Internal Logistics Optimization in the Automotive Industry

Marcelus Fabri Lima

TESI DOCTORAL UPF / Year 2019

DIRECTORS DE LA TESI
Professor Dr. Helena Ramalhinho and Professor Dr. Miquel Oliver
Department Department of Information and Communication Technologies | Universitat Pompeu Fabra

upf. Universitat Pompeu Fabra Barcelona

I am grateful to God for guiding and blessing me throughout this journey.

I would like to thank Iara Alkmim, my wife, and the love of my life. Thank you for making my life lighter and meaningful. Also, thank you for your supporting, care and patience. Thank you for listening to the same presentations over and over again. Thank you for being there for me in every single situation that came not only during this doctor degree phase but in all the other circumstances. That degree is yours as much as it is mine. I love you.

I have no enough words to thank my parents Marilene Fabri Lima and Marcelus Fernandes Lima for their love. Thank you for your infinite love, support, dedication, sacrifices, education, and knowledge. Also, I am thankful to my brothers Larissa Fabri Lima and Vinicius Fabri Lima to their friendship and to make my life happier.

I am immensely thankful to my thesis advisor Helena Ramalhinho. Thank you, Helena, for your support and teachings during these years. Also, thank you for all the advises. You have been much more than a thesis' advisor to me. I learn a lot from you. I am also thankful to my advisor Miquel Oliver for his support since my arrival in Barcelona.

I would like to thank all my family and my friends that are in around this immense world. It does not matter if we are close or far away. I am thankful for your thoughts, support, kindness, and concern.

I am always grateful to my Master degree's advisor Martín Gómez Ravetti, who is responsible for encouraging me to start a Ph.D. Thank you for all the support and teaching throughout these years.

I wish to express a deep sense of gratitude to SEAT S.A. I would like to thank my advisor Juan Carlos Muñoz, for giving me this opportunity in SEAT and for his guidance throughout these years, as well as his feedbacks over the work. Also, thanks to Simona Kusinova, Montserrat Oriol and Matias Ubogui for their support. I am also thankful for each person of the former PL-5 department, who kindly welcomed me during these years. Moreover, I am grateful to Silvia Roca, who is responsible for structuring and starting the SEAT's Ph.D. program. Also, I would like to thank Vanesa Gimenez, Nuria Mitjan, Aline Bosle and Susana Gonzalez for the following conduction. Besides that, I would like to thank my SEAT Ph.D. colleagues and friends for their friendship during these years.

Special thanks to the UPF's Department of Information and Communication Technologies for all the infrastructure and support throughout these years. In particular, Lydia Garcia for her kindness and remarkable work. Also, I am grateful to Magda Castellnou, Montse Serrano, Vanesa Jimenez, Ruth Temporal, Gemma Tapia, and Georgina Folguera for all their work to help me and all the students, and professors, to execute our research. Moreover, I would like to thank my colleagues and friends Arezou Rezazadeh, Ivano Colombaro, Thays Oliveira, Windhya Rankothge, and Aljoscha Gruler for their friendship during these years.

Last but not least, I would like to thank the Generalitat de Catalunya for promoting the Doctorats Industrials program [2016 DI 022], which enriches my Ph.D. degree undoubtedly. The Doctorats Industrials program is a significant incentive to connect universities and industry through education, research, and innovation. I am sure that it is a bench-marketing program, in which all governments in the world should be inspired.

Without you all, nothing would have been possible....

Abstract

This thesis focus on internal logistics flows (ILF), which is defined as the flows of materials inside the same business or the same plant. Precisely, this work approaches the ILF of SEAT, a company in the Volkswagen group. So, a set of Operational Research or Business Analytics based methods is presented. These methods contribute both to enrich the literature and provide useful techniques to the industry. Those methods refer to new mathematical formulations, Iterated Local Search metaheuristics, simulation models applications as well as a data set. So, the main purpose of this work is providing suitable methods to face internal logistics routing problems in car-assembling companies. Moreover, these methods were developed and applied considering the SEAT's workshop and data. The results expose several opportunities that can improve the company's logistics operations as well as reducing some operational costs. The study was presented to the company's employees that found it interesting and appropriate.

Resum

Aquesta tesi es centra en els fluxos logístics interns (ILF), que es defineixen com els fluxos de materials dins del mateix negoci o la mateixa planta. Precisament, aquest treball s'apropa a la ILF de SEAT, una empresa del grup Volkswagen. Es presenta, per tant, un conjunt de mètodes basats en la Recerca Operativa o en Business Analytics. Aquests mètodes contribueixen tant a enriquir la literatura com a proporcionar tècniques útils per a la indústria. Aquests, es refereixen a noves formulacions matemètiques, metaheurística de cerca local iterada, aplicacions de models de simulació i un conjunt de dades. L'objectiu principal d'aquest treball és proporcionar mètodes adequats per afrontar els problemes de les rutes internes logístiques de les empreses fabricants de vehicles. A més a més, s'han desenvolupat i aplicat aquests mètodes tenint en compte el treball i les dades de SEAT. Els resultats presenten diverses oportunitats que poden millorar les operacions logístiques de l'empresa, així com reduir alguns costos operatius. L'estudi es va presentar als empleats de l'empresa que ho van trobar interessant i adequat.

Resumo

Esta tesis se centra en los flujos logísticos internos (ILF), que se define como los flujos de materiales dentro del mismo negocio o la misma planta. Precisamente, este trabajo considera los ILF de SEAT, una compañía del grupo Volkswagen. Por lo tanto, se presentan un conjunto de métodos basados en investigación operativa o Business Analytics. Estos métodos contribuyen tanto a enriquecer la literatura como a proporcionar técnicas útiles para la industria. Éstos, se refieren a nuevas formulaciones matemáticas, metaheurística de búsqueda local iterada, aplicaciones de modelos de simulación y un conjunto de datos. Por lo tanto, el objetivo principal de este trabajo es proporcionar métodos adecuados para hacer frente a los problemas de enrutamiento logístico interno en las empresas de ensamblaje de automóviles. Además, estos métodos se desarrollaron y se aplican teniendo en cuenta el trabajo y los datos de SEAT. Los resultados presentan varias oportunidades que pueden mejorar las operaciones logísticas de la compañía, así como reducir algunos costos operativos. El estudio fue presentado a los empleados de la compañía que lo encontraron interesante y apropiado.

Preface

The world is being transformed through the data connection and its interpretation. Consequently, terms such as Big Data, Internet of the Things (IoT) and data Cloud are getting established among the industry and the society. According to the World Economic Forum (WEF) [World-Economic-Forum (2016)], there were more gadgets and mobile phones than people in 2016. Moreover, by 2020, the forecast is that the total number of connected devices surpass 28.1 billion.

Likewise, the automotive industry is also passing for a moment of transformation that concerns the introduction of these technologies into its production systems, processes, and business models. As a result, terms like industry 4.0 and Smart Factory were born to refer to that new phase that the industry is facing.

So, taking into account observations done through reports provided by the World Economic Forum and some consulting companies, a Strengths, Weaknesses, Opportunities, and Threats (SWOT) matrix scheme is provided to present the main issues related to the introduction of these new technologies into the automotive industry. The SWOT table is illustrated in figure 1.

Strengths • Substantial economic resources to be applied in R&D; • Connection with the World-Class technological companies; • Great ability to retain talent.	**Weaknesses** • Slow reactiveness when facing a disruptive scenario; • Incorporation of new technologies among the workforce.
Opportunities • Introduction of the industry 4.0 concepts: ✓ Autonomous Automated-Guided-vehicle; ✓ IoT; ✓ Smart Warehouse; ✓ Additive manufacturing; ✓ Virtual reality; ✓ BIG DATA; ✓ Blockchain tracks; ✓ Machine learning; ✓ Automatic and flexible reports; • Costs reduction; • Reduce Time-to-Market; • Introduction of new business models.	**Threats** • More restrictive laws; • The decrease in the traditional market in the long-term; • Disruptive Technologies (Opportunities for new competitors).

Figure 1: The SWOT matrix for the current scenario of the automotive industry

The automotive industry is known for its influence in our daily lives.

Actually, according to WEF [World-Economic-Forum (2016)], the automotive industry has enough power to continue to influence the direction of our society. That can be view as a remarkable strength because it means the automotive industry has enough resources to allocate a tremendous amount of capital in Research and Development (R&D) as well as training and retaining high-qualified employees. Moreover, the automotive companies are leading important R&D projects in collaboration with world-class technological companies, such as the collaboration between Google and Volkswagen, through the development of better routing algorithms [Cristina Farrés (2017)]. As a result, the Automotive industry has enough resources and connections to innovate and introduce new technologies into the companies. Indeed, the WEF also pointed out that the exploding growth of data from the connected Internet of Things throughout the supply chain will demand new skills for workers and managers.

On the one hand, those novel technologies may represent substantial competitive advantages in such constraining market. On the other hand, companies must find out the best approach to implement those innovations into their business. Otherwise, those companies that not succeed in the phase of implementing new technologies will always find themselves as the last ones to have the technological concepts applied, which can be viewed as a weakness. It is especially true concerning manufacturing companies. According to a survey disclosed by McKinsey & Company [Altmeier et al., (2019)], in which participated 146 machinery and industrial automation companies, more than 90% of the respondents believe that they need to adapt their business to be more successful in future. In other words, those companies are not so agile when facing disruptive scenarios as well as introducing novelties into their businesses. That is an affirmation that is also true to the automotive industry that has many factories with more than ten years and an experienced workforce, e.g., the SEAT factory has been in operation since 1986. Furthermore, even though we see many products that are more and more connected, e.g., automatic-connected vacuum cleaners, the cars companies have not disclosed any similar disruptive product to the market yet. Indeed, it is not a simple task considering the size and the repercussion of the automotive industry in society.

Note that launching disruptive products requires remarkable effort in a variate of areas, such as engineering, marketing, legal, and quality. These tasks are especially difficult for the automotive industry due to its applications and scale. Despite that outlook, the automotive industry is expected to disclose disruptive products in a near future. Some companies have been testing Autonomous cars for some years, but public regulations neither allow then to be disclosed in public streets nor to be commercialized. Therefore, restrictive laws are viewed as a threat to the automotive companies because they may limit a businessâs revenue. Another threat is the demographic growth of some key markets that are facing aging issues on its population.

According to a study disclosed by Bain Company, [Gottfredson, Stricker & Tsang, (2018)], the aging issue means a limitation on the number of new car buyers. In addition, there is another significant threat according to the WEF [World-Economic-Forum (2016)], the digital evolution of the automotive ecosystem has also enabled several non-traditional and technology-based companies to enter at various points along the automotive value chain. In other words, the market's entry barriers are getting smaller.

So, the digital transformation of the automotive ecosystem may represent a threat in some sense. By contrast, it also means opportunities for the automotive industries. First, companies may set new business models and diversify their activities, e.g., SEAT has started a new business model that relies on car-sharing [Dolors (2019)]. Second, the increasing pace of innovation is also viewed as opportunities to reduce both new products' Time-to-Market and the manufacturing costs. Some examples of novel concepts that allow the companies to achieved such benefits would be Autonomous Automated-Guided-vehicle, IoT applications, Smart Warehouse, Additive manufacturing, Virtual reality, Big Data, Blockchain, Machine Learning, and Logistics Control Tower concept. See [Velandia et al.(2016), Lin et al.(2018), Ferràs-Hernández et al.(2017), Pelliccione et al.(2017)].

To conclude, this thesis aims to support the automotive sector to achieve those opportunities highlighted before. Precisely, this work intends to aggregate mathematical optimization procedures to the company's daily activities, as well as strategic planning projects. In particular, Operations-Research-based algorithms and a Discrete-Event-Simulation model were developed to offer novel tools to car-assembling companies to improve their internal logistics flows. That set of techniques decreases the amount of effort and time required to conduct the implementation of new internal logistics flows, as well as promoting evaluations over workshops' layouts. As a result, it is a step further towards the industry 4.0 concept.

Regarding the academic point of view, that thesis represents a contribution to the knowledge due to its novelty in terms of (i) novel mathematical formulations; (ii) a new class of Vehicle-Routing-Problem (VRP), which is defined as the In-house Logistics Routing Problem; (iii) novel applications of Metaheuristics algorithms; and (iv) a novel real-world dataset that regards to the company's orders.

