requests and therefore the freight movement growth will produce negative impact on costs and environment.

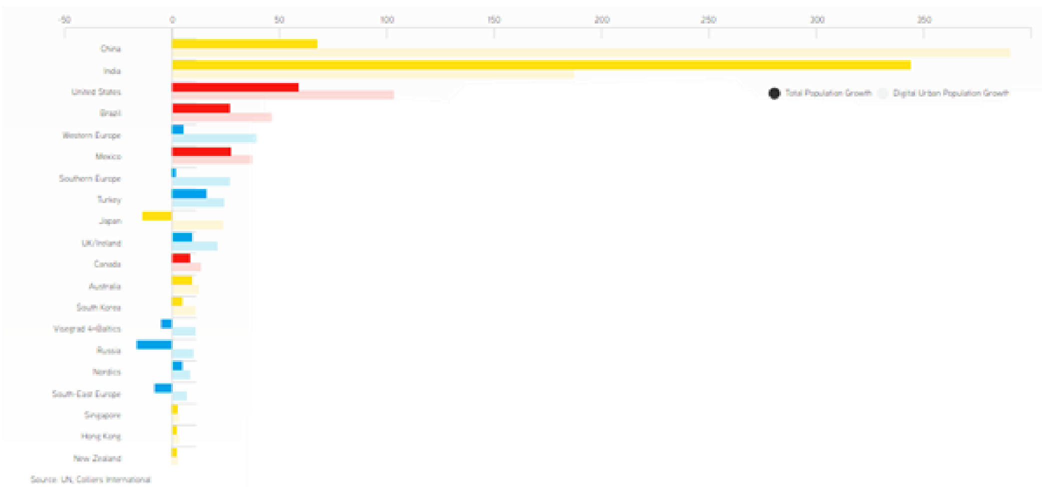


FIGURE 1.2: Population growth and last mile delivery ((Harrington, 2015))

- Climate change and sustainability

The increasing freight movement not only impact the costs, in addition it has a strong impact on GHG emissions. Road transport accounts for a significant percentage of CO_2 transportation-related emissions, estimated for over 20% in 2000 (Demir et al., 2011). Despite the fact that passenger cars account for the majority of these emissions, it is worth noting that between 1990 and 2013, greenhouse gas emissions from medium and heavy trucks climbed by 76.4%, compared to 16.2% for passenger cars.Therefore, optimizing the last mile activity is a critical aspect in reducing environmental costs, pollution, traffic jams, etc.

- Changing customer demand

City logistics will continue to grow with the urbanization and population growth. And the patterns of customers preferences will continue changing. In fact, the customers will continue to request a wide range of perishable food, but with additional requirement that is the trend emerging in recent year, which is the desire of speed. Each consumer wants their food as fast as possible or within a very short time frame, which is frequently during lunch or dinner. These trends have resulted in a challenge for decision-making in optimizing the routes and scheduling deliveries in order to meet the time constraint while maintaining cost efficiency.

1.4 Scope of study

The scope of this thesis is on the last mile delivery part of supply chain. Specifically, we focus on Business to Business (B2B) delivery of perishable food within urban areas. We consider only the operational aspect of the last mile delivery. Here the emphasis is placed on identifying the main challenges faced by food supply chain in the last mile, and propose models that follow the contemporary logistics trends (digitalization, reducing costs, sustainability, improving flexibility and responsiveness to customer demand).

The scope is also limited to the use of trucks to deliver B2B urban freight. Others modes of transport such rail or bikes are excluded in this study. In addition, the B2B include the retailers, groceries, restaurants, and distributors.

1.5 Research objectives

1.5.1 Overall objective

To improve the efficiency of the last mile delivery food supply chains, decision makers necessitates enhanced decision support models that accommodate logistic costs, transportation energy consumption and emissions, and/or product waste. Accordingly, the overall objective of this thesis is defined as follows:

Main Objective

To propose models and solving approaches that can support decision-making process in food supply chain through addressing concerns about transportation costs, carbon emissions, product quality, service level, etc.

In line with this overall objective, we have defined four main research objectives, which are introduced in the next subsection.

1.5.2 Specific objectives

In order to improve the efficiency of the last leg in the food supply chain, we need to better analyse the existing models dedicated to support decisions for last mile delivery. That would allow to identify the modelling challenges. This resulted in the first research objective of this thesis.

Objective 1

To identify the challenges associated to the freight last mile in food supply chain. Furthermore, analyse the available models that support the decision-making, and point out modelling challenges.

This objective is investigated through a conducted literature review study in the era of food distribution. As will be described in Chapter 2, the main findings of the literature review indicate that: (i) the existing studies are addressing the routing models to deliver products using customer-based graph representation that do not reflect the complexity of real road networks, and impact the quality of solution. (ii) Most of the studies propose single objective model that focus generally on the economical aspect. (iii) Most of the studies did not include jointly the economical, social, and environmental aspect in models. (iv) the majority of the proposed models are not customer-centred. These findings motivate us to work on the three following objectives:

Objective 2

Produce more realistic routes by addressing the vehicle routing problems on real road networks, considering different attributes to benefit from an efficient problem-solving.

This objective is investigated in Chapter 3 through (i) an agent based simulation model, (ii) the development of models for the capacitated vehicle routing problem on a real road networks, and considering multiple attributes associated to arcs.

Objective 3

Propose a many-objectives model for the perishable food distribution problem, that focuses on the cost, the quality of the product, and the service level improvement.

This objective is addressed in Chapter 4 through the development of a many-objectives customer-centric vehicle routing problem. A metaheuristic based approach is proposed to solve the model.

Objective 4

Propose a methodology to provide the decision maker with a set of alternative solutions that allows him/her to analyse the problem from different perspectives.

This objective is addressed in Chapter 5 by proposing a hybrid metaheuristic/Modeling To Generate Alternatives approach that allows to obtain interesting solutions over a set of criteria presenting the preference of decision makers.

1.6 Thesis structure

The thesis is organized in six chapters following the structure shown in Fig.1.3:

Chapter 1 Sets the context of this thesis. It introduces the research issue and justifies the study's relevance. It includes an overview of the study, a statement of the research topic, and a description of the study's scope. This chapter outlines the research goal and research questions. The research approach is also discussed in this chapter.

Chapter 2 focuses on the background literature and theoretical framework for the research. It discusses the city logistics, and last mile delivery and its challenges. The chapter also gives insight into the last mile vehicle routing problems that are the core of our study, and presents a set of optimization techniques to address these problems. Furthermore, the last mile delivery of perishable food in urban area is discussed.

Chapter 3 deals with a capacitated vehicle routing problem for perishable food delivery in urban areas. For such a problem, a simulation model is used to find the fastest routes to deliver products, as well as to assess the impact of congestion on vehicle tours. This chapter further present mathematical formulations and exact solving approaches for the problem.

Chapter 4 addresses another variant of routing problem of perishable, which is customer-centric. The problem is formulated as a many-objective optimization problem and a metaheuristic based approach is provided to solve it. Furthermore, we present an interactive map to visualize the solutions of interest.

Chapter 5 provides another solution approach for the customer-centric routing problem addressed in chapter 4. The proposed solving approach is a metaheuristic-based modeling to generate alternative solutions.

Chapter 6 summarizes the findings of the study, examines how the research questions were answered, and highlights the research's significant contributions and limitations. Finally, the chapter concludes with recommendations for further research and closing remarks.

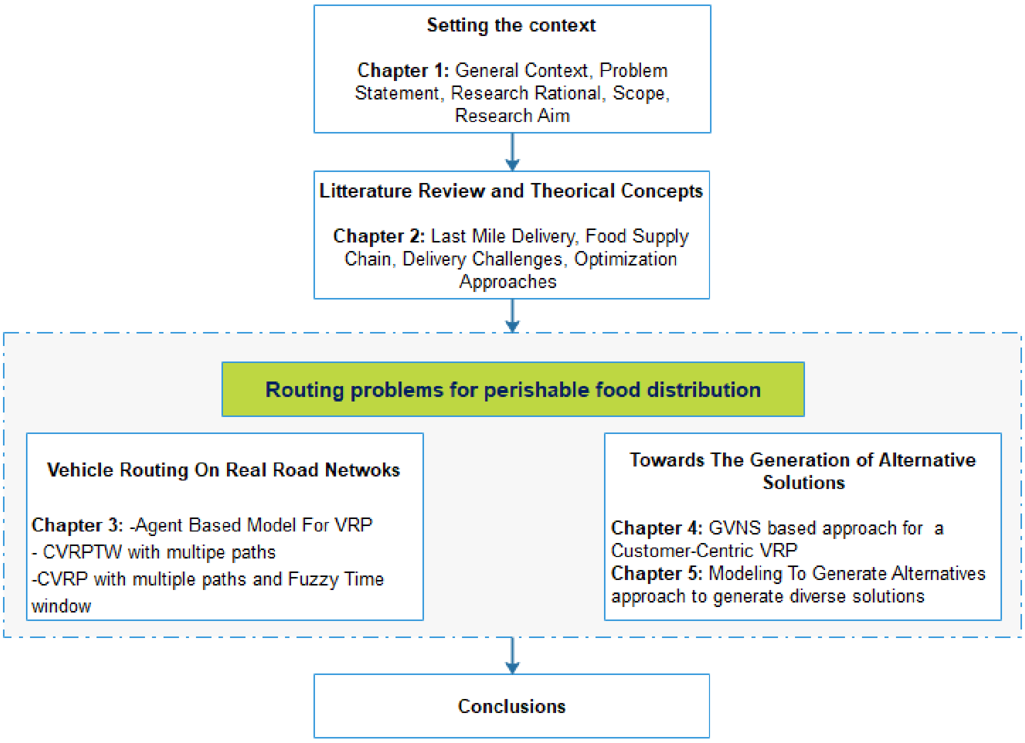


FIGURE 1.3: The thesis structure.

Chapter 2

The last mile delivery

This chapter describes the key concepts associated with the last mile delivery. We discuss last-mile delivery as a part of the city's overall system, and point out the challenges associated to this part of supply chains in general. Afterwards, we focus on the last mile for Food Supply Chains (FSC). We conduct an academic literature review on studies in FSC to identify the gaps and research opportunities. Vehicle Routing Problems (VRP) are the most known problems in the era of last mile delivery. Since the focus of our thesis is on solving these problems, in this chapter, we introduce the main versions of VRPs, and the optimization techniques that can be used to solve them.

This chapter is organized into six sections as follows: section 2.1 following the introduction, presents the concept of city logistics, section 2.2 introduces the last mile delivery, its characteristics and challenges, section 2.3 gives an overview on vehicle routing problems, and their solving approaches, section 2.4 reviews the literature on the last mile delivery for perishable food distribution, section 2.5 presents the summary of the key findings drawn from this chapter.

A part of the material presented in this chapter appears in:

- El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "Coupling Soft Computing, Simulation and Optimization in Supply Chain Applications: Review and Taxonomy." IEEE Access 8 (2020): 31710-31732.

2.1 The city logistics

City logistics is a system that links end users to logistics activities, such as freight distribution, as well as the administration processes and regulations of urban logistics (Lu and Borbon-Galvez, 2012), (Rodrigue et al., 2016). Several terms are used to describe the city logistics such as Urban Logistics (Alho and Silva, 2015), Urban Freight (Tipagornwong and Figliozzi, 2014);(Stathopoulos et al., 2012);(Cherrett et al., 2012), Urban Freight Logistics(Gonzalez-Feliu et al., 2012).

The authors in (Cardenas et al., 2017) conceptualize urban freight movement as a hierarchical structure of three levels (Fig.2.1). Starting from a macro level (city logistics) and working down to the micro level (last mile logistics) through the meso level (urban distribution).

City logistics is concerned with vehicle and goods traffic as well as products characteristics at the macro level, whereas at the meso level, urban good distribution is concerned with how goods are dispersed inside urban areas ((Fernandez-Barcelo and Campos-Cacheda, 2012), (Cardenas et al., 2017)). This level includes also the influence of freight on traffic flows and the livability of cities (Browne et al., 2010).

Several definitions of urban freight have been presented. (Hicks, 1977) was the first to introduce a formal definition as 'all journeys into, out of, and within a designated urban area by road vehicles specifically engaged in pick-up or delivery of goods (whether the vehicle is empty or not), with the exception of shopping trips'. There exist other various definitions of city logistics, we present some of them bellow:

- **(Taniguchi and Thompson, 2002)**:"The process for totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, its congestion, safety and energy savings within the framework of a market economy"
- **(Barceló et al., 2005)**:"Freight transport in urban areas and specifically the freight flows associated to the supply of goods to city centres"
- **(Bektas et al., 2015):**"Encompasses the routing and movement of freight across all transport modes, as well as associated activities such as warehousing and exchanging information for the management of freight at each end of its journey"
- **(Crainic et al., 2009):**"Concept that tries to optimize urban freight transport systems by considering all stakeholders and movements in urban areas"

2.2 The last mile delivery: characteristics and challenges

2.2.1 Last mile delivery

Last-mile logistics refers to the delivery of items as fast as possible from the last transit point to the final drop point in the supply chain process. The term 'last mile' (LM) is widely used to define the final leg of the telecommunication process that connects the telecommunication process to the end users (Bhagwat et al., 1996) and (Wongthavarawat and Ganz, 2003).

Within the supply chain process, the last mile refers to the final leg of delivering goods to the consumer. However, it should be clear that the last mile delivery and the last mile logistics are quite different. While the last mile logistics includes all services to send the goods to the final consumer, storage and warehousing, sorting, routing and delivery to the final consumer (Mason

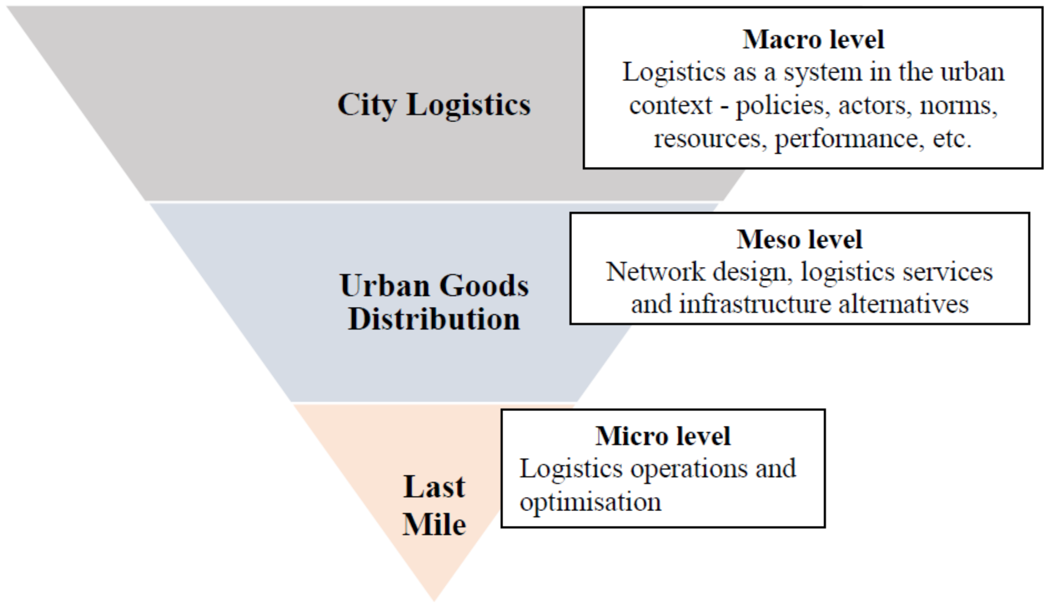


FIGURE 2.1: Hierarchical structure of urban freight logistics (Cardenas et al., 2017)

and Lalwani, 2006).The "last mile delivery" refers to the delivery part of the last-mile logistics operation.

Different definitions of the last mile delivery have been proposed in the literature. Below, we capture some of them:

- **(Morganti, 2011):** "The physical distribution occurring in the last part of supply chain"
- **(Morganti and Gonzalez-Feliu, 2015)):** “Small scale distribution of goods in urban environment, which includes delivery to retailer”.
- **(Morris, 2009)**: “Pick-up /drop-off point to the end customer in commercial buildings”
- **(Aized and Srai, 2014):** “One important step in supply chain and business-to-customer paradigms and is responsible for efficient and economical final delivery of goods to customers with final mode of delivery of orders via road.

2.2.2 Characteristics of the last mile freight logistics

Freight Last Mile Logistics (LML) has a major negative influence on urban development sustainability (Pronello et al., 2017), as it’s most known as fragmented and inefficient part of the supply chain. To develop a more sustainable LML system for an urban area, it is necessary to first understand the basic characteristics of freight LML. Freight LML is characterized by the fact of involving different actors such as carriers, suppliers, and end customers, routes are relatively short, and speed driving is low, space restriction, limited traffic infrastructure compared to high demand for transport, a high environmental impact. In addition, LML is inefficient due to the empty running, and the low load factor since the courier may travel ten of miles to deliver a small parcel (Alvarez and Calle, 2011); (Kin et al., 2018). Freight LML is also renowned for its reliance on local factors and infrastructural limits such as unloading spaces. In particular, LML is characterized by a high degree of freight flow fragmentation, the employment of smaller trucks, and a low utilization of vehicle capacity.

2.2.3 Challenges of last mile freight logistics

The last mile is the most expensive, polluting, and less efficient part of the supply chain (Nenni et al., 2019); (Visser et al., 2014); (Ehmke and Mattfeld, 2012). Because of the dynamic character of the urban environment and economic activity, urban freight delivery is particularly inefficient. In addition to the economic and environmental aspect, the increasing flow of vehicles implies congestion, traffic accidents, and impact the safety and life quality of citizens. Based on the literature, we have tried to identify and discuss the major challenges facing the last mile logistics. We classify the challenges into 4 categories based on the focus aspect: The economical aspect, the infrastructural aspect, the managerial aspect, and the technological aspect.

- **Economical aspect**

The cost associated with last mile logistics can be estimated to 28% of the total delivery good delivery cost (Ranieri et al., 2018); (Cleophas and Ehmke, 2014); (Melacini et al., 2018); (Ehmke and Mattfeld, 2012). The last mile cost drives are the customer service, the management of vehicles, the environmental effect, and the delivery type (Gevaers et al., 2014). The costs associated to the last mile are sensitive to factors such as the geographical area, investment cost, the driver wages. Indeed, the latter could affect the delivery cost in case of using alternatives to vehicles such as bikes that leads to longer driving duration.

In the context of online retailer grocery delivery, additional costs may occur due to delivery failure. In fact, the courier may need to make several delivery attempts to attend the customer at home.

Another source of complexity in last mile, is that in e-commerces deliveries, the benefit margins are very poor, and the customers have high expectations of service quality (Cleophas and Ehmke, 2014).

The acquisition of alternatives, such as electrical trucks, represents also a challenge for some firms, given the higher operational and purchasing costs (Oliveira et al., 2017).

- **Infrastructural aspect**

The structure and the geographical location of the city play a key role in the last mile activities. In fact, there are problems related to the accessibility, and the distance travelled in urban areas. Geographical challenges, population density, and truck movement restrictions all pose obstacles. The performance of last mile operations is impacted by challenges such as urban tight streets, transportation regulations, and a lack of facilities for parking and fast loading and unloading (Perboli and Rosano, 2019); (Ewedairo et al., 2018). With the increasing traffic flow, and freight volume, It's difficult to change the infrastructures to hold with the growth. Alternatives, such as e-cargo bicycles, can help in these situations. However, the geographical conditions may make it impossible to employ a cargo bicycle/tricycle (Oliveira et al., 2017)

Moreover, the new technology may need the construction of new infrastructure and facilities. For example, there is insufficient road infrastructure, capacity constraints in terms of weight and dimension for electric cargo bicycles/tricycles. In addition to insufficient charging stations for electrical engines, and such logistical infrastructures come at a considerable cost of investment.

- **Managerial aspect**

There are many researches and solutions proposed to address the urban freight distribution problem. However, the last mile is still a complex part of the supply chain management. Urban freight distribution is characterized by the uncertainty and dynamic conditions which make the coordination between actors of supply chain a complex task (Gómez-Marín et al., 2018). Conflicting interests of actors such as city councils, people, dealers, carriers, and suppliers, for example, make urban delivery more complex, especially when stakeholders do not interact (Pronello et al., 2017); (Alvarez and Calle, 2011).

The customers' satisfaction in online retailing is challenging. Nowadays, customers need just in time deliveries and same day delivery service, which complicate the task for online retailers and logistics providers. In many cases, the retailers reject customers demand due to operational constraints such as the strict time windows, the mismatch between transport capacity and orders volume which impact the satisfaction of customers. Furthermore, customers are not ready to pay extra costs for a fast and good service level, therefore couriers need to optimize the delivery process to maintain a benefit range.

The delivery failure is one of the management challenges associated with negative impact on environment. A study of (Dell'Amico and Hadjidimitriou, 2012) estimates that the carbon emission could increase by 15% and 75% for a failure rate of 10% and 50% respectively. The failure risk can be reduced by specifying a time range for deliveries, but this solution make the routing complex.

- **Technological aspect**

Currently, Logistics providers tend to use alternatives to vehicles, such as electric cargo bikes. Nonetheless, these alternatives are associated with many problems. Their usage is constrained by speed and capacity limits. Despite the fact that the speed limit varies depending on the city, bicycle/tricycle speeds typically range from 2 to 6 km/h1, whereas light cars can attain speeds of up to 25 km/h. Vans travel at around 30 km/h1 in crowded metropolitan settings, while electric bikes travel at around 24 km/h1 (Sheth et al., 2019).

In urban areas, there is the prospect for a major shift from van-based goods delivery to drone-based delivery. However, there are some challenges associated to the usage of drones, such as the limited service area, the legal restrictions, the low productivity compared to vans, noise disturbance in service area due to the limited flying altitude.

2.3 Vehicle routing problems

2.3.1 History

VRP is one of the most well-known combinatorial optimization problems that was introduced by (Dantzig and Ramser, 1959). VRP is becoming an important field in operations research that deals with the transportation of items from a depot to a set of customers, an example is depicted in Fig.2.2. The objective is to determine the routes that satisfy all customers requests while minimizing costs. VRPs are complex to solve. (Lenstra and Kan, 1981) investigated the complexity of VRPs and concluded that they are all NP-hard. (Solomon and Desrosiers, 1988) also established that the VRPTW is an NP-hard problem. The complexity depends on the objective functions, the constraints, and the parameters that need to be considered.The latter differs from a variant of VRP to another. In the next subsection, we introduce the major variants of VRP and their characteristics.

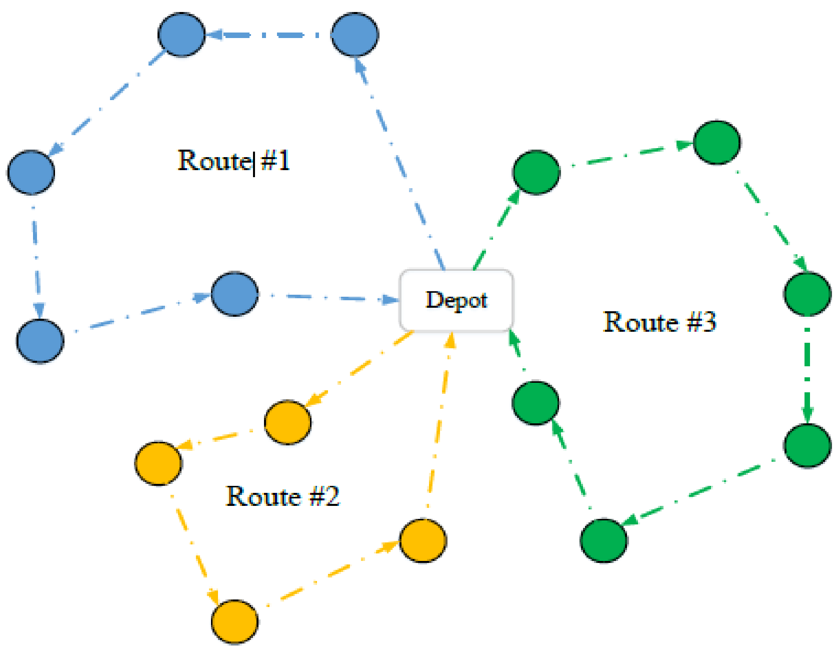


FIGURE 2.2: Vehicle routing problem example (Serrano Hernández, 2018)

2.3.2 Variants of vehicle routing problems

- **Capacitated vehicle routing problem**

Capacitated Vehicle Routing Problem (CVRP) is a variant of VRP in which the vehicles have a limited capacity. The objective is to find the best routes to serve customers from a central depot at a minimum cost.

- **Multiple depot VRP**

In this variant of problems, clients are served from several depots.This problem can be solved in two stages: first, customers are assigned to a depot using clustering strategies, then the routes are designed to link the clients assigned to the same depot.

- **Heterogeneous fleet VRP**

This variant considers that vehicles are different in terms of capacities, characteristics, and fixed costs.

- **VRP with time windows**

This variant is an extension of CVRP, that includes a time dimension constraint. A time window is associated to each customer, specifying a time range in which the customers have to be served to ensure his satisfaction. The distribution of perishable food is one of the real life applications of this problem.

- **Green VRP**

In this type of VRP, the environmental issues are included in the optimization process. The objective is to find the right balance between the economic issues -focusing on cost minimization-and the environmental issues.

- **Rich VRP**

Rich vehicle routing problem (RVRP) was first introduced by (Toth and Vigo, 2002). This variant combines multiple constraints for tackling realistic problems.

- **VRP with pick-up and delivery**

In this variant, vehicles are not only required to deliver goods to clients, but also to pick-up some items from customers location. We can distinguish between three types of pick-up and delivery problems.

1. *VRP with simultaneous pickup and delivery:* This sort of VRP represents a customer that has both a delivery and a pickup demand. As a result, we must consider the fact that goods returned to the delivery vehicle must fit within it.

2. *VRP with backhauls:* Customers can request or return products through this VRP. However, this variant presumes that all deliveries on each route must be completed before any pickups may be done. The things that customers return to the delivery vehicle must fit into it in this situation.

3. *VRP with mixed pickup and delivery:* It's a kind of VRP with pickup and delivery in which clients have either a pickup or delivery desire, and pickups and deliveries can occur in any order.

- **Dial a ride Problem**

The Dial-a-Ride Problem (DARP) consists of designing vehicle routes and schedules for customers with special needs and/or disabilities, animals and goods, time sensitive transportation, taxis, courier service, etc.

2.3.3 Optimization techniques for VRP

In this section, we explore the near-full spectrum of optimization techniques that can be used to solve vehicle routing problems. A taxonomy of these techniques is given in Fig.2.3.

2.3.3.1 Stochastic gradient estimation

The goal of stochastic gradient estimation approaches is to estimate the gradient of the performance measure when input parameters are continuous. They can be classified to gradient-based and non-gradient based methods.

- Gradient-based methods

Gradient-Based Methods (GM) are used to solve deterministic optimization problems. These methods require a mathematical expression of the objective function. To solve a simulation optimization problems, the gradients of the simulation responses to the variables should be estimated first, and then the gradient search methods developed for non-linear programming problems are employed to determine the optimum (Long-Fei and Le-Yuan, 2013). An enormous amount of research has focused on techniques for estimating gradients. The four main approaches used are described below:

1. Perturbation analysis (PA): Finite Perturbation Analysis (FPA) and Infinitesimal Perturbation Analysis (IPA) are the two principal types of perturbation analysis, FPA estimates the derivatives of discrete variables and IPA can estimate from a single run all gradients of the objective function (Ho and Cao, 2012). In the latter, if the decision variable is perturbed by an infinitesimal amount, the sensitivity of the response of the objective function can be estimated by tracing related statistics of certain events during a simulation run (Long-Fei and Le-Yuan, 2013).

2. The Likelihood Ratio (LR): allows to estimate both, the sensitivities and the performance measure through the same simulation. Details about this method are discussed in (Rubinstein and Shapiro, 1993).

3. Frequency Domain Method (FDM): a method that estimates the sensitivity and gradients of the performance values or responses of simulation models to the variables is proposed. The idea behind FDM is to oscillate the value of a variable according to a sinusoidal function during simulation. This technique is detailed in (Heidergott, 1995; Morrice and Schruben, 1989; Schruben and Cogliano, 1981).

4. Harmonic Analysis (HA): a methodology which consists of varying input parameters during the simulation rather than holding them constant. This technique was studied by (Swisher et al., 2000).

5. Finite Difference (FD): determines partial derivatives of the output variable (Carson and Maria, 1997).

- Non-gradient methods

1. Sample Path Optimization (SPO): also known as stochastic counterpart method, or sample average approximation method. This method needs some simulation replications to be performed first, and the expected value of the objective function is approximated by the average of the observations. This method can effectively deal with difficulties faced by stochastic approximation such as low convergence rates, absence of robust stopping rules and complicated constraints. This method can effectively deal with difficulties faced by stochastic approximation such as low convergence rates, absence of robust stopping rules and complicated constraints. The sample path method converges under conditions presented in (Gurkan et al., 1994).

2. Nelder mead simplex: is a direct search method that was originally dedicated to unconstrained optimization of deterministic functions and then has been frequently applied to the optimization of stochastic simulation models. This method presents an advantage for simulation optimization due to its insensitiveness to stochastic perturbations in function values. For further details, see (Barton and Ivey Jr, 1996).

3. Hook and Jeves: also called pattern search method is a sequential technique in which each step consists of two moves, an exploratory move to explore the local behaviour of the objective function and a pattern move to take advantage of the pattern direction (Hooke and Jeeves, 1961).

2.3.3.2 Statistical selection methods

- Ranking and selection methods

Ranking and Selection methods (R&S) are frequently used in practical problems such as finding the best facilities' location to minimize costs. This technique consists of selecting the best set from a given set of alternatives by estimating the performance of alternatives and comparing them (Goldsman and Nelson, 1994). The goal behind is to minimize the number of simulation runs while ensuring certain probability of getting the best solution. However, to achieve these, there is a restriction; simulation runs should be conducted independently to ensure that the outputs from each run are independent. A review of ranking and selection methods is provided by (Goldsman, 1983).

- Multiple comparison

Multiple comparison is alternative to ranking and selection methods, they can efficiently find the optimal alternative from a finite set. A number of simulation replications are performed on all the potential designs, and conclusions are made by constructing confidence intervals on the performance metric (Amaran et al., 2014). Three main types of multiple comparison procedures can be used: all pairwise Multiple Comparisons (MCA), Multiple Comparisons with the Best (MCB), and Multiple Comparisons with a Control (MCC). Further details about this technique are presented in (Hochberg and Tamhane, 1987) and (Hsu, 1996).

- Ordinal optimization

Ordinal Optimization (OO) is suitable when the number of alternatives is very large, thus it can effectively deal with such a difficulty faced by ranking and selection. This method was first proposed by (Ho and Cao, 2012). Ordinal optimization aims at finding the good solution rather than searching the very best one, which is computationally expensive. This idea is called "goal soften", further explanations are given in (Ho and Deng, 1994) and (Lee et al., 1999).

- Random search

Random Search (RS) is very close to meta-heuristics where a neighbourhood can be defined for each incumbent solution. However, the next move is probabilistically chosen, based on a given probability distribution (Figueira and Almada-Lobo, 2014), RS can work on an infinite parameter space, it was originally developed for deterministic problems and then extended to the stochastic setting. More details about RS are presented in (Andradóttir, 2006).

- Nested partitions

Nested Partitions method (NP) is a randomized method attempt to solve complex system optimization problems. The idea behind this method is that some parts of the feasible region may be most likely to contain the global optima. Hence, it is efficient to concentrate the computational effort in these regions. The advantages of the NP method include flexibility, convergence to a global optimum, high compatibility with parallel computer structures and so on (Long-Fei and Le-Yuan, 2013). NP combines global search through global sampling of the feasible region, and local search that is used to guide where the search should be concentrated. For further explanations, see (Shi et al., 2000).

2.3.3.3 Meta-model-based methods

- Response surface methodology

Response Surface Methodology (RSM) consists of a group of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest, y, and a number of associated control (or input) variables denoted by $x_1, x_2, ..., x_k$ (Khuri and Mukhopadhyay, 2010). RSM were originally developed to analyse the results of physical experiments to create empirically based models of the observed response values (Simpson et al., 2001a).

- Kriging models

Kriging Models (KM) were first used in mining and geostatistical applications involving spatially and temporally correlated data. These metamodels offer a wide range of spatial correlation functions for building the approximation. KM can approximate linear and non-linear functions equally well (Simpson et al., 2001b).

- Artificial neural network

Artificial Neural Network (ANN) is a biologically inspired computer program designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn through experience, not from programming. The applications of ANNs are various such a classification or pattern recognition, prediction and modeling. For further details, see (Agatonovic-Kustrin and Beresford, 2000).