Contents

List of figures xvi

List of tables xviii

1 INTRODUCTION 1

1.1 The company's main processes . . . 2
1.1.1 Production Processes . . . 2
1.1.2 Logistics Processes . . . 3
1.2 The current company's Logistics Flows analysis . . . 10
1.3 Research Objectives . . . 11
1.4 Organization and Thesis Overview . . . 12

2 LITERATURE REVIEW 17

2.1 Linear Programming Formulations . . . 17
2.1.1 Complexity . . . 19
2.1.2 The Lagrangean Relaxation . . . 21
2.2 Iterated Local Search Metaheuristic . . . 24
2.2.1 Iterated-Local-Search framework . . . 26
2.2.2 Simulated-based Iterated-Local-Search . . . 27
2.3 Vehicle Routing Problems . . . 29
2.4 Simulation analysis . . . 31
2.4.1 Logistics and Production works . . . 34
2.4.2 Monte Carlo Simulation and the Vehicle Routing Problem with Stochastic Demand . . . 38

3 OPTIMIZING INTERNAL LOGISTICS FLOWS OVER DETERMINISTIC DATA 41

3.1 Introduction and problem statement . . . 41
3.1.1 Methodology . . . 42
3.2 The Solution Method . . . 43
3.2.1 The Integer Linear Programming model . . . 43
3.2.2 The Monte Carlo Simulation . . . 45
3.3 Experiments . . . 46
3.3.1 ILP Output . . . 46

3.3.2 Simulations Outputs 48
3.4 Conclusion 49

4 THE IN-HOUSE LOGISTICS ROUTING PROBLEM 53
4.1 Introduction and problem statement 53
4.2 The Integer Linear Programming model 57
4.3 The simulation-based Iterated Local Search 60
4.3.1 The Initial Solution 63
4.3.2 Local Search phase (Intra-Route Neighborhood Search) 63
4.3.3 Local Search phase (Inter-Route Neighborhood Search) 63
4.3.4 Simulation Phase 64
4.3.5 Perturbation Phase 66
4.3.6 The SimILS Stopping Criterion 67
4.4 Experiments 67
4.4.1 The instances 67
4.4.2 The Experiment 1 70
4.4.3 The Experiment 2 71
4.5 Conclusion 77

5 ASSESSING IN-HOUSE LOGISTICS FLOWS 81
5.1 The internal logistics routing management system 81
5.2 The internal logistics routing management system 82
5.2.1 The Current System - Scenario 1 83
5.2.2 The Variable Routes and Current Orders System - Scenario 2 84
5.2.3 The Variable Routes and Automatic-Orders System - Scenario 3A 84
5.2.4 The Variable Routes and Forecasted Orders - Scenario 3B 85
5.3 Demand data analysis 86
5.3.1 The automatic-placing-orders process 87
5.3.2 The forecasting-orders data process 88
5.4 The Integer Linear Programming model 89
5.5 Routing Problem and Large-scale applications 92
5.5.1 The Initial Solution 93
5.5.2 The local search phase and the acceptance criterion . 94
5.5.3 Perturbation Phase 95
5.5.4 The ILS-Stopping Criterion 96
5.6 The current-routes simulation 97
5.7 Experiments 98
5.7.1 The instances 99
5.7.2 The Experiment 1 100
5.7.3 The Experiment 2 101
5.7.4 Experiment 3 101

5.7.5 Experiment 4 101
5.7.6 The large-scale experiment's results 103
5.8 Conclusion 105

6 INTERNAL LOGISTICS FLOWS SIMULATION 113
6.1 Introduction 113
6.2 The Internal Logistics Flows Simulation in assembling lines . 115
6.3 The Simulation Model Description 117
6.3.1 Problem Description 117
6.3.2 Model Construction 118
6.3.3 Data Collection 120
6.3.4 Experiments and validation 123
6.4 Conclusions 130

7 APPLYING LAGRANGEAN RELAXATION TO SOLVE THE FLOW SHOP SCHEDULING PROBLEM WITH PRECEDENCE CONSTRAINTS, RELEASE DATES AND DELIVERY TIMES 131
7.1 Introduction and problem statement 131
7.2 The Integer Linear Programming model 134
7.3 The Lagrangean Relaxation 136
7.4 Experiments 139
7.5 Conclusion 147

8 CONCLUSION 149
8.1 Main contributions and future research 149
8.1.1 Research in Progress 153
8.2 The Industrial Ph.D. remarks 157

List of Figures

1 The SWOT matrix for the current scenario of the automotive industry . . . vii

1.1 The main car's manufacturing processes . . . 2
1.2 Example of two car models that share the same assembling line. . . . 3
1.3 The main logistics processes . . . 3
1.4 The summary of the processes of a non-regular departure logistic flow. . . . 4
1.5 An illustration of SEAT's Stock Keeping Units (SKU) . . . 5
1.6 The summary of the processes of a regular departure logistic flow. . . . 6
1.7 Production and warehouse layout . . . 7
1.8 Clustering orders into periods . . . 8
1.9 An example of the factory workshop and two routes. . . . 9
1.10 An example of two workstations requests' pattern over three months. . . . 9
1.11 An scheme to locate the application of the following chapters. 13

2.1 A scheme of the Lagrangean Relaxation method solved through the subgradient algorithm. . . . 24
2.2 The VRP literature review outline. . . . 32

3.1 Methodology phases' interaction . . . 42
3.2 Simulation scheme . . . 46
3.3 The workload distribution between the proposed routes and current solution. . . . 50

4.1 The In-house Logistics Routing Problem description . . . 54
4.2 The In-house Logistics Routing Problem simulation . . . 55
4.3 The data clustering scheme. . . . 56
4.4 An Or-opt2 (I) and a 2-Shift-complete (II) moves examples. . . . 64
4.5 The ILRP experiment 1 . . . 69
4.6 The ILRP experiment 2 . . . 70

5.1 The proposed scenarios outline. 83
5.2 Current demand pattern 86
5.3 Creating the automatic-placing-orders processes. 87
5.4 Computing the average time window between two consecutive orders. 88
5.5 ILS's perturbation outline 95
5.6 The number of orders applied for scenarios 1, 2, 3A, and 3B, regarding instance number 30. 104
5.7 The number of routes applied for scenarios 1, 2, 3A, and 3B, regarding instance number 30. 105
5.8 The summary of the scenarios' conclusions. 106

6.1 The summary of the processes of a non-regular departure logistic flow. 115
6.2 The summary of the processes of a regular departure logistic flow. 116
6.3 The classical simulation modeling framework and the best practices over an DES assembly-line model construction. . . . 117
6.4 The layout of the studied workshop. 119
6.5 The demand behavior of a workstation throughout five consecutive days. 119
6.6 A piece of layout that shows two convoys supplying their respective workstations. 120
6.7 Heat Map - Scenarios A and B 126
6.8 Heat Map - Scenario C 126

7.1 The outbound processes' scheme 132
7.2 An example of a precedence constraint violation 136
7.3 An Upper Bound solution example. 139
7.4 A Lower Bound solution example. 140
7.5 A Lagrangean Relaxation convergence example 144
7.6 A Lagrangean Relaxation non-convergence example 144

8.1 The WHS Simulation scheme 154
8.2 Warehouse's traffic evaluation 154
8.3 Current Platforms consumption 156
8.4 Platforms per periods 156
8.5 Methodological framework 157
8.6 Users interfaces A 158
8.7 Users interfaces B 158
8.8 Users interfaces C 159

List of Tables

1.1 Summary of logistics flows observed. 4
1.2 Chapters' scope 15

2.1 Logistics and Production related works. 38

3.1 Scenarios' description 45
3.2 ILP Solution and the current one comparison in terms of the number of routes and the sum of these routes' distances. . . . 47
3.3 Monte Carlo Simulation Solutions: scenarios 0 and 1 48
3.4 Monte Carlo Simulation Solutions: scenarios 2 and 3 48
3.5 Monte Carlo Simulation Solutions: scenarios 4, 5 and 6 . . . 49

4.1 The summary of the instances' structure. 68
4.2 The experiments outline. 69
4.3 The summary of the experiments 1's (SB) results. 72
4.4 The summary of the experiments 1's (LC) results. 73
4.5 The summary of the experiments 2 (cluster 1) results. 74
4.6 The summary of the experiments 2 (cluster 2) results. 76
4.7 Chapter 4 - Appendix A 79

5.1 The ILRM system experiments outline. 98
5.2 The summary of the instances' structure. 100
5.3 The summary of the SB SKU Experiment 1's results. 102
5.4 The summary of the LC SKU Experiment 1's results. 108
5.5 The summary table of the experiments 2, 3, and 4 regarding the SB. 109
5.6 The summary table of the experiments 2, 3, and 4 regarding the LC. 110
5.7 Chapter 5 - Appendix B 111

6.1 Summary of the parameters' structure. Notice that LC means Large Containers and SB means Small Boxes. 121
6.2 Summary of logistics flows applied. 121
6.3 The summary of the instances applied in the DES model. . . 122
6.4 Scenarios evaluated through the simulation. 123

6.5 The summary of the aisles' result. 125
6.6 Summary of the interferences during the DES experiments . . 127
6.7 The summary of the logistics flows' results. 128

7.1 Summary of the instances. 141
7.2 Results for the ILP model running CPLEX with a time limit of 7,200 seconds. 142
7.3 Results for the ILP model running CPLEX with a time limit of 7,200 seconds. 143
7.4 Results obtained with the linear relaxation and the LR on instances of Groups 1 and 2. 146

Nomenclature

Abbreviations

AGV	Automated-Guided Vehicle
EBITDA	Earnings Before Interest, Tax, Depreciation and Amortization
CVRP	Capacited Vehicle Routing Problem
DES	Discrete-Event Simulation
IL	Internal Logistics
ILF	Internal Logistics Flow
ILRM	Internal Logistics Routing Management
JIT	Just in Time
LB	Lower Bound
LC	Large Containers
LS	Local Search
LR	Lagrangean Relaxation
MHF	Material Handling Flow
MRP	Manufacturing Resource Planning
SB	Small Boxe
SD	Standard Deviation
SimOF	Simulated Objetive Function
SEAT	Sociedad Española de Automóviles de Turismo
SQL	Service-Quality Level
SKU	Stock-Keeping Unit
SWOT	Strengths, Weaknesses, Opportunities, and Threats
UB	Upper Bound
VRP	Vehicle Routing Problem
VRPSD	Vehicle Routing Problem with Stochastic Demand
WEF	World Economic Forum
WHS	Warehouse
WSM	Warehouse Simulation Model
WKT	Workstation

Chapter 1

INTRODUCTION

Designing efficient logistics systems has been one of the main topics in many industries, including the manufacturing ones. The logistics field is related to a flow of materials between and within organizations. Indeed, companies focus more and more on the logistics field because they see that area as a strategical one to gain competitiveness in the market by reducing costs as well as providing a better service's level to customers, [Muñuzuri et al. (2005)].

In the literature, most of the works published in Logistics focus on external logistics, i.e., flows of materials and products between different companies or customers. See [Braekers et al.(2016)]. However, this thesis focus on internal logistics operations, which means flows of materials inside the same business or the same plant, for example from the warehouse to an assembly line. The improvement of these flows can lead to a reduction of the delays, disruptions, accidents, and also contribute to minimizing logistics costs. Precisely, this work considered the automotive sector to conduct the research over the internal logistics.

That thesis was carried out under collaboration and agreement with SEAT S.A., which provided us with all the necessary data and support. SEAT (Sociedad Española de Automóviles de Turismo) is a Spanish company, a subsidiary of the Volkswagen Group (*www.seat.es*). In 2018, SEAT was present in more than 75 countries. Moreover, SEAT achieved a volume of sales of more than 517,600 units and an EBITDA equal to €254,000,000 in the same year.

In order to provide suitable guidance to the reader, the next sections present the essential pillars used to conduct this work, which are (i) the main SEAT's production and logistics processes and (ii) the procedures used by the company to compute the logistics flows. Afterward, the research objectives and the thesis' content are summarized.

1.1 The company's main processes

This section is divided into two subsections. The first subsection presents the company's main processes under the production point of view. Then, the second subsection describes those processes under the logistics point of view.

1.1.1 Production Processes

Currently, SEAT's factory is placed in Martorell, which is a city located in the Barcelona's Province in Spain. That factory is compound by several workshops that are in charge of executing the entire cars' production phases. These phases are summarized as follows: Body Shop, Paint Shop, and Assembly Shop. Figure 1.1 illustrates these phases.

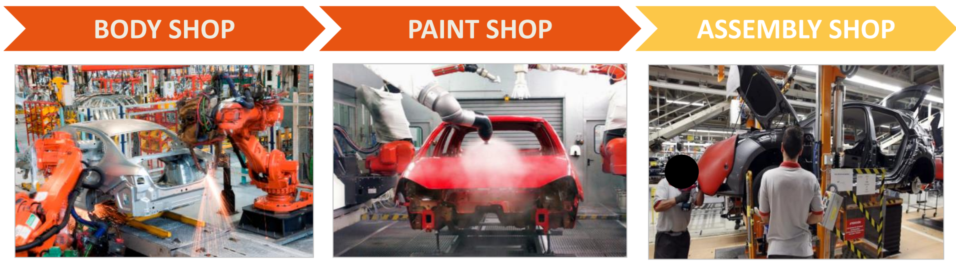
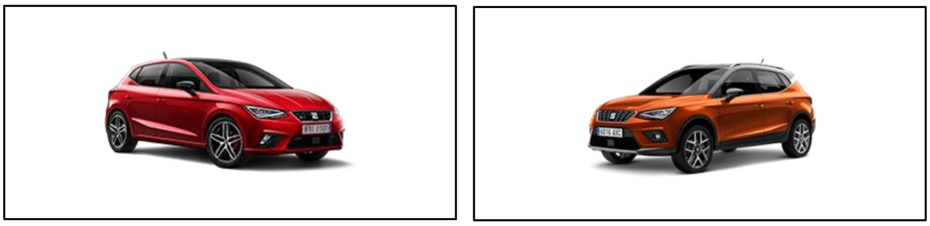


Figure 1.1: The main car's manufacturing processes: Body Shop, Paint Shop and Assembly Shop. The Assembly Shop phase is highlighted because it is the main focus of this work.

This work concerns with the assembly shop only, and there is a major reason to justify that approach. Generally, a standard car is compound by nearly 3,000 materials on average. Most of the 3,000 materials are supplied and assembled in the assembly shop. Consequently, the logistics issues in that phase tend to be more significant than the previous ones. Besides that, the level of automation in the assembly shop is lower than the others. Therefore, the assembling processes tend to present higher variability than the body shop and the paint shop ones. These reasons suggest that the assembly shop is the one that deserves to be the focus on, regarding the study over internal logistics.

Currently, SEAT's factory counts with one assembling line dedicated to assembling engines and others three car-assembling lines that produce up to 2,400 cars each day. Moreover, more than one car model can be produced in the same assembling line. That is the case for the

SEAT Ibiza and the SEAT Arona models, see figure 1.2. These models share both the same chassis platform and assembling line.



(I) (II)

Figure 1.2: Example of two car models that share the same assembling line. The number (i) refers to the SEAT Ibiza model and the number (ii) refers to the SEAT Arona.

1.1.2 Logistics Processes

Regarding the logistics processes, those can be also clustered into three main groups that are: Inbound, Inhouse and Outbound. The Inbound phase refers to the materials arrival into the company. It can be done through trucks and trains. Then, the Inhouse phase refers to the materials handling inside the company. Later, the Outbound phase concerns the final products distribution towards the clients. See figure 1.3.

Figure 1.3: The main logistics processes: Inbound, Inhouse and Outbound. The Inhouse phase is highlighted because it is the main focus of this work.

The main focus in this work is on the inhouse activities. The inhouse activities are in charge of storing the received materials in the warehouse, execute the picking of these materials, and proceed with the supply of the orders in the assembling lines directly.

Those placed orders are supplied through routes or logistics flows. These logistics flows are presented by table 1.1 and defined as follows: (i) supplying routes; (ii) cycle routes Automated-Guided-Vehicle (AGV); (iii) cycle routes operator; and (iv) Just-in-Time (JIT).

To summarize, the supplying routes are the logistics flows responsible for delivering those materials whose consumption rate is not regular. The supplying routes main processes are presented in table 1.4.

Logistics Flow	Main Characteristics
Supplying routes	Non-regular departure; Overtaking allowed
Cycle routes AGV	Regular departure; Overtaking not allowed
Cycle routes Operator	Regular departure; Overtaking allowed
JIT	Regular departure; Overtaking allowed

Table 1.1: Summary of logistics flows observed.

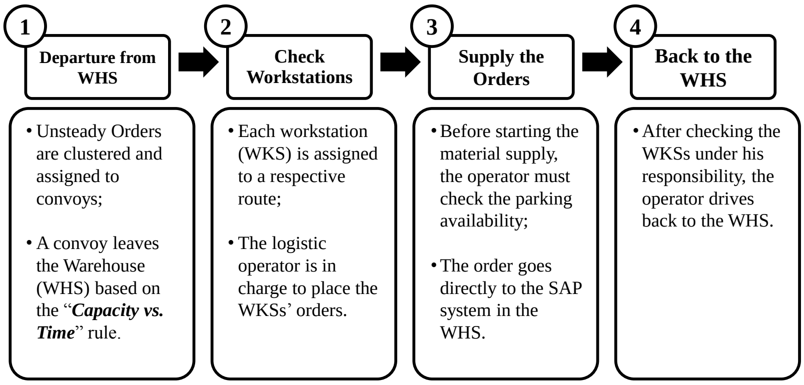


Figure 1.4: The summary of the processes of a non-regular departure logistic flow.

There are four main steps to be considered that are: (i) departure from the warehouse (WHS), (ii) check workstations, (iii) supply workstations and (iv) return back to the WHS. Each step is explained next.

First, the WHS receives orders through the commercial system SAP. Notice that these orders are not steady in this case, which results in a non-regular departure. Consequently, a "Capacity vs. Time" rule is defined. This rule ensures that each convoy leaves the WHS as soon as it is either loaded completely or a defined amount of time is achieved since the first order had been assigned to that convoy. So, there are two criteria that regulate the departure that refer to the capacity and the time. So, after the arrival of the first orders, the maximum time a convoy can wait to be loaded is 30 minutes, for instance. Moreover, there is a relevant materials' classification that concerns to the Stocking Keeping Unit's (SKU) size. In the company, there are two main classes of SKU, i.e., the Small Boxes class (SB) and the Large Container (LC) one. So, there is a premise that establishes the division between SB convoys and LC ones. In other words, it is not allowed to mix SB and LC in the same convoy. Figure 1.5 illustrates both classes of SKU.

(I)

(II)

Figure 1.5: An illustration of tof SEAT's Stock Keeping Units (SKU). The (i) refers to the materials stored in Large Container (LC), which volume can reach one m^3, for instance. Likewise, the (ii) refers to the materials stored in Small Box (SB), which volumes can reach 0,175 m^3, for instance. Note that there are different containes and boxes sizes. Also, one convoy is not allowed to receive both classes of SKU.

Afterward, the second phase is checking workstations. In Seat, one operator is assigned to one route is compounded by a set of workstations that must be visited. Moreover, one workstation cannot be served by more than one route. As a result, a workstation is not allowed to be supplied by different routes. That premise is valid for routes of the same SKU class only. Other relevant premises refer to the logistics flows' trajectory. By definition, a logistics flow must complete all its trajectory whenever it starts. Also, the set logistics flows are considered to be kept fixed for a long-term period, e.g., months. It is justified because the logistics operators are in charge of both supply the material and place the orders. As a result, the routes are fixed to keep the placing orders and supplying activities under control.

Later, the third phase refers to the supplying activity. During a route trajectory, an operator must park the convoy to supply a workstation, and each workstation has its own parking spot. So, if there is not any spot available, the operator must wait for an empty spot. Then, the operator will supply the material and restart its trajectory.

Lastly, the final step is the return to the WHS. After checking the workstations' under his/her responsibility, the operator returns back to the WHS to deliver the empty racks and get new loaded ones. Later, the convoy departs from the WHS towards the assembly line, and the cycle starts again.

There are also other logistics flows that receive materials with constant consumption rate. Therefore, all of them follow a regular departure routine that is defined as regular departures. Therefore, note that the departure frequency of a route depends on the material consumption rate.

Among the regular departure flows, there are the "cycle routes AGV" and "cycle routes Operator" that are conducted by an AGV and a logistics operator, respectively. Finally, there are the JIT flows that are executed by outsourced employees. These are the main flows that circulate throughout the warehouse, supermarket and Assembly lines. Figure 1.6 presents the processes for those logistics flows that have a regular departure from the WHS (for example each 15 minutes).

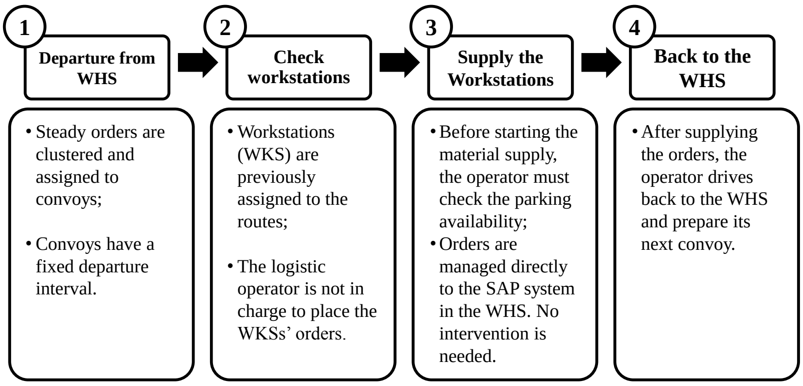


Figure 1.6: The summary of the processes of a regular departure logistic flow.

The processes represented in figure 1.6 are quite similar to those in the non-regular departure. On the one hand, the routes are divided into SKU class and the routes do not share supplying locations. On the other hand, the materials supplied here are viewed as steady ones because its consumption rate is well defined. Therefore, there is no need to ask the logistics operator to place orders because it is ruled by SAP.

Concerning to the assembling workshops, each one is compound by more than 120 workstations. Those workstations are able to produce nearly 2,400 personalized cars each day. As a result, the logistics manager must define the best set of routes to supply all the required materials throughout the day from the warehouse to the production line. Currently, the placed orders are sent to the SAP system. Then, an outsourced company organizes all the orders and execute the picking activities in the warehouse according to the First-In-First-Out (FIFO) criterion.

Afterward, those materials are placed in a turnover area located in the warehouse. The turnover area is the place where the SEAT's logistics operators organize the racks to be supplied following the FIFO fashion as well. The racks are set together to form a convoy, which delivers the orders to the assembly line.

Figure 1.7 illustrates a small example of a layout compound by a warehouse, a turnover area, a supermarket and an assembly line.

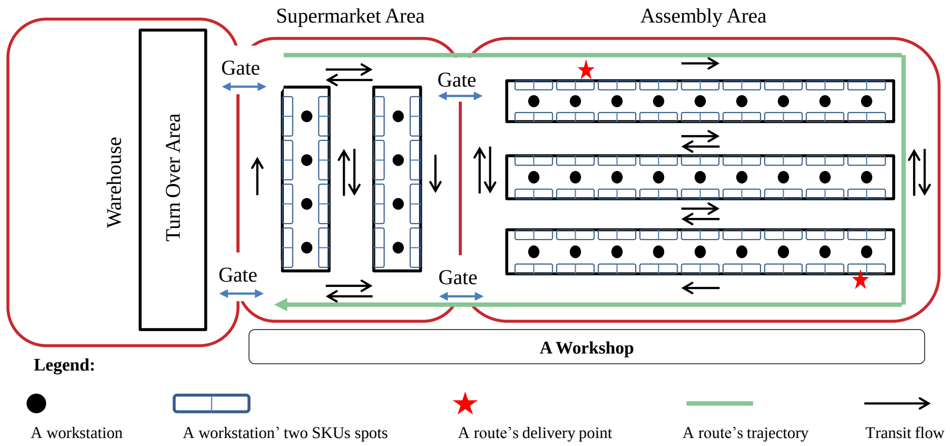


Figure 1.7: An illustration of the warehouse, turnover area, supermarket, and the assembly line distribution. A workshop is compound by the aggregation of one supermarket and assembling line.

The dimensions of the workshops studied are nearly 350 meters in width by 60 meters in height. A workshop is compound by the aggregation of one supermarket and assembling lines. Also, a workshop is divided into two main parts, with different logistics operations. The left-hand part contains verticals aisles as the majority, and it is called Supermarket. Next, the right-hand part has horizontal aisles as a majority and is viewed as the assembly line area. Notice that both of these areas are considered in this work because both of them must receive materials through the logistics flows. However, the supermarket is also a location where logistics flows depart as well.

As said, once the logistics flows reach the assembling lines, they should look for their respective workstations to supply the orders. For each workstation, there are four areas where to place the materials: on the right-hand side and on the left-hand side of the workstation. So, on each side, there are two spots to place the material, as illustrated by figure 1.7. As a result, one of these spots is a temporary buffer while the second one is being consumed, which is defined as a double presence rule. As a result, the probability that a workstation runs out of materials is minimized.

So, to sum up, the Internal Logistics Routes Management (ILRM) system applied by SEAT is summarized by the following characteristics: (i) long-term and fixed routes; (ii) the logistics operator is the one responsible for both placing orders and delivering the materials; (iii) First-In-First-Out criterion; (iv) each workstation is assigned to one logistics operator only; (v) convoys are loaded with one type of product only, which are large containers or small boxes; and (vi) unsteady demand.

On the one hand, one may state that the advantages of that system are: (i) the production operator is totally focused on the assembling operations because he/she is not supposed to check the level of the workstations' materials; (ii) each workstation is continuously supervised by the logistics operators; and (iii) there is no need to add support systems to check the level of the workstations' material. On the other hand, there are some drawbacks such as unsteady orders and the possible presence of backorders, which are the orders that are not delivered at the expected period.

Figure 1.8 illustrates what a period means in this work. By definition, a period is a discrete part of any time horizon. e.g., a time horizon of two weeks may be partitioned into periods of one hour. The period concept is useful to cluster the company's orders chronologically, as illustrated in figure 1.8.