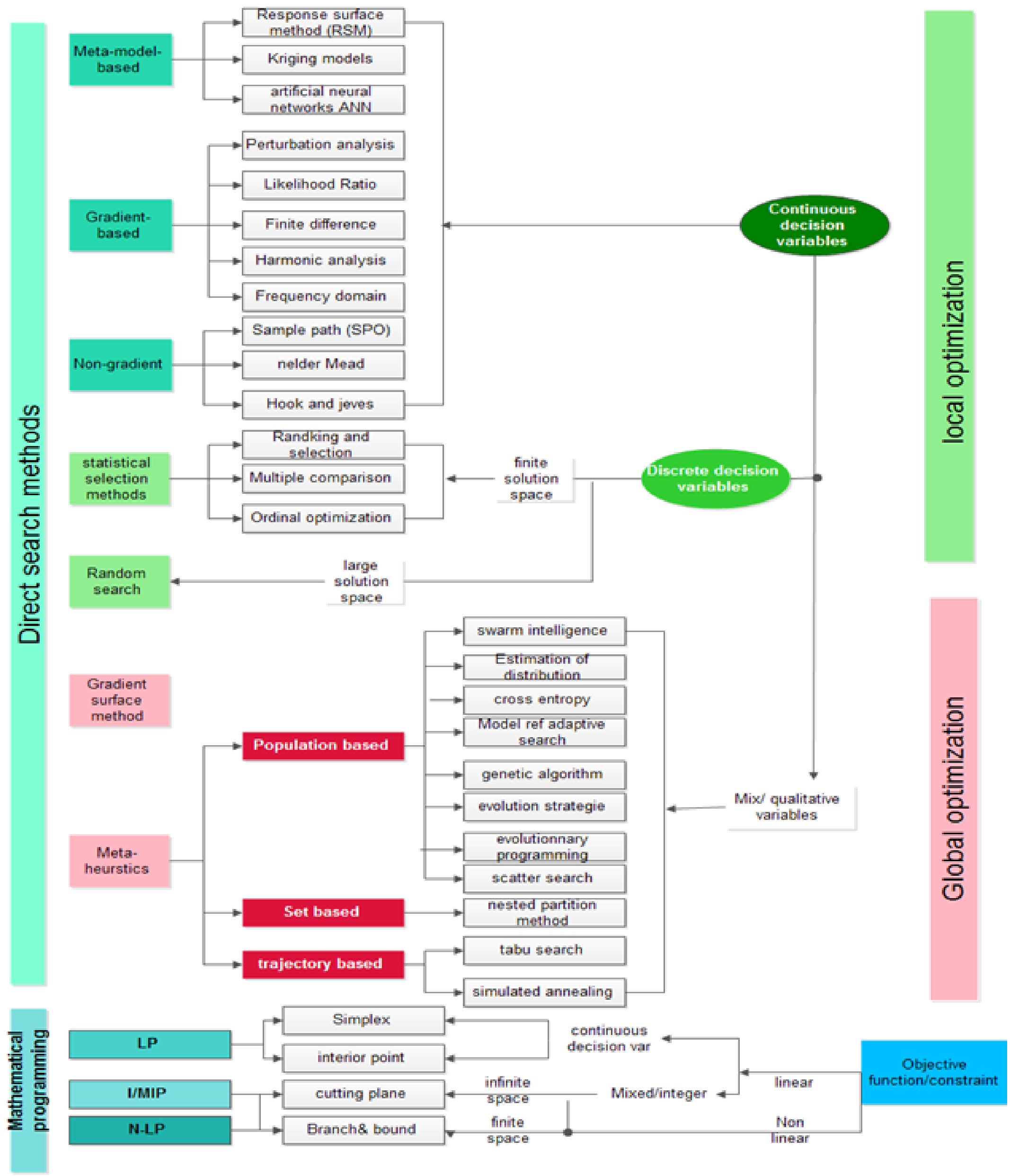


FIGURE 2.3: Optimization methods taxonomy.

2.3.3.4 Metaheuristics

- Population based metaheuristics

1. Ant Colony Optimization (ACO): was first introduced by Dorigo (Dorigo and Blum, 2005) to solve hard combinatorial optimization problems in a reasonable computation time. ACO approach is inspired from the foraging behaviour of real ants. This technique was applied to different problems such as vehicle routing problems, scheduling problems. See (Dorigo and Blum, 2005) for further details.

2. Estimation of Distribution Algorithms (EDA): are powerful stochastic optimization techniques that explore the space of potential solutions by building and sampling a variety of probabilistic models of promising candidate solutions, which allows solving a variety of problems. Furthermore, the ability of the EDA to provide useful information about the problem landscape makes this technique desirable compared to other optimization techniques, see (Hauschild and Pelikan, 2011) for more details.

3. Cross-Entropy Method (CE): is an efficient technique for probabilities estimation of rare event, as well as for combinatorial problems. The CE method involves an iterative procedure where each iteration can be broken down into two phases (1) generating a random data sample (2) Updating the parameters of the random mechanism to get a "better" sample in the next iteration. The method has been successfully applied for diverse problems such as assignment problems, travel salesman problems, scheduling problems, and buffer allocation problems. For much detail about the CE procedure, see (De Boer et al., 2005).

4. Model Reference Adaptive Search: is a randomize search method for solving both continuous and combinatorial optimization problems. As in EDAs, this approach updates a parameterized probability distribution, and like the CE method, it also uses the cross-entropy measure to project a parameterized distribution (Fu et al., 2005), for further details see (Hu et al., 2007).

5. Genetic Algorithm (GA): is a stochastic search procedure based on the mechanism of natural selection and natural genetics, developed by John Holland 1975. GA has three main operators, selection, crossover, and mutation. It is used to search large, non-linear search spaces where expert knowledge is lacking or difficult to encode and where traditional optimization techniques fall short (Goldberg, 1989); (Ding et al., 2005). For much detail about GA procedure you can see (Bäck and Schwefel, 1993).

6. Evolution Strategies (ES): a robust method similar to GA, which imitate the principle of natural evolution as an optimization technique to solve deterministic problems. ES was introduced by Rechenberg in 1964 at the Technical University of Berlin to optimize the shape of a pipe and nozzle. Further details about ES are given in (Carson and Maria, 1997).

7. Evolutionary programming: techniques developed by Lawrence Fogel, they aimed at evolution of artificial intelligence in the sense of developing ability to predict changes in an environment. For further details about these techniques, the interested reader can see (Michalewicz, 2013).

8. Scatter Search (SS): Scatter Search (SS) is an evolutionary algorithm that proved its effectiveness to solve hard optimization problems. The SS algorithm operates on a set of reference points. That constitutes good solutions obtained thought previous solving efforts. For defining "good" includes special criteria such as diversity that purposefully go beyond the objective function value (Fu et al., 2005). The implementation of SS is based on five methods: diversification generation method, improvement method, a reference set update method, subset generation method, and solution combination method. For further details on the SS method see (Martí et al., 2006).

- Trajectory based methods

1. Tabu Search (TS): first introduced by Glover and McMillan (Glover and McMillan, 1986), Tabu search uses special memory structures (short-term and long-term) during the search process that allows the method to go beyond local optimality to explore promising regions of the search space. The basic form of Tabu search consists of a modified neighborhood searchprocedure that employs adaptive memory to keep track of relevant solution history, together with strategies for exploiting this memory (Amaran et al., 2014).

2. Simulated Annealing (SA): was first proposed by (Kirkpatrick et al., 1983). SA is inspired by the annealing technique used by the metallurgist to obtain a "well-ordered," solid state of minimal energy (while avoiding the" metastable" structures, characteristic of the local minima of energy). This technique consists in carrying a material at high temperature, then in lowering this temperature slowly (Boussaïd et al., 2013).

2.3.3.5 Gradient surface method

Gradient Surface Method (GSM) is a technique that combines the advantages of Response Surface Methodology (RSM) and estimation techniques like Perturbation Analysis (PA) or Likelihood Ratio method (LR). In GSM, the gradient estimation is obtained by PA (or LR), and the performance gradient surface is obtained from observations at various points in a fashion similar to the RSM. Zero points of the successive approximating gradient surface are then taken as the estimates of the optimal solution. Compared to RSM, GSM is more efficient, indeed it's a single run method (Ho et al., 1992).

2.3.3.6 Bayesian/sampling algorithms

The Bayesian/Sampling (B/S) methodology is an iterative search strategy, where at each iteration; the next guess is chosen to be the point that maximizes the probability of not exceeding the previous value by some positive constant (Lorenzen, 1985; Ammeri, 2011).

2.3.3.7 Mathematical programming methods

- Linear programming

Linear Programming (LP) was developed to solve linear programs. A LP is an optimization problem characterized by linear objective functions of the unknowns, and the constraints are linear equalities or linear inequalities in the unknowns. Linear programming problems are structured into the following form:

$$
\begin{aligned}
&\text{Minimize } Z = c_1x_1 + c_2x_2 + \ldots. + c_nx_n \\
&\text{Subject to} \\
&a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n = b_1 \\
&a_{21}x_1 + a_{22}x_2 + \ldots. + a_{2n}x_n = b_2 \\
&. \\
&. \\
&a_{m1}x_1 + a_{m2}x_2 + \ldots. + a_{mn}x_n = b_m \\
&x_1 \geq 0, x_2 \geq 0, \ldots\ldots x_n \geq 0
\end{aligned}
$$

Where Z is called the objective function, the variable $x_1 \ldots. x_n$ the decision variables to be determined, and $c_1, c_2, \ldots, c_n, b_1$, $\mathrm{b}_2, \ldots, \mathrm{b}_n, \mathrm{a}_{11}, \mathrm{a}_{12}, \ldots, \mathrm{a}_{mn}$ are fixed real constants.

Linear programming arises in different areas. The most reasons of its popularity are the simpler computation, as well as, its ease to define. In the supply chain context, linear programming was used for planning production, distribution and inventory operations (Martin et al., 1993) to solve integrated supply, production and distribution planning (Chen and Wang, 1997). Simplex is the most popular method for solving LP problems.

1. Simplex: developed by George Dantzig, a member of the U.S. Air Force, in 1947 in order to solve linear programming problems. The idea behind simplex is to start from one basic feasible solution rather than checking the entire extreme. Then, each iteration of the algorithm takes the system to the adjacent extreme point with the best objective function value. These iterations are repeated until there are no more points with better objective function values, thus the optimality is reached (Lewis, 2008). Simplex can converge to an exact solution in a finite number of steps.

2. Interior point method: was introduced first by (Hoffman et al., 1953) and (Frisch, 1955) to solve LP. However, it was weak compared to simplex due to the expensive computational steps, and numerical instability in calculation. (Karmarkar, 1984) Have presented then a novel interior point method faster than simplex and does not require a feasible starting point. The interior-point is appropriate when the problems are large and convex. In addition, this approach has the advantage that the system of linear equations to be solved at each iteration has the same dimension and structure throughout the algorithm, making it possible to exploit any structure inherent in the problem (Rao et al., 1998).

- Mixed integer programming

Mixed-Integer Linear Programming (MILP) problems are problems where some or all variables are integer-valued and the objective function and the constraints are linear. Techniques for solving MILP differ from those used for LP. Indeed, the solution of an entire LP problem is required at each step of the algorithm. The most popular techniques to solve MILP are branch and bound and cutting plane. MILP have been widely used in the supply chain context for production, transport, and distribution planning

1. Branch and bound: the idea behind this technique is that since the initial problem is hard to solve, it's subdivided to sub-problems. A search strategy is used at each stage of the algorithm to select an unsolved problem. A bounding strategy is used to compute a lower bound on the objective value of a solution available from this sub-problem. If this lower bound exceeds a known incumbent solution value, then this sub problem is eliminated. Otherwise, the sub-problem is further partitioned using the branching strategy, and the process continues until all sub problems are fathomed. For further details, see (Sen and Sherali, 1985).

2. Cutting plane: the fundamental idea is to start with the integer linear program and solve its LP relaxation. If the solution is integral, it's the optimal for the original problem, otherwise find a linear constraint that excludes the LP solution but does not exclude any integer Points called the CUT. Then, add the CUT constraint to the problem and return to the first step.

- Non-linear programming

Non-Linear Programming (NLP) deals with problems characterized by a non-linearity of the objective function and/or the non-linearity of the constraints. A NLP problem is structured as follows:

$$\begin{aligned}
&\text{Minimize } f(x)\\
&\text{Subject to}\\
&g_i(x) \leq 0 \text{ for i} = 1, \ldots, \text{m}\\
&h_i(x) = 0 \text{ for i} = 1, \ldots, \text{p}\\
&x \in X
\end{aligned}$$

Where $f(x)$ is the objective function,$g_i(x) \leq 0$ is the inequality constraints and $h_i(x) = 0$ is the equality constraints.

2.4 Perishable food distribution: literature review

2.4.1 Approach for selecting and reviewing the literature

To collect and select the papers to be included in this review, we adopt the process described in Fig.2.4 inspired from the systematic mapping process

(Petersen et al., 2008). The essential process steps are the definition of research questions, conducting the search, screening of papers to identify relevant ones, at last data extraction and analysis. Each process step has an outcome.

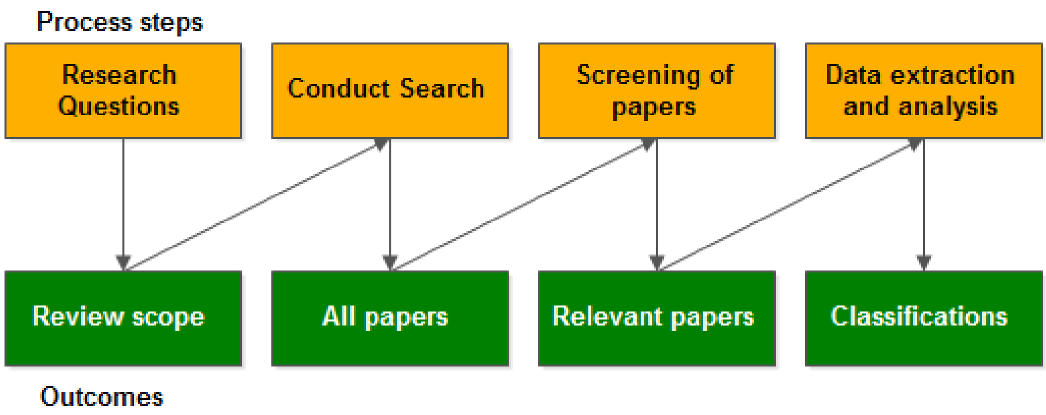


FIGURE 2.4: The research process

- Research questions

The overall focus of our thesis is the distribution of food on urban areas. To gain a detailed view on this topic, we have conducted an extensive search focused on the practices adopted by cold supply chains to distribute products, and the main challenges encountered whiting the distribution process. These researches helped us to identify one of the main research questions, which is the scheduling of a fleet of vehicles to distribute food efficiently. Therefore, we have focused on reviewing researches about Vehicle Routing Problems (VRP) for perishable food delivery. The following research questions are addressed:

1. What are the different ways to model VRP for food distribution.
2. What are the main objectives considered while modeling VRP.
3. What are the optimization techniques that can be used to solve such VRP.

- Conduct search

Based on the research scope identified, the following combination keywords were initially used for scraping papers:'food delivery','cold chain distribution problems','VRP for food delivery','food distribution network'.These keywords were expanded to include other ones after an initial review of selected researches.

The articles reviewed are gathered from the scientific databases presented in table 2.1

- Screening of papers

TABLE 2.1: List of databases consulted

Databases	
Scopus	ProQuest
IEEE Xplore	Wiley online library
Emerald insight	dblp computer science bibliography
EBSCO	Google Scholar
ACM Digital library	Mendeley
Web of science	Springer

The research based on the proposed keywords have resulted on a set of 120 articles. The titles and abstract were initially examined to select the relevant papers to the research questions predefined. The following criteria are used to determine the relevance: article focus on food distribution and VRP, modeling of the problem, proposal of a solving approach, and availability of numerical results demonstrating effectiveness of proposed model.

- Data extraction and analysis

The final database of papers is analysed based on content analysis research method. Content analysis is an observational research method that is used to systematically evaluate the literature in terms of various categories, transforming original texts into analysable representations (Ford, 2004). The data extracted from papers include the literature type, date of publication, the models used, objectives considered, solving approaches proposed. In the next subsection, the papers reviewed are classified into 3 categories based on their focus and analysed.

2.4.2 Articles classification

The articles selected in the previous step can be classified based on the aspect they are focusing on, which can be economic, environmental, social, o a combination of the latter. Table 2.2 presents the distribution of the reviewed paper into 5 categories, based on the aspects aforementioned, namely: 1) Transportation, 2) quality, 3) transportation and environment, 4) transportation and quality, 5) transportation, quality, and environment. In the next subsections, we review the papers based on three major factors considered: Transportation, quality, environment.

TABLE 2.2: Classification of reviewed papers

Category	*References*
Transport	(Garcia Caceres et al., 2015) (Al Theeb et al., 2020)
Quality	(Lin et al., 2018)
Transport And Quality	(Akkerman et al., 2010) (Rong et al., 2011) (Flamini et al., 2011) (Wang and Yu, 2012) (Yue et al., 2013) (Abousaeidi et al., 2016) (Fikar, 2018) (Tsang et al., 2018) (Wang et al., 2018a)
Transport And Environment	(Huang et al., 2009) (Bektaş and Laporte, 2011) (Hariga et al., 2017) (Tordecilla-Madera et al., 2018) (Lin et al., 2019) (Micale et al., 2019)
Transport, Quality, Environment	(Bortolini et al., 2016) (Hsiao et al., 2017) (Stellingwerf et al., 2018) (Li et al., 2019) (Stellingwerf et al., 2021)

2.4.2.1 Transportation

The distribution of perishables in food supply chains can be modelled as a variant of VRP, the common variants used are capacitated vehicle routing problems, or VRP with time windows constraint. Others real life constraints are also considered. In VRP problems, the routes are determined such that all customers are satisfied, and the cost is minimized. The transportation cost can be influenced by several factors. The distance travelled is one of the major factors. Indeed, the distance affects the fuel consumption, the refrigeration cost, and other cost components. Different factors can influence the fuel consumption such as the vehicles' speed, the load, congestion, slops (Abousaeidi et al., 2016), (Bektaş and Laporte, 2011), (Stellingwerf et al., 2018).´ The fuel consumption is captured in different ways by researchers. In some works, they split it into the consumption during the transportation process, and during the unloading at customers (Hsiao et al., 2017). While others distinguish between the consumption by the vehicle, and the consumption by refrigerated equipments (Li et al., 2019), (Al Theeb et al., 2020). Another important elements that need to be contemplated while computing the transportation cost, is the vehicle's capacity and the fleet of vehicles available, since these elements impact the number of tours needed to serve the clients, and therefore impact the costs (Garcia Caceres et al., 2015), (Fikar, 2018), (Tsang et al., 2018). Generally, in the literature, the number of trucks is considered as a constraint. Nonetheless, some works regard it as a decision variable, such as (Hariga et al., 2017). Other cost elements can be added to the transportation cost such as the toll payment (Tordecilla-Madera et al., 2018), the driver wages (Bektaş and Laporte, 2011), (Hsiao et al., 2017), (Li et al., 2019). In addition to variables costs, fixed cost related to the maintenance of trucks, check-up, tiers and depreciation (Wang et al., 2018a), (Lin et al., 2018).

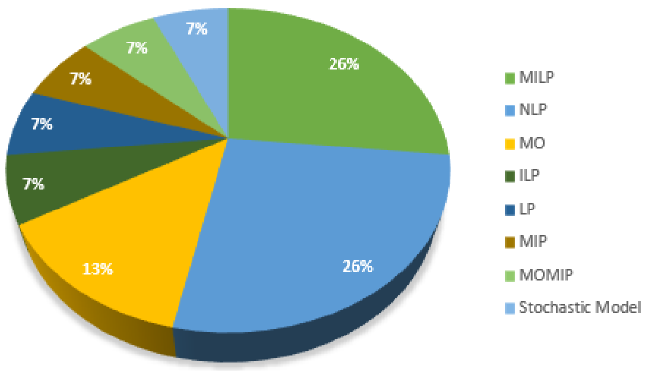
2.4.2.2 Quality

The quality of perishable food decay over the time, in order to maintain the quality of products additional costs are imputed. The temperature range required differs function to the type of the handled product. We distinguish between three types: frozen chain such as ice cream, chilled chain such as fish and potatoes, and ambient chain that does not require cooling such as canned products (Akkerman et al., 2010). The quality cost can be modelled as function of the temperature range, and the quantity of products loaded such as in (Rong et al., 2011), (Li et al., 2019) separate between the cost of maintaining the temperature during the transport, and the unloading process. because once the truck is open, the energy required to maintain the cooling temperature within the truck is affected by the ambient temperature outside the vehicle, which has an impact on the total cost. (Yue et al., 2013) examined the effect of ambient temperature and storage temperature changes on the quality of products. The ambient temperature can be treated as constant if it doesn't change significantly during the transportation of products. The frequency of opening the truck's door is another important factor that is included in the damage cost (Wang and Yu, 2012), (Li et al., 2019), (Stellingwerf et al., 2021). Besides the quality of products, the quality of service is another aspect that induce additional cost. For example, a penalty cost is included if the customer is served outside the time windows (Flamini et al., 2011), (Wang and Yu, 2012), (Li et al., 2019), (Lin et al., 2019).

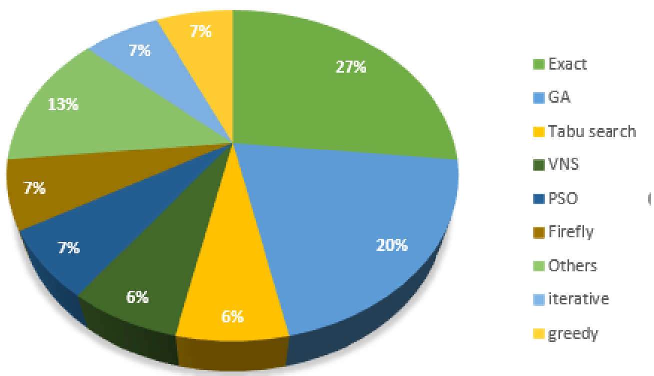
2.4.2.3 Environment

Recently, the environmental impact of transportation has become a severe issue.The rising amount of greenhouse gas (GHG) emissions during transportation is one of the key causes. On average, carbon emissions of the supply chain accounts for more than 75% of the carbon footprint of an industrial sector (Huang et al., 2009). Energy consumption during transportation and for the refrigeration is an important aspect in calculating the cost of GHG emissions. One method of estimating GHG transportation emissions is to convert the amount of fuel spent during vehicle travel and unloading into carbon emissions using carbon emission coefficients,(Bortolini et al., 2016), (Hsiao et al., 2017), (Li et al., 2019), (Micale et al., 2019), (Lin et al., 2019). Since the energy consumption is essential to estimate the GHG emissions, therefore it should be estimated accurately. One way is to evaluate the energy consumed function to the distance travelled, the truck's speed and the load of vehicle (Stellingwerf et al., 2018), (Stellingwerf et al., 2021). As for the transportation cost, the number of trucks used and their capacity also impact the emissions (Hariga et al., 2017), (Tordecilla-Madera et al., 2018).

Table 2.3 summarizes the type of models used to formulate the perishable food distribution problem, as well as the proposed solving approaches. We have found that most of the researchers have proposed a Mixed Integer Linear Programming formulation to the problem, as shown in Fig 2.5 (a). Other model types have been found including the Multi-Objective (MO), the Linear Programming (LP), and non-linear programming (NLP), the integer linear programming (ILP), the Multi-Objective Mixed Integer Programming (MOMIP).



(A)



(B)

FIGURE 2.5: Reviewed papers by models(A), and optimization method (B)

To solve these models, several approaches have been proposed, depending on the complexity of the model. Metaheuristics and Heuristics are found

TABLE 2.3: Models and solving approaches of reviewed papers

References	Type of Mathematical Model	Solving Technique
(Rong et al., 2011)	MILP	Exact (CPLEX)
(Bektaş and Laporte, 2011)	ILP	Exact (Branch and cut)
(Flamini et al., 2011)	Stochastic Model	Tabu search
(Garcia Caceres et al., 2015)	MIP	Exact (Lingo)
(Bortolini et al., 2016)	LP	Exact
(Hsiao et al., 2017)	NLP	Biography based optimization
(Hariga et al., 2017)	NLP	Exact+ iterative search
(Stellingwerf et al., 2018)	MILP	Exact
(Tsang et al., 2018)	MILP	Genetic Algorithm
(Wang et al., 2018a)	MO	Genetic Algorithm+ Variable Nieghborhood Search
(Tordecilla-Madera et al., 2018)	MOMIP	$\epsilon - constriant$
(Li et al., 2019)	MO	Particle Swarm Optimization
(Lin et al., 2019)	NLP	Genetic Algorithm+ Tabu Search
(Micale et al., 2019)	NLP	Firefly Heuristic
(Al Theeb et al., 2020)	MILP	Exact+ Greedy Random Search

to be the most common solving methods (Fig.2.5 (b)). Indeed, exact methods are exceedingly time-consuming as the size of the problem grows beyond a certain point, and their effectiveness decrease also. As the models for food distribution are complex and include several parameters, heuristics and metaheuristics are useful in this case. This is consistent with the observed trend. Furthermore, exact methods can be used in conjunction with heuristics as a support to validate its effectiveness.

2.4.3 Gap and research opportunities

Several gaps in the literature have been identified, indicating that additional targeted research is warranted. First, the integration of the three cost elements: Transportation, quality, environment. Most of the papers reviewed are focusing either on quality or environment, along with transportation, in both cases (Fig.2.6). in order to estimate how each of these cost elements contribute to the total cost, there is a need to include all the three. On the other hand, because of the significant losses that occur during distribution, food products have a higher demand. In addition, environmental consideration is becoming more critical recently. Indeed, the economical, social, and environmental aspects must be considered jointly. Moreover, the over increasing requirements of customers for a flexible, and just in time deliveries, brings into front the service level improvement. In the surveyed paper, the quality of products and the respect of time windows are the criteria commonly used to evaluate the quality of service. One additional area that is still open for

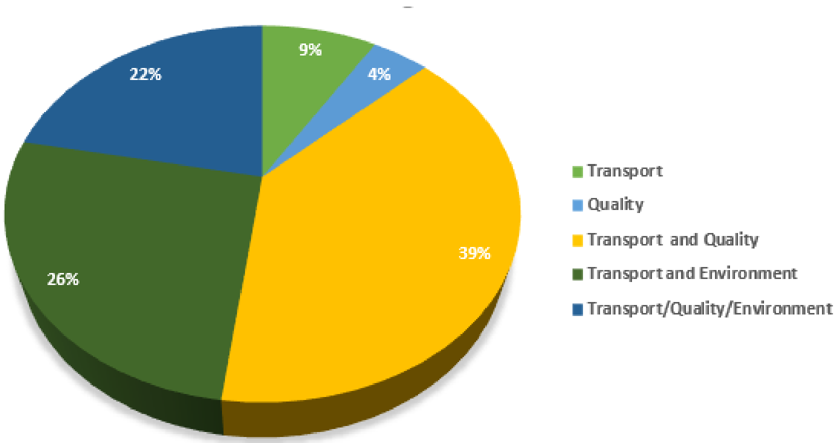


FIGURE 2.6: Distribution of reviewed papers by aspect

research is the inclusion of other parameters and indicators to evaluate the service level, such as the priorities respect.

Second, developing a comprehensive model that encompasses all three elements is a difficult task, therefore improving the solving approaches warrants further research work. In addition, Vehicle routing problems are traditionally defined on road networks, with service demand (pickup or delivery) points linked to specific locations. The approaches proposed in the literature to address VRP for perishables delivery are based on the assumptions that each origin-destination is connected by an arc that represent the best path. However, this representation may not fully replicate the original road network, and further road network data is required to properly address the routing problem. Therefore, the use of GIS and the real road network representation is another are that is worth exploring.

2.5 Conclusions

The key concepts used in last mile logistics were explained in this chapter. The last mile and city logistics were defined in detail. The last mile is defined as a part of the city logistics, and the final leg of the supply chain. This part is found as the most expensive and inefficient part of the whole supply chain.

The challenges constraining the last mile delivery were identified and categorized as economical, infrastructural, managerial, and technological. To face these challenges, and increase the competitiveness, companies have interest in improving the efficiency of the last mile. This task gives a rise to the well-known Vehicle Routing Problem (VRP). in this chapter gives a background of VRP, its variants and the optimization techniques to solve it.

As the scope of our thesis is the last mile delivery for food supply chains, we conduct literature review study to identify major challenges causing inefficiency of the last leg and opportunities for intervention. We have found several gaps that can be summarized as follows:

- Most of the papers reviewed are focusing either on quality or environment, along with transportation in both cases. Additionally, they did not include all the aspect. And in most of the studies the environmental aspect is neglected.
- The approaches to address VRP for perishables delivery presented in the literature are based on the assumption that each origin-destination is connected by an arc that represents the optimal path. This model, however, may not completely reflect the real road network.
- The evaluation of service quality is restricted into the respect of the time window, and the quality of products delivered. However, others factors maybe included as key performance indicators.

Chapter 3

Vehicle routing on road-network: the case of perishable food

This chapter investigates the second objective of the thesis, which consists of producing more realistic routes by addressing the vehicle routing problems on real road networks, considering different attributes, to benefit from an efficient problem-solving In line with this objective, we discuss the following contributions: (i) Agent Based Model (ABM) with Geographic Information System (GIS) function to design suitable routes for perishable product distribution (ii) a developed Mixed Integer linear Programming (MILP) models for the capacitated vehicle routing problem on a real road networks, and considering multiples attributes associated to arcs.

The remainder of this chapter is organized as follows. Following an introduction, In Section 3.2 we propose an ABM-GIS to model the problem of perishable food distribution. Section 3.3 provides a background on CVRP and VRP with multiples attributes. In Section 3.4 we study Capacitated vehicle routing problem with multiple attribute and soft time window for the delivery of perishables. A mathematical formulation and resolution approach is presented. Another version of CVRP with fuzzy time windows is proposed in section 3.5. Finally, the Section 3.6 provides the conclusions of the three studies.

The Material presented in this chapter is published in:

- El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "ABM-GIS simulation for urban freight distribution of perishable food." In MATEC Web of Conferences, vol. 200, p. 00006. EDP Sciences, 2018.
- El Raoui, Hanane, Mustapha Oudani, and Ahmed El Hilali Alaoui. "Perishable food distribution in urban area based on real-road network graph." In 2020 5th International Conference on Logistics Operations Management (GOL), pp. 1-6. IEEE, 2020.
- El Raoui, Hanane, Mustapha Oudani, David Pelta, Ahmed El Hilali Alaoui, and Abdelali El Aroudi. "Vehicle routing problem on a road-network with fuzzy time windows for perishable food." In 2019 IEEE International Smart Cities Conference (ISC2), pp. 492-497. IEEE, 2019.

3.1 Introduction

Nowadays, the growing demand for perishable food is challenging food distributors to meet the high-quality requirement of customers, due to the short shelf life of these products. Compared to regural product distribution, perishable food requires additional costs to maintain its quality. The food industries highly rely on cold chain to avoid damage or compromises during the distribution process. Cold chain logistics is the management of goods moved from one point to the other in a controlled temperature without interrupting the refrigerated production, distribution, and storage activities (Qiang et al., 2020).

Although the cold chain logistics business is growing, third-party logistics companies are still facing difficulties along the distribution chain. The complexity in cold chain distribution planning is due to the perishability of fresh products. In addition, urban delivery must also meet customers' requirements for fresh products within specific time windows, even if traffic jams or road closures occur in cities.

To ensure a cost-effective and timely delivery, food shippers must solve Vehicle Routing Problems (VRP) variants efficiently. Several research works have been proposed in the literature to address the VRP. However, the spatial dimension is practically neglected in research studies. Most of these studies address the problem using euclidean distance. Yet, in reality, the real road network is much more complex. Thus, the Euclidean distances used is far from accuracy and cannot hold any more. Moreover, researchers are addressing VRP using the so called customer-based graph approach (Huang et al., 2017). The latter is built on the assumption that each pair of nodes is connected by one arc considered as the best origin-destination path and calculated generally in keeping with the travel time or the distance. However, in real life, several attributes can be defined in each road segment (travel cost, distance, travel time, carbon emission, etc.). Therefore, each pair of nodes may be linked with a bunch of alternative routes. Hence, tending to the issue using a customer-based graph approach can discard good solutions and lead to non-optimal solutions. This issue was handled using two types of approaches (Ben Ticha et al., 2018), the first consists of representing the road network with a multi-graph, while the second solves the problem directly on a road-network graph.

In this chapter, we discuss three contributions. In the first one we propose an Agent Based Model (ABM) with Geographic Information System (GIS) function to design suitable routes for perishable product distribution, as well as to estimate with more accuracy the distances and travels duration, considering time-dependent speeds. Based on a case study, analyses of changes in traffic condition were conducted to get an insight into the impact of these changes on cost, service quality represented by the respect of time windows, and carbon emissions. In the second contribution, we propose a Capacitated Vehicle Routing Problem with Time Window and alternative Paths (denoted by CVRPTW-P). The problem is addressed on a real road network considering soft time windows, and two alternative paths. In the third contribution, we extend the proposed CVRPTW-P considering fuzzy time windows. The motivation behind is to mimic the real life case where the time windows are not always strictly obeyed due to operational or economic constraints. Therefore, some flexibility is allowed. It is here where fuzzy time windows appear. Up to now, few researchers have addressed VRP with fuzzy time windows adapted to cold chain, and to the best of our knowledge, we are the first to address a CVRP with fuzzy time windows adopting the real-road network approach.

3.2 Modelling the distribution of perishable food with the use of ABM and GIS

3.2.1 General context

Freight transport is fundamental to modern urban civilization. No urban area could exist without an efficient freight transport system. Considering the demand for high-quality fresh food, transportation requirements for fresh food delivery have been continually increasing in urban areas (Hsu and Chen, 2014). The delivery of these goods is perceived as a source of problems. This is owing to specific characteristics of perishable foods, traffic congestion, the increasing requirement of customers in terms of delivery time, and environmental impact. Traffic growth presents a new challenge for carriers in vehicle routing and scheduling to deliver products. Besides, it brings environmental problems due to the increase in carbon emission. Therefore, establishing the fastest routes, optimal departure from the distribution center to deliver these time-sensitive products is a major problem encountered by carriers. This study is focused on a time-dependent vehicle routing problem with time windows for distributing perishable foods in urban areas. Vehicle routing problem (VRP) had a spatial dimension which is practically neglected in research studies. Therefore, handling geographic data is requisite for efficient routes based on real distances. The most promising solution for so is GIS. In fact, we propose an Agent-Based simulation Model integrated with the Geographic Information System (ABM-GIS) to use real-case while performing distances between customers. In this work, we aim to produce the fastest routes to deliver perishable foods and estimating the Vehicle Hours Travelled (VHT) and the Vehicle Kilometers Travelled (VKT) which are valuable for transportation, through the simulation model. The impact of congestion on commercial vehicle tours in an urban area is assessed in this study. And as for short-term planning, for daily operations, we propose a time-dependent scheduling approach to optimize departure times from the distribution center.

3.2.2 Agent based model and GIS integration

Agent-based modeling is a relatively new method compared to system dynamics and discrete event modeling. This modeling paradigm is developed to simulate complex systems through the study of active entities' behaviour, known as agents. Agent Based System (ABS) has been adopted to solve complex problems, from various domains, such as logistics optimization, traffic, and urban planning. ABS can be used for different purpose: (1) Understanding observed dynamics, processes, and systems, (2) Designing or engineering of processes or systems, (3) Managing a system or process, (4) Formulating theory and explanatory models,(5) Predicting, (6) Optimizing resources, capabilities, and processes. For further details, refer to (Gómez-Cruz et al., 2017). Geographic Information Systems (GIS) are recognized as one of the new technologies which can be usefully introduced to Decision Support System (DSS) for vehicle routing (Keenan, 2006). GIS is well-defined as an information technology which stores, analyses, and displays both spatial and non-spatial data. Combining these two techniques provides us with the advantages of both and allows a better modeling of the vehicle routing problem, which is also a spatial problem.

3.2.3 Simulation model

- **Case study description**

This study presents an agent-based model of a food service distributor that provides perishable foods to restaurants, associated with GIS map of Casablanca, one of the most crowded cities in Morocco, where the Distribution Center (DC) and different customers are located.

- **Modelling environment**

For our modeling environment, we use AnyLogic software, Version 8.2 developed by XJTechnologies.The advantage of this software is its ability to support different simulation methodologies, including discrete event simulation, system dynamics and agent-based simulation, in which we are interested. Anylogic has an integrated GIS space where we can drag different objects (agents) and define their properties.

- **Agents**

In our model, agents represent the distribution center, customers, and vehicles used for delivering. After generating agents, the setting is defined in order to make agents live in the GIS Space. Locations of agents (DC, customers) were defined in a database to let Anylogic place it on the GIS map, through sending the address to an open street map server to obtain the corresponding coordinates.

- **Vehicle controlling**

In the developed model, we use a statechart to provide refrigerated vehicle movement. Anylogic statechart consists of a sequence of states and transitions that enable the user to define the behaviour of an object. Fig.3.1, 3.2, 3.3 illustrate the state charts used to control vehicles movements during the simulation of different scenarios presented below.

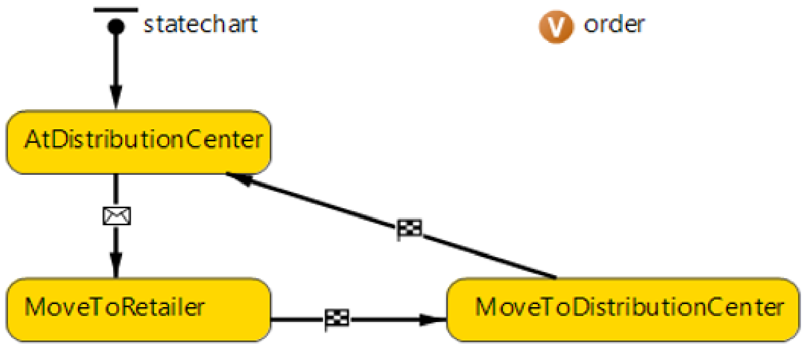


FIGURE 3.1: Statechart of vehicles in scenario A

- **Simulated scenarios**

In our case study, we simulate two scenarios corresponding to two types of tours. Within scenario A, the customer order is equal to the capacity of the truck, otherwise known as a Full TruckLoad (FTL). It's a degenerated type of VRP since the vehicle will visit only one customer before returning to the DC. In scenario B, the customer's order is relatively small, and the delivery is Less Than Truckload (LTL).

- **Routes**

During the distribution of frozen, refrigerated, and fresh goods it may be important to minimize the travel time, because these products have a short

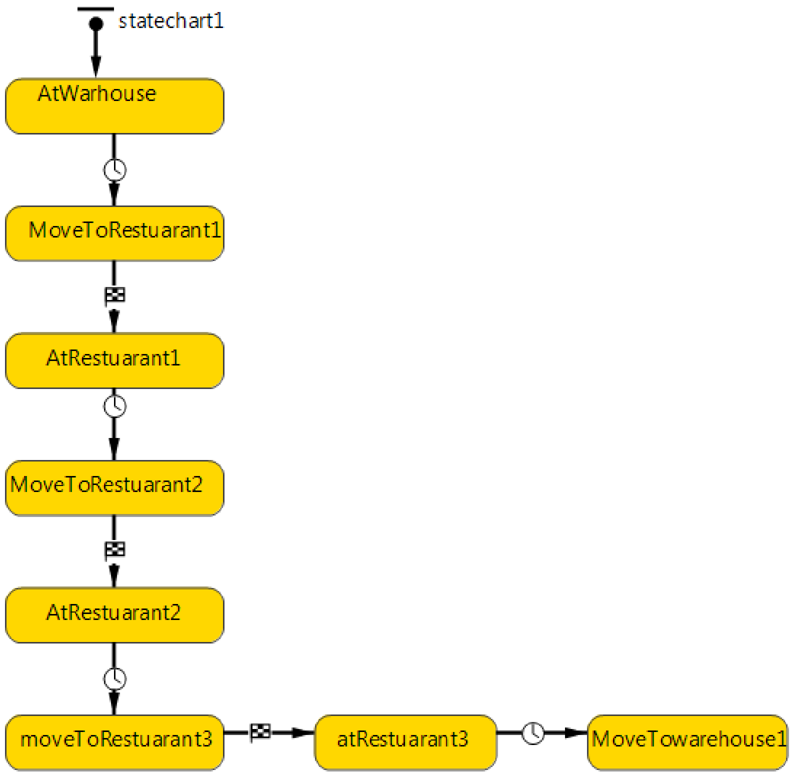


FIGURE 3.2: Statechart of vehicles in scenario B -Tour 1

shelf life and their quality decay with the variation of temperature. And since keeping the adequate temperature adds significant costs, selecting efficient fastest routes would consequently reduce the whole transportation costs. To find a suitable path for distributing perishable foods, several techniques have been applied in the literature. However, the shortfall of most researches is that authors apply mathematical equations instead of using spatial data for efficient routes. For example, (Tarantilis and Kiranoudis, 2002a) undertook the fresh meat distribution problem by applying several algorithms to find optimal sets of routes. To reach customers in time, real route network should be considered, hence the interest of GIS that was adopted by (Chen et al., 2008) to determine optimal transportation routes. In (Sharifi et al., 2009) authors apply GIS to transportation to find optimal roads among sets of routes. To identify the best routes for waste collection, (Bhambulkar, 2011) developed an application of ArcGIS Network Analyst tool. In view of this, we opt for GIS in our study. In the first scenario, customers get delivered directly. Routes that connect the distribution center to each customer are established by using GIS map route on Anylogic. Since we are dealing with time-sensitive products that should be delivered as fast as possible, we choose the fastest routing method option in the routing properties. In the second scenario, customers are subdivided into balanced tours determined according to this criterion: (1) tours have the same number of stops and (2) the service areas are the same across tours (Figliozzi, 2007). In both tours, each node is

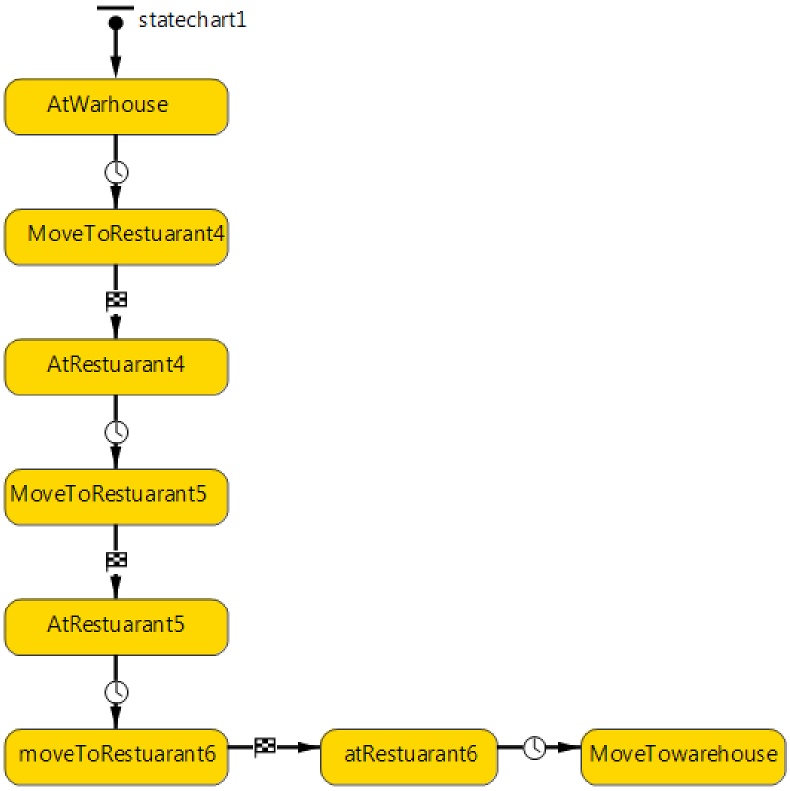


FIGURE 3.3: Statechart of vehicles in scenario B -Tour 2

linked to the nearest one through the fastest path set up by the same technique used in the first scenario.

3.2.4 Estimation of VKT and VHT

In transport planning, it's necessary to estimate the Vehicle Kilometers Travelled (VKT), as well as the Vehicle Hours Travelled (VHT). These two elements are important for carriers to get an insight into variable costs. Furthermore, VHT is valuable for scheduling vehicles departure from the DC. In the literature, there are several works that deal with the approximation of VKT. In a typical work, (Erera, 2000) proposes a continuous approximation to estimate VKT for a Capacitated Vehicle Routing Problem (CVRP). In (Chien, 1992) authors combine simulations with linear regressions to estimate the length of Traveling Salesman Problem (TSP). In (Kwon et al., 1995) they have used the same techniques in addition to neural networks for an accurate approximation. In most of the previous research, authors compute the VHT and VKT based on direct links. However, in reality, vehicles travel on a real road network. Thus, the Euclidean distances used are far from accuracy and cannot hold any more. This fact prompts us to adopt GIS function to approximate the real road network. After building the AB-GIS model, a simulation run was performed on anylogic software to estimate the VKT and VHT for both scenarios corresponding to FTL and LTL. We assume that roads are not congested, and then the vehicle travel with the speed limit in each arc of the tour. Travel speed limit can be found by open street browser [1]. And based on statistic outputs about the model execution in the log file, VHT and VKT are measured. Results are shown in Fig.3.4 and Fig.3.5.

FIGURE 3.4: VKT and VHT in scenario A

FIGURE 3.5: VKT and VHT in scenario B

3.2.5 Study of congestion impact

In this section we evaluate the impact of congestion on the vehicle hours travelled, the costs, and carbon emissions. The set of indices, variables, and parameters used in this study are presented in Table 3.1.

[1]www.openstreetbrowser.orgReferences.

TABLE 3.1: Variables and parameters

Sets and Indices	
V	Set of nodes
$\mathcal{C}$	Set of customers
K	Set of vehicles $k \in K$
i,j	Indices of nodes
Variables and parameters	
$x^k_{(i,j)}$	a 0-1 variable, equal to 1 in case the truck k travels from node i to j, 0 otherwise.
y^k_i	a 0-1 variable, equal to 1 in case the customer i is served by the truck k, 0 otherwise.
t^k_i	the starting service time at node i using the truck k.
$C_{(i,j)}$	the transportation cost from node i to j related to the distance
$C'_{(i,j)}$	the fuel consumption per unit time from node i to j
$VHT^k_{(i,j)}$	the vehicle hours travelled from i to j by the vehicle k.
$d_{(i,j)}$	the distance between node i and j.
C_e	the cost per unit time for the refrigeration during the transportation process.
U_i	the unloading time at customer i.
C'_e	the unit refrigeration cost during the unloading.
K	the fleet of trucks
α	The waiting cost per time unit if the vehicle arrive in advance.
β	The penalty cost per time unit if the vehicle arrive late.
$[a_i, b_i]$	the time window of customer i
VKT^i	the vehcile kilometers travelled to serve the customer i
LPH_{ij}	the fuel consumption per unit time form node i to j.
KPL_{ij}	the kilometer per liter consumed by a vehicle traveling from node i to j.
D_i	the departure from the node i, with i=0 for the depot
K_{sup}	the upper bound of the time interval K
V_{ij}	the speed on arc {i,j}
VHT^i_K	the vehicle hours travelled whiting the time interval K to serve the customer i
VHT^i_{K+1}	the vehicle hours travelled whiting the time interval K+1 to serve the customer i
V_K	the speed in the interval K

3.2.5.1 Impact of congestion on VHT

Nowadays, customers' requirement for fresh food delivery conditions is increasing in urban areas. Customers have become more exigent about the delivery time. They require to be delivered within a specific time window. In urban areas, the traffic flow is growing steadily, which makes the delivery of fresh food in time seen as a problem, and this is mostly due to traffic congestion. Traffic jams may be reached during different times of the day. Therefore, the delivery time will also depend on the time of the day. However, in today's planning systems, the time dependency is not recognized, and the speed is assumed to be constant. The travel time estimation on those bases cannot be accurate, which may lead to additional costs, customer frustration and penalties due to the violation of time windows. In this study the variation of speed during the travel time due to the congestion will be considered. Thus we are dealing with a time-dependent travel speed. Our study is based on the distribution of speed shown in Fig.3.6.

- Impact of congestion in scenario A

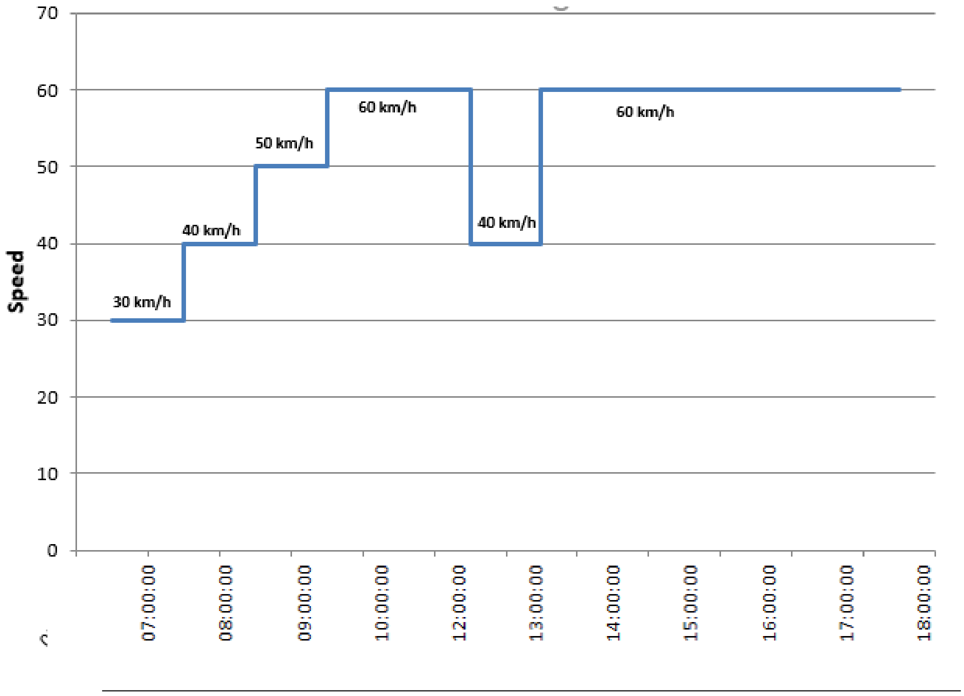


FIGURE 3.6: Speed distribution

Before evaluating the impact of road congestion on travel time, we start by getting an insight into the possibility of serving different customers in time under normal conditions. Thus, we calculate the speed required on each arc using the moveToInTime() anylogic function that makes the agent move to a destination in a specified duration. To evaluate how these changes on road condition may affect the VHT, and the service quality represented by the respect of the time window, we test 2 scenarios:

Scenario 1:

- Customer Demand is received during a traffic peak (rush hour).
- The speed required to deliver this customer in time lower than or equal to the average speed during the traffic peak interval.

Scenario 2:

- Customer Demand is received during a traffic peak (rush hour).
- The speed required to deliver this customer in time is higher than the average speed during the traffic peak interval.

For an accurate estimation of the VHT, speed changes within the travel time are taken into account. Two cases are considered, in the first case the departure from the depot D_0 and arrival time of the at a customer t_i^k are in the same time interval [K], thus no speed changes have occurred. In the second case, when the arrival time of a vehicle is estimated to be in the interval [K+1] it means the speed has changed during this period.

- Impact of congestion in scenario B

Algorithm 1: Algorithm to calculate the VHT

if D_0 *and* $t_i^k \in [K]$ **then**
    $VHT^i \leftarrow \frac{VKT^i}{V_k}$
else
    $VHT^i \leftarrow VHT_k^i + VHT_{k+1}^i$
    $VHT^i = (K_{sup} - D_0) + (t_i^k - K_{sup}) \times \frac{V_k}{V_{K+1}}$
end

In this scenario customers have the same time windows form 8 to 9 in the morning, because customers are restaurants and this time demand ensures that they can process and serve fresh food to their customers.

3.2.5.2 Impact of congestion on costs

To provide insight into the relationship between cost, and changes in the road network, the distribution costs considered in this study include the transportation costs, damage costs, refrigeration, and penalty costs. Since we are interested in measuring the variation, fixed cost will not be included.

- **Transportation costs**

The transport costs include maintenance and repair costs, tires and depreciation costs, and the major component related to the fuel consumption. Fuel consumption, in our study, is weight and time-dependent, because the travel speed and travel time, which depend on departure time, and the loading weight, are taken into consideration in the procedure.

Let KPL_{ij} be the kilometer per liter for a vehicle traveling from the customer i to customer j. The consumption per unit time corresponding LPH_{ij} is calculated as follows:

$$LPH_{ij} = \frac{V_{ij}}{KPL_{ij}} \tag{3.1}$$

V_{ij} is the corresponding travelling speed form customer i to customer j. The transportation costs can be expressed as:

$$C_{tr} = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} \left(C_{(i,j)} x_{(i,j)}^k d_{(i,j)} + C'_{(i,j)} x_{(i,j)}^k VHT_{(i,j)}^k \right) \tag{3.2}$$

- **The refrigeration costs**

The refrigeration is crucial during the transportation of perishable food. Refrigeration costs include the cost caused by energy consumption to keep the adequate temperature during delivery, as well as the cost of additional energy supplied by the refrigeration system during the unloading process.

The refrigeration cost during transportation can be expressed as:

$$C_t = c_e \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{(i,j)}^k VHT_{(i,j)}^k \tag{3.3}$$

Refrigeration cost during the unloading process:

$$C_u = c'_e \sum_{k \in K} \sum_{i \in V} y_i^k U_i \tag{3.4}$$

$$C_{\text{ref}} = C_t + C_u \tag{3.5}$$

- **Penalty costs**

Generally, in the distribution of food, customers require to be delivered within a time window. And if the goods do not reach the destination within the time agreed on by the customer, thus the time window is violated, and additional penalty cost will be applied. These costs can be expressed as follows:

$$C_p = \sum_{k \in K} \sum_{i \in c} \left(\alpha \max \left\{ a_i - t_i^k, 0 \right\} + \beta \max \left\{ t_i^k - b_i, 0 \right\} \right) \tag{3.6}$$

3.2.5.3 Impact of congestion on carbon emission

The traffic growth in urban areas brings further problems of environmental aspects. In recent years, there has been increasing interest in estimating the environmental effects of vehicle routing policies. In our work, we aim to discover the relationship between traffic congestion, restrictive time windows, and Co2 emission. For this purpose, we use the "ASIF" equation (Schipper et al., 2007) to quantify carbon emissions in the simulated scenarios.

3.2.6 Experimental design and results

This section provides a numerical example to quantify the impact of traffic jams on the VHT, costs, and emissions. In the subsection 3.2.6.1 we describe the problem and parameter setting; the experimental results are analysed in the subsection 3.2.6.2.

3.2.6.1 Experimental design and parameter settings

The delivery service provider places a premium on service quality. Hence all scenarios use hard time windows, to guarantee that promised delivery times would be met. To simplify the problem, we make the following assumptions:

- The service provider has a homogenous fleet with one type of refrigerated vehicles.
- In the scenario A, the customer order does not exceed the vehicles' capacity, and the time spent to serve each customer is 15 min.
- In the scenario B, the vehicle can serve 3 customers and spend 10 min at each one.

The distribution center DC start operating at 7. In the first scenario corresponding to direct delivery, orders in the simulation model are generated as an event sent to the distribution center randomly during the day. Since we are interested in evaluating the impact of congestion, we took a sample of orders received during the morning, characterized by the higher congestion level. We assume that order preparation requires 30 min and the time windows' length is 15 min.

In the second scenario, the time window is [8h,9h]. Since the level of congestion from 7 to 8 is high, simulation run was performed to estimate the travel time for both tours with an average speed corresponding to this time window figure to determine if this time interval is sufficient for delivery, thus:

- If $T_{delivery} < 1h$: we start delivery at 8h to avoid congestion.
- Else $T_{departure} = 8h - VHT^{i}_{K-1}$

with VHT^{i}_{K-1} the vehicle hour traveled to deliver the client i from the warehouse during the time interval $K-1$.

Parameters of refrigerated vehicles are shown in table 3.2.

Based on the mileage and the estimated VHT, costs and carbon emissions were measured and compared to those in normal conditions.

TABLE 3.2: Vehicle parameters

Parameter	**Value**
Load capacity (kg)	795
Fuel type	gasoline
Maximum speed (km/h)	120
Fuel consumption when loaded(km/l)	2,65
Fuel consumption when empty(km/l)	6,06

3.2.6.2 Results and analysis

In this section, we will illustrate experimental results. The VHT has evidently increased during rush hours. This augmentation did not affect customers in scenario A.1, since the demand can be delivered in agreed time. However, in the scenario A.2, the time is violated, which leads to additional penalty costs and impacts customer satisfaction. In this case, the time window agreed with these customers should be reviewed to be less restrictive. Another way is to limit the reception of demands to a specific period less congested, but this solution is not practical since we are dealing with a restaurant that needs food in a precise time, so they can process and serve fresh food to customers (breakfast, lunch...). The fuel consumption is time-dependent; hence its heavy increases in the scenario A.2. As we are delivering perishable foods, refrigeration costs are a very important component that should be considered. Regarding the latter, we can say that congestion has a deeply negative impact since even for a slight increase on the VHT, the costs increased by an average of 30%. Since the Co2 emissions are directly related to the fuel consumed, it remains relatively flat as the trip length and the travel time increase.

In the direct delivery, we have demonstrated that fuel consumption increases with the VHT, however strangely we have noticed in scenario B that with a slight increase in VHT the fuel consumption is less under congestion than under normal traffic conditions in some arcs of the tour and consequently, the carbon emissions are reduced because the travel time saved is not really important. In these arcs, it is not really wise to speed up for saving 1 or 2 min in the travel time. These findings give us an idea about the optimal speed in each segment of the tour. But since we have another crucial component related to the VHT that should be considered while deciding either the speed is advantageous or not. For this reason, we have analysed the impact on refrigeration cost, and we have found that congestion has a strong impact. It increases costs with an average of 37% on each tour trip.

3.2.7 Scheduling and time windows extension

Through the analysis of different scenarios, we have proved that travel time during rush hours is longer than in other periods, which leads to additional cost, impact the service quality and increases the carbon emissions. With strict time windows, businesses have difficulties in optimizing these costs. These findings imply that carriers should reduce travel time. After showing how the departure time of each vehicle from the distribution center affects costs and service, this goal can be achieved by changing route start times to avoid congested times and travelling as fast as is allowed by the traffic conditions, and combined with more flexibility in delivery time windows. For this purpose, we have developed two algorithms to schedule departure in the direct delivery scenario and the LTL delivery while extending the time window. To discover how these changes in policy may lead to cost saving.

3.2.7.1 Scheduling algorithm

To plan the departure of the vehicle from the distribution center, we have developed two algorithms for each scenario (direct delivery and LTL). These algorithms are used when the demand is received during a rush hour followed by a time interval with less congestion. The concept consists of programming the departure as late as possible to avoid congestion and travel as fast as possible while respecting the time windows.

Scheduling technique for scenario A
The demand is received during the time interval K, let TW be the length of time windows. For a delivery from the distribution center to a customer, the departure is programmed as follows:

Scheduling technique for scenario B
The procedure starts by setting the arrival date to the last customer in the

Algorithm 2: Scheduling algorithm for scenario A

if $VHT^i_{K+1} + Ksup - D_0 < TW$ **then**
    $D_n \leftarrow Ksup$
else
    $VHT^i_{K+1} \leftarrow bi - Ksup$
    $D_n \leftarrow Ksup - \frac{D_r}{V_k}$
    $D_r \leftarrow VKT^i - VHT^i_{K+1} \times V_{K+1}$
end

route to the upper bound of the time windows. The departure from the upstream customer is then calculated (Fig.3.7).

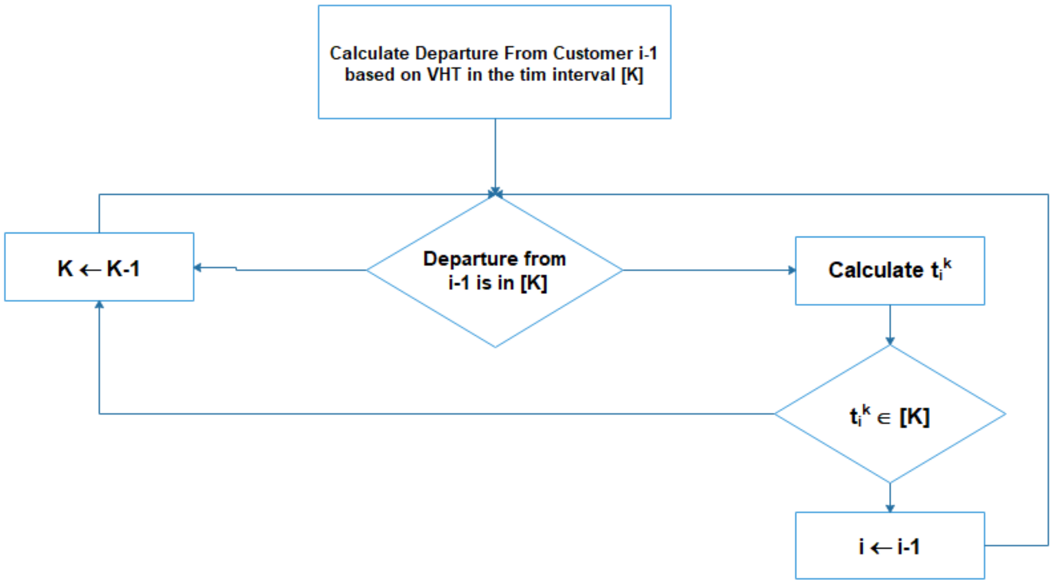


FIGURE 3.7: Scheduling procedure for scenario B

3.2.7.2 Experience and results

To validate the proposed algorithms, they were applied to plan departures for scenario A and B. In the scenario A, the algorithm is tested to determine the departure from DC to customer 5, which is critical as shown in our previous analyses. The time window is extended by 15 min. In the scenario B, we extend the time windows by 1 hour, and we plan departures for 2 vehicles serving the customers in 2 tours. Experimental results have proved the efficiency of these policy changes in saving costs and reducing emission. Interestingly, for a slight delay of the departure in the scenario A, fuel consumption as well as the Co2 emissions have been reduced by 12% and refrigeration cost by 19%. In the scenario B, policy changes lead to good results, since the travel time was decreased by 20 % even if the improvement in terms of costs is negligible.

3.2.8 Summary

This study aims to solve one of the major problems encountered by carriers, which consist of choosing the optimal routes and program departure to deliver customers in time. Therefore, agent-based simulation combined with GIS is used. Simulation runs were performed to estimate the VKT and VHT. Analyses of network changes (congestion) were conducted to provide insight into the impact of these changes on these 2 values (VHT and VKT) also on cost, service quality, and emissions. A time-dependent scheduling technique was developed and proved its success in achieving a potential saving, in terms of costs and Co2 emissions. As a future research, this time-dependent vehicle routing problem will be represented as an optimization model and integrated with ABM-GIS.

3.3 Capacitated vehicle routing problems with multiple attributes: a background

3.3.1 Capacitated vehicle routing problems

In Capacitated Vehicle Routing Problems (CVRP), a set of vehicles with a uniform capacity Q must serve clients requests from a common depot at a minimum cost.

Given a set of customers C, and a fleet of homogenous or heterogeneous vehicles that have each a capacity of Q_i. A route is considered feasible if $\sum\limits_{i \in C} d_i \leq Q$.

To solve CVRP several exact algorithms and heuristics have been proposed in the literature.(Fukasawa et al., 2006) presented branch and cut and price, which is a combination of branch and cut and column generation method. This approach was afterward extended by (Pecin et al., 2017) to propose a new one with new families of cuts which also deals with the worst complexities of pricing problem. A combination of Branch-and-cut and adaptive memory programming metaheuristic was used by (Gounaris et al., 2011) to find fairly good solutions. A Granular tabu search is proposed by (Escobar et al., 2013).(Jin et al., 2014) proposed a Cooperative parallel metaheuristic which consists of multiple parallel tabu search threads that cooperate by asynchronously exchanging best-found solutions through a common solution pool. A hybrid Multiple phase neighbourhood search and GRASP was proposed by (Marinakis, 2012). GRASP was used in another hybrid approach with integer linear programm in (Contardo et al., 2014).

3.3.2 Vehicle routing with multiples attributes on arcs

In practical applications of Vehicle Routing Problems (VRPs), arcs are frequently labelled with different attributes. The latter may be required to evaluate the quality of a routing solution. As well as, in terms of operational restrictions, these attributes can be used to ensure route feasibility. As previously stated, these VRPs are commonly addressed using a customer-based graph, in which it's assumed that the best path between a pair of nodes can be represented by a single arc. However, the best path for an attribute, may not be the best for another. For example, the shortest path is unlikely to be the fastest one due to congestion. When only one path between two nodes is considered, good solutions may be discarded from the solution space as a result. Therefore, addressing the problem using a customer-based graph is not efficient. To handle this issue, two alternative approaches have been investigated in the literature. In the first one, the road network is represented using a multigraph. In the second approach, the problem is solved directly on a graph that mimics the real road network. The latter is called road-network graph approach. In the next subsections, we describe and review these approaches.

3.3.2.1 Multigraph

A multigraph representation of the road network is one way to keep track of all efficient paths between each pair of nodes. Every efficient (in terms of the considered qualities) path in the original network is represented by an arc in this representation. As far as we can tell, the fact that employing a customer-based graph when multiple attributes are defined on each road segment could lead to an inaccuracy of the solution was first demonstrated by (Garaix et al., 2010). To handle this issue, they proposed a multi-graph representation approach. The latter was successfully used in DIAL-A-RIDE problems to achieve an effective cost time compromise. Two solving strategies were used, the branch and price algorithm and an insertion heuristic. Experiments have highlighted the gain from multi-graph modelling over customer-based graph. A number of VRP variants were studied using the multigraph modelling approach. For a VRPTW (Ticha et al., 2019) developed a hybrid Adaptive Large Neighbourhood Search and multigraph representation for the road network. For a green VRP, (Andelmin and Bartolini, 2019) proposed multi-start local search approach based on multigraph. The advantages of using a multigraph rather than customer-based graph were established clearly in all the aforementioned papers.

3.3.2.2 Road network representation

The idea behind this representation approach is to conserve the entire solution space by solving VRP directly on a graph that mimics the real road network. Where arcs represent road segments, while nodes represent the ends of these segments. (Ticha et al., 2017) also investigated the VRPTW on a road network graph and propose a branch and price algorithm to solve it. To evaluate the efficiency of road network graph representation against multigraph modelling, experiments on real instances were conducted. Results have shown that the multigraph-based branch and price is not always outperformed by road network graph representation, and several factors can affect their efficiency. (Letchford et al., 2014) worked on multiple Traveling

Salesman Problem under Time Windows constraint (m-TSPTW) to demonstrate the disadvantages of multigraph by showing that it is easier to model the problem on a road network graph instead of a multigraph that need exponential time and space to store it. Only few research works have represented VRP on a road network graph. But, they switch to customer-based graph during the heuristic search process. The development of tourist sightseeing itineraries was addressed by (Huang et al., 2006). A tourist is required to visit a specific subset of a road network's destinations. Each road segment is specified by four characteristics that are related to four objectives: travel time, vehicle operating cost, safety level and surrounding scenic view quality. The authors simply aggregate the four attributes, allowing them to find the optimum paths connecting the points of interest and construct a customer-based graph. A decision support system for hazardous material transportation is developed by (Zografos and Androutsopoulos, 2008). The objective is to find the most cost-effective and risk-free vehicle routes for the transportation of hazardous materials. A travel time and a risk measure are assigned to each road stretch. The authors combine these two attributes once again and switch to a customer-based graph.