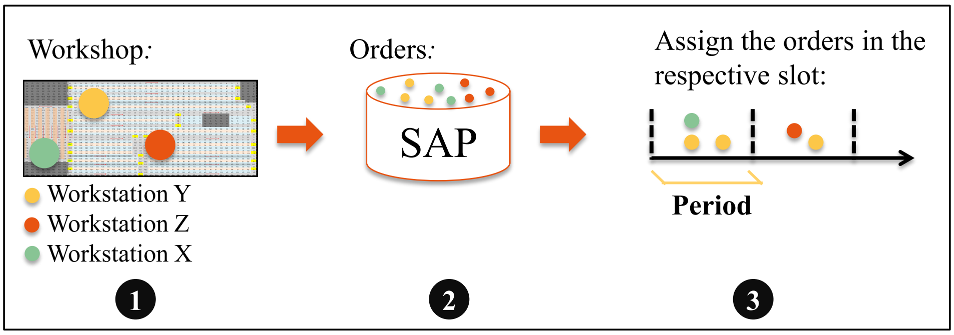


Figure 1.8: Steps to Cluster orders into periods: (1) to select the workstations in the workshop; (2) to collect the respective orders in the Orders' system; (3) to place them in the time-horizon chronologically. Later, those orders may be clustered considering the time-window assigned to a period.

Next, an example that illustrates the trajectory of two routes is presented in figure 1.9.

The first route (yellow) is in charge of supplying the orders of the workstations 6, 7, and 8. In contrast to the first route, the second route (green) is responsible for supplying the orders of workstations 1, 2, 3, 4, and 5. The workstations 1, 2, 3, and 8 represent those ones that are placed inside the Supermarket, and the workstations 4, 5, 6, and 7 represent those located inside the Production Line. The cars that are

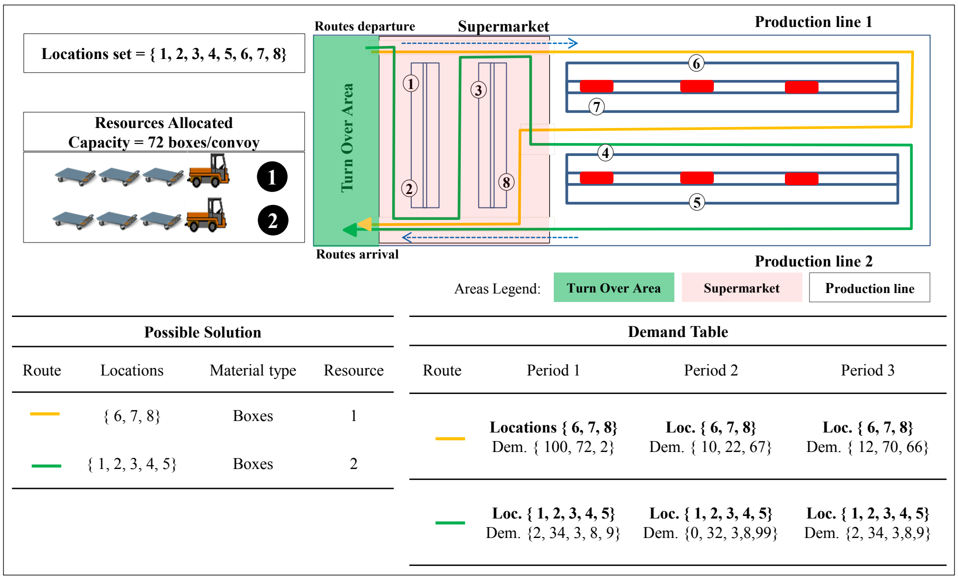


Figure 1.9: An example of the factory workshop and two routes.

being produced are represented by red blocks. Each route begins its trajectory from the Turn Over area. The route must pass through its respective workstations and finishes at the Turn Over area. Also, the routes' path can be partially shared. Moreover, the logistics operator must pass through the Supermarket, even though there is not a single workstation to supply. That premise is applied to the flows that depart from the WHS. Also, figure 1.9 depicts fictitious workstations' orders during three periods.

To illustrate how the orders are placed in SEAT, the figure 1.10 is presented.

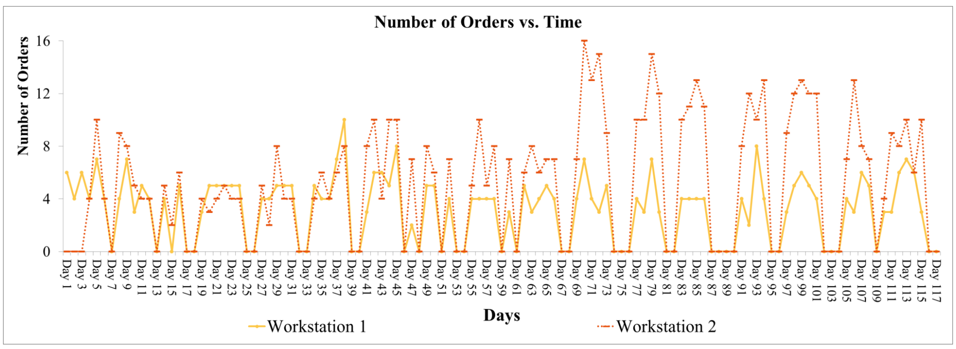


Figure 1.10: An example of two workstations requests' pattern over three months.

Figure 1.10 illustrates the amount of orders placed over 117 days. That data correspond to two workstations' orders. Notice that the orders present an unsteady behaviour. In this work, the orders data introduced in the methods was gathered through the SAP system. As a result, real-historical data was approached.

Therefore, note that the definition of the logistics flows in SEAT is a challenging task. Furthermore, it becomes even more inspiring when fixed routes scenario is considered along unsteady orders behaviors.

1.2 The current company's Logistics Flows analysis

This section presents the main steps conducted by the company during the phase of logistics flows calculations. Usually, whenever the production of a new car model is approved by the company's executives, a series of meetings are scheduled to tackle the production issues. In fact, these meetings are workshops that deal with many production concepts, such as layouts evaluation, workstations' tasks, assignment of materials to classes of containers, and so on. Those workshops meetings are scheduled to occur up to model's start-of-production (SOP) and follow standard procedures developed by the Volkswagen group.

To summarize, the following phases resume the actual procedures to evaluate a new workshop layout and the logistics flows: (i) Car dissembling process; (ii) Materials assignation; (iii) Routes definition; and (iv) Comparison with the current scenario.

So, first, a multi-functional team conducts a range of workshop to evaluate which tasks to assign to the workstations as well as the materials that these workstations will require. So, the main methodology here is the disassembling process. The objective is to learn about the car assembling processes by disassembling it. So, at each step, a set of procedures is defined. These procedures refer to the necessary activities to be executed in that phase and the required components. Consequently, the workstations' tasks are defined during the disassembling process as well as the materials assigned to them.

Second, during a car disassembling process, each car's component is assigned to a SKU according to three main factors: volume, weight, and quantity. Regularly, the Larger Containers (LC) are preferred under the logistics point of view because it incurs in a lower supplying frequency. On the contrary, the Small Boxes (SB) may be preferred under the production point of view because it requires less space in the assembling line.

Third, once the workstations' tasks and its SKU are set, the routes configuration phase starts. Usually, the company's experts execute routes calculations based on the previous workshop' routes. Also, the company's experts decide which materials should be assigned to JIT flows and those that must be sequenced inside the company's supermarkets (Cycle ones). One typical material assigned to JIT are tires because of its dimensions, combustion properties, and necessity to be sequenced. It is noteworthy to say that JIT flows are more expensive than the internal ones. Also, the flows are modified taking into account the workload that each new route receives. The workload is calculated based on the distance covered, the departure frequency, and the time spent to manage a convoy's racks.

Lastly, the new routes are ready to be tested in real pilots inside the factory. Frequently, it suffers adjustments at the beginning, but it tends to be steady after the proofing phase. Moreover, the company's experts always look for the most economical solutions. In other words, a good solution is a set of different routes categories that are able to supply the orders in time and incurs in the cheapest cost possible. The factors that most impacts on a solution cost are: (i) the route classification because a JIT flow is more expensive than a standard flow, for instance; (ii) the number of routes because each one will incur in several costs, such as convoy rent and operator's wage; and (iii) the distance covered by all the convoys that are also important because it implies on battery recharging costs and traffic volume inside the workshop.

To the best of the author's knowledge, there is not any standard procedure to follow, regarding the logistics flows and workshops' layouts evaluations after the SOP of a new model.

Therefore, regarding those concepts presented so far, the research's objectives are stated in the next section.

1.3 Research Objectives

As described in the last sections, there are many challenges to tackle concerning the internal logistics flows in a car-assembly company. Each of these challenges could be faced as a broad research topic that can be approached from a number of perspectives. As a result, it is necessary to determine and delimit the scope of the research presented in the thesis, as well as setting the objectives of the thesis clearly. So, the broad research objective of this work is to study the internal logistics flows of an actual car-assembly line. Nevertheless, that broad objective may be divided as follows:

- The first objective of the research is to understand the company's routing calculation procedures and propose mathematical optimization methods to support that activity.

- The second objective is to propose simulation models, which are able to simulate a set of routes through the company's workstations demands and premises.

- The third objective is to develop a simulation model, in which several internal logistics flows are inserted, as well as any desired layout. The major goal is to evaluate the main traffic issues in a workshop.

Consequently, numerous questions come up aiming at determining the thesis' scope. However, all those questions may be summarized into a broad one, which is: **what is the best approach to deal with the in-house supplying routes design, regarding a car-assembling company scenario?**

Therefore, this work pursues these research objectives as well as aims to answer the proposed question. Next, the thesis' structure is presented.

1.4 Organization and Thesis Overview

The company's central processes are those described in the previous paragraphs. Next, the scope of each thesis' chapter is presented.

The chapter 2 presents the literature review of the main topics approached in this work. So, each chapter's section refers to one of the following topics: Linear Programming formulations, Iterated-Local-Search Metaheuristic, Vehicle Routing Problems, and Simulation analysis. Note that at the end of each section, the related research contributions are presented.

Next, the chapters 3 to 7 represents the works developed throughout the doctor degree. In order to guide the reader throughout this work, figure 1.11 is presented. That figure is a scheme that represents the warehouse, the assembling workshop, and a dispatching area. Then, each chapter's scope is represented by the respective yellow circle. Later, the chapters' content are summarized and presented in table 1.2.

Consequently, chapters 3, 4, 5, and 6 compound the first part of this thesis that is called **Simulation-Optimization over car-assembly lines**. Here, both optimizing and simulating methods are developed and presented. Those methods' goal is to support SEAT to improve

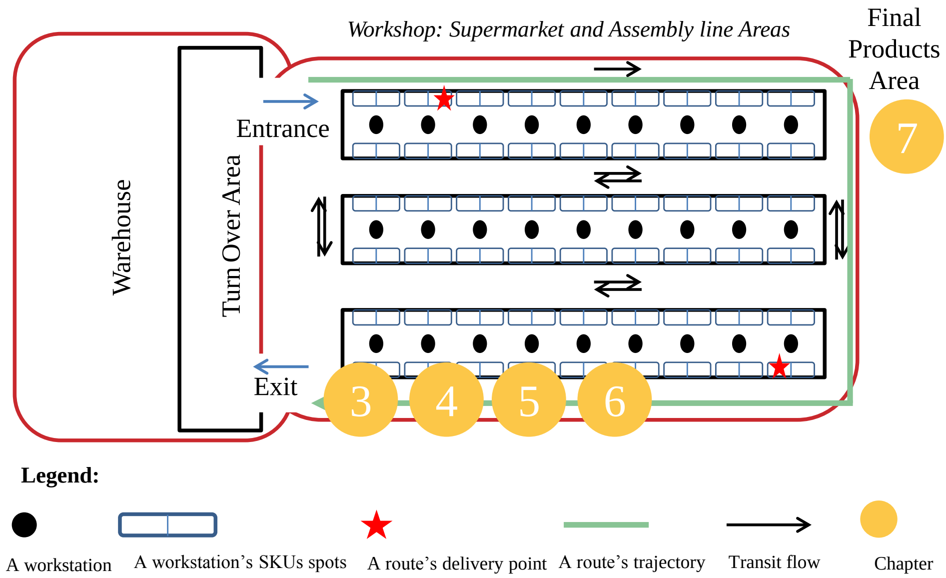


Figure 1.11: An scheme to locate the application of the following chapters.

its internal logistics operations in the assembling lines. Also, to contribute to the literature by providing a novel data set as well as new Integer Linear Programming formulations and Metaheuristics that fit the SEAT's background. These chapters are detailed next:

- Chapter one presents the first attempt to optimize a specific logistics flow inside an assembling workshop of this work. A feasible solution was obtained through an Integer Linear Programming (ILP) model, and its solution is compared with the current company's solution through data generated by the Monte Carlo Simulation. The proposed solution achieved excellent performance in terms of the KPIs set by the company. However, it has limitations on the way to deal with the orders variability.

- Chapter 4 is a step further in comparison to the previous one. Here the orders' stochastic property is the main issue to deal with. Consequently, the In-house Logistics Routing Problem and a simulation-based Iterated Local Search (ILS) Metaheuristic are presented. These methods have in common an objective function that aims to minimize the total of routes applied, the distance covered by those routes and the number of backorders. Moreover, these new methods are more realistic than the chapter 3 one because the company's historical orders are considered individually. As a result, this chapter presents a more robust approach than in the previous chapter. However, high level of backorders is still observed in the new proposed solutions. Concluding, the results show that the ordering premise, which states that logistics operators are in charge of placing orders is likely one of the factors that contribute to a significant number of backorders found in this work so far.