3.4 Capacitated vehicle routing problem with multiple attributes and soft time window

3.4.1 Model formulation

3.4.1.1 Problem description

In this work we study a CVRPTW-P for perishable food distribution. The problem can be set by means of the following. Let DC be a Distribution Center that serves fresh foods to a set of customers C using refrigerated trucks. Let G = (V, A) be the road network graph. $V = \{0, 1, \ldots, n+1\}$ is the set of nodes, where the node 0 and $n+1$ represent the Distribution Center (DC). The aim is to construct a transportation plan that minimizes costs, while completing all customers' requirements. $C = \{1, \ldots, n\}$ is the set of customers to serve. Let $A = \underset{(i,j)\in V^2}{U} A_{(i,j)}$ be the set of arcs, where $A_{(i,j)} = \left\{(i,j)^p; p = 1, \ldots, \left|A_{(i,j)}\right|\right\}$ is the set of alternative paths between node i and j. We associate with each arc $(i,j)^p$, a travel cost and a travel time. To each customer i we associate a time window $[e_i, l_i]$.

3.4.1.2 Variables and parameters

Decision variables:

- $x^k_{(i,j)^p}$: A binary variable equals to 1 if vehicle k travels on arc $(i,j)^p$ and 0 otherwise.
- t^k_i : The starting service time at customer i if it is served by vehicle k.

- y_i^k : is a binary variable equal to 1 if the vehicle k serves for customer i, and 0 otherwise.

Parameters:

- $C_{(i,j)^p}$: The transportation cost per unit distance when the vehicle travel from i to j through the arc $(i,j)^p$.
- $d_{(i,j)^p}$: The length of the arc $(i,j)^p$.
- $C'_{(i,j)^p}$: The fuel consumption costs per unit time when the vehicle travel from i to j through the arc $(i,j)^p$.
- $t^k_{(i,j)^p}$: The travel time of vehicle k on arc $(i,j)^p$.
- c_e : The refrigeration costs during the transportation process by unit time.
- c'_e : The refrigeration costs during the unloading process by unit time.
- U_i : The unloading time needed to serve the customer i.
- α :The waiting cost per time unit if the vehicle arrive in advance.
- β :The penalty cost per time unit if the vehicle arrive late.
- $[e_i, l_i]$: The time window of client i.
- z_i^k: A variable equal to 0 if the vehicle k arrives during the time window and equal $a_i - t_i^k$ to if it arrives in advance.
- w_i^k: A variable equal to 0 if the vehicle arrives during the time window and equal $t_i^k - b_i$ to if it arrives late.
- d_i : The demand of customer i.
- Q : The vehicle capacity.
- K : The set of vehicles.
- S_i: The service time at customer i.

3.4.1.3 Mathematical model

When assigning a refrigerated truck to a distribution task, several fixed and variable costs are generated. The main purpose is to minimize the total costs, composed of the sub-costs (damage costs, transportation costs, refrigeration, and penalty costs) detailed in follow:

- **Transportation costs**

The transportation costs C_{tr} can be divided to two cost components,$C_{(i,j)^p}$ represent the costs related to the distance which involve repair and maintenance costs, tires and depreciation cost. And the fuel consumption cost $C'_{(i,j)^p}$. The latter is time-varying because it's influenced by the speed, which fluctuate with the daytime. We calculate the fuel consumption by unit time in the road segment with the following relation used by (Schipper et al., 2007).

$$LPH_{ij} = \frac{V_{ij}}{KPL_{ij}} \tag{3.7}$$

Where LPH_{ij} is the fuel consumed per hour consumed in arc (i,j), V_{ij} is the vehicle speed on arc (i,j)

The transportation costs are expressed as follows:

$$C_{tr} = \sum_{k\in K}\sum_{i\in V}\sum_{j\in V}\sum_{P=1}^{|A(i,j)|}\left(C_{(i,j)^p}x^k_{(i,j)^p}d_{(i,j)^p} + C'_{(i,j)^p}x^k_{(i,j)^p}t^k_{(i,j)^p}\right) \tag{3.8}$$

- **Refrigeration costs**

Refrigeration costs $\mathrm{C_{ref}}$ include the cost of energy consumption during the transportation process C_t, as well as the supplementary energy costs during the discharging process $\mathrm{C_u}$. Therefore, the refrigeration costs can be formulated as:

$$\mathrm{C_{ref}} = C_t + C_u = c_e\sum_{k\in K}\sum_{i\in V}\sum_{j\in V}\sum_{p=1}^{|A(i,j)|} x^k_{(i,j)^p}t^k_{(i,j)^p} + c'\sum_{k\in K}\sum_{i\in V} y^k_i U_i \tag{3.9}$$

- **Penalty costs**

Penalty costs C_p are applied in case of violation of the time windows agreed on by the customer. Penalty costs can be expressed by the following formulation:

$$C_p = \sum_{k\in K}\sum_{i\in C}\left(\alpha \max\left\{a_i - t^k_i, 0\right\} + \beta \max\left\{t^k_i - b_i, 0\right\}\right) \tag{3.10}$$

Where $\max\left\{a_i - t^k_i, 0\right\}$ represent the advance arrival time of vehicle k to the node i and $\max\left\{t^k_i - b_i, 0\right\}$ the tardiness of service at customer i.

The model CVRPTW-P is formulated as follows:

$$\text{Min } C_{tr} + C_{ref} + C_p \tag{3.11}$$

Subject to:

$$x^k_{(i,1)^p} = 0, \quad \forall i \in V, \quad \forall k \in K, \quad 1 \le p \le |A(i,j)| \tag{3.12}$$

$$x^k_{(0,n+1)^p} = 0, \quad \forall k \in K, \quad 1 \le p \le |A(i,j)| \tag{3.13}$$

$$\sum_{k\in K}\sum_{j\in V}\sum_{p=1}^{|A(i,j)|} x^k_{(i,j)^p} = 1, \quad \forall i \in C \tag{3.14}$$

$$\sum_{j \in V} \sum_{p=1}^{|A(i,j)|} x^k_{(i,j)^p} = \sum_{j \in V} \sum_{p=1}^{|A(i,j)|} x^k_{(j,i)^p} \quad , \quad \forall i \in V, \quad \forall k \in K \tag{3.15}$$

$$\sum_{i \in V} \sum_{p=1}^{|A(0,i)|} x^k_{(0,i)^p} = 1, \quad \forall k \in K \tag{3.16}$$

$$\sum_{i \in V} \sum_{p=1}^{|A(0,i)|} x^k_{(i,n+1)^p} = 1, \quad \forall k \in K \tag{3.17}$$

$$\sum_{i \in V} \sum_{j \in V} \sum_{p=1}^{|A(i,j)|} d_i x^k_{(i,j)^p} \leq Q, \quad \forall k \in K \tag{3.18}$$

$$t^k_i + s_i y^k_i + t_{(i,j)p} x^k_{(i,j)^p} - M\left(1 - x^k_{(i,j)p}\right) \leq t^k_j$$

$$\forall i, j \in V, \forall k \in K, 1 \leq p \leq |A(i,j)| \tag{3.19}$$

$$e_i \leq t^k_i \leq l_i, \quad \forall i \in C, \quad \forall k \in K \tag{3.20}$$

$$\sum_{k \in K} \sum_{j \in V} \sum_{p=1}^{|A(i,j)|} x^k_{(0,j)^p} \leq K \tag{3.21}$$

$$\sum_{k \in K} \sum_{j \in V} \sum_{p=1}^{|A(i,j)|} x^k_{(i,j)^p} \leq y^k_i, \quad \forall i \in C \tag{3.22}$$

$$t^k_i \geq 0, \quad \forall i \in C, \quad \forall k \in K \tag{3.23}$$

$$y^k_i \in \{0,1\}, \quad \forall i \in C \tag{3.24}$$

$$x^k_{(i,j)^p} \in \{0,1\}, \quad \forall i, j \in V, \quad \forall k \in K, \quad 1 \leq p \leq |A(i,j)| \tag{3.25}$$

The objective (3.11) is to minimize the total traveling cost. Constraint (3.14) ensures that every client is visited only once. Constraint (3.15) make certain that once a truck visit a customer, it will leave to another one. Constraints (3.16) and (3.17) ensure that every vehicle leaving the distribution center node 0 is returning to the distribution center node $n+1$, inequality in (3.18) make sure that the vehicle is loaded with respect to its capacity. Inequality (3.19) establishes the connection between the service starting time at a customer and its follower. Constraint (3.20) guarantees the respect of time windows. Constraint (3.21) ensure the respect of fleet size. Constraint (3.22) ensures that the vehicle go through the arc $(i,j)^p$ to serve the customer in node j. This model is a Mixed 0-1 Non-Linear Program (MINLP). The non-linearity of the problem comes from the max expression in the penalty cost. To linearize the problem we introduce two variables z^k_i and w^k_i as follows:

$$\begin{aligned} z^k_i &= \max\left\{a_i - t^k_i, 0\right\} \\ w^k_i &= \max\left\{t^k_i - b_i, 0\right\} \end{aligned} \tag{3.26}$$

The objective function becomes as follows:

$$\begin{aligned}
&\text{Min} \left(\sum_{k\in K} \sum_{i\in V} \sum_{j\in V} \sum_{P=1}^{|A(i,j)|} \left(C_{(i,j)^p} x_{(i,j)^p} x^k d_{(i,j)^p} + C_{(i,j)^p}{}' x_{(i,j)^p} t^k t^k (i,j)^p \right) \right. \\
&+ \left(c_e \sum_{k\in K} \sum_{i\in V} \sum_{j\in V} \sum_{p=1}^{|A(i,j)|} x^k_{(i,j)^p} t^k_{(i,j)^p} \right) + \left(c' \cdot \sum_{k\in K} \sum_{i\in V} y_i U_i \right) \\
&+ \sum_{k\in K} \sum_{i\in c} \left(\alpha z_i^k + \beta w_i^k \right)
\end{aligned} \tag{3.27}$$

And we add the following constraints:

$$a_i - t_i^k \leq z_i^k \quad k \in K \quad i \in V \tag{3.28}$$

$$t_i^k - b_i \leq w_i^k \quad k \in K \quad i \in V \tag{3.29}$$

$$z_i^k \geq 0 \quad k \in K \quad i \in V \tag{3.30}$$

$$w_i^k \geq 0 \quad k \in K \quad i \in V \tag{3.31}$$

The size of the problem depends on the number of nodes, vehicles and paths. Let $|\mathrm{V}| = \mathrm{n}$ be the cardinal of the set of nodes, $|\mathrm{K}| = \mathrm{k}$ be the number of vehicles and $|\mathrm{C}| = \mathrm{n} - 2$ the number of customers. The Number of decision Variables (NV) is $2n^2k + 3nk + n$ and the Number of Constraints (NC) is $2n^2k + 10nk + 2n + k - 3$.

3.4.2 Graph construction

The design of the graph forms a key step in the vehicle routing problem resolution. The design of a road network graph for the problem in hand is discussed in this section. Several approaches were proposed in the literature to find the optimal routes for distributing perishable goods. To handle the problem of food delivery in a cattle ranch, (Mullaseril et al., 1997a) formulate the problem as a VRP with time windows. Research on the issue of fresh milk distribution considering a fixed heterogeneous fleet was provided by (Tarantilis and Kiranoudis, 2001a). The shortcoming of the research listed is that instead of spatial data, authors use mathematical equations to find efficient routes. To serve customers in the desired time range, real route network needs to be considered. The use of Geographic Information Systems (GIS) is therefore of interest. The integration of GIS for optimal routing have attracts many researchers. (Keenan, 2006) investigated vehicle routing modelling in GIS. (El Raoui et al., 2018a) combined agent based simulation with GIS to find the fastest routes to deliver fresh products in time. (Chen et al., 2008), used GIS in the area of nuclear waste transport to design optimal routes. To deliver fresh goods (Bosona et al., 2013), used GIS for location and route analysis. In this work, we use the GIS feature in Anylogic software to position points based on Open Street Map (OSM) server 3.8. The set of alternative paths is obtained using the A* algorithms and possibly the Dijkstra algorithm. Only two alternative paths are considered, because even in real life, the humans cannot imagine many alternative roads. These paths are the shortest path and the min- travel time path, taking into account the speed limitation and the traffic jams. On each one, we define two attributes, the travel time and cost.

FIGURE 3.8: The road network graph of the studied case

3.4.3 Computational experiments

To evaluate the efficiency of our mathematical model, we conduct computational experiments. The model was implemented and solved with the CPLEX. For all the instances, we use a limit of 1-hour CPU time to get the solution with the standard parameter settings of the software.

3.4.3.1 Instances

The model was tested using five classes of instances (A, B, C, D, and E) with different number of vehicles (V), with different capacities denoted Cap, and Time windows extent (Tw). In the class A, V= 3, cap=80 and Tw=160, Class B has V=13, cap=90 and Tw=200, Class C has V=20, cap=100 and Tw=200, class D has V=30, cap=90 and Tw=200, and Class E has V=90, cap= 36 and Tw=180. Each class consists of two instances, with a number of customers multiple of five. The instance name is composed of the class name and the number of customers, for example A20 is the instance in class A with 20 customers. We study the case with a single depot, and we generate randomly the coordinates (x, y) in the interval [0,100]. The nodes are then located in the GIS space. Customers' Demands take values in the interval [20, 60].

3.4.3.2 Results

Experimental results are provided in Table 3.3. The first column identifies the instance, for each one we provide the objective value, the time, the Number of Variable NV and the Number of Constraints (NC). We use (N/A) if no feasible solution is found during the time limit (1 hour). In Table 3.3, we observe that CPLEX can solve to optimality within the time limit only small instances. Due to the NP- hardiness property of CVRPTW-P, CPLEX cannot provide optimal solution for large-scale problem instances within a reasonable time. Thus, exact resolution cannot hold, and heuristics are appropriate, since they have already proved their success in solving large scale instances of vehicle routing problems.

TABLE 3.3: Experimental results

Instance	Objective	Time (S)	NC	NV
A5	2422.35	0 .08	856	605
A10	5600.29	1 .81	2066	1632
B15	9732.95	1.44	9768	8194
B20	11291 .6	595.5	15498	13464
C25	14049 .83	1144.09	34631	30807
C30	——	——	56917	51488
D35	——	——	93341	85507
D40	——	——	142245	131586
E45	——	——	176095	164171
E50	——	——	266906	250432

3.4.4 Summary

A vehicle routing problem for the perishable food delivery under capacity and time windows constraint is discussed in this study. The proposed approach to handle the problem is based on real road network, taking into account two paths (fast and short) between every couple of nodes. We associate to each arc two attributes (times, cost). The problem is formulated as a Mixed Integer Program MIP and solved using CPLEX. The results of computational experiments using random instances show that exact resolution cannot solve large scale instances to optimality in a reasonable time.

3.5 Capacitated vehicle routing problem with multiple attributes and fuzzy time windows

3.5.1 Problem formulation

3.5.1.1 Problem description

In this work, we study a capacitated vehicle routing problem under fuzzy time window constraint CVRPfTW-P for perishable food distribution. The problem can be set by means of the following. Let DC be a Distribution Center that serves fresh foods to a set of customers C using refrigerated trucks. Let G = (V, A) be the road network graph. $V = \{0, 1, \ldots, n+1\}$ is the set of nodes, where the node 0 and $n+1$ represent the Distribution Center (DC). The aim is to construct a transportation plan that minimizes costs, while completing all customers' requirements. $C = \{1, \ldots, n\}$ is the set of customers to serve. Let $A = \underset{(i,j)\in V^2}{U} A_{(i,j)}$ be the set of arcs, where $A_{(i,j)} = \left\{(i,j)^p; p = 1, \ldots, \left|A_{(i,j)}\right|\right\}$ is the set of alternative paths between node i and j. We associate with each arc $(i,j)^p$, a travel cost and a travel time. To each customer, i we associate a time window $[e_i, l_i]$.

3.5.1.2 Mathematical model

The objective function considered include the transportation cost, and the refrigeration costs, described in the subsection 3.4.1.3, and reformulated by the equations 3.8, 3.9 respectively. The problem is formulated using the same parameters and variable of the previous model (subsection 3.4.1.3) as follows:

$$\text{Min}\, C_{tr} + C_{ref} \tag{3.32}$$

Subject to:

$$(3.12) - (3.13) - (3.14) - (3.15) - (3.16) - (3.17) - (3.18)$$
$$(3.19) - (3.20) - (3.21) - (3.22) - (3.23)$$
$$(3.24) - (3.25))$$

3.5.2 Towards fuzzy model

In real life applications, time windows cannot always be strictly obeyed and can be violated due to economic and operational reasons. Let us suppose that the customer has an endurable time window, and allows violations up to the values $e - \Delta^e$ and $l + \Delta^l$. Thus, we define the Endurable Earliness Time (EET) and an Endurable Lateness Time (ELT) as:

$$EET = e - \Delta^e \tag{3.33}$$

$$ELT = l + \Delta^l \tag{3.34}$$

The flexibility allowed by the customer can be modeled using a fuzzy constraint. In our model, we consider the following fuzzy constraint:

$$e_i \leq_f t_i^k \leq_f l_i \quad i \in V \quad k \in K \tag{3.35}$$

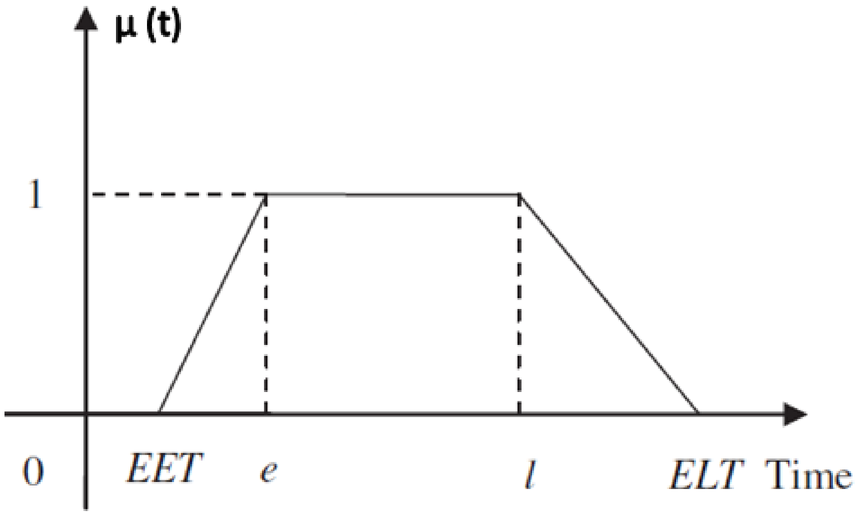


FIGURE 3.9: The satisfaction degree of fuzzy time windows

Where $\leq_f$ implies that the time window could be partially satisfied. Thus, the membership function that represents satisfaction degree of the time window constraint (21) is the following (also shown in Fig.3.9):

$$\mu(t) = \begin{cases} 0 & ; t < EET \\ f(t) & ; EET \leq t < e \\ 1 & ; e \leq t < l \\ g(t) & ; l \leq t < ELT \\ 0 & ; ELT \leq t \end{cases} \tag{3.36}$$

Where $f(t)$ is a non-decreasing function and $g(t)$ is a non-increasing function, expressed as follows:

$$f(t) = 1 - \frac{e - t}{\Delta^e} \tag{3.37}$$

$$g(t) = 1 - \frac{t - l}{\Delta^l} \tag{3.38}$$

3.5.3 Solution approach

To the best of our knowledge, no method can solve directly the problem in its fuzzy form. However, one can transform the original fuzzy problem into a set of crisp problems, as the Parametric Approach (Verdegay, 1982a) does. This approach consists of transforming the fuzzy problem into an equivalent "crisp" problem, using the concept of $\alpha - cuts$. The parametric problem is then solved based on different values of α (where $\alpha \in [0,1]$), using exact or heuristic optimization techniques. The parametric approach has been widely used in routing problems, like in (Brito et al., 2009); (Brito et al., 2011); (Brito et al., 2012); (Melian and Verdegay, 2011). And has been also applied in other fuzzy optimization problems ((Verdegay, 1982b); (Guzmán et al., 2016)). We will adopt this parametric approach to solve our fuzzy problem.

- $\alpha-$ CVRPTW-P

For a given α and the fuzzy membership function previously defined, the earliest and latest service times that the customer i can accept, respectively $\hat{e}_i$, $\hat{l}_i$ (Fig.3.10) can be calculated as follows:

$$\hat{e}_i = f_i^{-1}(\alpha) = e_i - \Delta^e(1-\alpha) \tag{3.39}$$

$$\hat{l}_i = g_i^{-1}(\alpha) = l_i + \Delta^l(1-\alpha) \tag{3.40}$$

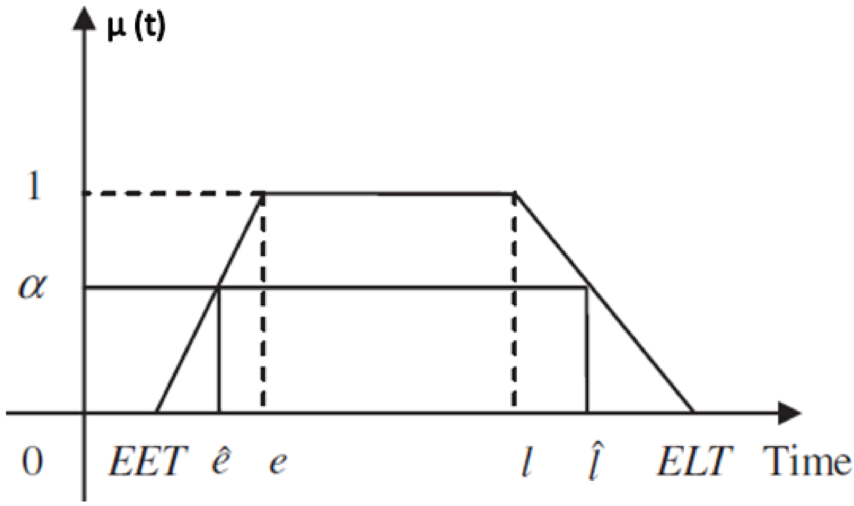


FIGURE 3.10: The satisfaction degree of fuzzy time windows

For each $\alpha - CVRPTW - P$ the new time window constraint is:

$$e_i - \Delta^e(1-\alpha) \leq t_i \leq l_i + \Delta^l(1-\alpha) \tag{3.41}$$

3.5.4 Computational experiments

To illustrate the usefulness of the model proposed, we use real road data from the Moroccan city 'Casablanca'. The model was implemented using the IBM OPL modeling language and solved with the IBM CPLEX optimization studio version 12.8.0.

3.5.4.1 Test instances

We have created two instances denoted A and B, with a different number of vehicles (V), number of customers (NC), vehicle capacities (Cap), and Time windows width (Tw). Instance A has, NC =10, V = 5 Cap = 80 and Tw = 3h30min, and instance B has, NC = 15, V =13 Cap = 90 and Tw = 4h. In both instances, we assume that all the customers have the same time window and $\Delta^e = \Delta^l = 30min$. We consider only a single depot, and the coordinates

(x, y) of nodes are generated randomly in the interval $[0, 100]$ and integrated into the GIS space. Demands of customers are drawn from the interval [20, 60].

3.5.4.2 Computational results

We solve the problem for both instances for each $\alpha \in [0, 0.1, ..., 1]$. The results are shown in Table 3.4.

TABLE 3.4: Experimental results for each value of α

	Instance A		*Instance B*	
α Value	**TW bounds**	**Obj. function**	**TW bounds**	**Obj. function**
0	[0.00,4.50]	5600	[0.00,5.00]	9732
0.1	[0.05,4.45]	5600	[0.05,4.95]	9732
0.2	[0.10,4.40]	5600	[0.10,4.90]	9734
0.3	[0.15,4.35]	5600	[0.15,4.85]	9755
0.4	[0.20,4.30]	5600	[0.20,4.80]	9755
0.5	[0.25, 4.25]	5600	[0.25, 4.75]	9755
0.6	[0.30,4.20]	5600	[0.30,4.70]	9757
0.7	[0.35,4.15]	5629	[0.35,4.65]	9763
0.8	[0.40,4.10]	5631	[0.40,4.60]	9765
0.9	[0.45,4.05]	5631	[0.45,4.55]	9766
1	[0.50,4.00]	5635	[0.50,4.50]	9767

The variation in the objective function in terms of α is shown in Fig. 3.11. Recall that $\alpha = 1$ corresponds to the fully restricted time window constraint and $\alpha = 0$ to the fully relaxed. As it is expected, the more relaxed the problem is ($\alpha = 0$) the lower the distribution cost is. We can observe clearly in Fig. 3.11, instance A, that when no flexibility is allowed by customers ($\alpha = 1$), the highest distribution cost is incurred. However, if the customer allows a flexibility of 40% ($\alpha = 0.6$) in the time window, then up to 0.5% of the distribution cost can be saved. For instance B, we have found that generally for each 10% increase in α, the distribution cost increases heavily about 0.012% but particularly when $\alpha = 0.3$ costs increased by almost 0.22%.

Computational results clearly reveal that using restrictive time window leads to additional costs. In this case, the decision-maker has two alternatives: decrease the service level or pay some extra cost to reach the customer in time. By analysing the costs corresponding to each value of α, the decision-maker can assess a reasonable time windows violation degree that will not lead to higher logistics costs while maintain a good service level, and increasing the performance of a company. For example, in instance A, a flexibility of 60% is the most suitable, since lower than this level, the company will not save any costs.

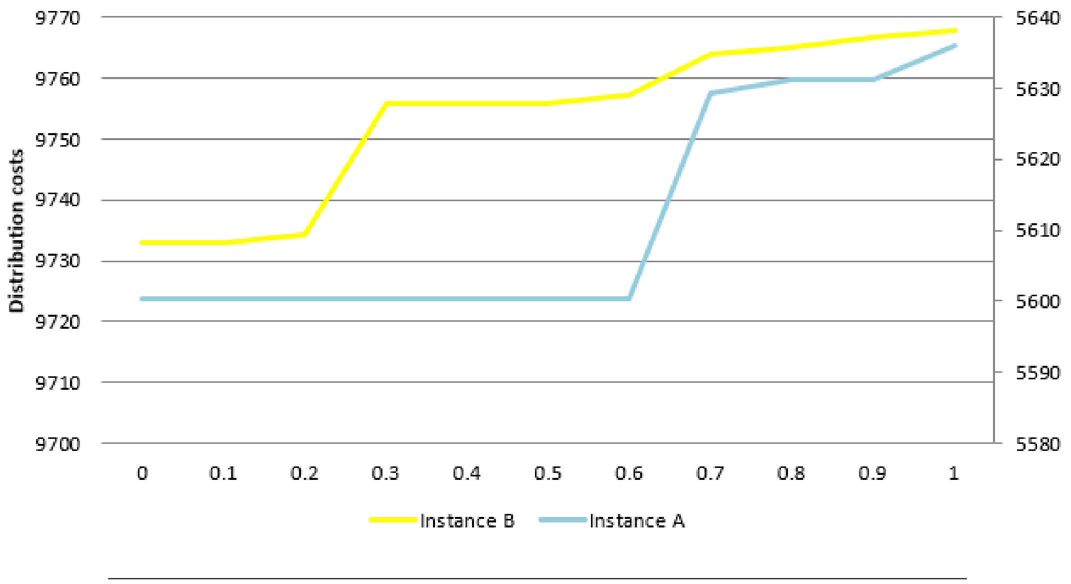


FIGURE 3.11: Distribution cost variation in terms of α-cuts

3.5.5 Summary

In this study, we propose to model the distribution of perishable food in urban area as a capacitated vehicle routing problem with fuzzy time windows. The problem is addressed on a real road network, where two alternative paths corresponding to the fastest and shortest routes are considered between every pair of points. The parametric approach is used to decompose the fuzzy original problem into a set of crisp models for each value of alpha and then solved by using CPLEX.

Although further and larger scale instances should be considered, the designed computational experiments and their results clearly convey that considering fuzzy time windows in the model can provide routing with lower distribution costs and a good service level.

3.6 Conclusions

The operational research literature has devoted a lot of attention to vehicle routing issues. The plurality of proposed approaches are adressed using euclidean distance, and they are founded on the assumption that the optimal path between two customer nodes can be easily determined. As a result, the problem can be solved by depicting the road network as a customer-based graph. However, in many real-world applications, several attributes must be defined on road segments. In this case, there could be multiple paths connecting each pair of nodes, each with a different compromise. The quality of the answer may decrease if these alternative paths are not considered.

In this chapter, we point out how the real road network approach can be used to determine efficient routes for perishable food distribution through 3 studies. In the first study, we propose a ABM-GIS modelling approach for a time-depent vehicle routing problems.This simulation model consists of determining the quickest routes to transport fresh products, estimating Vehicle kilometer traveled VKT and vehicle hour traveled VHT where speeds and travel times depend on the time of the day. Based on a real case study, analyses of changes in traffic condition were conducted to get an insight into the impact of these changes on cost, service quality represented by the respect of time windows, and carbon emissions. The results reveal that traffic jams and restrictive time windows lead to additional cost, cause delays, and increase Co2 emissions. As for a short-term planning, time-dependent scheduling algorithm was proposed and assessed while extending time windows. Results have proved the potential saving in cost, travel time, and carbon emission.

In the second and third study, we propose a capacitated vehicle routing problem, considering respectively soft and fuzzy time windows. For both studies, the problem is addressed on real road network, considering two alternative path and cost and time attributes associated to each segment. Exact resolutions approach are used to solve the mathematical models. We conduct a computational experiments based on instances from the literature and instances derived from real road network data. Obtained results show that in most cases it is more interesting to tackle the problem using the real road networks representation. Furthermore, the results clearly convey that the proposed models can provide routing with lower distribution costs and a good service level.

Chapter 4

A customer-centric routing problem: the case of perishable food delivery

This chapter dives into the thesis's third goal, which is to propose a many-objectives model for the perishable food distribution problem, that focuses on the cost, the quality of the product, and the service level improvement.

The chapter is organized as follows: Section 4.2 provides an overview of related works. In Section 4.3 we present the model formulation of the problem, and Section 4.4 describes the proposed strategy to solve it. After that, we provide an overview of the GVNS approach in Section 4.5. Section 4.6 is devoted to assess the performance of GVNS, doing comparisons against CPLEX software.The approach adopted to select the solutions of interest is presented in 4.7. A full example showing all the steps of the proposed solving strategy is shown in Section 4.8. The last section concludes the paper and proposes some perspectives for future research.

The material presented in this chapter is published in:

- El Raoui, Hanane, Mustapha Oudani, David A. Pelta, and Ahmed El Hilali Alaoui. "A Metaheuristic Based Approach for the Customer-Centric Perishable Food Distribution Problem." Electronics 10, no. 16 (2021): 2018.

4.1 Introduction

The global food and grocery retail market has shown significant growth in recent years. This has increased the challenges in the global logistics market for perishable food. The processing of the latter is widely known to be distinct from the distribution of other goods because they deteriorate continuously, and have an expiration date. The most critical phase of the food supply chain is the transportation process, where the trip path length have the potential to influence the deterioration rate (Yakavenka et al., 2020; Tuljak-Suban and Suban, 2015).

According to the Food and Agriculture Organization FAO (2018) (Boge, 2019), one third of food produced for human consumption, and almost half of fruit and vegetables are wasted across the global Food Supply Chain (FSC). Therefore, assuring food quality and safety has become a major focus which must be ensured to satisfy consumers.

In addition to product quality, the service quality is another drive of customer satisfaction. As a determinant of service efficiency, responsiveness stands as a key factor for differentiation, and can be evaluated through the punctuality of service delivery. It is therefore becoming extremely critical that goods can be delivered within the time range desired by customers.

Furthermore, customers may have a specific target time, in which they prefer to be served. For instance, some restaurants tend to implement the Just In Time (JIT) inventory management strategy to ensure the freshness of their meals. Therefore, the service fulfilment in the customer preferred time is a key indicator to evaluate the service level.

In some other situations arising from real life, customers may have different priority levels. This issue can be very significant, for instance, when deliveries to small restaurants are considered. In fact, such restaurants need to be cyclically supplied since their storage capacities are limited.

The perishable food distribution problem is usually modelled as a multi-objective Vehicle Routing Problem (VRP). For example, taking into account the total cost minimization and average freshness maximization (Utama et al., 2020). However, as long as we know, other objectives such as the quality of service improvement, the freshness level maximization, the damage minimization and so on are less explored.

In this paper, we study a Customer-Centric Vehicle Routing Problem with Time Window (CCVRPTW). Unlike the classical VRP, this variant covers, in addition to the cost minimization, other objectives centred on the quality of service issues. Each customer has preferences to be considered in the scheduling process. The latter are expressed through the time windows, a specific target time, and pre-defined priority index. The objectives of the problem are to minimize the total cost, to maximize the average freshness, to maximize the service level, and to minimize the tardiness resulted from non-respect of priorities.

As the objectives are conflicting, there is no unique best solution with respect to all criteria. Instead, we may consider a *set of alternative solutions* that are characterized by the fact that an improvement in an objective would decrease the performance in at least one other objective. Therefore, the decision maker must incorporate his/her preferences, in order to come up with a single solution. This can be done through three different ways (Raseman et al., 2019). 1) *A priori*: where the decision-maker preferences are incorporated before the search, or 2) *A posteriori* manner: by considering the preferences after the search process, and the 3) *Progressive* way when the decision-maker preferences are incorporated during the search process. In this paper, we adopt the *a posteriori* approach.

We propose a model with four-objectives. In order to solve it, we proceed as follows: we solve a sub-problem using a General Variable Neighborhood Search algorithm, which generates a set of different solutions. Afterwards, using the decision-maker preferences, those solutions are ranked using a possibility degree approach. In this way, the best compromise solution can be selected.

The chapter is organized as follows: Section 4.2 provides an overview of related works. In Section 4.3 we present the model formulation of the problem, and Section 4.4 describes the proposed strategy to solve it. After that, we provide an overview of the GVNS approach in Section 4.5. Section 4.6 is devoted to assess the performance of GVNS, doing comparisons against CPLEX software.The approach adopted to select the solutions of interest is presented in 4.7. A full example showing all the steps of the proposed solving strategy is shown in Section 4.8. The last section concludes the paper and proposes some perspectives for future research.

4.2 Related works

Vehicle routing problems for perishable food are challenging compared to classical VRP, due to the sensitivity of the handled products. Several works have addressed this problem in different contexts, considering a single objective. To handle the problem of food delivery in a cattle ranch, authors in (Mullaseril et al., 1997b) formulate the problem with a set of split delivery capacitated rural postman problems with time windows. In (Tarantilis and Kiranoudis, 2001b), a threshold-acceptance-based algorithm was developed to solve the vehicle routing and scheduling problem for fresh milk, considering a fixed heterogeneous fleet. While in (Tarantilis and Kiranoudis, 2002b) a real-world fresh meat delivery problem is addressed as a multi-depot VRP. A stochastic search meta-heuristic algorithm was proposed to solve the problem. In a different work(Faulin, 2003) a hybrid of heuristic-exact method to solve a VRP with strict delivery quantities and narrow time windows was presented. An application service provider that would offer fresh food delivery services was suggested by authors in (Prindezis et al., 2003). A VRP was proposed and solved via appropriate meta-heuristic techniques. A decision support tool for grocery delivery service was proposed in (Campbell and Savelsbergh, 2005). The tool help in deciding to accept or reject deliveries, as well as define routes and schedules to maximize profit. In (Ambrosino and Sciomachen, 2007), the authors describe a case-study of perishable food delivery through the national highway. Considering an homogeneous fleet able to carry dry, fresh and frozen products, the randomness in food delivery process is considered in (Hsu et al., 2007) through a stochastic VRP-TW model with time-dependent travel times.

For the distribution of fresh vegetables, authors in (Osvald and Stirn, 2008a) solve the problem using a heuristic. In (Doerner et al., 2008), authors proposed an exact and approximate algorithms for the pickup of perishable goods (blood). An integrated production-distribution for perishable food products was studied by authors in (Chen et al., 2009), where they propose an iterative scheme to solve the problem in which the production part is solved using the Nelder-Mead method, and the distribution part is solved by a constructive heuristic. In (Hasani et al., 2012), the authors designed a closed-loop multi-echelons supply chain for perishable goods considering uncertain demand, multiple periods, and multiple products. An agent-based simulation was combined with geographic information system in (El Raoui et al., 2018b), to find the quickest routes for delivering fresh products. In another study (El Raoui et al., 2019), the authors propose a model and solving approach to address VRP for perishables distribution on a real road network considering fuzzy time window. The real-road network approach was also adopted by authors in (El Raoui et al., 2020) for perishables delivery.

Some researchers have considered several objectives. In (Gong and Fu, 2010), the authors propose a metaheuristic procedure to solve the vehicle routing problem for perishable food. The problem considers two main objectives : the total cost minimization, and the maximization of the product freshness. The latter objectives were also addressed in (Amorim and Almada-Lobo, 2014) using an evolutionary algorithm. To minimize the total cost of distribution, and the total cost of environmental impact for a two-echelon supply chain of perishable food, a particle swarm optimization algorithm was proposed by authors in (Govindan et al., 2014). Authors in(Khalili-Damghani et al., 2015) applied a Genetic Algorithm (GA) to maximize the average freshness, and minimize the total transportation cost.

Meanwhile, the Gradient Evolution (GE) algorithm was used in (Kuo and Nugroho, 2017) to solve a multi-objective routing problem with time windows, and time-dependency. The GA was suggested by (Sahraeian and Esmaeili, 2018) to reduce the total cost of delivery, and reduce the overall cost of environmental effect on a two-stage capacitated vehicle routing problem. Recently, the GE algorithm was implemented by (Zulvia et al., 2020) to solve a green VRP for perishables delivery, considering four objective functions. These objectives were minimizing the total cost distribution, reducing the environmental impact, maximizing the service level, and minimizing the damage.

Table 4.1 presents a summary of related researches in the field of perishables distribution. Summing up the critical synthesis, we have identified the following gaps in the literature:

- Most of the problems studied in the literature are bi-objective focusing on cost minimization, and freshness maximization or service level improvement.
- There are a few studies that propose multi-objective models that take into account simultaneously the economic, social and environmental aspects.
- Those reviewed works, considering the service level improvement objective, evaluate the quality of service with respect to the satisfaction of the time window constraint. However, the service level can be related to other criteria.

This paper is an attempt to fill-in these gaps by proposing a many-objective model that focus on the cost, the quality of the product, and the service level improvement by considering not only the time window respect, but also the target time and priority respect.

Our approach differs from the reviewed ones, in the sense that exploits all the alternative solutions' generated by a metaheuristics and rank them afterwards for a set of non-modeled criteria using scores intervals and a possibility degree approach. To the best of our knowledge, we are the first to jointly integrate these aspects.

TABLE 4.1: A review of the papers solving perishable food distribution problem.

References	Sustainability Aspect			Sustainability Measure	Objective Functions	Methods
	Economic	Environmental	Social			
(Mullaseril et al., 1997b)	*		*	Distribution cost Time window respect	Min. total cost	Heuristics
(Tarantilis and Kiranoudis, 2001a)	*			Distribution cost	Min. travel cost	Heuristics
(Tarantilis and Kiranoudis, 2002b)	*			Distribution cost	Min. travel cost	Heuristics
(Faulin, 2003)	*			Distribution cost	Min. total distance	Heuristics+ Exact
(Prindezis et al., 2003)	*			Distribution cost	Min. total cost	Metaheuristics
(Campbell and Savelsbergh, 2005)	*			Profitability	Max. profit	Heuristics
(Ambrosino and Sciomachen, 2007)	*			Distribution cost	Min. total cost	Heuristics
(Hsu et al., 2007)	*		*	Distribution cost Time window respect	Min. total cost	Heuristic
(Osvald and Stirn, 2008a)	*		*	Distribution cost Products quality	Min. total cost	Heuristics
(Doerner et al., 2008)	*		*	Cost efficiency Time window respect	Min. total distance	Exact+ Heuristics
(Chen et al., 2009)	*		*	Cost efficiency Products quality Time window respect	Max. profit	Exact+ Heuristics
(Hasani et al., 2012)	*		*	Cost efficiency Products quality	Max. profit	Exact
(El Raoui et al., 2018b)	*	*	*	Cost efficiency Time window respect Carbon emission	Min. total travel time	Simulation
(El Raoui et al., 2019)	*		*	Distribution cost Time window respect	Min. total cost	Exact
(El Raoui et al., 2020)	*		*	Distribution cost Time window respect	Min. total cost	Exact
(Gong and Fu, 2010)	*		*	Distribution cost Products quality	Min. total cost	Heuristic
(Amorim and Almada-Lobo, 2014)	*		*	Cost efficiency Products freshness Time window respect	Min. total cost Max. freshness	Mulit-objective evolutionary algorithm
(Govindan et al., 2014)	*	*	*	Cost efficiency Products quality Time window respect Environmental impact	Min. total cost Min. carbon emissions	Metaheuristics+ Pareto optimality
(Khalili-Damghani et al., 2015)	*			Distribution cost	Min. total cost	Evolutionary computation
(Kuo and Nugroho, 2017)	*		*	Distribution cost Time window respect	Min. total cost Min. variance of vehicles	Multi-objective Gradient Evolutionary algorithm
(Sahraeian and Esmaeili, 2018)	*	*	*	Cost efficiency Service level Environmental impact	Min. total cost Min. waiting time Min. carbon emissions	NSGA-II
(Zulvia et al., 2020)	*	*	*	Distribution cost Products freshness Time window respect Environmental impact	Min. operational cost Min. deterioration cost Min. carbon emission Max. service level	Many-objective Gradient Evolutionary algorithm

4.3 Model formulation

Let $G = (V, A)$ be a directed graph. $V = \{0, 1, \ldots, n+1\}$ is the set of nodes, where the nodes 0 and $n+1$ represent the depot, and $C = \{1, \ldots, n\}$ is the set of customers to serve. We associate to each customer i a time window denoted by $[e_i, l_i]$.

To model the problem, we assume that the fleet of vehicles is homogeneous: all the vehicles have the same refrigeration characteristics, the same load capacity, and the same constant velocity. Table 4.2 summarize the sets, parameters, and decision variables used to model the problem

TABLE 4.2: Sets, parameters and decision variables for model formulation.

Sets and Indices	
V	Set of nodes
$\mathcal{C}$	Set of customers
K	Set of vehicles $k \in K$
i,j	Indices of nodes
Decision Variables	
$x^k_{(i,j)}$	a 0-1 decision variable, equal to 1 in case the truck k travels from node i to j, 0 otherwise.
y^k_i	a 0-1 decision variable, equal to 1 in case the customer i is served by the truck k, 0 otherwise.
t^k_i	a decision variable representing the starting service time at node i using the truck k.
Parameters	
$C_{(i,j)}$	the transportation cost from node i to j.
F	fixed cost associated to a vehicle.
$T_{(i,j)}$	the travel time from i to j.
$d_{(i,j)}$	the distance between node i and j.
C_e	the cost per unit time for the refrigeration during the transportation process.
U_i	the unloading time at customer i.
C'_e	the unit refrigeration cost during the unloading.
S_i	the necessary time to serve customer i
q_i	the demand of customer i
P	the price per unit product
q_{in}	the products remaining on the vehicle after serving the customer i
Q	the loading capacity of trucks.
K	the fleet of trucks
∂_1	the spoilage rate of products during the transportation process
∂_2	the spoilage rate of products during the unloading process
$[e_i, l_i]$	the time window of customer i
T^i_g	the target time of customer i
$SL_i(t)$	the service level for customer i if we deliver his demand at time t.
M	Large positive constant.

4.3.1 The optimization goal setting

Objective 1: Minimize the total cost

The overall cost Z_1 includes: the fixed costs for using a vehicle denoted C_1, transportation costs C_2, the refrigeration costs C_3, and the damage costs C_4.

- **The fixed costs**

  The fixed costs of a vehicle are not related to the mileage, and represent the maintenance, and depreciation costs. Assuming that the depot has k refrigerated trucks to provide distribution services for the set of customers.

F represents the fixed cost related to a vehicle. The fixed costs can be formulated as:

$$C_1 = F \sum_{k \in K} y_0^k \tag{4.1}$$

- **The transportation costs**

  We denote these costs by C_2, They are proportional to the vehicle mileage. We consider only the fuel consumption cost and express it as:

$$C_2 = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} C_{(i,j)} x_{(i,j)}^k d_{(i,j)} \tag{4.2}$$

- **The refrigeration costs**

  Include two types of costs: the costs incurred by the vehicle's energy usage to maintain a specific temperature in the process of transportation, in addition to the costs of extra energy during the unloading.
  The refrigeration costs during transportation process denoted C_3^1 are expressed as follows:

$$C_3^1 = C_e \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{(i,j)}^k T_{(i,j)} \tag{4.3}$$

  The cost of energy supplied during the unloading C_3^2 is expressed as:

$$C_3^2 = C_e' \sum_{k \in K} \sum_{i \in \mathcal{C}} y_i^k U_i \tag{4.4}$$

  the total refrigeration cost

$$C_3 = C_3^1 + C_3^2 \tag{4.5}$$

- **The damage costs**

  The quality of perishable foods decay with the time extension, and the temperature changes during the transportation and handling process. If product quality falls to a certain level, damage costs are incurred. The quality of refrigerated goods can be expressed using the following function (Wang et al., 2017): $D_t = D_0 e^{-\partial t}$

  where D_t, and D_0 are respectively the quality of product at time t and from the depot 0. The parameter ∂ is the spoilage rate of the product, and it's assumed as an increasing function of the temperature. Thus, we differentiate between the damage cost during the delivery C_4^1, and the damage cost during the unloading C_4^2 due to the temperature changes (∂ varies also). The damage cost C_4^1 is expressed as follows:

$$C_4^1 = \sum_{k \in K} \sum_{i \in C} y_i^k P q_i \left(1 - e^{-\partial_1 \left(t_i^k - t_0^k\right)}\right) \tag{4.6}$$

Where the coefficient ∂_1 represents the spoilage rate of product when the vehicle is closed, t_i^k the arrival time of vehicle k at customer i, t_0^k the departure time of vehicle k from the depot, and y_i^k is 0-1 decision variable taking the value 1 in case the vehicle k is servicing the customer i, and 0 otherwise.

The damage cost during the unloading C_4^2 is defined as:

$$C_4^2 = \sum_{k \in K} \sum_{i \in C} y_i^k P q_{in} \left(1 - e^{-\partial_2 S_i}\right) \tag{4.7}$$

With q_{in} the remaining quantity of product after servicing the customer i, the necessary time to serve is customer i is S_i , and ∂_2 is the spoilage rate when the vehicle is opened.

The total damage cost is therefore:

$$C_4 = C_4^1 + C_4^2 \tag{4.8}$$

Given the cost components defined above, the total cost can be formulated as :

$$Z_1 = C_1 + C_2 + C_3 + C_4 \tag{4.9}$$

Objective 2: Maximize the average freshness

The average freshness can be defined as in (Wang et al., 2018b) by the following formula:

$$Z_2 = \frac{\sum_{k \in K} \sum_{i \in C} y_i^k q_i e^{-\partial_1 \left(t_i^k - t_0^k\right)}}{\sum_{i \in C} q_i} \tag{4.10}$$

Objective 3: Maximize the service level

Our research was motivated by the real life distribution problem of perishable food. Indeed, customers may prefer to receive the products at a specific time in order to start preparing meals for example. In addition, restaurants tend to implement the Just In Time inventory management strategy to reduce the storage cost. Thus, instead of serving the customers within a time window, we focus on fulfilment of customer request as much as we can at a specific target time. To assess the service level, we use the target time as an indicator by means of the following function:

$$SL_i(t) = \begin{cases} 0 & t < e_i \\ f(t) & e_i \le t < T_g^i \\ 1 & t = T_g^i \\ g(t) & T_g^i < t \le l_i \\ 0 & t > l_i \end{cases} \tag{4.11}$$

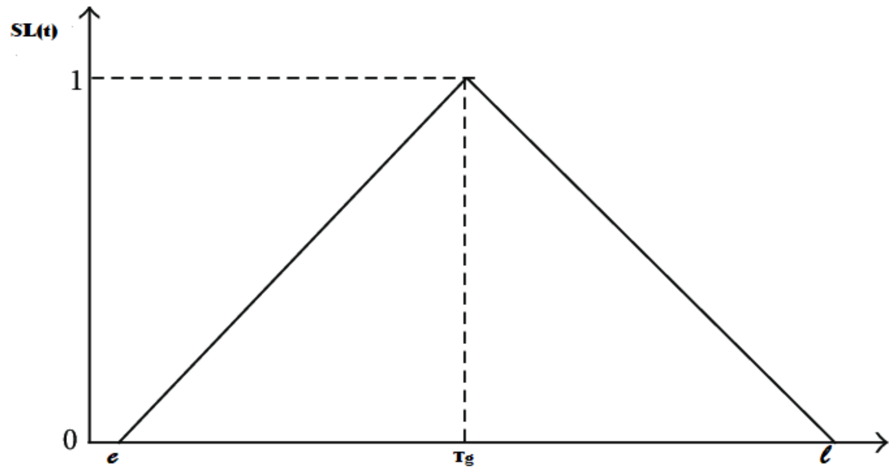


FIGURE 4.1: The service level function.

Function $SL_i(t)$, shown in Fig. 4.1, represents the service level ensured for the customer i if we deliver his demand at time t. T_g^i is the target time, e_i and l_i are respectively the lower, and upper bounds of the time window.

The function f is non-decreasing, while g is a decreasing function that are defined as follows:

$$f(t) = \frac{t - e_i}{T_g^i - e_i} \tag{4.12}$$

$$g(t) = \frac{l_i - t}{l_i - T_g^i} \tag{4.13}$$

Thus the objective is to maximize the following function:

$$Z_3 = \sum_{i \in C} SL_i(t) \tag{4.14}$$

Objective 4: Minimize the total tardiness

In this work, we study a customer-centric version of routing problems which focus on customer satisfaction. In this variant, we consider serving the customers according to priority level. Such a problem arises when customers have different levels of attention. The motivation behind including priority indexes to our problem is that a customer may have a set of locations to be serviced, and preferences to serve each node. Priorities of customers can be defined by the decision-maker. We assume that we have pre-defined priorities. To consider priority indexes, we define a precedence matrix P, where $P_{ij} = 1$ indicate that the customer i should be supplied before the customer j, and $P_{ij} = 0$ if customer i might be supplied after customer j.

The aim is to reduce overall tardiness as much as possible. The latter arises when a lower-priority customer is served before a higher-priority customer, these customers are either on the same route, or served by two different vehicles. In other words, the arrival time of a vehicle $k \in K$ at a customer with lower priority (t_i^k) is less than the arrival time of a vehicle $l \in K$ at a customer with higher priority (t_j^l), with ($l = or \neq k$). The arising tardiness in this case can be denoted τ_{ij}, and can be expressed as the difference between arrival times (when $P_{ij} = 1$, with $i \neq j$) as follows:

$$\tau_{ij} = \begin{cases} t_j^l - t_i^k & P_{ij} = 1 \\ 0 & P_{ij} = 0 / i = j \end{cases} \tag{4.15}$$

Therefore the tardiness of the system can be computed using the following formula:

$$Z_4 = \sum_{i \in \mathcal{C}} \sum_{j \in \mathcal{C}} \tau_{ij} \tag{4.16}$$

4.3.2 Mathematical model

Considering the objectives described above, the problem can be formulated as a Mixed integer Program (MIP) giving by the following:

$$\text{Min } Z_1 = C_1 + C_2 + C_3 + C_4 \tag{4.17}$$

$$\text{Max } Z_2 \tag{4.18}$$

$$\text{Max } Z_3 \tag{4.19}$$

$$\text{Min } Z_4 \tag{4.20}$$

subject to:

$$x^k_{(i,i)} = 0, \quad \forall i \in V, \quad \forall k \in K \tag{4.21}$$

$$x^k_{(0,n+1)} = 1, \quad \forall k \in K \tag{4.22}$$

$$\sum_{k \in K} y_i^k = 1, \quad \forall i \in \mathcal{C} \tag{4.23}$$

$$\sum_{i \in V} x^k_{(i,j)} = y_j^k, \quad \forall j \in \mathcal{C}, \quad \forall k \in K \tag{4.24}$$

$$\sum_{j \in V} x^k_{(i,j)} = y_i^k, \quad \forall i \in \mathcal{C}, \quad \forall k \in K \tag{4.25}$$

$$\sum_{j \in V} x^k_{(0,j)} \leq 1, \quad \forall k \in K \tag{4.26}$$

$$\sum_{i \in V} x^k_{(i,n+1)} \leq 1, \quad \forall k \in K \tag{4.27}$$

$$\sum_{i \in \mathcal{C}} D_i y_i^k \leq Q, \quad \forall k \in K \tag{4.28}$$

$$t_i^k + S_i + T_{(i,j)} x_{(i,j)}^k - M(1 - x_{(i,j)}^k) \leq t_j^k, \quad \forall i, j \in V, \quad \forall k \in K \tag{4.29}$$

$$e_i \leq t_i^k \leq l_i, \quad \forall i \in V, \quad \forall k \in K \tag{4.30}$$

$$\sum_{j \in \mathcal{C}} \sum_{k \in K} x_{(0,j)}^k \leq |K| \tag{4.31}$$

$$x_{(i,j)}^k \in \{0,1\}, \quad \forall i, j \in V, \quad \forall k \in K \tag{4.32}$$

$$t_i^k \geq 0, \quad \forall i \in V, \quad \forall k \in K \tag{4.33}$$

$$y_i^k \in \{0,1\}, \quad \forall i \in \mathcal{C}, \quad \forall k \in K \tag{4.34}$$

The objectives (4.17)-(4.18)-(4.19)-(4.20) correspond respectively to, minimize the total cost, maximize the average freshness, maximize the service level, and minimize the total tardiness. Constraint (4.21) avoids going from a point to itself. Constraint (4.22) avoids going from the depot to node $n+1$ which represent the depot. Constraint (4.23) states only one vehicle visits each customer exactly once. Constraint (4.24) and (4.25) indicate the flow balance of input and output in each node. They state that for every truck and for every served client, i there is at most one client j such that the truck traverses the arc (i, j). The vehicle depart from the depot 0, and return to the depot node $n+1$ according to the Constraint (4.26) and (4.27). Constraint (4.28) guarantees the respect of vehicle loading capacity. Constraint(4.29) establishes the relationship between the service starting times at a customer and its successor. Constraint (4.30) is the time window constraint. The maximum number of routes is controlled by Constraint (4.31) to guarantee that the number of trucks departing from the depot do not exceed the available fleet of trucks $|K|$.

4.4 Solving strategy

The problem under study is a many-objective optimization problem. As the objectives are conflicting, finding a single optimal solution is not possible. Instead, there is a set of optimal solutions. To come up with a single solution, the decision maker has to make the choice about the importance of each objective at some stage.

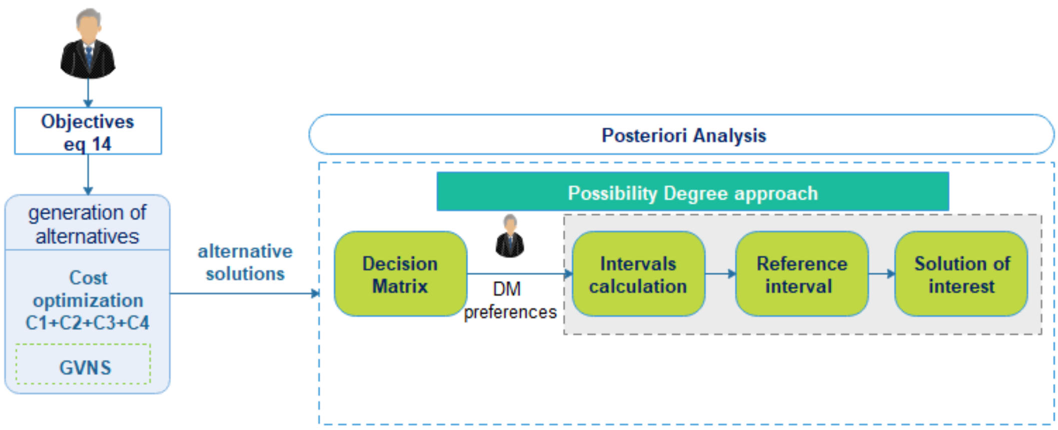


FIGURE 4.2: Workflow diagram proposed to solve the problem

The idea of this paper is to articulate the preferences after the optimization process as an (*a posteriori* approach). To the best of our knowledge, there is no effective tool to solve the problem on its original form, considering simultaneously all the objectives. Therefore, we propose to follow the steps described in the workflow diagram of Fig.4.2. We start by solving a subproblem using General Variable Neighborhood Search (GVNS) by considering a single objective (4.17). Afterwards, we exploit the fact that metaheuristics can generate a set of alternative solutions. These alternatives are good with respect to the modeled objective, and expected to perform relatively well with respect to unconsidered objectives (the average freshness, the service level, and the tardiness).

The alternative solutions provided by the GVNS will be then ranked using the possibility degree approach proposed in (Torres et al., 2020), allowing the DM to choose the best solution with respect to his preferences for each criterion. The proposed ranking approach consists of assigning an interval to each solution, where the intervals correspond to the potential scores depending on the DM preferences. The solutions are then ranked through comparing their corresponding intervals using the possibility degree. The steps of the possibility degree approach are described in the section 4.7. For further details, you can refer to (Torres et al., 2020).

4.5 General variable neighbourhood search for solution generation

4.5.1 Variable neighbourhood search

Variable Neighbourhood Search (VNS) is a trajectory based-meta-heuristic proposed in (Mladenović and Hansen, 1997) to solve combinatorial, and global optimization problems. The main concept of the method is a systematic change of neighbourhoods in an effort to arrive at an optimal (or close-to-optimal) solution. The VNS heuristic is made-up of three major phases: neighbour generation, local search, and jump.

The VNS heuristic is made-up of three major phases: neighbour generation, local search, and jump. Let N_k,$k = 1, ..., k_{max}$ be a set of predefined neighbourhood structures, and let $N_k(x)$ be the set of solutions in the k-th order neighbourhood of a solution x. In the first phase, called shaking or diversification phase, a neighbour $x^{'} \in N_k$ of the current solution is applied. Next, a solution $x^{''}$ is obtained by applying local search to $x^{'}$. Finally, the current solution jumps from x to $x^{''}$ in case the latter improved the former. Otherwise, the order of the neighbourhood is increased by one, and the above steps are repeated until some stopping condition is satisfied.

The VNS heuristic has many variants that are recognized as efficient for solving hard optimization problems. The commonly used variants are the Basic VNS (BVNS), the Variable Neighbourhood Descent (VND), the General VNS (GVNS), and the Reduced VNS (RVNS). In the field of vehicle routing problems, VNS has been widely used. To solve the multi-depots vehicle routing problem with time windows, a VNS approach was designed in (Polacek et al., 2004). A guided VNS was proposed by (Kytöjoki et al., 2007)to solve the large scale VRP and compared with tabu search heuristic. authors in (Goel and Gruhn, 2008)introduced a RVNS to solve the VRPTW. VNS for periodical VRP is presented in (Hemmelmayr et al., 2009).

4.5.2 The framework of the GVNS

GVNS is a variant of VNS in which the variable neighbourhood descent (VND) is used for local search.

In designing a GVNS, one should specify the following choices: the number of neighbourhood structures, the order in which they will be explored, how the initial feasible solution is generated, the acceptance criterion and the stopping conditions. These elements define the configuration of the GVNS.

The algorithm starts by an initialization phase (line 1) in which a feasible solution is generated, we detail in the next subsection the heuristic used for initialization. The best solution is set as the first feasible solution (line 2). After selecting the neighbourhood structures of shaking N_s and for local search N_k (line 3), the stopping condition is then chosen (line 4).The stopping condition corresponds to a number of iterations M that will be set in the computational experience. The loop corresponding to lines 4-25 is repeated M times. The shaking process (line 8), the local search (line 9) and the move decision (line 19) are repeated until $S = S_{max}$. In the shaking phase, a solution X' is generated randomly at the S^{th} neighbourhood of $X^*(X' \in N_s(X^*))$. Then the local search is performed, a better solution X'' from X' using the N_K neighbourhood structures.

Algorithm 3: GVNS

Initialization;
Set the current best solution $X* \leftarrow X_0$;
Select the set of neighbourhood structures to be used in shaking phase $N_S(s = 1, \ldots, s_{max})$ and the set of structures for local search N_k $(k = 1, \ldots, k_{max})$;
Choose a stopping condition M;
while *the stopping condition M is not meet* **do**
  $S \leftarrow 1$;
  repeat
    Shaking : randomly create a solution X′ from the S^{th} neighborhood of $N_s(X^*)$, the current best solution;
    Perform Local search using Variable Neighborhood Descent;
    set $K \leftarrow 1$;
    repeat
      explore the K^{th} neighborhood searching for the best neighbor X" of X′ in $N_k(X')$;
      if $f(X'') \leq f(X')$ **then**
        Update $x' \leftarrow X''$ and $K \leftarrow 1$;
      else
        $K \leftarrow K + 1$
      end
    until $K = K_{max}$;
    Move or not;
    if *the local optima is better that the current best solution* **then**
      Update $x^* \leftarrow X'$ and $S \leftarrow 1$
    else
      $S \leftarrow S + 1$
    end
  until $S = S_{max}$;
end

4.5.3 GVNS implementation

4.5.3.1 Initial solution

Solution construction refers to the creation of a set of routes for the vehicles by selecting nodes (customers) and inserting them in one of the partial routes already created, or in a new route. The two famous types of solution construction used for VRP are the sequential construction and the parallel construction. In the current work, we use the insertion heuristic called $I1$ to find a first feasible solution.
The insertion heuristic $I1$ belongs to the sequential construction heuristics described by Solomon in (Solomon, 1987). It's based on expanding the current initialized route by inserting unrouted customers. The main idea is described in Fig.4.3 where a customer k is inserted between the two nodes i and

j.

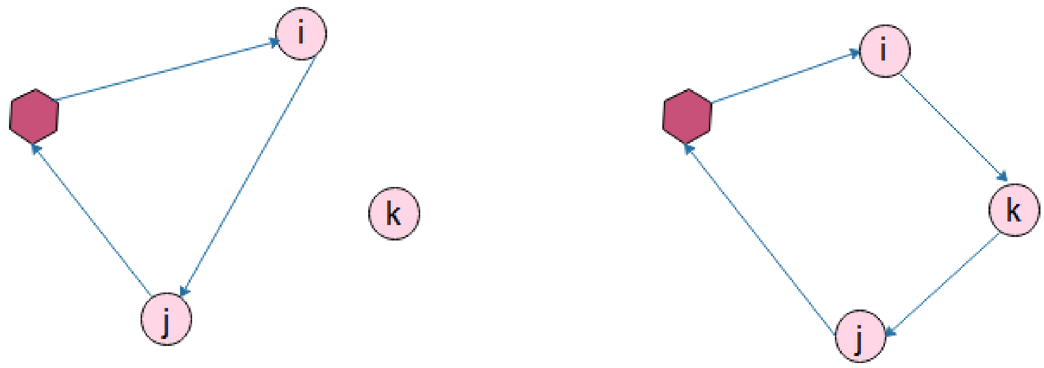


FIGURE 4.3: Insertion heuristic

The insertion heuristic $I1$ starts by initializing the route with a 'seed' customer, which is either the farthest from the depot or the one with the lowest allowed starting service time. In our approach, we initialize the route with the farthest customer. Afterwards, the method uses two criteria $C_1(i,u,j)$ and $C_2(i,u,j)$ to insert at each iteration an unrouted customer u into the current route, between two adjacent customers i and j. Let$(i_0, i_1, i_2, ..., i_m)$ be the current route where$i_0 = i_m = depot$. For each unrouted customer u, we compute its best feasible insertion position in the route as follows:

$$C_1(i(u), u, j(u)) = \min_{P=1...m} C_1(i_{p-1}, u, i_p) \tag{4.35}$$

In the literature the criterion C_1 is calculated based on the extra travel time, and the extra euclidean distance resulted after the insertion of customer u.

$$C_1(i,u,j) = \alpha_1 C_{11}(i,u,j) + \alpha_2 C_{12}(i,u,j) \tag{4.36}$$

where

$$\alpha_1 + \alpha_2 = 1, \quad \alpha_1 \geq 0 \quad \alpha_2 \geq 0 \tag{4.37}$$

$$C_{11}(i,u,j) = D^{ST}_{iu} + D^{ST}_{uj} - \mu D^{ST}_{ij'} \tag{4.38}$$

$$C_{12}(i,u,j) = b_{ju} - b_{j'} \tag{4.39}$$

D^{ST}_{iu}, D^{ST}_{uj} , and $D^{ST}_{ij'}$ are distances between customers i and u, u and j, and i and j, respectively. b_{ju} denotes the new starting service time at customer j, given and $b_{j'}$ is the starting service time at j before inserting u. Parameter μ controls the savings in distance. Next, the best customer u^* to insert in the route is selected based on the second criteria as the one for which
$C_2(i(u^*), u^*, j(u^*)) = Max_u\{C_2(i(u), u, j(u))$

$$|U \text{ is unrouted and the route is feasible} \tag{4.40}$$

When no more feasible insertion is found, the method starts a new route unless inserting all unrouted customers. The criterion C_2 is calculated as follows:

$$C_2(i,u,j) = \lambda d_{0u} - C_1(i,u,j), \quad \lambda \geq 0 \tag{4.41}$$

The parameter λ is used to define how much the best insertion place for an unrouted customer depends on its distance from the depot d_{0u}, and on the other hand how much the best place depends on the extra distance and extra time required to visit the customer by the current vehicle.

4.5.3.2 The neighbourhood structures

The choice of neighbourhood structures and the order in which we explore them is of crucial importance.Indeed, local search methods sequentially accept solutions that improve the objective function value. Thus, the solution quality depends heavily on initial solutions and the neighbourhood structure NS. The NS can be based on several moves (operators). The following terms are used: intra-route and inter-route. Intra-route operator performs a move inside one route. In order to reduce the travelling cost, while inter-route operator involves moves between two different routes in attempt to reduce the fixed costs as well. We used in our approaches 4 neighbourhood structures corresponding to moves presented in Fig.4.4, in the following order: Geni, Cross, 2-Opt, Relocate. This order is based on cardinality, which implies moving from relatively poor to richer neighbourhood structures. We note that generally in the literature, the neighbourhood structures NS used in the shaking phase are different from the NS in the local search. But we choose to use the same neighbourhood structures in both phases.