- Chapter 5 aims to provide to SEAT feasible alternatives to improve its logistics activities by reducing the number of backorders. This chapter conducts an assessment of an Internal Logistics Routing Management (ILRM) system in the car-assembling company. Therefore, this chapter works over a strategic-decision level, in which SEAT's current ILRM system is evaluated, and three new scenarios are suggested. To evaluate and optimize these scenarios, an ILP model and an ILS algorithm are developed to calculate variable routes to ILRM systems. Furthermore, a simulation procedure is presented to evaluate and compare all these scenarios in a realistic environment using real data. From the optimization point of view, the ILS was able to reduce the total distance covered throughout the considered time-horizon and it generates no backorders solutions. Finally, the advantages and challenges of each scenario are presented. As a result, this chapter presents interesting problems in a car-assembly company, proposes an ILP model and an ILS algorithm and evaluates a real case in SEAT company. This proposed methodology can be applied and extended to any car-assembling company.

- Chapter 6 proposes an Internal Logistics Flows simulation based on a Discrete-Event-Simulation (DES) model to evaluate the interaction between assembly lines' aisles and logistics flows. The major objective is to identify the main bottlenecks in the assembly line under the logistics perspective. Moreover, a case study that evaluates the introduction of new premises is conducted through the DES model.

The second part refers to the delivery of the final products (cars) to clients. That part is represented by the chapter 7 that presents a methodology to support any car assembling company on scheduling the jobs on its final processes, which are (i) checking the final product and (ii) loading the delivery trucks. Usually, these activities are found in the outbound area of any manufacturing company. Moreover, this chapter tackles a problem that is defined as the Flow shop problem with precedence constraints, release dates, and delivery times. The main target is to minimize the latest date a client receives its products.

Then, a time-indexed ILP model is presented. Also, a Lagrangean Relaxation procedure is developed to compute valid Lower and Upper Bounds for that problem. To conclude, the results showed that the proposed methodology was able to compute feasible solutions for all the instances tested. Also, the Lagrangean Relaxation approach was able to calculate better bounds in a shorter computational time than the ILP for the more complicated instances.

Finally, the chapter 8 concludes the thesis.

Table 1.2 summarizes each chapters' applications, regarding the data approach, the used optimization methods, and the scope.

C.	Data Approach	Opt. Method	Scope
3	Average Orders	- Det. ILP - Monte Carlo Simulation	Warehouse and Shipping Problem *(Fixed routes)*
4	Actual Individual Orders	- Det. ILP - SimILS algorithm - Simulation procedure	Internal Logistics Routing Problem *(Fixed routes)*
5	Actual Individual Orders	- Data Analysis - Det. ILP - ILS algorithm - Simulation procedure	Internal Logistics Routing Management Systems Evaluations *(Fixed and Variable routes & Placing orders systems)*
6	Actual Individual Orders	- DES model	Internal Logistics Flows Simulation *(Flows and Layout analysis)*
7	Randon Generated Data	- Det. ILP	Flow shop problem with precedence constraints, release dates, and delivery times *(An outbound jobs scheduler)*

Table 1.2: Chapters' scope. The first column *C.* refers to each chapter's number. The second column regards to the orders data approach. The third column presents the main chapters' methods. Lastly, the fourth column refers to each chapter's main applications. Note that the Deterministic Integer Linear models are represented by *Det. ILP*.

Chapter 2

LITERATURE REVIEW

The Literature Review chapter aims to introduce the main components approached in this work. So, the methodologies applied in this thesis are introduced as well as several related works. Also, the thesis' contributions will be discussed at the end of each section. Consequently, the reader may find the main methodologies of this work all summarized in the same chapter.

Consequently, the topics approached in this work are presented in the following sections: Linear Programming Formulations; Iterated Local Search Metaheuristic; Vehicle Routing Problem; and Simulation analysis.

2.1 Linear Programming Formulations

According to [Hillier & Lieberman (1995)], the creation of linear programming has been viewed as one of the most significant scientific advances of the mid-20^{th} century. Nowadays, the linear programming is a standard tool that has saved a remarkable amount of resources for many companies or businesses, of even moderate size, in the various industrialized countries of the world.

[Hillier & Lieberman (1995)] state that linear programming uses a mathematical formulation to describe the problem of concern. The term linear means that all the mathematical functions in this formulation are asked to be linear functions. Moreover, the term "programming" does refer as a synonym for planning. Consequently, linear programming concerns to the planning of activities to obtain an optimal result, i.e., a result that reaches the specified goal best (according to the mathematical formulation) among all feasible alternatives.

So, it is right to affirm that any problem whose mathematical model fits the very general format for the linear programming model is a linear programming problem. Moreover, an efficient solution procedure, called **the simplex method**, is available for solving linear programming problems of even huge size. These are some of the reasons for the remarkable impact of linear programming in recent decades. Details about the simplex method can be found in [Hillier & Lieberman (1995)].

According to [Wolsey (1998)], a linear program is defined as follows:

$$max\{cx : Ax \leq b, x \geq 0\} \tag{2.1}$$

Where A is an mxn matrix, c an n-dimensional row vector, b an m-dimensional column vector, and x an n-dimensional column vector of variables.

So, if the variables assume integer values only, the term *integer* will refer to the fact that the variables must take these integer values. Those variables are placed in the model's constraints and the objective function. As a result, the formulation will be called as an Integer Linear Programming model.

Notice that there are other possibilities such as the Mixed Integer Program (MIP) and Binary Integer Program (BIP). A MIP describes a model compound by both integer and real variables. Also, BIP refers to a model that is compound by binary variables.

Moreover, there is another type of problem that is relevant in this work, the **Combinatorial Optimization Problem** (COP). According to [Grasas et al.(2016)], COP is a problem, in which the best solution needs to be obtained from a finite or countably infinite set of objects, such as permutations, graphs, etc.

[Wolsey (1998)] defined COP as follows: for a given infinite set N = $\{1,...,n\}$, weights c_j for each $j \in N$, and a set F of feasible subsets of N. The problem of finding a minimum weight feasible subset is a COP:

$$(COP) \longrightarrow min_{S \subseteq N}\{\sum_{j \in S} c_j : S \in F\} \tag{2.2}$$

Next, one example that illustrates the concepts stated before is the Traveling Salesman Problem (TSP). In this problem, a salesman must visit each of n cities exactly once and then return to his initial point. Considering that the time spent to travel from city i to city j is c_{ij}. The goal is to find the order in which the salesman should make his tour to finish as quickly as possible. Likewise, one may state that problem on many other forms, such as an internal logistics operator has a list of workstations he/she must visit on a given shift. Indeed, that is the model chosen in this work to sort the SEAT current routes, as explained further ahead. The TSP is presented by [Miller et el. (1960)] as follows:

The set N represents the total of locations to visit ($n \in N$). The variables $x_{ij} = 1$ if the salesman goes directly from city i to city j, and $x_{ij} = 0$ otherwise. The U_i variable represents the load of the salesman after visiting city ($i \in n$).

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} xij \tag{2.3}$$

$$\sum_{j:j \neq i} x_{ij} = 1 \qquad \forall i \in N \tag{2.4}$$

$$\sum_{i:i \neq j} x_{ij} = 1 \qquad \forall j \in N \tag{2.5}$$

$$U_j - U_i + Cx_{ij} \leq C - d_j \qquad \forall i \in N, j \in N \backslash \{i \neq j\} \tag{2.6}$$

$$D_i \leq U_i \leq C \qquad \forall i \in N \tag{2.7}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in N, j \in N \backslash \{i \neq j\} \tag{2.8}$$

$$U_i^+ \in \mathbb{Z} \qquad \forall i \in N \tag{2.9}$$

The 2.3 refers to the objective function, whose objective is to minimize the total travel time. Constraints 2.4 and 2.5 state that the salesman must leave and arrive at each city exactly once. Constraints 2.6 and 2.7 avoid sub-tours to happen. Finally, constraints 2.8 and 2.9 define the variables.

The TSP is stated as a combinatorial problem because the optimal solution is a subset of a finite set. Consequently, in principle, that problem can be solved by enumeration. If the salesman starts at city 1, he has (n-1) possibilities to proceed to the next city. For the next choice, there are (n-2) cities to be chosen, and so on. Therefore, there are (n-1)! feasible tours to be selected. By curiosity, a SEAT's workshop has 120 workstations. So, it will have 6,68 x 10^{198} possibles tours to be executed.

So, enumerating can be an useful method for small cases only. To overcame this issue for those large cases or the real-world ones, many algorithms have been developed to enable the calculation of feasible and optimal solutions. One of them is the Lagrangean Relaxation, which is explained in subsection 2.1.2. Before, the term complexity is discussed in the next subsection.

2.1.1 Complexity

The primary purpose in this subsection is briefly explaining what **P** and **NP** problems mean. Note that there is not any tentative to go further than explain to a standard reader what complexity refer about. These concepts matter because they are important to understand the reason why one problem is viewed as more complicated than others.

So, back in the seventies, researchers were exploring how to deal with several problems that were considered somehow important. Also, they were pursuing procedures to make difficult problems easier to solve. The reader may think that the terms easy and difficult may be subjective. Consequently, in this work, these terms will refer to the computational effort to solve a problem. Then, a difficult problem requires much more effort to be solved than an easy one.

Afterward, the researches have succeeded to improve the methods to solve some classes of problems, but there were still many problems that no improvement was observed, in terms of solutions calculation. Indeed, most of these complicated problems are not easily solved up to present date. Examples of easy problems are those related for sorting or multiplications. One example of a complicated one is the TSP, which was presented in the previous subsection 2.1.

According to [Wolsey (1998)], the easiest classes of problems are stated as **P** ones because they can be solved in polynomial time. In other words, the time spent to solve those problems is a polynomial function of the problems' size. On the contrary, the complexity to solve a TSP does not polynomially increase as the number of cities increases, but exponentially. So, those classes of problems are defined as **NP**, which means *Nondeterministic polynomial time*. It is noteworthy to state that the Moore's law, [Schaller (1997)], could not help in this issue because a problem's complexity may become intractable even for the most powerful computer.

To sum up, problems defined as **P** ones are much easier to solve than the **NP** ones. So, nowadays, the questions that researchers do is: Is it possible to tackle NP problems as P ones? Likewise, there exist some problems that are indeed more difficult than others?

These questions were stated in 1971 and, surprisingly, up to the date of the publication of this thesis, there is not an answer to these questions. That topic is so important under the research and practical point of view because it would change the way many problems are faced today deeply. Indeed, it was stated as a Millennium Prize Problem by the Clay Mathematics Institute (*https://www.claymath.org*) that offered a considerable prize to whom get it solved. Unfortunately, answering that question is not a contribution of this thesis.

To conclude, notice that these two classes do not cluster all the possible problems, but the ones that are studied in this work. For example, a parallel interpretation for the NP problems refers to the effort to prove that a solution is feasible. Considering the TSP, it is not so difficult to verify if a tour considers all the stated premises. On the other hand, it is challenging to affirm which is the best move to do in the middle of a chess game because there are numerous possible scenarios to evaluate after a move done by one player. So, chess games are viewed as problems more difficult to solve than NP ones.

2.1.2 The Lagrangean Relaxation

Before defining the Lagrangean Relaxation algorithm, concepts like Lower Bound, Upper Bound, relaxation and optimality must be stated. So, considering the following COP, which is quite similar to the equation 2.2:

$$z = \min\{cx : x \in X\} \tag{2.10}$$

An optimal solution x^* is the one that produces the best value for $\boldsymbol{z}$. So, the questions is how to guarantee that the x^* is the best solution. One practical way to prove it is to find a lower bound ($\underline{z} \leq z$) and an upper bound ($\overline{z} = z$) such that ($\underline{z} = \overline{z} = z$).

Notice that, for minimization problems, an upper bound is defined as any feasible solution and it defines the primal bound. Also, it is interesting to achieve the minimum upper bound possible because that value refers to the optimal solution. Taking the TSP model as an example, for a minimization objective function, any feasible tour would be an upper bound or a primal bound.

Likewise, for the minimization problems, there is the lower bounds or the dual bound. These bounds may be calculated through a procedure called relaxation. In other words, a relaxation makes the original problem less constrained or easier to be solved.

So, relaxations are able to provide information about the original problems optimality through its dual bounds. If the provided dual bound matches the primal bound, then the computed solution is the optimal solution. Otherwise, other relaxation methods must be executed to improve the dual bound value, in this case, a dual bound that matches the primal bound. So, relaxations are an important tool to prove solutions optimality. However, a dual bound may be unfeasible for the original problem because it is a relaxed solution.

Examples of relaxations are the Linear Relaxation that permits integer or binary variables to achieve real values. Also, there is the Lagrangean Relaxation that is explained next based on the work of [Vanderbeck & Wolsey (2010)].

Considered that the presented problem 2.10 is a difficult one. On the contrary, there is a set defined as Z that is a subset of the constraints of X. Also, that subset Z contains less constrained restrictions that let the optimization over the set Z easier than all set X. Consequently:

$$z = \min\{cx : Dx \geq d, Bx \geq b, x \in \mathbb{Z}_+^n\} \tag{2.11}$$

In equation 2.11, $\{Dx \geq d, Bx \geq b, x \in \mathbb{Z}_+^n\}$ represents the previous set X. Also, constraints $Dx \geq d$ represent the most complicated constraints of the model and define the integer set $Y = \{x \in \mathbb{Z}_+^n : Dx \geq d\}$. The constraints $Bx \geq b$ represent the more tractable constraints and define the set $Z = \{x \in \mathbb{Z}_+^n : Bx \geq b\}$.

So, the Lagrangean Relaxation (LR) consists of relaxing those complicated constraints and solve the problem for the simpler set Z. Moreover, if the LR computes solutions that do not respect or violate the constraints placed in set Y, the objective function will be penalized. Therefore, that method produces dual bounds by relaxing the difficult constraints and penalizing their violation in the objective function. Also, the dual variables, which are associated with each constraint placed in the objective function, are called Lagrange multipliers or prices. The goal is to choose most suitable Lagrange multipliers to try to enforce satisfaction of the complicating constraints $Dx \geq d$. That gives rise to the Lagrangean sub-problem, defined below:

$$L(\alpha) = \min\{cx : \alpha(d - Dx) : Bx \geq b, x \in \mathbb{Z}_+^n\} \tag{2.12}$$

Where α represents the Lagrange multipliers. According [Vanderbeck & Wolsey (2010)], the Lagrangean sub-problem is assume to be relatively tractable. Moreover, notice that the equation 2.12 provides a dual bound on the optimal value of $\boldsymbol{z}$ (equation 2.11). As a result, the maximum α values of that dual bound may lead to the optimal solution for $\boldsymbol{z}$, considering that dual bound respects the constraints placed beforehand ($Bx \geq b$). So, the problem of maximizing this bound over the set of admissible penalty vectors is known as the Lagrangean dual (LD):

$$z_{LD} = \max_{\alpha \geq 0} L(\alpha) = \max_{\alpha \geq 0} \min_{x \in Z}\{cx : \alpha(d - Dx)\} \tag{2.13}$$

One classical method to solve the Lagrangean dual is the subgradient one. According to [Vanderbeck & Wolsey (2010)], even though its convergence in practice is worse than other methods, such as a column generation approach, it remains useful because of their easy implementation and their ability to tackle large size problems. The sub-gradient algorithm is summarized next. The detailed algorithm can be found in [Vanderbeck & Wolsey (2010)] and [Beasley (1993)].

Algorithm 1: The Sub-Gradient Algorithm

1 Initialize $\alpha^0 = 0$, t = 1, where t is the number of iterations
2 Iteration t,
3 Solve the Lagragean sub-problem (eq. 2.12) to obtain the dual bounds $L(\alpha^t)$ and an optimal solution x^t
4 Calculate the x^t 's violation of the dualized constraints $(d - Dx^t)$, which provide a type of sub-gradient that may guide to modify the dual variables.
5 Update the dual solution using $\alpha^{t+1} = max\{0, \alpha^t + \beta_t(d - Dx^t)\}$, in which β is an appropriately chosen step-size.
6 If $t \leq Max_{iterations}$, increment t and return to 3.
7 **Return** a dual bound over problem z.

So, on the one hand, one may think that Linear Relaxations are so much easier to be implemented than the Langragean one, which is a true statement. On the other hand, the Lagrangean Relaxations are able to provide better dual bounds than the Linear one, according to [Vanderbeck & Wolsey (2010)]. That justifies the effort invested on Lagrangean relaxations.

As a result, the Langrangean relaxation achieves an optimal solution whenever the computed Upper (primal) bound and the Lower (dual) bound values are the same. Consequently, it requires that both bounds converge to an equal value to obtain the optimal solution. Figure 2.1 illustrates that scenario.

Research Contribution

In the remainder of this section, the author summarizes the main topics approached in this work that are related to the methodology present so far.

- Chapter 3 studies and analyses a real case of a warehouse shipping and routing problem at a car-assembling factory. An Integer Linear Programming (ILP) model for a deterministic version of the problem is proposed to provide feasible solutions or a set of routes.

- Chapter 4 presents a novel ILP model that tackles the stated **In-house Logistics Routing Problem**.

- Chapter 5 also presents a novel ILP model that copes with an extension of the In-house Logistics Routing Problem.

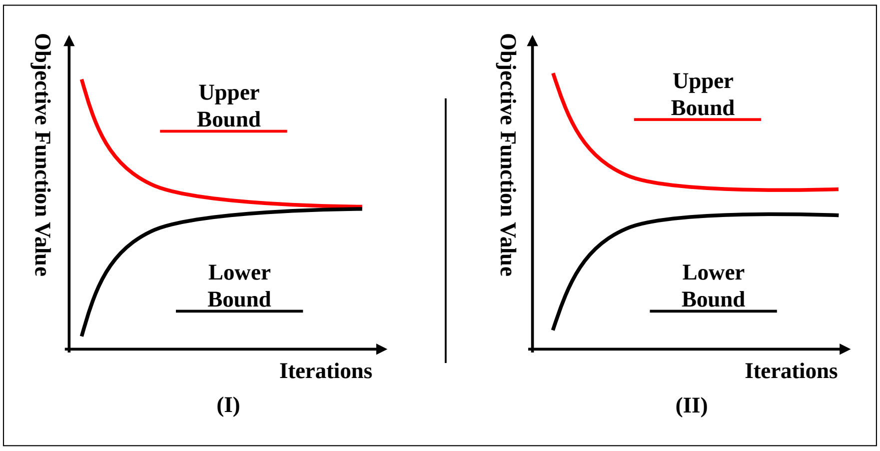


Figure 2.1: A scheme of the Lagrangean Relaxation method solved through the subgradient algorithm. The first figure represents a scenario that the optimal solution was found because the LB and UB achieved the same value. On the contrast, the second figure represents a scenario that the optimal solution was not found.

- Chapter 7 presents an ILP that faces the two-machine Flow shop Scheduling problem with precedence constraints, release dates and delivery times. Also, a method based on a Lagrangean Relaxation procedure was executed to provide optimal solutions.

2.2 Iterated Local Search Metaheuristic

Before introducing the concept of Iterated Local Search, two important concepts will be presented first, which refer to Exact Methods Algorithms and Heuristics.

According to [Glover (1977)], Exact Methods Algorithms are compound by a set of finite mathematical steps that are able to ensure a problem's optimal solution. Therefore, Exact Methods are largely used both in the literature and in industries to achieve optimal solutions for relevant problems. The Lagrangean Relaxation methods presented in subsection 2.1.2 is an Exact Method example. So, on the one hand, Exact Methods can ensure that a solution is the optimal one. On the other hand, these methods are not always successful, as indicated by the non-convergence cases in the Lagranegan Relaxation.

Consequently, heuristics can be applied to overcome the disadvantages of the Exact Methods. Heuristics are a set of procedures that relies on both mathematical methods and practical assumptions. On the one hand, these methods are able to produce excellent solutions in a short amount of time. On the other hand, those solutions cannot be stated as the optimal ones because heuristic procedures are not able to guarantee it by itself. The mathematical procedures that embedded heuristics are not sufficient to give that information.

Also, heuristics methods are mostly based on searches over a set of feasible solutions. That search can be guided by a method called Local Search. As the name says, it looks for feasible solutions over a limited or local space of solutions. Consequently, one heuristic must avoid the risks to be trapped in a solution that is optimal, but locally and not globally. Therefore, there is a necessity to extend the search to other regions to look for the optimal global solution, which is a problem's optimal solution. To do so, there are perturbation methods that are in charge of bringing the search over a different set of solutions.

Consequently, one may say that heuristics may not be so useful, but it not true at all. As said, solutions are computed really fast because there is no need to prove that it is the best one. For many practical cases, solutions must be computed in milliseconds, and there are problems, which are so robust, that even calculating a feasible solution will take hours of computational time. For those cases, heuristics are a good call. Practical cases of heuristics applications are presented by [Feo & Resende (1989)], [Koç et al. (2016)] and [Cota et al.(2016)]. Moreover, Exact Methods and heuristics can be joined to take advantage of the benefits that each method brings. That class of problems is called Hybrid Metaheuristics or Matheuristics. See [Boschetti et al. (2009)], [Fischetti & Lodi (2003)] and [Glover & Laguna (1997)].

Later, the literature developed an extension of the heuristic concepts, which is the Metaheuristics algorithms. These algorithms were developed to cope with difficult problems, such as the Combinatorial Optimization ones presented before. These methods were introduced by Fred Glover in 1986 in his paper *Future Paths for integer programming and links to artificial intelligence*, see [Glover (1986)]. Also, a formal definition of the concept of metaheuristics may be: a heuristic solution developed to regulate and guide specific problem-oriented heuristics.

Regarding the metaheuristics' practical point of view, there are four main topics to be considered, according to [Cordeau et al. (2002)]: (i) accuracy, (ii) speed, (iii) simplicity, and (iv) flexibility. So, metaheuristics need to be accurate and fast to compute, in a short computational time, solutions that are close to the optimal one. Moreover, these methods should be simple and flexible in the sense that it can be quickly setup to work with other problems.

In the literature, there are many metaheuristic procedures that are based on different concepts. [Gendreu & Potvin (2019)] presents the main metaheuristics applied in the literature in their handbook. Some of the presented methods are: Tabu Search, Greedy Randomized Adaptive Search Procedures (GRASP), Genetic Algorithms (GA), Ant Colony Optimization, Hybrids Metaheuristic, Variable Neighborhood Search (VNS), and Iterated Local Search (ILS). In this thesis, the ILS is the metaheuristic chosen to tackle the stochastic COPs that will be introduced further ahead. By the way, for a survey of metaheuristics applications over stochastic COPs, see [Bianchi et al. (2006)]. The ILS framework is presented next.

2.2.1 Iterated-Local-Search framework

The Iterated-Local-Search (ILS) is presented by [Lourenço et al.(2019)]. According to the authors, the ILS has been applied to complex Combinatorial Optimization Problems (COP) successfully. See [Coelho et al. (2016)], [Penna et al.(2013)] and [Vansteenwegen et al. (2009)].

The main idea of ILS relies on the fact that it focuses on a smaller subset of solutions, instead of considering the whole space of solutions. This subset is defined by the local optimum of a given optimization procedure [Lourenço et al.(2019)]. Also, [Grasas et al.(2016)] affirm that the ILS extends a local search method by introducing a perturbation at each new local optimal solution before restarting the search for a new local optimal solution.

The ILS metaheuristic implementation is compound by four main steps, which are defined as follows: (i) compute an initial solution; (ii) execute a Local Search, which improves the solution initially obtained; (iii) execute the perturbation phase, where a new starting point is computed through a perturbation of the solution returned by the Local Search; (iv) acceptance Criterion, which decides from which solution the search should continue. Algorithm 2 presents the ILS framework.

Algorithm 2: The ILS Algorithm

$(S_0) \leftarrow$ Generate_Initial_Solution
$(S^*) \leftarrow$ Execute a Local_Search(S_0)
while *Stopping criterion is not met* **do**
    $(S^{'}) \leftarrow$ Perturb(S_*)
    $(S^{**}) \leftarrow$ Execute a Local_Search$(S^{'})$
    $(S^*) \leftarrow$ Acceptance_Criterion (S^{**}, S^*)
end
Return (S^*)

So, the ILS's target is to escape the disadvantages of random restarts by exploring the region of feasible solutions using procedures that move from one locally optimal solution S^* to a close (related) one. Given the current solution S^*, a change or perturbation is first applied to lead to an intermediate feasible solution, $S^{'}$. Next, a Local Search is applied in $S^{'}$ to obtain a new local optimal solution, S^{**}. If S^{**} is approved by an acceptance test, it becomes the new current solution; otherwise, one returns to the previous one, S^*.

Also, according to [Grasas et al.(2016)], a well-designed ILS is characterized by all the essential attributes described in [Cordeau et al. (2002)].

2.2.2 Simulated-based Iterated-Local-Search

As presented before, heuristics may be linked with other approaches such as exact methods. Additionally, heuristics can perfectly work with simulation procedures as described by [Glover et al. (1996)].

Moreover, those works that cluster both heuristics and simulation methods refer to the simulation-optimization or the Simheuristics fields. In the literature, there are authors that refer to these class of problems as simulation-optimization ones, see [Carson & Maria (1997)]. On the contrary, there are authors that use the Simheuristics term as well, see [Juan et al. (2015)] for a complete review of related works.

So, this subsection presents the Simulated-based Iterated Local Search (SimILS) Metaheuristic. It is based on the methodology proposed by [Grasas et al.(2016)], which refers to the aggregation of ILS with simulation procedures.

The reason to select the SimILS is due to the remarkable results of the ILS to solve COP. Also, it is a suitable method to solve Stochastic COPs, such as real problems that demand is unknown, see [Lourenço et al.(2019)] and [Grasas et al.(2016)]. Therefore, the SimILS is considered as an appropriate method to handle real-based problems.

According to [Grasas et al.(2016)], the aggregation of a standard SimILS framework and a simulation-optimization procedure result in a method capable of dealing with stochastic COPs. The SimILS's framework is described in Algorithm 3.