- Relocate: this operator simply moves a customer visit from one route to another.
- Geni: this operator is an extension of the relocate in which a customer can also be inserted between the two customer nodes on the destination route that are nearest to it, even if these customer nodes are not consecutive.
- Cross: the main idea of cross exchange is to remove two edges $(i-1,i)$ and $(k,k+1)$ from the first route, and remove $(j-1,j)$ and $(l,l+1)$ from the second route. Then, the segments $i-k$ and $j-l$ are swapped by introducing the new edges $(i-1,j)$,$(l,k+1)$, $(j-1,i)$ and $(k,l+1)$.
- 2-Opt: tries to improve the tour by replacing two of its edges by two other edges, and iterates until no further improvement is possible.

4.6 GVNS performance evaluation

4.6.1 Data description

The performance of the proposed GVNS algorithm is assessed through computational experiments on a subset of the well-known Solomon instances:

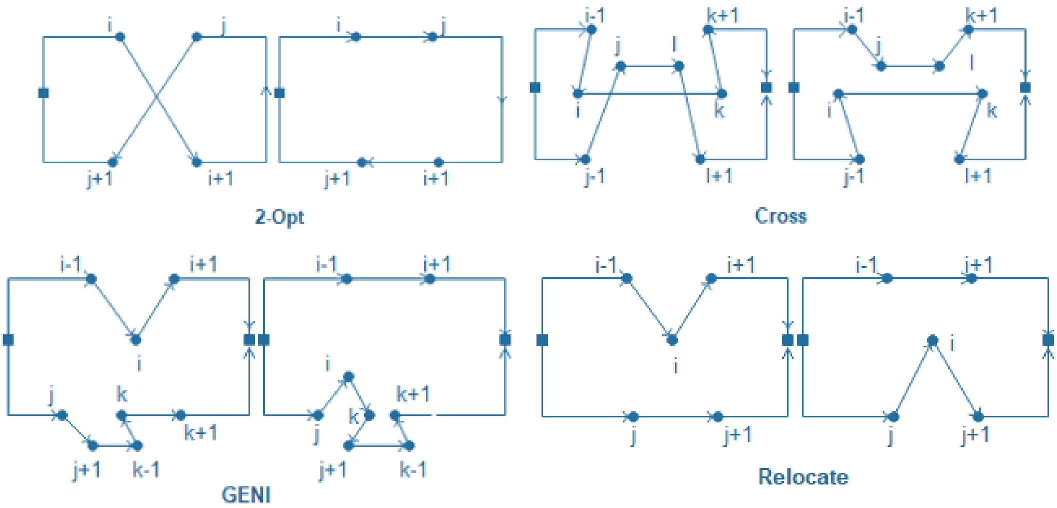


FIGURE 4.4: The neighbourhood structures used

R1, RC1, and C1. In R1 customers locations are generated randomly; in C1 instances have clustered distributions of customers, while in RC1 instances have semi-clustered with a mix of randomly distributed, and clustered customers. We conduct experiments on the following selected instances: R101, C104, and RC107. We denote the instances as in the following example: R101-20 is the instance of class 'R1' with 20 customers.

The parameters of the algorithm are set to the following values: $\alpha_1 = 0, \alpha_2 = 1, \Lambda = 2, \mu = 1$. The stopping criteria, M which correspond to the number of iterations, is fixed to 10. The experiments were performed on an Intel Core i7 processor with 1.99 GHz speed and 8 GB RAM.

4.6.2 Computational experiments

Using a sub-model of the MIP problem presented before, we run a set of experiments to assess the GVNS performance.

The sub-model is:

$$\text{Min } C_1 + C_2 + C_3 \tag{4.42}$$

Subject to:

$$(4.21) - (4.22) - (4.23) - (4.24) - (4.25) - (4.26) - (4.27)$$

$$(4.28) - (4.29) - (4.30) - (4.31)$$

$$(4.32) - (4.33) - (4.34)$$

The GVNS algorithm was coded in Python and the mathematical model was implemented using the IBM OPL modelling language, and solved with the IBM CPLEX optimization studio version 12.8.0. For CPLEX, we set the run time limit to 900 (s).

Table 4.3 provides the best results obtained by GVNS (out of 10 runs), the CPLEX solutions, and also the percentage gaps between both solutions. The

GAP is calculated as follows:

$$GAP = \frac{Z_{GVNS} - Z_{CPLEX}}{Z_{CPLEX}} \times 100 \tag{4.43}$$

The results indicate that our algorithm achieved the same objective value as CPLEX in 4 instances (R101-10, R101-20, R101-40, RC107-10). Furthermore, CPLEX failed to solve 22 instances within the time limit. The CPU time consumed by GVNS is less than the time spent by CPLEX. This can be clearly identified in Fig.4.5.

TABLE 4.3: Comparison between best GVNS and CPLEX solutions.

Instance	GVNS Solution		CPLEX Solution		Gap(%)
	Objective	*Time(s)*	*Objective*	*Time(s)*	
R101-10	630.520	0.03900	630.520	1.76000	0
R101-20	1224.18	3.59000	1224.18	7.15000	0
R101-30	1665.78	3.64500	1664.10	11.2000	0.1
R101-40	2223.10	6.50800	2223.10	363.000	0
R101-50	2600.48	14.3600	2589.92	858.000	0.4
R101-60	2969.64	26.4400	No Sol		
R101-70	3543.04	35.7400	No Sol		
R101-80	3794.16	51.7700	No Sol		
R101-90	4159.70	84.9900	No Sol		
R101-100	4398.88	111.700	No Sol		
RC107-10	436.320	0.06200	436.320	1.74000	0
RC107-20	771.700	1.45800	No Sol		
RC107-30	1147.52	4.08700	No Sol		
RC107-40	1469.18	8.20600	No Sol		
RC107-50	1860.02	20.3300	No Sol		
RC107-60	2434.92	45.7800	No Sol		
RC107-70	2657.12	180.100	No Sol		
RC107-80	3023.60	249.300	No Sol		
RC107-90	3401.92	358.500	No Sol		
RC107-100	3591.20	589.600	No Sol		
C104-10	1068.34	0.01000	1068.34	0.65000	0
C104-20	2121.10	5.01600	2118.96	15.1500	0.1
C104-30	3111.16	23.7500	No Sol		
C104-40	4279.34	51.1300	No Sol		
C104-50	5228.74	75.1000	No Sol		
C104-60	6341.10	69.5700	No Sol		
C104-70	7572.30	151.300	No Sol		
C104-80	8591.68	590.800	No Sol		
C104-90	9636.78	777.900	No Sol		
C104-100	10740.6	943.400	No Sol		

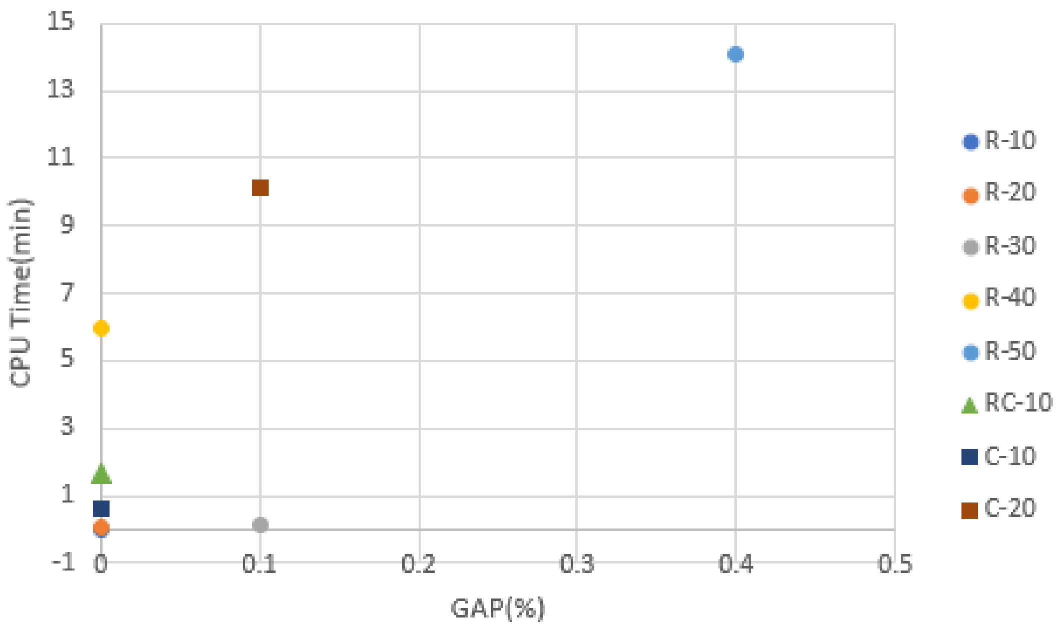


FIGURE 4.5: The GAP and CPU time difference between GVNS and CPLEX, for every instance that was exactly solved.

4.7 Solutions of interest identification

After solving the problem, we obtain a set of alternatives that can be presented in a decision matrix as follows:

	C_1	C_2	$\dots$	C_n
A_1	x_{11}	x_{12}	$\dots$	x_{1n}
A_2	x_{21}	x_{22}	$\dots$	x_{2n}
A_m	x_{m1}	x_{m2}	$\dots$	x_{mn}

where $A_1, A_2, ..., A_m$ are the alternatives among which decision makers have to make a choice, $c_1, c_2, ..., c_n$ are criteria for which alternative performance are measured. x_{ij} is the value of alternative A_i under the criterion c_j. One way to sort the alternatives is to first combine their performance values using an aggregation function in order to have a score, and second to sort them using such scores.

A basic aggregation function is the weighted aggregation, where in simple terms, the decision maker provides a set of weights $W = \{w_1, w_2, \dots, w_n\}$ and then the score of an alternative A_i is calculated as $\sum_{j=1}^{m} w_j \times x_{ij}$ with $\sum_{j=1}^{m} w_j = 1$. If criteria c_i is more relevant than c_j for the decision maker, then $w_i \geq w_j$.

Let's suppose we have just three criteria and the given preference order is c_2, c_1, c_3. Then we need to define $w_2 \geq w_1 \geq w_3$ with $w_1 + w_2 + w_3 = 1$. As the reader may notice, there are infinite values for w_i that verifies both conditions, and every possible set of values will give a different score for the alternative.

So instead of assigning a single score value, the proposed approach calculates an interval of the potential scores that an alternative can attain.

The main steps are detailed below.

- Decision matrix normalization

Before applying an aggregation function, the decision matrix needs to be normalized, so it becomes dimensionless and all of its elements are comparable. While there are different normalization techniques, the following method is adopted here: For benefit criteria:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, \ldots, m, \quad j = 1, \ldots, n$$

For cost criteria:

$$n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, \ldots, m, \quad j = 1, \ldots, n$$

- Intervals calculation

Let's assume that the DM express his/her preferences using an ordinal relation among criteria denoted as $c_1 \succeq_p c_2 \succeq_p \ldots \succeq_p c_n$. The symbol $\succeq_p$ is to be read as "at least as preferred to". This implies that the weights are ordered as $w_1 \geq w_2 \geq w_3 \ldots \geq w_m$.

All the potential scores that an alternative A_i can attain are included in the interval denoted as $I_i = [L_i, U_i]$ with L_i, U_i are respectively the minimum, and the maximum scores obtained through solving two simple linear programming problems

$$L_i = MIN \sum_{j=1}^{m} w_j \times x_{ij}$$

$$U_i = MAX \sum_{j=1}^{m} w_j \times x_{ij}$$

s.t. for both problems

$$w_1 \geq w_2 \geq w_3 \geq \ldots \geq w_m$$

$$\sum_{j=1}^{m} w_j = 1$$

$$w_i \in [0, 1]$$

- Reference interval and interval's comparison

At this point, every alternative A_i has an associated interval $I_i = [L_i, U_i]$.

Next, a reference alternative A^* and its corresponding interval $I^* = [L^*, U^*]$ are identified. Such alternative A^* is the one with the greatest lower bound $\forall\, i, L^* \geq L_i$, thus there is no solution that always scores better than A^*.

Then, every alternative A_i is compared against A^* using a possibility function that calculates the possibility degree of an alternative being better than another using their corresponding intervals.

Let $A = [a_l, a_r], B = [b_l, b_r]$ be two non-negative interval numbers with $a_l, a_r, b_l, b_r \in R_0^+$. The possibility degree of A being greater than B namely $P(A \geq B)$, proposed in (Liu et al., 2018) is defined as follows:

1. if $A \cap B = \emptyset$

$$P(A \geq B) = \begin{cases} 0 & a_r \leq b_l \\ 1 & a_l \geq b_r \end{cases}$$

2. if $A \cap B \neq \emptyset$

$$P(A \geq B) = \frac{\int_{b_l}^{a_r} f(x)\mathrm{d}x}{\int_{b_l}^{a_r} f(x)\mathrm{d}x + \int_{a_l}^{b_r} f(x)\mathrm{d}x}$$

Where $f(x)$ is the prescribed attitude function. In this paper, we assume that the decision maker have a neutral attitude where $f(x) = c$. Then, the corresponding possibility degree can be expressed as follows: $P(A \geq B) = \frac{a_r - b_l}{a_r - a_l + b_r - b_l}$

- Ranking of alternatives

Now, for every alternative A_i the value $P(A_i \geq A^*)$ is calculated. Then, the alternatives are sorted based on such possibility degree values.

4.8 Application example

Once verified the efficiency of the GVNS, we provide here a complete example of the proposed solving approach, shown in Fig.4.2. This section reports the test instance used, the computational experiments performed and the results obtained.

4.8.1 Data and parameter setting

The proposed approach is applied to identify the solutions of interest for a set of 100 customers. For the data, we conduct experiments on the the category RC101 of Solomon's instance presented in the subsection 4.6.1, that we adapted to our problem. For setting the customer's target time, we assume that it's the midpoint of the corresponding time window. The refrigerated vehicles used to deliver products have a fixed cost of 25 €, and the fuel consumption is estimated to 3 €/km. For the GVNS parameters, we use the same as in previous experiment section 4.6.1. The other parameters are given in the Table 4.4.

TABLE 4.4: Values of used parameters

Parameter	Value
P	20 €/Unit
∂_1	0.002
∂_2	0.003
C_e	0.03 €/unit
C'_e	0.04 €/unit
α	0.8

TABLE 4.5: The set of alternative solutions

	Total cost	**Average freshness**	**service level**	**tardiness**
solution 1	18294.37	62.17000	29.02000	1455295
solution 2	18323.90	58.64000	25.71000	1621316
solution 3	18256.38	62.02000	30.06000	1498330
solution 4	18120.14	61.03000	28.32000	1716339
solution 5	18277.78	62.12000	30.71000	1328918
solution 6	18011.75	61.74000	27.91000	1504620
solution 7	18179.60	61.08000	27.16000	1467776
solution 8	18013.66	61.76000	27.51000	1480522
solution 9	17966.30	61.66000	26.87000	1562182

4.8.2 Generation of alternative solutions

We run 9 times our GVNS metaheuristic to obtain the alternative solutions reported in Table 4.5. The algorithm provides only the total cost for each solution. Afterwards, we compute the average freshness, the service level, and the tardiness corresponding to each alternative solution. We can observe that the total cost varies between 17966.3 and 18323.9, the average freshness between 58.64 and 62.17, the service level from 25.71 to 30.17 and the total tardiness varies from 1328918 and 1716339.

Table 4.5 can be understood as a decision matrix, where solutions (1-9) are the alternatives among which the DM have to choose, and the total cost, average freshness, service level, and tardiness are the criteria for which the performance of alternatives is measured.

4.8.3 Decision maker preferences and ranking of solutions

At this point, the preferences of the decision maker should be considered to rank the alternatives. These will be done using scores intervals and the possibility degree approach described in Section The preferences are established through a linear ordering of the criteria and every order corresponds to a DM profile. We define the following three profiles:

- Economic-centric (E-c): Cost $\succeq_p$ Average freshness $\succeq_p$ Service level $\succeq_p$ Tardiness.

- Product-centric (P-c): Average freshness $\succeq_p$ Cost $\succeq_p$ Service level $\succeq_p$ Tardiness.
- Customer Satisfaction-centric (C-c): Service level $\succeq_p$ Cost $\succeq_p$ Average freshness $\succeq_p$ Tardiness.

where the symbol $\succeq_p$ should be read as "at least as preferred to"

The rankings of solutions under the three profiles are shown in Table 4.6.

TABLE 4.6: Ranking of solutions for every DM profile.

Rank	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
E-c	S_5	S_3	S_6	S_8	S_1	S_4	S_9	S_7	S_2
P-c	S_5	S_1	S_3	S_8	S_6	S_7	S_9	S_4	S_2
C-c	S_5	S_3	S_1	S_6	S_8	S_7	S_4	S_9	S_2

The results show that every profile lead to a different rank of the solutions. Analyzing the highly ranked alternative over different scenarios, we can note that the solution S_5 presented in Figure 4.6 retain the first position among all scenarios. For the second-ranked alternatives, S_3 retain the position for both economic and customer-centric scenarios. However, there is a rank reversal for the profile P-c, where the alternative S_1 moves to the second position. We can also notice that S_1 and S_3 interchange their positions in profiles **P-c** and **C-c**.

By analysing the top-ranked solution S_5 represented in Figure 4.6, we found that 13 vehicles are used to deliver the products under customer requirements. Furthermore, we observe many arcs crossing in the tours. Indeed, in the literature, many solving strategies for VRP are based on crossing avoidance hypothesis, which is stated in Fontaine et al., 2020; Van Rooij et al., 2003. However, crossing arcs appeared in our solutions due to customers requirement (time windows, priority indexes).

4.8.4 Sensitivity of ranking results to one-dimensional weight

When performing a one-dimensional weight analysis, the weights of the most important criterion is varied within a feasible range. in order to satisfy the condition that $\sum_{i=1}^{m} w_i = 1$, the remain criteria must be adjusted proportionally. As this approach is based on scoring the solution at three set of weights as explained previously. Furthermore, because the highest possible value of a weight is 1, we apply only a decreased adjustment. First, the weight of the most preferred criteria is decreased by 5% then 50% in the three set of weights mentioned in step one of our approach. To analyse the sensitivity of the approach to each criterion, the sensitivity coefficient was calculated. the latter is equal to the number of changes in the ranking. for instance, is the ranking is stable the coefficient is 0, else if the ranking position of an alternative increase or decrease the coefficient is thus equal to 1. Table 4.7 reports the sensitivity coefficient for the criterion C_1, C_2 and C_3 that represent respectively the total

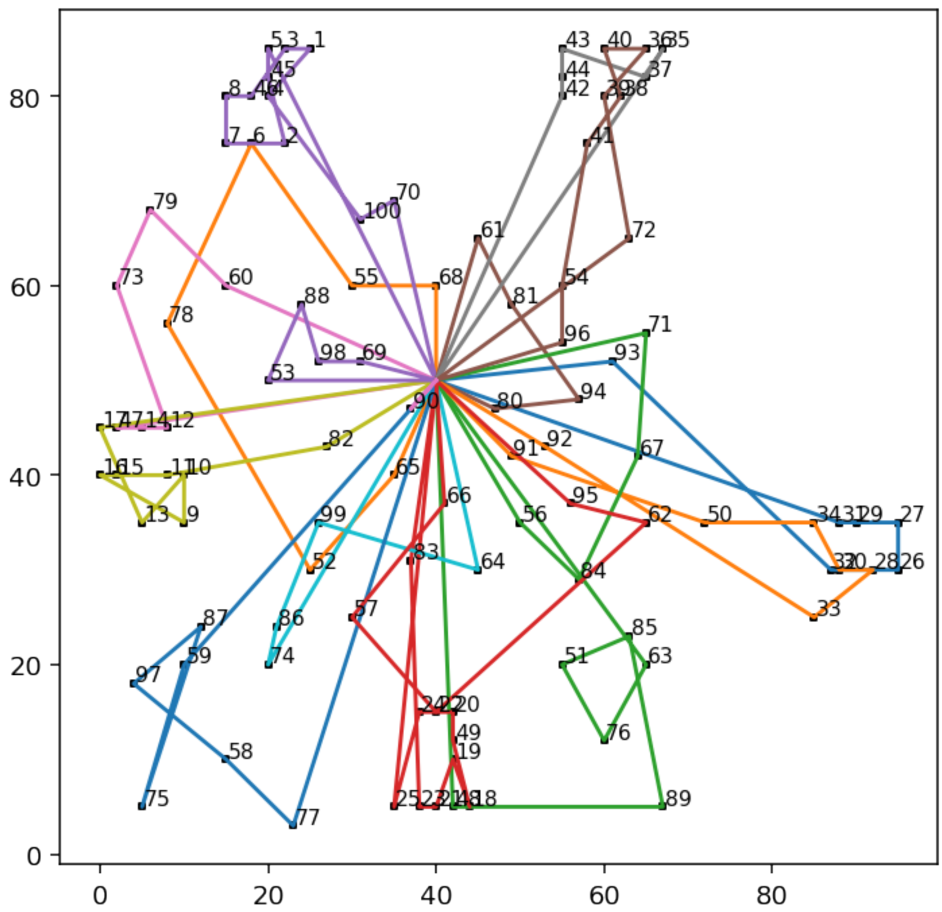


FIGURE 4.6: The top-ranked solution S_5 represented on graph

cost, the average freshness and the service level. Results show that C_3 is the lest sensitive criterion. For instance, when the weight of C_3 decrease by 5%, the ranking remain the same.As can be clearly seen that C_1 and C_2 is the most sensitive criterion, indeed 4 positions changed in the ranking.

4.9 Representation of routings solutions on an interactive map

Using visualization and interaction techniques is essential for decision support. The motivation of developing an interactive map tool is to provide an interface to visualize the routes obtained by the algorithm, which help the decision maker to better understand the space of solutions to a decision problem.

TABLE 4.7: Sensitivity coefficient

	Change Criterion weight	
	-5%	**-50%**
	Sensitivity Coefficient	
C_1	2	4
C_2	2	4
C_3	0	2

4.9.1 Interactive map design

4.9.1.1 Inputs

As inputs, the tool needs the coordinates (latitude and longitude) of depot and customers, and the routes solutions obtained by the approach.

4.9.1.2 The interface

The interface allows the decision maker to explore the set of alternative solutions depending on his preference in an interactive manner. The interface comprises two panels:

The control panel:

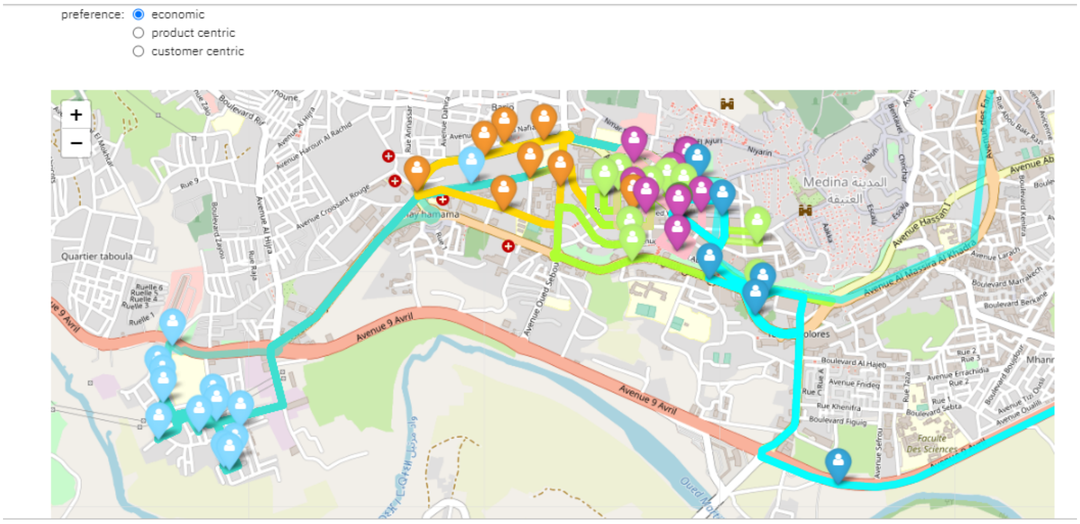
allow the DM specifying his preference by mean of python widgets. We consider tree user profiles defined before: economic, product centred, and customer centred. Based on this choice the routes will be displayed on the map using the interact function (ipywidgets.interact).

The street map panel:

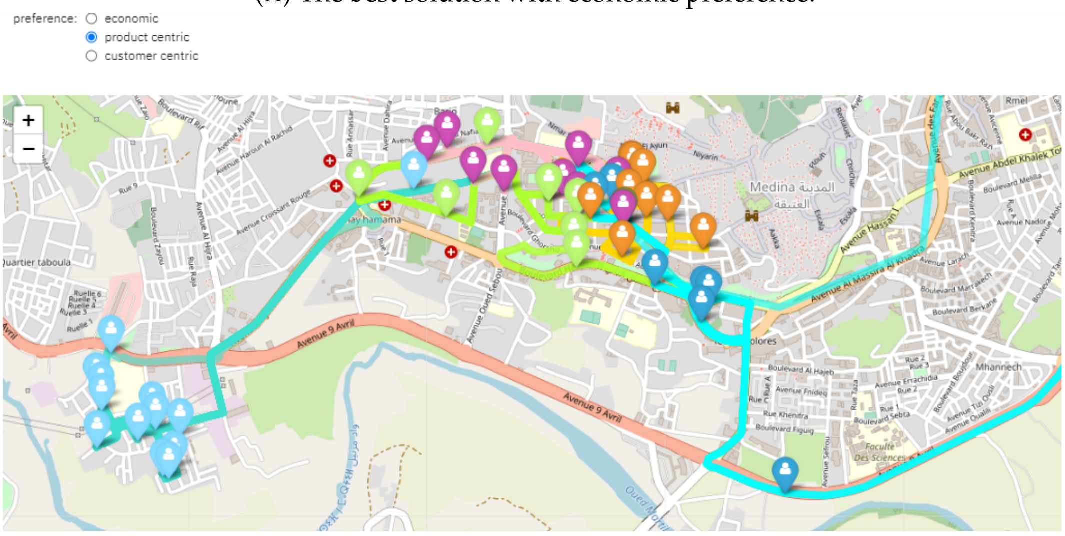
Displays the geographic information about the customers, depot and the vehicles routes. Each route is represented with a different color and the customers served by the same truck are marked with the same color. the route from one location to another can be complex with many intersections and roundabouts.to get a realistic routing on streets, we use the Open Street Routing Machine (OSRM) with Leaflet and folium packages. to get the driving route between two locations, we sent a request to the OSRM server API supplying latitude and longitude for both nodes.the response to the request contain routes encoded using google's Polyline Algorithm. Afterwards, we use python package polyline to decode it into coordinates.

4.9.2 Test case

We have an instance of 50 grocery stores located in Tetouane (Moroccan city), the coordinates of the depot are manually generated.The time window and the demand take random values respectively between [0,240] and [10,40]. For the refrigerated truck characteristics and the parameter setting, we use the parameters in the Subsection 4.8.1. The problem instance is solved using the GVNS algorithm and the possibility degree approach is then applied to the set of alternatives to select the best solution depending on the DM preference. The solutions provided are then stored and visualized depending on the choice of the DM (economic, product-centred, customer-centred) as shown in Fig.4.7. To make the task easier for the used, we add an interactive popup figure to further provide the following data for each solution : the total cost, the average freshness, the service level, and the total tardiness.



(A) The best solution with economic preference.



(B) The best solution with a product centred preference.

FIGURE 4.7: Solutions visualization depending on DM preference.

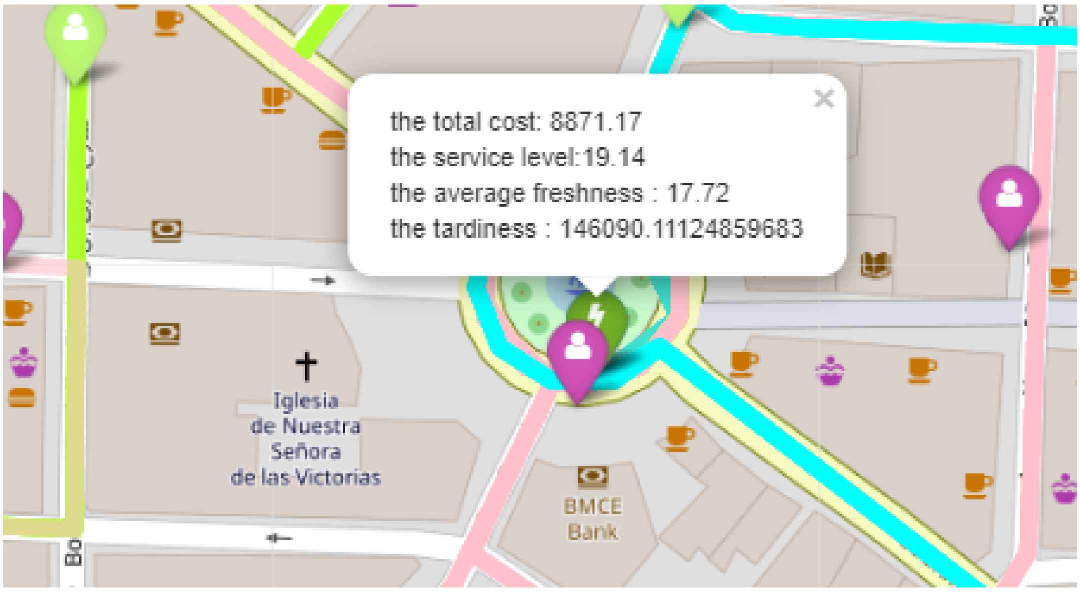


FIGURE 4.8: Interactive popup for solution data

4.10 Conclusions

In this chapter, we propose a customer-centric vehicle routing problem with time windows. The model distinguishes four objectives: minimize the overall cost, maximize the average freshness of products, maximize the service level by fulfilling the customer demand within the time range required, and in the target time if possible. We also minimize the tardiness of the system resulted from the non-respect of customer's priority.

To solve the problem, we propose a strategy that starts by solving a sub-problem considering only the cost minimization objective, using a General Variable Neighbourhood Search algorithm (GVNS). The algorithm generates a set of diverse solutions that are then evaluated to integrate the other criteria (average freshness, service level, tardiness). To come up with a single solution of interest for the decision maker among those generated by the GVNS, we used a possibility degree approach, allowing the DM to rank the set of alternatives solutions based on his/her preferences. The combination of GVNS and the possibility degree approach is tested on a full example that allows to assess the impact of criteria preferences on the solutions ranking.

Moreover, we compared the performance of GVNS in the sub-problem considered against CPLEX allowing us to clearly show the efficiency of the proposed algorithm.

Chapter 5

On the generation of alternative solutions for a perishable food distribution problem

This chapter delves into the thesis's last objective, which is to propose a methodology to provide the decision maker with a set of alternative solutions that allows him/her to analyse the problem from different perspectives.

This chapter is structured as follows: After an intoduction, In Section 5.2 we present the 'Modeling to Generate Alternatives' approach (MGA). In Section 5.3 we provide the problem-solving framework. Section 5.4 state the problem of perishable food delivery, and introduce the modelling to generate alternatives approach to solve it. Section 5.5 presents experiments to assess the performance of the proposed GVNS-MGA approach. A full example showing all the steps of the proposed GVNS-MGA approach is shown in Section 5.6. The last section wraps up the chapter 5.7.

The material presented in this chapter is accepted for publication in:

- The book "Computational Intelligence methodologies applied to Sustainable Development Goals" to be published in the series Studies in Computational Intelligence (Springer Nature)

5.1 Introduction

In recent years, the global food and grocery retail industry has seen a significant growth. The distribution of perishable food has become challenging due to the characteristics of these goods. Indeed, it is generally acknowledged that the handling of perishable food differs from the processing of other products. Perishables have a short shelf life, and their quality decay over the time during the distribution process up to the consumption. Consequently, ensuring food quality has become a top priority that must be met in order to satisfy customers.

In addition to product quality, customer's satisfaction is often influenced by the punctuality of service delivery. Therefore, it's becoming increasingly important that the customer's request arriving within the time frame he/she specified.

In real life, other specifications may need to be included in the decision-making/optimization process, making of the latter a quite complex task. For instance, since we are dealing with a time sensitive products, customers such as restaurants may adopt the Just in Time (JIT) inventory management strategy to ensure the freshness of their meals. As a result, the customer may specify a target time to receive the product, and the fulfilment of this condition is a key factor to improve the service level.

Another delivery constraint that may arise in real life is related to the priority level of customers. This issue of priority may be very significant when it comes to delivery to small restaurants. In fact, since their storage capacities are small, such restaurants must be cyclically supplied. Therefore, during the scheduling process, the DM need to prioritize this category of customers.

The distribution of perishable food in a real world setting involves a set of complex specifications that may be difficult to integrate into the mathematical models. Such parameters are often conflicting, and characterized by unquantifiable parameters (Brugnach et al., 2007),(Janssen et al., 2010),(Matthies et al., 2007).

Many mathematical optimization algorithms are devoted to finding single optimal solutions to single-objective problems or, in the best case, to determine sets of non-inferior solutions to multi-objective formulations (Janssen et al., 2010)(Walker et al., 2003) (Brill Jr et al., 1982). In any case, it should never be forgotten that we are, hopefully, obtaining the optimum solution for the model. The single best solutions provided by optimization techniques for a mathematical model can not be considered as optimal for the real world, since they may lack information about certain unmodelled features.