Algorithm 3: The SimILS Algorithm

$(S_0) \leftarrow$ Generate_Initial_Solution
$(S^*) \leftarrow$ Execute a Local_Search(S_0)
$(S^*, of(S^*)) =$ Simulation$(S^*$, long$)$
while *Stopping criterion is not met* **do**
  $(S^{'}) \leftarrow$ Perturb(S_*)
  $(S^{**}) \leftarrow$ Execute a Local_Search$(S^{'})$
  $(S^{**}, of(S^{**})) =$ Simulation$(S^{**}$, short$)$
  $(S^*) \leftarrow$ Acceptance_criterion $(S^{**}$, $S^*)$
end
$(S^*, of(S^*)) =$ Simulation$(S^*$, long$)$
Return $(S^*, of(S^*))$

From the algorithm 3, the simulations procedures are placed after applying the Local Search to evaluate the current local optimal solution (S^* and S^{**}). These simulations consider both a solution and a parameter, which indicates if the simulation should be run for a long time ($Simulation(S^*, long)$) or a short time ($Simulation(S^{**}, short)$). So, the SimILS obtains the corresponding simulated objective function, of(*solution*), as well as other relevant statistics that can be used later to improve the search (eg., level of backorders). Finally, a simulation procedure is also inserted at the end of the ILS process. The algorithm 3 resumes the SimILS Metaheuristic developed.

As a result, the simulation has two main functions: (i) estimate the expected cost value of a newly generated solution; (ii) check that a newly generated solution satisfies some probabilistic constraints. Those cases are applied whenever a problem has stochastic components in both objective function and constraints.

Research Contribution

In the remainder of this section, the author summarizes the main topics approached in this work that are related to the methodology present so far.

- Chapter 4 presents a novel SimILS metaheuristic that tackles the stated **In-house Logistics Routing Problem**, which is a stochastic COP.

- Chapter 5 also presents a novel ILS metaheuristic that tackles an extension of the In-house Logistics Routing Problem.

2.3 Vehicle Routing Problems

As the Travel Salesman Problem (TSP), the Vehicle Routing Problem (VRP) is a classical problem in the Operations Research literature. Indeed, one may say that the VRP is an extension of the TSP because both problems share some components, such as routes calculation. On the contrary, VRP permits more than one route to be computed. That idea is supported by the first work that approaches the VRP [Dantzig & Ramser (1959)] back in 1959. Also, according to the authors, the VRP is a NP problem, likewise the TSP.

According to [Laporte (2009)], the VRP is stated as the problem of designing least-cost delivery routes from a depot to a set of geographically sparse customers, subject to side constraints. Consequently, due to a significant variety of side constraints, as well as different optimization goals, there are several variants of the problem because of the diversity of operating rules and constraints found in real-life applications. To a further explanation about the VRP methodology, the reader is invited to see [Toth & Vigo(2002)]. Also, for a complete survey of the VRP literature, see [Braekers et al.(2016)], [Laporte (2009)], [Koç et al. (2016)], and [Laporte (2000)].

Notice that the amount of literature that compound the VRP area is huge. So, from now on, only the VRP works that are similar to the thesis' approach will be discussed. These studies are presented next.

According to the surveys presented by [Laporte (2009)] and [Braekers et al.(2016)], the Traditional VRP's primary objective is to minimize the total cost of routing a fleet of vehicles to supply a set of clients. Both the fixed-routes and the variable-routes scenarios consider the minimization of the total number of vehicles. Among the traditional VRP is the Asymmetric Capacited VRP (ACVRP), which is defined by a asymmetric distance matrix and capacited fleet, [Crainic & Laporte(2012)].

Regarding the Consistent VRP, the problem was introduced by [Groër et al.(2009)]. In this scenario, the routes are kept fixed, and the drivers with the routes as well. Orders are known in advance by the managers. Also, when a customer receives service, the same driver visits the client at roughly the same time over the planning horizon.

Concerning the Stochastic VRP, it arises whenever any part of the data is stochastic or unknown in advance such as stochastic travel times or stochastic demand, see [Gendreau et al.(1996), Adulyasak, & Jaillet(2015)]. The main idea of the Stochastic VRP is to compute a set of routes that perform well considering the stochastic data input. In this work, the data input that is considered as stochastic one is the demand. That approach can also be observed in [Bertsimas(1992),Novoa, & Storer(2009)].

The Dynamic VRP is described by [Braekers et al.(2016)], in which relevant data is continuously updated over the considered time horizon, such as the costumers' demand. Then, based on these inputs, the vehicles could adapt their routes dynamically. [Albareda et al.(2014)] consider probabilistic information to compute each period's set of routes.

The VRP with Balance main goal is to compute a set of routes, in which each router should have about the same amount of work for each period of the time horizon. Related work is presented by [Levy & Bodin(1988)], [Sniezek & Bodin (2006)], and [Jozefowiez et al. (2002)]. Moreover, [Campbell & Wilson(2014)] extended that approach by joining the Balanced VRP with the periodic one. The authors stated that found little work on variants of the problem that explicitly address the stochasticity of customer demand or travel times.

Regarding the Periodic VRP application, it assumes that the customers require visits on one or more days within a planning period. Also, there are a set of feasible visit options for each customer. A VRP is solved for each component in the planning period. Usually, the main goal is to minimize the total distance traveled over the planning period. [Francis et al.(2007)] define the operational complexity in implementing a solution to the periodic VRP, such as crew size definitions.

Lastly, [Coelho et al.(2013)] and [Moin, & Salhi(2007)] present a literature review of the Inventory-Routing Problem (IRP), in which the demand is stochastic, and there are not clients' orders. Instead, the supplier decides when to visit each customer, based on forecasts, communications, and monitoring. The planning horizon is multiple periods in length. Note that the IRP and the VRP are different categories of problems. However, they share some concepts, such as the routing calculations and pursuing solutions with a minimal number of routes.

Regarding the Vehicle Routing Problem tackled by this work, it is defined as **In-house Logistics Routing Problem** (ILRP). Also, to the best of the author's knowledge, it represents a novel Vehicle Routing problem approach. The In-house Logistics Routing Problem is summarized as follows: (i) stochastic and unknown demand; (ii) self-ask-supply approach; (iii) long-term and fixed routes; (iv) drivers must return to the depot after concluding the route; (v) orders are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are allowed; (viii) each customer is assigned to a route; (ix) fixed-customer-sequence definition; (x) capacitated; and (xi) homogeneous fleet.

So, these characteristics are observed in many problems presented in the literature. However, those aspects are not viewed all together to compound a similar VRP approach. So, figure 2.2 presents the VRP works that are most related to this thesis' approach. Moreover, the table presents some comments about the consolidate VRP approach and the In-house Logistics Routing Problem.

Research Contribution

In the remainder of this section, the author summarizes the main topics approached in this work that are related to the VRP methodology.

- To the best of the author's knowledge, chapters 4 and 5 present a novel Vehicle Routing approach stated as **In-house Logistics Routing Problem**, which is a stochastic COP. Also, chapter 4 introduces both ILPs and ILS metaheuristics to tackle this problem.

- Chapter 5 present four scenarios that fit the Internal Logistics Routing Management (ILRM) system of a car-assembly company. These scenarios refer to the ILFP, periodic VRP and IRP. As a result, a real interesting problem in a car-assembling company is considered. That problem consists of finding the most suitable ILRM system that is responsible for both placing orders and delivering them.

2.4 Simulation analysis

Section 2.1 describes analytic models that aim to represent reality through mathematical equations. Likewise, this section presents other classes of models that aim to reproduce real problems, which are the simulation models.

According to [Banks et al.(2005)], simulations reproduce the operation of a real-world process or system over time. That involves the generation of an artificial history of a system and the observation of that artificial history to draw inferences, concerning the operating characteristics of the real system. Moreover, a simulation analysis is conducted through a model that takes the form of a set of premises regarding the operation of the system. These premises are expressed in mathematical, logical, and symbolic relationships between the entities, or objects of interest.

Notice that these models must be checked to verify its ability to reproduce the real-world system. For this reason, simulation models

Item	Characteristics	Comments
Traditional VRP	The major objective of the VRP is to minimize the total cost of routing a fleet of vehicles to supply a set of clients.	Likewise, the major objective of the ILRP is to minimize the total cost of routing a fleet of vehicles to supply a set of clients. The ILRP aims to minimize the total number of vehicles, the routes' distance and the number of backorders.
Consistent VRP	The routes are kept fixed and the routers with the routes as well. Orders are known in advance by the managers. Also, when a customer receives service, the same router visits the client at roughly the same time over the planning horizon.	In the ILPF, the routes must be kept fixed on the long-term horizon as well. On the contrast, the router is the one in charge of placing orders instead of the client (self-ask-supply procedure). That procedure contributes to making the demand stochastic.
Stochastic VRP	To find a set of routes that perform satisfactory, considering the stochastic data input. A set of routes may be constructed at the beginning of each period. Moreover, in some cases, that set of routes may be adapted as soon as new demand information is revealed.	In the ILFP, the demand is viewed as stochastic and unknown due to the following factors: (i) self-ask-supply procedure; (ii) issues in the assembly line, and (iii) the cars-production scheduling is not shared among the departments.
Dynamic VRP	There is a continuous input update over the considered time horizon. Then, based on these new inputs, the vehicles could adapt their routes dynamically. The routers receive information online. A practical example is the taxi fleet management.	On the one hand, the ILFP does not allow routes adaptations. On the other hand, chapter 5 presents scenarios that variable-routes are considered. So, these routes are computed at the beginning of each period, considering the previous period's demand. As a result, it may state the variables routes approach as the first period of a Dynamic VRP only, but not as a standard Dynamic VRP. Routes are not updated within a period.
VRP with Balance	For each period of the time horizon, each router should have about the same amount of work.	In SEAT's current scenario, one of the most important criteria is the work balance among the routes. As a result, the purpose is to distribute equally the total workload between the routers. By contrast, the ILFP prioritizes the three main factors discussed in the Traditional VRP' line.
Periodic VRP	Customers require visits on one or more days within a planning period, and there are a set of feasible visit options for each customer. A VRP is solved for each day in the planning period. Usually, the main goal is to minimize the total distance traveled over the planning period.	In the variable-routes scenario (chapter 5), the customer's orders are allocated in periods. Also, a VRP is solved at the beginning of each period. In this point, there is an issue regarding the current demand because it is not steady. As a result, a scenario without steady demand may be viewed as a traditional VRP.
Inventory-Routing Problem	In the IRP, demand is stochastic and there are not clients' orders. Instead, the supplier decides when to visit each customer, based on forecasts, communications, and monitoring. The planning horizon is multiple periods in length.	The ILFP states the logistics operators are in charge of placing orders. That is the main difference between the ILFP and the IRP. By contrast, chapter 5' variable routes and automatic placing orders system may fits to the IRP correctly.

Figure 2.2: The VRP literature review outline.

should be validated by experts who know that system.

Afterward, analysts can somehow play with the simulation model to investigate a wide variety of "what if" questions about the real-world system. By the way, that is the great advantage of simulation models because it enables one person to experiments a vast range of scenarios, such as new policies and operating procedures scenarios. Consequently, simulation models give support in performing bottleneck analysis by understanding how a complex and random system operates, for instance.

On the contrary, [Banks et al.(2005)] and [Chwif & Medina (2006)] state that there are some drawbacks and not appropriate conditions concerning the application of simulations methods. First, simulation models maybe not so easy to build and also time demanding. Second, the simulation by itself neither guarantee that a solution is optimal nor propose another solution. Finally, usually simulation models need to be fed with much data and, in many cases, there is not even a clue to estimate then. As a result, the simulation models are not the answer for all situations.

This work considers two simulation approaches, which are the Monte Carlo Simulation (MCS) and the Discrete-Event Simulation (DES). These methods are briefly introduced next.

[Banks et al.(2005)] define MCS as a static simulation model that represents a system at a particular point in time. Also, [Hillier & Lieberman (1995)] describe it as straightforward simulation approach that involves generating some random observations from a statistical distribution or a set of data, for instance. So, MCS simulates a system through the generation of data from a specific pre-defined set of data. One application may be the generation of workstations' orders based on a set of historical company's orders, for example.

Contrasting with MCS, the DES can simulate a bit more complex system. According to [Banks et al.(2005)], DES is the modeling of systems in which the considered variables changes only at a discrete set of points in time. For example, in a queueing system where the state of the system is the number of orders in the system, the discrete events that change this state are: (i) the arrival of an order; (ii) the elimination of an order due to its supply. Moreover, [Hillier & Lieberman (1995)] state that several applications of simulation in practice are based on DES. However, in the last years, the agent-based simulation is becoming an interesting and efficient procedure to deal with real-world problems. In that approach, the objects or entities are viewed as autonomous ones. Also, they can learn from the system and take decisions by themselves.Agent-based simulation's applications can vary from logistics and assembling lines to healthcare issues, see [Bonabeau (2002)] and [Macal & North (2010)].

In this work, MCS and DES were approached to develop simulation models that cope with internal logistics flows (ILF) in an assembling line of a manufacturing company. Consequently, this thesis is placed among those simulation-based works that are related with the Logistics and Production fields. Also, the MCS is applied to cope with the Vehicle Routing Problem with Stochastic Demand. So, next sub-sections highlight several works that share some concepts with this thesis.