Assuming the existence of unmodelled (or hard to model) goals and parameters implies that non-conventional solving approaches are needed, not only to search the decision space for optimal solutions, but also to explore the decision region for alternative solutions with good quality. Such solutions can be sub-optimal for the model point of view, but valuable from additional perspectives.

It is here where the role of metaheuristics as solutions' generators becomes relevant in two senses: firstly because several runs (a single one, in the case of population based techniques) allow to obtain a set of potentially good solutions, and secondly, if a reference solution is available, one can set up a new optimization problem that allows to obtain solutions with similar quality but maximally different structure.This last approach is similar to the so-called 'Modeling to Generate Alternatives' (MGA, in what follows) approach proposed by (Loughlin et al., 2001),(Brill Jr et al., 1982),(Zechman and Ranjithan, 2004).

The concept behind MGA approach is to generate a set of alternative solutions that are near to, but maximally different from the best solution. In such a way, these solutions need to perform well with respect to the modeled objective, while being interesting with respect to other criteria that can not be modelled.

Most of the MGA applications proposed in the literature use incremental approaches to generate alternatives, by iteratively rerunning the optimization algorithm whenever a new solution is needed (Loughlin et al., 2001),(Gunalay and Yeomans, 2011),(Brill Jr et al., 1982),(Baugh Jr et al., 1997),(Zechman and Ranjithan, 2007).

The aim of this work is to approach the solution of a perishable food distribution problems by means of the MGA approach. Initially, a transportation cost minimization problem is solved using a General Variable Neighbourhood Search (GVNS) metaheuristic. Then, the obtained solution is used as a reference to generate (using again GVNS) a set of maximally different solutions for which, other criteria are taken into account. Compared to the earlier MGA algorithms proposed in the literature, the proposed procedure can generate a number of diverse solutions in a single run. Another novelty, is the use of a fuzzy constraint in the admissible difference between the reference and alternatives transportation costs.

This chapter is structured as follows: In Section 5.2 we present the 'modeling to generate alternatives' approach. In Section 5.3 we provide the problem-solving framework. Section 5.4 state the problem of perishable food delivery, and introduce the modelling to generate alternatives approach to solve it. Section 5.5 presents experiments to assess the performance of the proposed GVNS-MGA approach. A full example showing all the steps of the proposed GVNS-MGA approach is shown in Section 5.6. The last section wraps up the chapter 5.7.

5.2 The modeling to generate alternatives approach

The 'Modeling to Generate Alternatives' (MGA, in what follows) approach, proposed by (Loughlin et al., 2001),(Gunalay and Yeomans, 2011),(Brill Jr et al., 1982) and (Zechman and Ranjithan, 2004), tries to generate a set of solutions that are quantifiable good across all the modelled goals while remaining as different as possible from each other.

Let's assume that the best solution from a mathematical model is X^*, with $Z^* = F(X^*)$ as the objective value. To generate alternative solutions X that are maximally different from the best solution X^*, the following problem is proposed:

$$Max \Delta(X, X^*) \tag{5.1}$$

Subject to:

$$X \in D \tag{5.2}$$

$$|F(X) - Z^*| \leq T \tag{5.3}$$

where Δ represents the difference between the alternative solution and the best one. The parameter T is the tolerance threshold related to the optimal objective value Z^* and should be defined by the decision maker.

5.3 Basic problem-solving framework

The role of metaheuristics as solutions' generators is best seen when integrated in the following problem-solving framework. Although every step is clear enough, we describe the mains aspects considered here.
Let's depart from an optimization problem P. The following steps are required to solve it.

1. **Problem description**: determine a set of solutions' features for problem P, $\mathcal{F} = \{f_1, f_2, \ldots, f_n\}$. Such features are used to assess the quality of a solution.

2. **Model formulation**: Define the subset of features to be used in P optimization model $\mathcal{F}' = \{f_i, f_j, \ldots, f_t\}$. For every feature, either a maximization or minimization goal should be established.

3. **Problem-Solving**: "Solve" the problem P. Depending on the solver algorithm:

   (a) an optimum solution s^* (or at least a reference solution) is obtained. From such solution, generate new ones with similar quality but as different as possible.

   (b) a set of solutions is obtained.

4. **Analysis of Solutions**: For every solution, calculate the corresponding values for the features in $\mathcal{F} - \mathcal{F}'$.

5. **Ranking**: Rank the solutions according to the user's preferences.

Let's illustrate these steps with the well known travelling salesmen problem (TSP). Given a solution (a route), features like the distance travelled, time of the route, fuel consumption, average length of the inter-city paths, the length of the longest path, and so on can be measured.

In a basic TSP formulation, a single goal is defined: distance minimization.

It is in Step 3 where metaheuristics comes into play. Suppose we solve the problem using a genetic algorithm, so it is easy to obtain a set of routes (Step 3.b). For example, the best m solutions from the final population are kept.

Then, in Step 4, those m solutions can be organized in a matrix M as:

	$\mathcal{F}$		$\mathcal{F}'$	
	f_1	f_2	$\ldots$	f_n
s_1	M_{11}	M_{12}	$\ldots$	M_{1n}
s_2	M_{21}	M_{22}	$\ldots$	M_{2n}
s_m	M_{m1}	M_{m2}	$\ldots$	M_{mn}

where M_{ij} is the value achieved by solution s_i on feature f_j. Those values M_{ij} with $j \in \mathcal{F}'$ are given as the output of the optimization process, while those for $j \in \mathcal{F}$ are calculated after the optimization.

Finally, in Step 5 the values in every M row can be combined (for example using some aggregation function (Beliakov et al., 2007)) to obtain a score q_i for every solution s_i. The relevance of the objectives for the user can be expressed through a set of weights. Sorting according to q_i allows to rank the solutions.

Many options are available for this step. Here, we will use the approach in (Torres et al., 2020) that allows to select a solution of interest from a set of solutions. The user states the preferences, just providing a linear ordering of the objectives. A brief summary of the approach follows.

5.4 An MGA for perishable foods delivery

5.4.1 Problem statement

The sustainability of perishable food distribution is difficult to optimize owing to temperature control requirements. A perishable product's shelf life is heavily influenced by temperature. The latter rises during the transportation process, and when the vehicle stops to make a delivery. As a result, an estimated damage to 8-23% may occur (Osvald and Stirn, 2008b). This deterioration in quality increases the risk of food waste.

A well-designed distribution plan that emphasizes short transit times and distances can preserve the quality of products, and reduce the amount of wasted products. However, improving the sustainability of perishables distribution network necessitates balancing several competing goals, such as minimizing the travel costs (e.g., fuel consumption costs, refrigeration costs, the damage cost), maximize the average freshness, meeting consumers requirements to ensure their satisfaction (e.g., on-time delivery, good service level), and reducing environmental effect.

These trade-offs highlight the need of including multiple objectives when studying the issue of perishables distribution. However, it is not evident how to include all these conflicting goals in a single model, due to the complexity of the problem when considering a large number of parameters. To deal with this issue, we propose an initial model that focus on the travel cost minimization. Afterwards, we propose the application if a Modeling to Generate Alternatives approach to obtain other solutions that can be assessed with respect to the unmodelled objectives.

5.4.2 Model formulation and solution procedure

In this study, we use a sub-model of the one presented in Chapter 4, Subsection 4.3.2. The objective function considered include the fixed costs, the transportation cost, and the refrigeration costs, described in the subsection 4.3.1, and reformulated by the equations 4.1, 4.2, 4.5 respectively. The problem is formulated using the same parameters and variable of the previous model as follows:

$$\text{Min } C_1 + C_2 + C_3 \tag{5.4}$$

Subject to:

$$(4.21) - (4.22) - (4.23) - (4.24) - (4.25) - (4.26) - (4.27)$$

$$(4.28) - (4.29) - (4.30) - (4.31)$$

$$(4.32) - (4.33) - (4.34)$$

5.4.3 Generation of alternatives

In order to generate a set of alternative solutions to the problem described, a MGA approach is adopted. As explained in section 5.2 the objective in a MGA is to maximize the difference between the best (or a reference) solution, and the obtained alternatives 5.1.

Therefore, we first need a way to measure the difference between the routing solutions. In this work, we use the Jaccard's coefficient to measure the dissimilarities between routes. This method is detailed in the subsection 5.4.3.1.

The good alternatives are the ones that minimize the Jaccard's coefficient while respecting the threshold constraint 5.3. So in second place, we describe how such constraint is managed as a fuzzy constraint, and we propose to deal with it using the parametric approach.

Finally, the whole solving procedure to generate alternative routes using GVNS is described.

5.4.3.1 Measuring similarity of solutions

Several methods and indices have been proposed in the literature on vehicle routing problems in order to quantify the dissimilarities between solutions. The Hamming distance is the most common metric. In our study, we use the Jaccard's similarity coefficient.

The Jaccard's similarity coefficient is a statistic metric used for comparing the similarity of two sets. It is defined as the cardinality of the intersection of the sets divided by the cardinality of the union of them, i.e.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{5.5}$$

It is easy to see that if sets A and B contain the same elements, $A = B = A \cap B = A \cup B$, then Jaccard's similarity coefficient $J(A,B) = 1$. On the other hand, if sets A and B do not share any element at all, $|A \cap B| = 0$, so $J(A,B) = 0$.

We can now define the similarity between two routing solutions according to the Jaccard's similarity coefficient as the ratio of the number of shared arcs to the number of total arcs used in both solutions.

Let $y_{ijk} = 1$ if arc (i,j) from vertex i to vertex j is used by any vehicle in solution r_k, and $y_{ijk} = 0$ otherwise. Then the similarity ζ_{pq} between solutions

p and q is

$$\zeta_{pq} = \frac{\sum_{i=0}^{n}\sum_{j=0}^{n} y_{ijp} \cdot y_{ijq}}{\sum_{i=0}^{n}\sum_{j=0}^{n} sign(y_{ijp} + y_{ijq})} \tag{5.6}$$

where $y_{ijp} \cdot y_{ijq} = 1$ if arc (i, j) is used by both solutions, and $sign\left(y_{ijp} + y_{ijq}\right) = 1$ if any of the solutions use it. If solutions p and q are the same, the sum in the numerator will equal the sum in the denominator, and therefore $\zeta_{pq} = 1$. On the other hand, if they are two completely different solutions with no arc in common, the numerator will equal 0, and then $\zeta_{pq} = 0$

5.4.3.2 Fuzzy constraint for the transportation cost difference

As stated before, besides the maximization of the solutions differences, we need to deal with the following constraint:

$$|F(X) - Z^*| \leq T \tag{5.7}$$

where T is the allowed increase in the transportation cost for the alternative solutions.

As the solutions represents routes on a map, it is not possible to assess if other alternatives are available so it has sense to define:

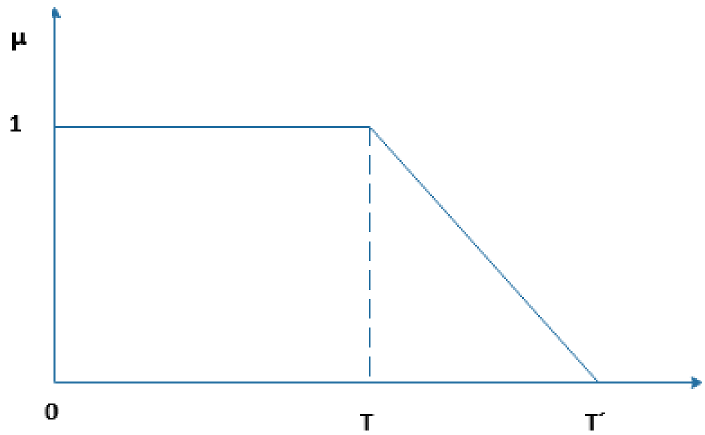


FIGURE 5.1: The satisfaction degree of the fuzzy constraint

The flexibility allowed by the decision maker can be modeled using fuzzy constraint in the model for generating alternatives considering the following constraint:

$$|F(X) - Z^*| \leq_f T \tag{5.8}$$

Where $\leq_f$ implies that restriction in the threshold could be partially satisfied.

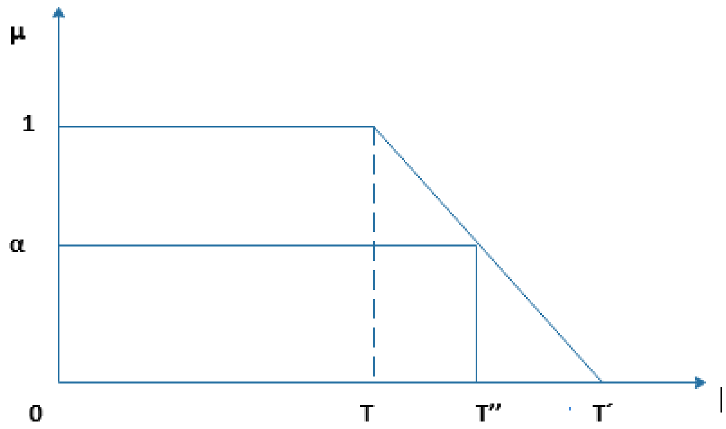


FIGURE 5.2: The threshold function to α

Then the membership function that represents the satisfaction degree of the fuzzy constraint is shown in Fig. 5.1 and it is defined as:

$$\mu(\tau) = \begin{cases} 1 & ;\tau < T \\ f(\tau) & ;T \leq \tau < T' \\ 0 & ;\tau \geq T' \end{cases} \tag{5.9}$$

where $T' = T + \Delta^t$ is the endurable distance threshold, $\tau = |F(X) - Z^*|$ is the difference of distance between the reference solution and the obtained alternative. $f(\tau)$ is a non-increasing function that is defined as:

$$f(\tau) = 1 - \frac{\tau - T}{\Delta^t} \tag{5.10}$$

To our knowledge, no approach can solve the problem in its fuzzy form directly. The original fuzzy problem, on the other hand, can be transformed into a series of crisp problems.The Parametric Approach (Ho and Cao, 2012) can be used for this purpose, transforming the fuzzy problem into a set of crisp problems using the concept of $\alpha - cuts$.

The problem is solved afterwards for each value of α using an optimization technique. This approach has been widely used in fuzzy optimization problems, as in (Rubinstein and Shapiro, 1993; Heidergott, 1995; Morrice and Schruben, 1989; Schruben and Cogliano, 1981). In the context of routing problems, the approach was applied in (Ho and Cao, 2012; Gurkan et al., 1994), just to cite some examples.

Given the predefined membership function and a value of α, the threshold T''that can be accepted by the decision maker is shown in Fig.5.2 and defined by the following formula:

$$T'' = f^{-1}(\alpha) = T + \Delta^t(1 - \alpha) \tag{5.11}$$

After some basic transformations, the fuzzy constraint is transformed into:

$$|F(X) - Z^*| \leq T + \Delta^t(1-\alpha) \tag{5.12}$$

5.4.4 Solving strategy flowchart

Let's assume that the best solution obtained for the problem is X^*, with $Z^* = F(X^*)$ as the objective value. To generate alternative solutions X that are maximally different from X^*, the following problem is addressed:

$$Min\ Jaccard(X, X^*) \tag{5.13}$$

$$|F(X) - F(X^*)| \leq T + \Delta^t(1-\alpha) \tag{5.14}$$

The whole approach is depicted in Fig. 5.3.

At the beginning, it starts solving the initial problem using the GVNS. After several runs, the best solution obtained will be used as the reference solution X^*. Then, the new problem is solved by an adapted GVNS using the new objective function and constraint.

Then, alternatives solutions are generated as follows:

1. Initialize the GVNS with the obtain the best solution X^* .
2. Apply the shaking to the best solution to obtain a solution X' . Next, a solution X'' is obtained by applying the local search to X'.
3. Measure the similarity between X'' and the best solution X^*.
4. If X'' is better than X' (in terms of the Jaccard coefficient) and satisfies the constraint, the current solution jump from X^* to X''. Otherwise, the order of the neighbourhood is increased

The generated alternatives (the solutions obtained by GVNS) are then evaluated according to new criteria not covered in the original problem. These criteria are: the damage cost, the average freshness, the service level, and the tardiness. Then, an a posteriori analysis will allow the decision maker to study the problem from different perspectives, in order to select an appropriate solution according to his/her preferences.

5.5 GVNS-MGA performance evaluation

5.5.1 Data and parameters

The proposed approach is illustrated in a problem with 50 customers. Data is taken from instance RC101, from Solomon's data set. For customer's target time, we assume that it's the midpoint of the corresponding time window. The refrigerated vehicles used to deliver products have a fixed cost of 25 €, and the fuel consumption is estimated to 3 €/km. For the GVNS parameters,

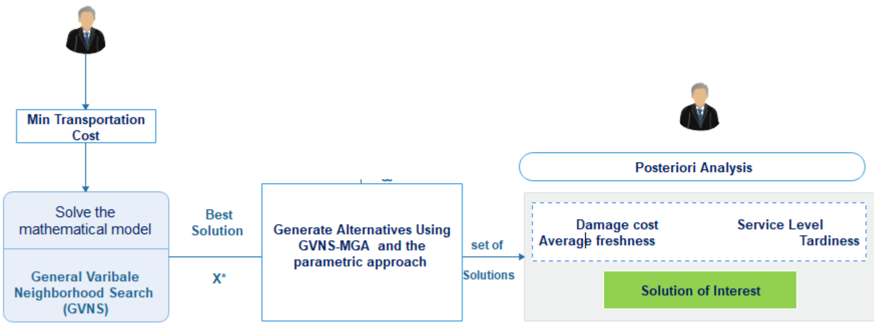


FIGURE 5.3: The adopted solving strategy to generate alternative solutions

we use the following values: $\delta_1 = 0, \delta_2 = 1, \Lambda = 2, \mu = 1$. The stopping criteria M which correspond to the number of iterations, is fixed to 10. The other parameters are: $P = 20$ €/Unit, $\partial_1 = 0.002$, $\partial_2 = 0.003$, $C_e = 0.03$ €/unit, $C'_e = 0.04$ €/unit and $\delta = 0.8$

The experiments were carried out on an Intel Core i7 processor with 1.99 GHz speed and 8 GB RAM.

5.5.2 Computational results

To generate a set of alternative solutions, we start by finding the best solution. For so, we solve the proposed mathematical model using GVNS. The best solution is obtained by performing 10 runs, and it is used to initialize the GVNS in order to obtain other solutions that are maximally different from it.

Then, the new problem is solved for different values of α, with $\alpha \in [0, 0.1, \ldots, 1]$. For each value of α, we run the algorithm 10 times. The algorithm provides the routing solutions with their corresponding objective values (the total travel cost). We start by running the algorithm for $\alpha = 1$ and report the alternative solutions, Afterwards we decrease the value of α by 0.1 and re-run the algorithm.

Table 5.1 shows the results obtained. For each α, just different solutions are reported. Every solution is compared against the reference solution in terms of the Jaccard's coefficient and all the other criteria: the damage cost, the average freshness, the service level, and the tardiness. A positive value refers to an increment, and the negative one to a decrement. The interpretation of the percentages depends on the criteria evaluated: a positive percentage in the transportation cost, damage cost and tardiness is not desirable. However, in the average freshness and service level, positive values means improvements.

We can observe that the proposed approach allows us to generate a set of diverse solution that shows a different behaviour for each criterion. Thus, the decision maker (DM) can analyse the alternatives from different perspectives and select the appropriate solution depending on his preference. Indeed, if the DM has an economic-centric preference, he would select the cheapest solution considering both the transportation and damage cost. Otherwise, if the DM is more focused on the quality of product and service, he would

TABLE 5.1: Experiment results of 10 runs for each value of α

		Jaccard Coefficient	Travel cost	Damage cost	Average freshness	Service level	Tardiness
	Ref Solution	1	3158.98	6297.407	31.99	14.66	226698.47
$\alpha = 1$	s_1^1	0.78	0.08	-0.09	-0.15	5.51	1.39
	s_1^2	0.51	0.75	0.41	-1.68	19.15	5.07
	s_1^3	0.81	0.31	0.22	0.05	14.49	-15.44
	s_1^4	0.84	0.87	0.26	-2.09	2.12	2.33
	s_1^5	0.87	0.64	2.07	-1.75	-5.05	3.06
	s_1^6	0.81	0.35	0.27	-1.59	-0.86	-4.79
	s_1^7	0.81	0.56	1.82	-2.07	-8.25	-3.62
$\alpha = 0.9$	_	_	_	_	_	_	_
$\alpha = 0.8$	s_3^1	0.63	0.30	-1.07	0.02	-0.57	-11.93
	s_3^2	0.49	0.53	1.37	-2.04	-3.44	3.36
	s_3^3	0.66	0.95	0.17	-2.22	7.65	3.74
$\alpha = 0.7$	s_4^1	0.81	0.21	-0.99	0.15	-6.10	-13.43
	s_4^2	0.63	0.65	1.73	-2.19	-2.71	4.24
$\alpha = 0.6$	s_5^1	0.68	1.08	-0.73	-1.94	-3.98	-11.16
$\alpha = 0.5$	s_6^1	0.66	0.66	0.49	-1.54	13.63	-20.08
$\alpha = 0.4$	s_7^1	0.66	0.78	0.83	-1.91	-14.35	-10.46
$\alpha = 0.3$	s_8^1	0.63	0.40	0.14	-0.08	20.01	-13.89
	s_8^2	0.63	0.43	0.18	-1.72	4.67	-3.40
$\alpha = 0.2$	_	_	_	_	_	_	_
$\alpha = 0.1$	_	_	_	_	_	_	_
$\alpha = 0$	s_{11}^1	0.68	1.18	0.48	-2.04	16.60	10.88

opt for the routing solution that maximize the average freshness, the service level, and minimize the tardiness.

By analysing the given solutions, we have found that the more we relax the problem (in terms of α), we get new interesting solutions. To illustrate, let's consider the solution S_1^3 given by $\alpha = 1$ (when no flexibility in the threshold is allowed), compared to the reference solution (the best). The latter improves slightly the average freshness by 0.05%, but the service level is increased by 14.49%, and the tardiness is reduced by 15.44%. Which can be considered as significant enhancement. For $\alpha = 0.7$ a new solution is generated S_4^1, that has the same Jaccard coefficient but performs differently for the given criteria. S_4^1 reduce the damage cost by 1%, the tardiness by 13.43%, and improve slightly the average freshness by 0.15%. Furthermore, the obtained enhancement implies just an increment of 0.21% in the travel cost, which implies that this solution could be a compromise one for that has economic focus as well as customer satisfaction focus. For $\alpha = 1$ we have found solutions that improve only one criterion compared to the reference solution, such as S_1^6 which only reduce the tardiness. Yet, when we relax the problem for $\alpha = 0.3$ we obtain solutions S_8^1 and S_8^2 that have almost the same travel cost as S_1^6, but too different from the best solution with a Jaccard equal to 0.63. S_8^1 and S_8^2 respectively improves the service level by 20% and 4.67%, and reduce the tardiness by 13.89% and 3.4%. We can conclude that by considering fuzzy threshold, we increase our chances of getting diverse solutions. These solutions perform well for a set of criteria that are relevant for the studied problem, and help the decision maker in analysing different aspect instead of considering only the cost criteria.

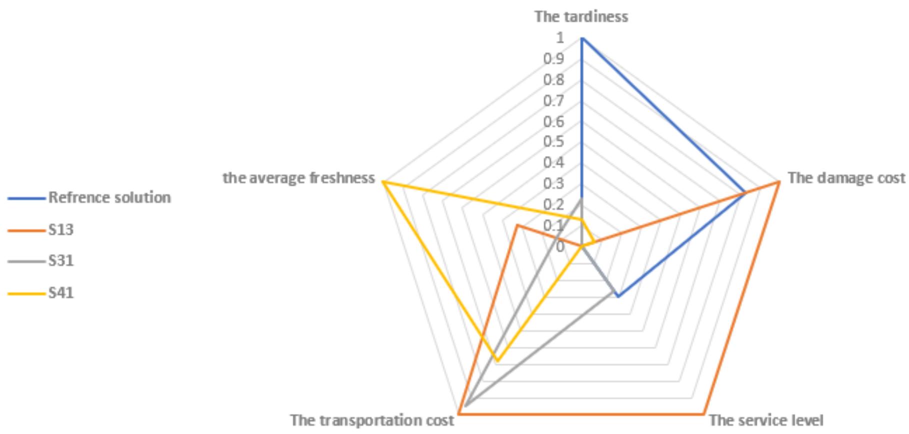


FIGURE 5.4: The three compromised solutions compared to the reference solution for each criteria

For the set of alternatives, we can observe that there are some solutions producing improvements in only one criterion, other for two criteria, and best ones allows an improvement in three criteria. By focusing on the latter, we have found three solutions S_1^3, S_3^1 and S_4^1 that are shown in Fig. 5.4 in order to analyse them in terms of the evaluation criteria, and help the DM in selecting the compromised one. From the plot we can see that the solution S_1^3 is the best one in terms of service level improvement, and in terms of average freshness the solution S_4^1 is the best. However, the solution S_3^1 is the one that minimize at most the damage cost. Thus, we have three different good solution dependant to the DM preferences, but if the latter focus most on customer satisfaction then the solution S_1^3 is the best one because instead of the service level, this solution is the one that minimize at most the tardiness.

Another interesting solution for the decision maker is S_1^1 shown in Fig. 5.5. This solution is quite different from the reference solution (Jaccard coefficient 0.78), but interestingly allows an improvement in the service level, and reduce the damage cost with almost the same transportation cost. S_1^1 lead to a slight decrement in the average freshness, and an increase of the tardiness, but it can be considered as a good alternative if the DM has an economic and customer-centric perspective.

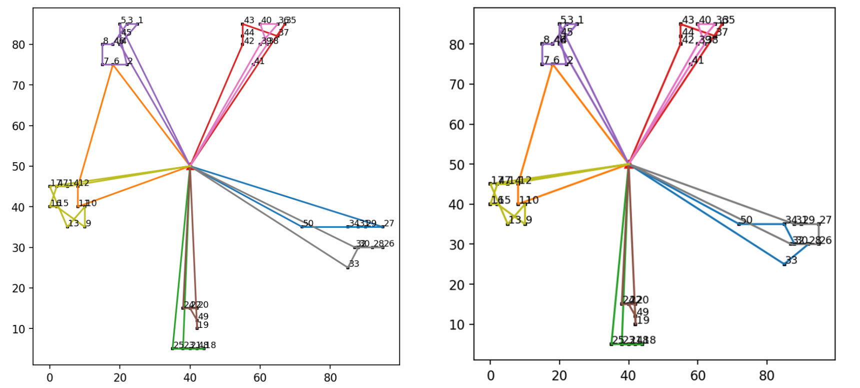


FIGURE 5.5: Left: the reference solution. Right: an alternative one S_1^1.

5.6 Application example

Once verified the efficiency of the proposed GVNS-MGA in generating alternative solutions, we provide here a complete example of the proposed solving approach, shown in Figure 5.3. This section reports the test instance used, the computational experiments performed and the results obtained.

Experimental Scenarios

In order to access the impact of the threshold T on the quality of generated solutions, we conducted experiments for two scenarios corresponding to different levels of flexibility.

1. Scenario A: the endurable distance threshold $T' = 30$
2. Scenario B: the endurable distance threshold $T' = 15$

Dataset

The proposed approach is evaluated through a dataset of 50 customers in Granada, Spain. The customers' time window takes a random value in the interval $[0, 240]$ with an interval width ≥ 45. For customer's target time, we assume that it's the midpoint of the corresponding time window. The refrigerated trucks consumptions and the other parameters used are the same as in the section 5.5.1.

5.6.1 Analysis of solutions' diversity

A set of 62 alternative solutions was obtained in the scenario A, and a set of 77 solutions in the scenario B. For each value of α we report the set of solutions with their corresponding jaccard coefficient and features values (travel cost, total damage, average freshness, tardiness, service level) as shown in Table 5.2, and Table 5.3.

TABLE 5.2: Set of solutions for the perishable food distribution problem in terms of each α value (Scenario A). X^* is the reference solution.

		Jaccard Coeff	Travel cost	Total damage	Average freshness	Tardiness	Service level
	X^*		**1168.40**	**8024.42**	**21.52**	**134158.60**	**17.45**
$\alpha = 1$	**1**	0.47	1168.35	8024.43	21.53	134158.60	17.45
	2	0.45	1218.24	7871.47	21.53	160106.88	18.81
	3	0.58	1220.88	7759.02	21.31	77340.90	18.19
	4	0.44	1211.40	7642.49	20.80	150318.80	16.34
	5	0.75	1170.63	7574.83	20.57	94747.56	16.42
	6	0.78	1170.01	7654.86	20.56	113959.93	17.84
	7	0.45	1183.76	7593.93	20.96	172670.60	19.66
	8	0.58	1184.17	7647.87	20.92	134514.11	20.10
	9	0.87	1170.28	7769.21	21.21	110974.37	17.88
	10	0.62	1167.85	7613.17	20.19	114563.32	17.84
	11	0.70	1172.65	7665.73	20.62	129750.23	17.06
	12	0.62	1196.22	7989.30	21.64	129427.45	18.24
	13	0.47	1242.50	7719.73	21.16	145819.23	17.91
	14	0.44	1224.65	7530.24	20.12	179372.30	17.95
	15	0.72	1198.04	7988.70	22.39	132493.70	19.14
	16	0.51	1205.16	7774.37	21.70	163477.79	20.08
	17	0.62	1236.82	7581.91	20.45	145892.33	18.78
	18	0.49	1188.44	7732.66	21.21	88179.91	19.27
	19	0.42	1235.29	7753.68	21.27	121543.30	15.96
	20	0.56	1244.36	7745.72	21.81	189232.09	17.86
	21	0.33	1239.06	7594.26	20.71	188649.18	18.59
	22	0.26	1243.11	7713.25	21.52	149117.63	18.95
	23	0.45	1228.98	7703.10	21.26	124985.42	17.27
$\alpha = 0.8$	**24**	0.62	1236.82	7581.91	20.45	161864.14	18.78
	25	0.56	1233.45	7842.50	21.78	115142.75	18.77
	26	0.49	1208.76	7631.62	20.74	75526.48	17.13
	27	0.56	1244.36	7745.72	21.81	216830.61	15.80
$\alpha = 0.6$	**28**	0.42	1185.46	7734.76	21.32	90998.06	17.04
	29	0.53	1187.79	7670.50	20.70	115110.98	18.45
	30	0.44	1235.87	7760.68	21.56	69137.18	19.12
	31	0.42	1214.54	7647.11	20.82	155266.90	16.94
	32	0.51	1202.58	7800.86	21.01	86761.52	16.65
	33	0.62	1236.82	7581.91	20.45	203346.27	18.78
	34	0.33	1245.61	7751.62	21.86	117838.20	18.20
	35	0.47	1200.82	7735.57	21.40	130465.05	16.65
	36	0.38	1244.21	7543.49	20.62	113774.55	17.98
$\alpha = 0.4$	**37**	0.37	1250.88	7694.87	21.05	75133.26	17.16
	38	0.38	1210.05	7669.48	20.86	104778.07	17.81
	39	0.58	1240.43	7729.76	21.06	179606.29	16.77
	40	0.37	1216.35	7702.60	20.96	105564.80	18.67
	41	0.62	1235.22	7830.84	21.72	119825.69	18.02
	42	0.47	1243.45	7605.22	21.20	175925.44	19.00
	43	0.44	1211.40	7642.49	20.80	141176.06	16.34

$\alpha = 0.2$	**44**	0.44	1224.65	7530.24	20.12	163449.29	17.95
	45	0.40	1214.36	7784.08	21.58	95139.87	18.97
	46	0.62	1210.16	7746.02	21.58	113320.22	17.99
	47	0.53	1239.28	7778.74	21.84	109442.38	18.28
	48	0.58	1240.43	7729.76	21.06	179606.29	16.77
$\alpha = 0$	**49**	0.51	1205.16	7774.37	21.70	163477.79	20.08
	50	0.49	1230.69	7570.80	20.39	176408.72	18.37
	51	0.75	1170.63	7574.83	20.57	139394.36	16.42
	52	0.60	1194.15	7858.23	21.83	95379.98	18.34
	53	0.45	1209.71	7640.73	20.16	86129.95	18.83
	54	0.53	1247.40	7721.07	21.20	187736.49	17.34
	55	0.56	1247.56	7696.99	21.08	182320.04	18.63
	56	0.49	1252.36	7717.77	21.18	195880.30	17.59
	57	0.47	1216.26	7955.55	21.68	126305.39	17.12
	58	0.47	1198.73	7679.40	20.83	158445.86	18.63
	59	0.62	1206.17	7641.84	20.75	115100.21	19.60
	60	0.40	1208.93	7632.71	20.95	148361.60	20.31
	61	0.40	1235.61	7747.33	21.33	125947.14	19.89
	62	0.40	1198.73	7686.03	21.22	81051.91	16.87

TABLE 5.3: Set of solutions for the perishable food distribution problem in terms of each α value (Scenario B). X^* is the reference solution.

		Jaccard Coeff	Travel cost	Total damage	Average freshness	Tardiness	Service level
	X^*		**1168.35**	**8024.43**	**21.53**	**134158.60**	**17.45**
$\alpha = 1$	**1**	0.42	1175.12	7626.45	20.75	157994.31	17.90
	2	0.70	1172.65	7665.73	20.62	141974.05	17.06
	3	0.81	1170.98	7854.65	21.27	132636.02	16.42
	4	0.70	1168.12	7772.50	20.85	105921.93	18.73
	5	0.58	1169.02	7594.35	20.68	76748.98	16.31
	6	0.62	1167.85	7613.17	20.19	128811.54	17.84
	7	0.62	1193.03	7947.94	21.29	183760.79	16.38
	8	0.67	1173.27	7581.99	20.61	142082.58	15.84
	9	0.51	1171.66	7601.51	20.72	159977.50	15.72
	10	0.70	1184.87	7959.11	21.97	155932.99	18.71
	11	0.65	1180.11	7683.96	20.74	95458.83	16.93
	12	0.75	1170.63	7574.83	20.57	151000.28	16.42
	13	0.78	1172.92	7776.37	21.25	107566.56	17.30
	14	0.47	1173.59	7606.88	20.38	162019.74	18.98
	15	0.62	1171.23	7786.82	21.24	139769.32	17.21
	16	0.58	1196.64	7755.14	21.50	78497.30	17.37
	17	0.40	1185.17	7655.04	20.79	159493.43	18.60
	18	0.56	1170.49	7624.03	20.25	94571.63	17.06
	19	0.81	1170.98	7854.65	21.27	132636.02	16.42
	20	0.65	1194.00	7744.27	21.44	91453.60	18.16

Table 5.3 continued from previous page

	21	0.47	1172.49	7615.58	20.70	142285.97	18.68
	22	0.53	1171.11	7543.90	20.24	152099.22	16.69
	23	0.58	1184.17	7647.87	20.92	170639.52	20.10
	24	0.60	1199.78	7803.69	21.73	213642.03	19.94
$\alpha = 0.8$	**25**	0.51	1190.98	7669.92	21.04	126627.88	20.03
	26	0.53	1196.72	7809.04	21.80	120381.85	19.02
	27	0.70	1188.42	7586.67	20.02	81291.65	17.83
	28	0.87	1170.28	7769.21	21.21	110974.37	17.88
	29	0.56	1170.49	7624.03	20.25	85182.34	17.06
	30	0.56	1187.07	7715.24	21.21	89481.93	17.16
	31	0.42	1176.23	7617.75	20.44	110596.66	18.20
	32	0.38	1193.80	7479.55	20.50	170278.76	18.90
	33	0.81	1190.13	7924.28	21.79	83131.08	19.75
	34	0.42	1192.12	7765.33	21.53	128978.13	17.83
	35	0.51	1171.66	7601.51	20.72	76957.09	15.72
	36	0.56	1201.55	7778.54	21.23	144878.54	18.71
	37	0.67	1185.55	7701.47	20.80	137662.49	18.89
	38	0.65	1188.84	7918.66	21.75	164074.80	19.16
$\alpha = 0.6$	**39**	0.62	1190.59	7753.02	21.58	132611.38	18.43
	40	0.65	1187.52	7996.47	21.66	121024.68	16.58
	41	0.45	1193.61	7680.78	21.09	156924.65	19.25
	42	0.62	1167.85	7613.17	20.19	128811.54	17.84
	43	0.75	1196.53	7744.86	20.97	63421.41	17.81
	44	0.37	1187.01	7505.45	20.61	178243.99	19.11
	45	0.60	1168.47	7536.74	20.20	73151.53	17.27
	46	0.67	1204.73	7544.16	20.29	133365.19	19.26
	47	0.53	1198.15	7774.52	21.29	110274.13	17.87
	48	0.44	1184.91	7677.15	20.84	85925.00	18.01
$\alpha = 0.4$	**49**	0.53	1200.34	7666.51	21.11	91731.01	16.98
	50	0.60	1171.31	7837.27	21.37	130288.62	17.18
	51	0.51	1194.42	7782.52	21.70	162274.88	18.95
	52	0.35	1187.81	7665.91	20.85	132686.65	17.81
	53	0.47	1202.23	7598.11	20.41	69614.84	16.87
	54	0.51	1201.15	7760.02	21.33	127630.98	17.47
	55	0.44	1201.35	7681.05	21.53	110445.46	18.55
	56	0.62	1188.21	7906.54	21.83	136341.81	18.57
	57	0.65	1186.17	7618.54	20.81	140399.13	17.63
	58	0.60	1171.31	7837.27	21.37	109988.63	17.18
	59	0.65	1188.84	7918.66	21.75	164074.80	19.16
	60	0.49	1208.76	7631.62	20.74	149766.95	17.13
	61	0.65	1191.52	7599.33	20.60	130929.98	20.20
	62	0.65	1186.17	7618.54	20.81	135528.45	17.63
	63	0.78	1172.92	7776.37	21.25	85548.78	17.30
	64	0.49	1186.81	7672.98	20.93	95658.37	16.80
	65	0.33	1181.27	7673.12	21.02	105732.94	18.04
	66	0.37	1196.12	7492.36	19.97	94128.22	18.59

Table 5.3 continued from previous page

	67	0.58	1202.73	7648.83	20.77	151142.76	16.41
	68	0.56	1208.71	7946.51	22.02	151962.20	18.35
$\alpha = 0.2$	**69**	0.40	1202.24	7623.18	21.05	116244.36	19.95
	70	0.58	1196.10	7827.33	21.25	85903.25	18.54
	71	0.42	1175.12	7626.45	20.75	164100.79	17.90
	72	0.47	1191.45	7575.25	20.51	118745.05	18.49
	73	0.56	1169.07	7501.12	20.43	145694.19	17.38
$\alpha = 0$	**74**	0.62	1198.91	7767.67	21.17	150143.62	19.49
	75	0.42	1176.23	7617.75	20.44	206409.94	18.20
	76	0.38	1209.56	7844.60	21.77	222063.74	17.60
	77	0.65	1188.58	7966.20	21.92	92395.58	19.12

Table 5.4, and Table 5.5 summarize the values of the features over the alternative solutions for respectively scenario A and B. It is clear that a wide variety of alternatives are available to choose from.

TABLE 5.4: Summary of values for every feature considered, over the generated solutions (Scenario A)

	Min	**Max**	**Mean**	**Std.Dev**
Travel Cost	1167.85	1252.36	1215.43	24.97
Total damage	7530.24	8024.43	7709.90	109.80
Average freshness	20.12	22.39	21.11	0.51
Tardiness	69137.18	216830.61	134649.45	36362.44
Service level	15.96	20.31	18.10	1.07

TABLE 5.5: Summary of values for every feature considered,over the generated solutions (Scenario B)

	Min	**Max**	**Mean**	**Std.Dev**
Travel cost	1167.85	1209.56	1185.44	12.09
Total Damage	7479.55	7996.47	7705.97	125.27
Average freshness	19.97	22.02	20.99	0.52
Tardiness	63421.41	222063.74	128166.25	34197.13
Service level	15.72	20.20	17.95	1.09

As we explicitly generate the set of solutions minimizing the similarity with X^*, it is interesting to observe the relation between the Jaccard coefficient, and the differences in the calculated values for every solution. This information is shown in Fig. 5.6 and Fig.5.7 (for visualization purposes, just a subset of solutions are shown in every case). The Y axis reflects the difference as percentage.

- Scenario A

When considering the distance (which is correlated with the travel cost), (Fig. 5.6 (a)) shows that all the solutions are worst in this feature. This is not surprising, as X^* has the lowest distance. There are several interesting solutions,

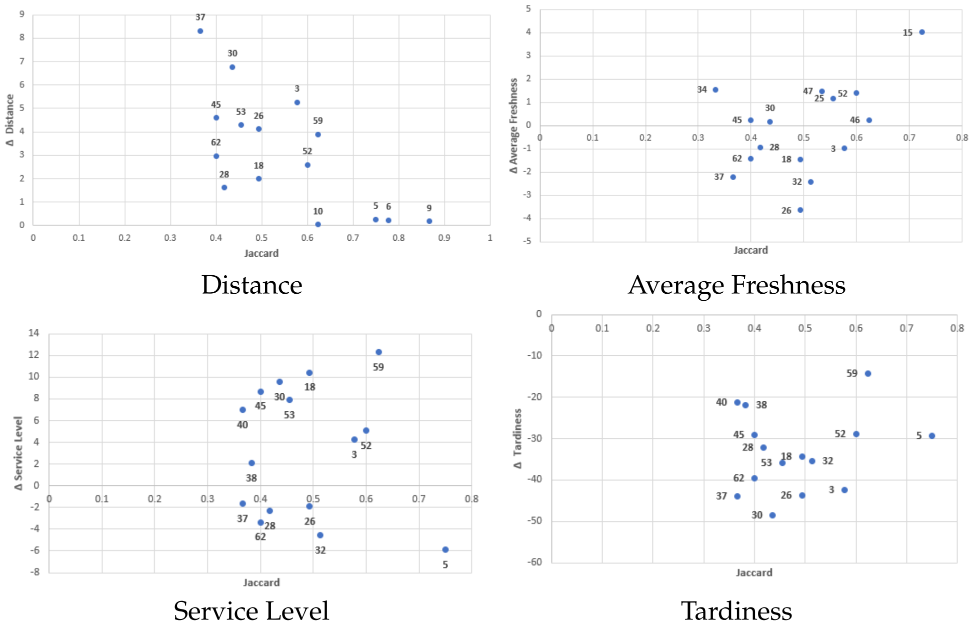


FIGURE 5.6: Variation of individual criterion and Jaccard's coefficient with respect to the reference solution (Scenario A). Just a subset of solutions is shown.

like 10, 5, 6, and 9, that had a quite similar distance but a Jaccard similarity below 0.9. Solution 28 is also interesting because it has a low level of similarity (less than 0.45), while attaining a quite similar distance value (less than 2% of difference).

With an increment in the distance between 2 and 5%, up to eight solutions can be found with a Jaccard value between $[0.4, 0.62]$.

For the Average Freshness and Service level, the situation is more interesting, because there are better and worse solutions than the reference one. Focusing on the Average freshness (Fig. 5.6 (b)), those solutions with a positive value in Y are better than the reference solution. Solution 15 allows improving up to 4% in the criteria while having a similarity value of 0.7. Other improvements between 1-2% can be obtained with quite different routes (solutions 47, 25, 52).

The results in terms of the service level are shown in (Fig. 5.6 (c)). Here, solution 59 provides more than a 10% of improvement with a moderate value of similarity (less than 0.65). Several solutions providing improvements higher than 6% and similarity below 0.5 are available. In this case, even solution 37 may be interesting, as it has a minor decrement in service level but very low level of similarity.

Finally, (Fig. 5.6 (d)) shows the solution in terms of the Tardiness criteria. Here, all the solutions are better than the reference one. It is clear here that Tardiness similar tardiness than the reference solution can not be attained. Great improvements can be obtained, but with quite different solutions (look at the low values for similarity).

- Scenario B

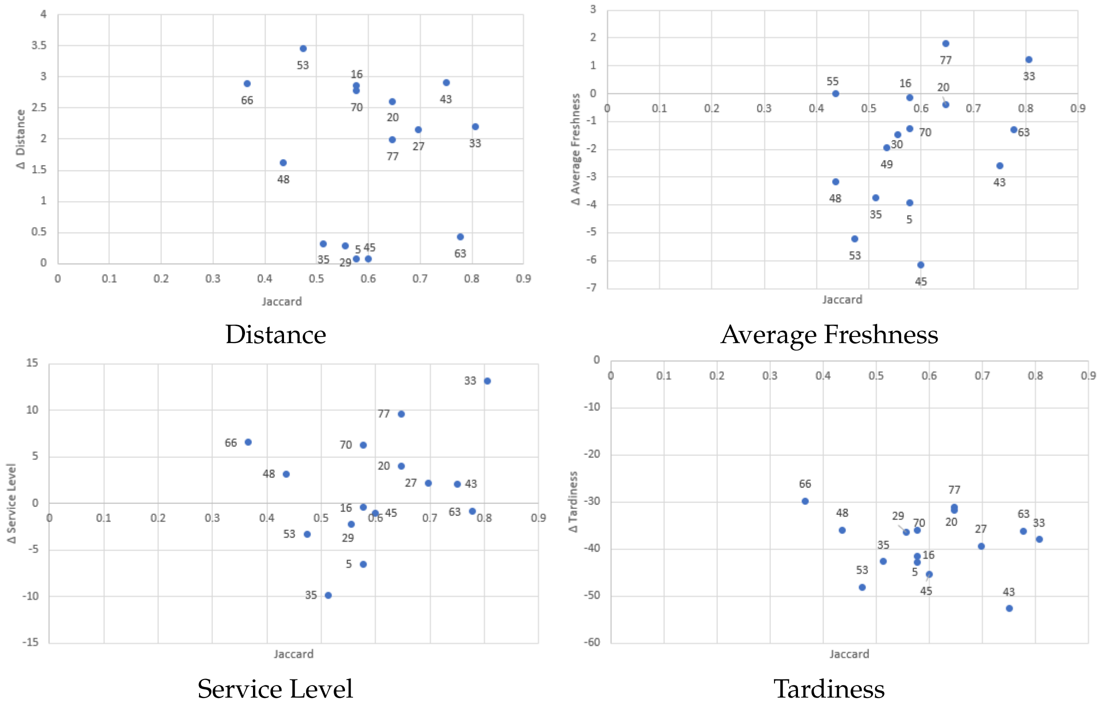


FIGURE 5.7: Variation of individual criterion and Jaccard's coefficient with respect to the reference solution (Scenario B). Just a subset of solutions is shown.

In terms of the distance, it's clear in fig. 5.7(a) that all the obtained alternatives are worst in this feature compared to the reference solution. However, there are interesting solutions that have a low level of similarity with a jaccard between [0.5, 0.6], with an increment in distance less than 0.5 % like solution 5, 29, 35, 45.

For the average freshness (Fig.5.7(b)), 70% of the obtained solutions are worst than the reference solution. only two solutions (33, 77) are providing improvement between 1 and 2%. A quite similar level of freshness with different routes(jaccard between [0.4,0.6]) is obtained in solution 55, and 16.

In terms of the service level (Fig.5.7(c)), 55% of the obtained solutions are better than the reference one. Solution 33 allows improving up to 14% with a quite similar route (jaccard=0.8).There also other interesting solution providing improvment of 10% with a higher level of dissimilarity (jaccard=0.65). Several solutions allowing improvement between 2 and 6% are available.

The results in terms of tardiness feature (Fig. 5.7(d)) are all better than the reference solution such the case in scenario A. The tardiness can be reduced up to 53% like in solution 43. The others alternative allows reduce between 30 and 50% which is very interesting

5.6.2 User profiles and ranking

The previous analysis is useful for detecting good solutions when analysed from just two points of view: similarity vs. a single criterion.

Here, we define three user's profiles, representing the preferences of a decision maker. As stated before, the preferences are indicated through a linear ordering of the criteria that is described below.

- Economic-centric (E-c): Travel Cost = Total Damage $\succeq_p$ Average freshness $\succeq_p$ Tardiness $\succeq_p$Service level.
- Product-centric (P-c): Average freshness $\succeq_p$ Travel Cost $\succeq_p$ Total Damage$\succeq_p$ Tardiness $\succeq_p$ Service level.
- Customer Satisfaction-centric (C-c): Tardiness = Service level $\succeq_p$ Travel Cost $\succeq_p$ Total Damage $\succeq_p$ Average freshness.

where the symbol $\succeq_p$ should be read as "at least as preferred to"

For every profile, the procedure described in chapter 4 Section 4.7 to rank the solutions is applied. The best 15 solutions under each user profile in scenario A, are shown in Table 5.6,5.7, 5.8. The ranking for scenario B is provided in Table 5.9, **??**, 5.10.

Every solution is compared against the reference solution in terms of the following criteria: travel cost, total damage, average freshness, service level, and tardiness. Values in red cells are worse than the reference value, while the green ones are better.

TABLE 5.6: Ranking of solutions under the Economic-centric profile (Scenario A).

	Travel cost	**Total damage**	**Average freshness**	**Tardiness**	**Service level**
Reference solution	**1168.4**	**8024.42**	**21.52**	**134158.6**	**17.45**
18	**1.72**	**-3.64**	**-1.46**	**-34.27**	**10.44**
30	**5.78**	**-3.29**	**0.17**	**-48.47**	**9.57**
26	**3.46**	**-4.90**	**-3.64**	**-43.70**	**-1.87**
53	**3.54**	**-4.78**	**-6.35**	**-35.80**	**7.88**
3	**4.50**	**-3.31**	**-0.99**	**-42.35**	**4.25**
62	**2.60**	**-4.22**	**-1.41**	**-39.59**	**-3.35**
5	**0.19**	**-5.60**	**-4.46**	**-29.38**	**-5.88**
28	**1.46**	**-3.61**	**-0.95**	**-32.17**	**-2.33**
45	**3.94**	**-3.00**	**0.24**	**-29.08**	**8.69**
52	2.21	-2.07	1.39	-28.91	5.09
37	7.06	-4.11	-2.21	-44.00	-1.67
10	-0.04	-5.13	-6.21	-14.61	2.23
9	0.17	-3.18	-1.48	-17.28	2.45
6	0.14	-4.61	-4.48	-15.06	2.22
59	3.24	-4.77	-3.61	-14.21	12.28

TABLE 5.7: Ranking of solutions under the Product-centric profile (Scenario A).

	Average freshness	Travel cost	Total damage	Tardiness	Service level
Reference solution	**21.52**	**1168.4**	**8024.42**	**134158.60**	**17.45**
30	0.17	5.78	-3.29	-48.47	9.57
52	1.39	2.21	-2.07	-28.91	5.09
3	-0.99	4.50	-3.31	-42.35	4.25
62	-1.41	2.60	-4.22	-39.59	-3.35
45	0.24	3.94	-3.00	-29.08	8.69
37	-2.21	7.06	-4.11	-44.00	-1.67
28	-0.95	1.46	-3.61	-32.17	-2.33
18	-1.46	1.72	-3.64	-34.27	10.44
26	-3.64	3.46	-4.90	-43.70	-1.87
47	1.47	6.07	-3.06	-18.42	4.74
32	-2.41	2.93	-2.79	-35.33	-4.58
15	4.01	2.54	-0.45	-1.24	9.68
34	1.53	6.61	-3.40	-12.16	4.29
25	1.16	5.57	-2.27	-14.17	7.58
46	0.23	3.58	-3.47	-15.53	3.11

TABLE 5.8: Ranking of solutions under the Customer-centric profile (Scenario A).

	Tardiness	Service level	Travel cost	Total damage	Average freshness
Reference solution	**134158.60**	**17.45**	**1168.4**	**8024.42**	**21.52**
30	-48.47	9.57	5.78	-3.29	0.17
3	-42.35	4.25	4.50	-3.31	-0.99
26	-43.70	-1.87	3.46	-4.90	-3.64
18	-34.27	10.44	1.72	-3.64	-1.46
37	-44.00	-1.67	7.06	-4.11	-2.21
53	-35.80	7.88	3.54	-4.78	-6.35
62	-39.59	-3.35	2.60	-4.22	-1.41
45	-29.08	8.69	3.94	-3.00	0.24
52	-28.91	5.09	2.21	-2.07	1.39
32	-35.33	-4.58	2.93	-2.79	-2.41
28	-32.17	-2.33	1.46	-3.61	-0.95
5	-29.38	-5.88	0.19	-5.60	-4.46
40	-21.31	6.99	4.11	-4.01	-2.64
38	-21.90	2.07	3.57	-4.42	-3.11
59	-14.21	12.28	3.24	-4.77	-3.61

We can observe that the proposed approach allowed to generate a variety of alternative solutions, each of which shows a different behaviour for each criterion. This diversity allows the decision maker (DM) to select the most appropriate solution, considering different perspectives and depending on his preference.

Regarding the E-c profile, solution 18 is the top-ranked alternative in scenario A. This solution is quite different from the reference solution X^* having a Jaccard coefficient $J(X^*, S_{18}) = 0.49$. S_{18} performs better than X^* in terms of service level, tardiness, and damage. On the other hand, has approximately the same travel cost as the reference solution. Solution 30 is slightly worse in terms of travel cost. However, it allows improvement in all the rest of criteria. In the scenario B, solution 45 is the top-ranked alternative with a jaccard coefficient $J(X^*, S_{45}) = 0.6$. this solution has approximately the same travel cost as the reference solution, and allows better improvement in terms of the damage and tardiness reduce, compared to solution 18. However, S_{45} is worst in terms of the other features. solution 33 is slightly worse than the reference one, but it provides improvement in all the other features. Moreover, we can say that S_{33} is the best alternative obtained in both scenarios for DM that aims improving in each of the features.

Regarding the P-c profile, in scenario A, solution 30 is now the best one. This solution has a worse travel cost than the reference solution, but it is better in the remaining criteria. Solution 52 appears in the second place. Note that it was ranked in the 10^{th} position for the E-c profile. In scenario B, solution 33 jumps to the first position, and solution 45 to the penultimate position. Another interesting solution S_{16} appears in the second position and which was ranked in the 10^{th} position for the E-c profile.

Regarding the C-c profile, solution 30 retain the first place in scenario A, by improving significantly all the criteria, with a slight increase in travel cost compared to X^*. In scenario B, solution 43 occupy the first position. This solution was among the Top-3 best alternatives for the E-c and C-C profile.

It should be noted that in scenario A, solutions 26 and 30 are among the TOP-3 best alternatives for both the E-c and C-C profile. Another interesting alternative is solution 3 which maintains its place in the TOP-3 for the P-C and C-c profile. Solution 18 is the best alternative for a DM that have economic focus, and retain the third position in terms of service level improvement. However, this solution doesn't have interest if the focus is on the product freshness or customer interesting solution for the DM.

By comparing both scenarios, we have found that the solutions obtained in scenario A which is the most flexible- in terms of threshold constraint- are more interesting. Indeed, the majority of solutions allow interesting improvement in all the posteriori features. In scenario B-which is most restricted- only the tardiness and service level are interestingly improved. But, in terms of average freshness, even in the P-c where the focus is on the later feature, the solutions obtained are worst. We can state that the much we relax the threshold constraint, we increase the possibility of getting better alternatives.

It is highly remarkable that the solution X^* doesn't appear among the top 15 solutions for all the profiles in both scenarios, which illustrate the ability of our proposed approach in generating performant and quite dissimilar solutions that will serve the decision maker to select the appropriate solution from his perspective.

TABLE 5.9: Ranking of solutions under the Economic-centric profile (Scenario B).

	Average freshness	Travel cost	Total damage	Tardiness	Service level
Reference solution	21.53	1168.35	8024.43	134158.60	17.45
33	1.23	1.86	-1.25	-38.04	13.16
16	-0.15	2.42	-3.36	-41.49	-0.45
43	-2.60	2.41	-3.48	-52.73	2.08
77	1.81	1.73	-0.73	-31.13	9.59
63	-1.30	0.39	-3.09	-36.23	-0.90
20	-0.40	2.20	-3.49	-31.83	4.03
70	-1.27	2.38	-2.46	-35.97	6.24
35	-3.74	0.28	-5.27	-42.64	-9.90
30	-1.48	1.60	-3.85	-33.30	-1.67
5	-3.93	0.06	-5.36	-42.79	-6.55
53	-5.21	2.90	-5.31	-48.11	-3.35
49	-1.94	2.74	-4.46	-31.62	-2.68
48	-3.18	1.42	-4.33	-35.95	3.18
45	-6.16	0.01	-6.08	-45.47	-1.03
55	0.02	2.82	-4.28	-17.68	6.27

TABLE 5.10: Ranking of solutions under the Customer-centric profile (Scenario B).

	Tardiness	Service level	Travel cost	Total damage	Average freshness
Reference solution	134158.60	17.45	1168.35	8024.43	21.53
43	-52.73	2.08	2.41	-3.48	-2.60
33	-38.04	13.16	1.86	-1.25	1.23
45	-45.47	-1.03	0.01	-6.08	-6.16
53	-48.11	-3.35	2.90	-5.31	-5.21
70	-35.97	6.24	2.38	-2.46	-1.27
16	-41.49	-0.45	2.42	-3.36	-0.15
77	-31.13	9.59	1.73	-0.73	1.81
27	-39.41	2.16	1.72	-5.46	-7.02
48	-35.95	3.18	1.42	-4.33	-3.18
5	-42.79	-6.55	0.06	-5.36	-3.93
20	-31.83	4.03	2.20	-3.49	-0.40
63	-36.23	-0.90	0.39	-3.09	-1.30
66	-29.84	6.52	2.38	-6.63	-7.23
29	-36.51	-2.26	0.18	-4.99	-5.96
35	-42.64	-9.90	0.28	-5.27	-3.74

5.7 Conclusion

The computational models of relevant optimization problems necessarily leave out of consideration several characteristics and features of the real world. So trying to obtain the optimum solution can not be enough for a problem-solving point of view. Moreover, it's doubtful that a single solution would be able to meet all the real specifications. Therefore, it's desirable for the decision maker to have a *set of solutions* that are good enough for the modeled objective, but can perform also well when it comes to other unmodelled criteria.

In the context of perishable food distribution, we propose a hybrid GVNS-MGA approach to generate a set of alternative solutions. Providing a set of solutions allows defining different user profiles and rank the available solutions. Using a similarity measure like the Jaccard's coefficient also allowed to better understand the relation of the reference solution and the other ones, not only in the objectives space, but also in the decision space.

This opportunity to consider different perspectives will grant a decision better suited to the real context.

Chapter 6

Conclusions and general discussion

6.1 Conclusions

In this PhD thesis, we focus on models and algorithms for food supply chain. The overall objective of the research was to propose models and solving approaches that can support decision-making process in food supply chain through addressing concerns about transportation costs, carbon emissions, product quality, service level, etc. In line with the overall objective, four research objectives were set as follows:

1. To identify the challenges associated to the freight last mile in the food supply chain. Furthermore, analyse the available models that support the decision-making, and point out modelling challenges.

2. Produce more realistic routes by addressing the vehicle routing problems on real road networks, considering different attributes to benefit from an efficient problem-solving.

3. Propose many-objective model for perishable food distribution Problem, that focuses on the cost, the quality of the product, and the service level improvement.

4. Propose an approach to provide the decision maker with a set of alternative solutions that allows him/her to analyse the problem from different perspectives.

The research contained in this thesis led to two journal publications, a book chapter, four conference articles. The research objective (1) in Chapter 2 by presenting a literature review on studies in perishable food distribution, to identify the modelling challenges and gaps. The research objective (2) was confronted in chapter 3 introducing (i) an Agent Based Simulation model to design the fastest routes to deliver food on real road network. (ii) a Mixed 0-1 Non-Linear Program (MINLP) for the capacitated vehicle routing problem with soft time window and multiple attributes on arcs, addressed using real road network representation. (iii) a mixed-integer linear programming model for a capacitated vehicle routing problem with fuzzy time windows CVRPFTW. Both of the latter problem were addressed on real road network, and defining multiple attributes on arcs. The research objective (3) was confronted in Chapter 4 by introducing a many-objective Customer-centric Perishable Food Distribution Problem that focuses on the cost, the quality of the product, and the service level. The research objective (4) was confronted in Chapter 5 propose a modelling to generate alternatives- metaheuristic based approach to generate a set of alternative solutions, which allow the decision maker to consider different perspectives, and non-modelled criteria.

6.2 Key findings and contributions

This section discusses the main findings and contribution of this thesis to the decision support modelling in food supply chains.

Key findings from Chapter 2, 3, 4, 5 contributes to the literature in last mile delivery for food supply chain by (i) reflecting the state of the art on the topic, and identifying the modelling challenges (ii) developing models, algorithms, and solving strategies that can be help the decision makers in optimizing the last mile delivery in terms of cost, energy consumption and consequently carbon emission, product quality, and service level.

In the following, we first present the main research issues identified from the literature reviews analysis. Next, the insight provided by the proposed models and approaches to the last mile are discusses.

- *Main research issues*

Literature reviews on optimization for last mile food supply chain were presented and analysed to understand the main modelling challenges and identify the gaps. In particular, the literature on the challenges for last mile delivery in general, and for food supply chain specifically, as well as the modelling gaps and modelling challenges for the latter are presented in Chapter 2. Chapter 3, 4, and 5 presented related literature review on the optimization models for the selected vehicle routing problems to draw attention to the gaps and justify the research contributions.

Results show that researches on the last mile delivery for food supply chain have been progressively developing with the global growth of food market. However, the characteristics of food product, the increasing demand of customers, and high service level expectations are posing many modelling challenges for decision makers, some of them are summarized as follows:

- Most of the papers reviewed are focusing either on quality or environment, along with transportation in both cases. However, each of these component has a contribution to the total cost. Therefore, there is a need to capture all the aspects.

- The majority of literature research propose single objective models. Real-life problems, on the other hand, are made up of several objectives that are conflicted with each other.

- The proposed vehicle routing problems proposed in the literature are addressed in the so-called customer-based graph to represent the road network. This modelling can have major repercussions in a variety of situations. When numerous attributes are defined on road segments, for example. Alternative paths with various compromises are not taken into account in the customer-based graph. In this case, this representation approach could have a negative impact on the quality of the solution.

- In the surveyed paper, the quality of products and the respect of time windows are the criteria commonly used to evaluate the quality of service. However, others factor can be integrated as key performance indicators.

- *Insights provided by the proposed models to the last mile delivery for FSC*

Mathematical models were presented in Chapter 3, 4, 5 for different last mile delivery problems. Case studies had clearly shown that the proposed models have a potential to optimize the last mile delivery part, and help the decision maker to improve the performance of the distribution process.

First, the proposed Agent Based Simulation Model proposed in Chapter 2 can be used to determine the best routes to transport fresh products, estimating Vehicle kilometre travelled VKT and vehicle hour travelled VHT for the case of time-depent travel times. Second, the adopted real road network representation approach help in producing more realistic routes.Furthermore, the consideration of alternative path and multiple attributes on segments can help to alleviate the impact on the quality of solution posed by the customer-base graph approach.

The Mixed 0-1 Non-Linear Program (MINLP) formulation proposed in Chapter 3 can be used to for vehicle routing problems for perishable food where the time windows is soft. this model allows the minimization of the total costs, consisting of transportation costs, food quality degradation costs, and time-window violation costs.

To model the preference of customers in terms f time window very well, we provide another model that represent this preference information as a fuzzy number with respect to the satisfaction of service time. This problem is formulated as a mixed-integer linear programming model. Results from case study shows that the proposed models can help reduce the operational costs of delivery while improving customer service.

To improve customer satisfaction, we provide in Chapter 4 a many-objectives customer-centric perishable food distribution problem that focuses on cost, product quality, and service level improvement by taking into account not only time frames but also the customers' target time and priority. Recognizing the complexity of solving such a model, we present a metaheuristic-based approach called General Variable Neighbourhood Search (GVNS) that allows us to solve a sub=problem quickly while obtaining a set of solutions. These options are weighed against a set of non-optimized criteria. The results are then ranked using an a posteriori method that requires very little information about the decision maker's preferences. The computational results show that (a) GVNS produced the same high-quality solutions as an exact solver

(CPLEX) in the sub-problem; (b) GVNS can generate a large number of candidate solutions; and (c) the a posteriori approach makes it simple to generate different decision maker profiles, allowing for different solution rankings.

the products characteristics, and the requirements of customers, are raising modelling challenges. In fact, a bunch of specifications should be included during the decision/optimization process to ensure a safe, quality product with a desired service level. Many times, the computational models necessarily leave out of consideration several characteristics and features of the real world, so trying to obtain the optimum solution can not be enough for a problem-solving point of view. To address this issue, we propose in Chapter 5 Modelling to generate Alternatives- metaheuristic based approach to generate a set of alternative solutions. we have shown through computational experiments that the proposed approach allows to generate a set of diverse solution that can help the decision maker to consider several non modelled aspect.

6.3 Limitations and future research directions

Despite the success of the research in developing models to support the decision-making for an efficient delivery in food supply chain, the limitations of the research should be acknowledged. These are highlighted in this section.

The models proposed in Chapter 3 were applied on case studies that can be regarded as small or medium size, larger case studies, which are more common in practice, will necessitate a significant computational time. Therefore, advanced solution approaches have to be developed to address large scale problems. The models and approaches proposed in this thesis can be used as a basis to validate the future approaches for large size studies.

The models proposed in this thesis are assuming that the quality decay of products is only function of time. However, there exist several factors that may impact the product's quality deterioration, such as the temperature variation during the travel. There is an ample opportunity to further improve the proposed models by using specific quality decay methodologies that account not just time but also other elements when evaluating product shelf life or quality.

The parameters such as quality decay, travel times are assumed to be deterministic in the proposed models. However, in reality they are subject to uncertainties.As a result, it would be worthwhile to look into parameters that aren't always predictable, and incorporate the identified uncertainties into the models. As well as propose solution approaches that can deal with the complexity that might be increased by adding this uncertainty.

The models proposed in Chapter 3 are addressing vehicle routing problem with multiple paths under the assumption that each pair of nodes is connected by 2 paths, it would be interesting as a future research to consider several paths. Furthermore, we are associating only two attributes to each arc which are the cost, and travel time. Other interesting parameters can be added such as the tolls, the carbon emission. Another interesting research direction, would be to design heuristics and metaheuristics that can Handel the real road networks settings.

With the recent advances in information and communication technologies, it would be interesting to use real-time information about the traffic condition. Such information can improve the quality of solution for vehicle routing problem by allowing an accurate estimation of travel times.

The scope of this study is on the last mile in the food supply chain for the Business 2 business market, as the Business to Customer B2C market is likely to grow rapidly in the future. Exploring the B2C scale is another research direction. On the other hand, the scope is limited to the use of trucks, others transportation modes can be explored in future research.

Nowadays, the use of crowdsourcing delivery is one of the last trends. Nevertheless, implementing a crowdsourcing delivery model is full of challenges. Therefore, it would be interesting to investigate models to support the crowdsourcing delivery network.

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