2.4.1 Logistics and Production works

Usually, the literature associates the logistics related works to Supply Chain Management (SCM) studies. That can be checked through the surveys and literature revisions executed by [Sachan & Datta (2005)], [Wilding et al.(2012)] and [Tako & Robinson(2012)]. These works are discussed next.

The survey conducted by [Sachan & Datta (2005)] reviewed 442 papers of SCM and logistics research to examine the state of logistics and SCM research. Surprisingly, only 20 out of these 442 papers used simulation as the main methodology.

Moreover, [Wilding et al.(2012)] conducted a review of the literature on manufacturing, organizational and supply chain agility from 1991 through 2010. The authors reviewed 175 papers and concluded that Supply chain agility has primarily been explored in the literature through a focus on manufacturing flexibility, supply chain speed, and lean manufacturing. Another curious point that those works brought is the fact that there is not any work in these surveys, whose main scope focus on internal logistics. However, internal logistics is a theme to be considered when facing logistics concepts.

Finally, [Tako & Robinson(2012)] presented a survey on simulation studies under Logistics and SCM perspectives and their application in several industries. Their work suggests that the DES has been applied more frequently to work on supply chains. On the other hand, System Dynamics is the preferred method to deal with the bullwhip effect.

Centralizing the search over manufacturing logistics, which is one of the main topics of this work, there are two surveys studies to highlight. These are the studies presented by [Negahban & Smith (2014)] and [Semini et al.(2006)].

[Negahban & Smith (2014)] conducted a review of 290 DES publications with a particular focus on applications in manufacturing. The authors classified the literature into three general classes: (i) manufacturing system design, (ii) manufacturing system operation, and (iii) simulation language/package development. Even though the authors did not create a specific category for logistics, the logistics-based works were somehow considered through the studies that focus on automated material handling systems. Also, the authors pointed out that logistics-based works were mostly related to automated-guided-vehicles (AGV). So, no further discussion about internal logistics flows concepts was provided.

Regarding the AGV-based works, a complete survey about design and control of AGV systems is presented by Vis2006. In this AGV systems survey, the author considers topics related to flow path layout, traffic management, and vehicle routing. So, issues like single loops, tandem and segmented flow configurations are discussed. However, the focus is always on the AGV itself and not on how an AGV interacts with the environment. Therefore, no work that considers both workshops' aisles utilization and flows strategies were presented by the authors.

[Semini et al.(2006)] presented a survey on the use of DES in real-world manufacturing logistics decision-making. It concludes that the majority of applications has been reported to the following fields: production plant design; evaluation of production policies; lot sizes; work in progress levels; and production plans/schedules. The sample of the survey consists of 52 application papers, which there are three points to highlight: (i) the considered papers are specially aligned to the topic of this work (real-world manufacturing logistics); (ii) it shows that the automotive industry is one of the industries that most demand simulation studies. In the paper's rank, that sector is placed in the second position in numbers of papers; (iii) it supports the argument that the literature lacks of works that consider both workshops' aisles utilization and flows strategies because the authors also did not present a work like that.

Therefore, from the best of the author's knowledge, there is not a similar work that faces the internal logistics flows and the traffic inside a workshop as proposed in this thesis.

On the contrary, it does exist works that share common aspects to the Internal Logistics Flows topic. So, these works are introduced through four categories: (i) production flow, (ii) layout evaluation, (iii) material handling flow, and (iv) routing strategy.

Works that tackle issues related to Production Flow are presented next. [Michalos (2010)] discusses technologies in the automotive assembly, along with techniques used in the vehicle assembly plants. The discussion involves technologies that deal with assembly processes such as handling, joining, and human resources. [Ruiz-Torres & Nakatani (1998)] presents a real-time simulation to assign due dates on logistic-manufacturing networks. Information from the manufacturing, transportation, and supplier elements was integrated into a simulation model of the system to help the assignment of consistent delivery dates. [Seebacher et al. (2015)] presents a DES model that has been constructed to model the workflow of a production system with discrete manufacturing processes and its in-plant logistics processes. The authors' goal is to evaluate both machines (workstations) and vehicles utilization, but nothing was reported regarding the aisles. [Ĉujan (2016)] presents a DES that evaluates a supplying process. The focus is on the transportation time and the usage of the capacity. Also, [Patchong et al.(2003)] describes a simulation study applied over the internal logistics in a PSA Peugeot Citroen factories. The work's target is on the body shop phase. The authors combine simulation and Markov-chain models of series-parallel systems to reduce the bottlenecks found.

In the same way, [Roman-Verdugo (2014)] develop a methodological framework concerning the construction of a simulation model of the process flow. The work took place at the body-shop sector of a car-assembling company. [Faget et al.(2005)] describing a method to detect bottlenecks in DES models and applied to the Toyota Motor Company. The goal is to automate the bottleneck analysis. Finally, [Ludavicius & Ali(2014)] present a DES model to identify process throughput for the automotive manufacturing powertrain sub-assembly line. The work explored any potential machine bottlenecks to improve process throughput.

Regarding issues linked to Layout Evaluation, [Martínez-Barberá & Herrero-Pérez (2010)] approaches the issue of navigation using an automated guided vehicle (AGV) in industrial environments. The work describes the navigation system of a flexible AGV intended for operation in partially structured warehouses and with frequent changes in the floor plant layout. [Wang & Chang (2015)] presents the Facility Layout Problem that aims to minimize the material handling costs by determining the most efficient arrangement of facilities within a space. [Horta et al. (2016)] propose a mathematical programming approach, based on a min-max formulation that returns the optimized layout of a cross-docking warehouse that feeds a just-in-time distribution operation.

Concerning works that focus on Material Handling Flow (MHF), [Zhou & Peng (2017)] investigate the just-in-time (JIT) in-house logistics problem for automotive assembly lines. A point-to-point JIT distribution model has been formulated to specify the destination station and parts quantity of each delivery for minimizing line-side inventory levels. Also, [Klug (2013)] discuss the consequences of the bullwhip effect in a car-manufacturing. The focus is on the impact on the processes. Finally, [Mason et al. (2003)] develop a DES model of a multi-product supply chain to examine the potential benefits to be gained from global inventory visibility and trailer yard dispatching and sequencing techniques.

Moreover, there are works that approaches both MHF and warehouse issues. [Atieh et al. (2016)] investigate the impact of a warehouse management system on supply chain performance that provides fewer resources effort and reliable inventory management system. It also highlights the gap between theory and practice. [Caridade et al. (2017)] develop a proposal to restructure and optimize a company's warehouse. The main goal is to improve the efficiency of warehouse functions, reduce stock quantities and enhance the capacity to meet customer's demand. Lastly, [Poon et al. (2009)] study the introduction of RFID technology to facilitate the collection and sharing of data in a warehouse. The author main objectives are: (i) a simplification of RFID adoption procedure, (ii) an improvement in the visibility of warehouse operations and (iii) an enhancement of the productivity of the warehouse.

Concerning works that use simulation to tackles MHF on warehouses, [Ribino et al.(2018)] considered an agent-based simulation to analyze the behavior of automatic logistics warehouses and get information for the decision-makers. Likewise, [Gagliardi at al.(2007)] worked on warehouse problem but based on a DES model instead. The authors faced a real high throughput warehouse which handles more than 12 millions of cases annually. Results presented potential savings by reducing the number of stock-outs at the picking area.

Finally, the Routing Strategy were the focus of the following works. [Mehami et al. (2018)] study AGVs in a real factory scenario. The authors highlighted three aspects to effectively implement a smart AGV system: reconfigurability, flexibility, and customizability. [Vavrík et al. (2017)] introduces a method of the determination of the number of AGV and choosing optimal internal company logistics track. Also, [Lima & Ramalhinho(2017)] present a study focus on internal logistics routes' construction and optimization in the SEAT S.A. The routes generated were evaluated through different levels of demand. The demand was generated by the Monte-Carlo simulation. Table 2.1 summarizes the cited works.

To sum up, although there are many references of works that approach both logistics and manufacturing activities through DES or other simulation-based methodologies, those works that focus on the simulation of Internal Logistics Flows (ILF), under an aggregate per-

The work's focus	References
Production Flow	[Michalos (2010)], [Ruiz-Torres & Nakatani (1998)], [Seebacher et al. (2015)] , [Ĉujan (2016)] [Patchong et al.(2003)], [Roman-Verdugo (2014)], [Faget et al.(2005)], [Ludavicius & Ali(2014)]
Layout Evaluation	[Martínez-Barberá & Herrero-Pérez (2010)], [Wang & Chang (2015)], [Horta et al. (2016)]
Material Handling Flow	[Zhou & Peng (2017)], [Klug (2013)], [Mason et al. (2003)], [Atieh et al. (2016)], [Caridade et al. (2017)], [Poon et al. (2009)], [Ribino et al.(2018)], [Gagliardi at al.(2007)]
Routing Strategy	[Mehami et al. (2018)], [Vavrík et al. (2017)], [Lima & Ramalhinho(2017)]

Table 2.1: Logistics and Production related works.

spective, are unusual. To the best of the author's knowledge, the simulation literature lacks of studies that integrate more than one class of ILF to evaluate how a workshop can absorb all the traffic, for instance.

Moreover, the automotive sector can be viewed as a particular case regarding manufacturing companies. First, a significant amount of data is required to conduct a DES study over an entire assembly line. Usually, that sector does not disclose that required data. Second, the complexity of the DES is significant in terms of the number of processes. There are many processes to be considered because many types of ILF are introduced into the model. Third, besides the ILF processes, there are the workstations' orders to take into account. In SEAT, one assembling line can produce more than 600 cars each day. Also, a car is assembled with more than 2,500 materials in those workstations. So, the scope of the DES model is quite significant. Therefore, from the author's point of view, the absence of simulation studies in the literature over ILF in the automotive sector may be explained by its complexity and confidential issues.

2.4.2 Monte Carlo Simulation and the Vehicle Routing Problem with Stochastic Demand

Concerning the use of MCS in Vehicle Routing Problem with Stochastic Demand (VRPSD), [Juan et al. (2015)] state that the classic goals applied to the VRPSD could be to minimize the total distance traveled and to minimize the number of vehicles employed. The authors also describe the main classes of constraints applied to that problem. These classes are: all routes must begin and finish at the same depot; the vehicles are capacitated, and the capacity is the same for all of them; all the clients' demand must be satisfied, and each client should be supplied by a single-vehicle. One example of the VRPSD problem application was done by [Juan et al. (2013)]. The authors combined the Monte Carlo Simulation and parallel-computing in the search for solutions to the VRPSD. Earlier, [Juan et al. (2011)] combine the Monte Carlo simulation with the splitting techniques and the Clarke and Wright savings heuristic to find solutions to the Capacitated Vehicle Routing Problem (CVRP).

Research Contribution

In the remainder of this section, the author summarizes the main topics approached in this work that are related to the simulation methodology.

- Chapter 3 presents a Monte Carlo simulation method that evaluates the performance of a set of Internal Logistics Flows (ILF), considering a realistic and stochastic environment.

- Chapter 4 introduces a SimILS algorithm to calculate suitable fixed ILF. The simulation that embedded the ILS is based on the MCS, which considers the company's historical data to generate data.

- Chapter 5 introduces a simulation algorithm to evaluate the performance of both the company's current ILF and the flows computed through an ILS method.

- Chapter 6 provides a DES model whose objective is **to assess the ILF in a car-assembling workshop**. Besides, it presents a set of best practices for bench-marketing purposes for those who want to develop DES models centered on ILF analysis.

Chapter 3

OPTIMIZING INTERNAL LOGISTICS FLOWS OVER DETERMINISTIC DATA

This chapter is based on the following work:

Lima, M. F., Ramalhinho, H. (2017, December). Designing internal supply routes: A case study in the automotive industry. In *2017 Winter Simulation Conference (WSC)* (pp. 3358-3369). IEEE.

3.1 Introduction and problem statement

This chapter represents the first mathematical optimization procedure conducted during this work. The company stated that the current methodology applied to compute and evaluate internal routes should be improved. So, an Integer Linear Programming (ILP) and a Monte-Carlo Simulation methods were developed. For further detail about the current processes applied by the company, see chapter 1.

The ILP model aims to compute an optimal set of routes that are responsible for supplying all placed orders, considering a determined type of SKU and a specific assembling line. So, it deals with one class of SKU. Also, the ILP must take into account the main Key-Performance-indicators (KPI), which are: (i) the number of routes calculated; (ii) the total distance traveled; (iii) the number of backorders; and (iv) the number of free spots in convoy. All these KPI were set by the company.

The problem is defined as the Warehouse Shipping and Routing problem. It can be seen as an extension of the well-known Capacitated Vehicle Routing Problem (CVRP), see [Crainic & Laporte(2012)], [Laporte (2009)], [Juan et al. (2015)], which is an NP-hard problem as stated by [Solomon (1987)].

Moreover, a Monte Carlo simulation was developed to evaluate different scenarios based on the real data provided by the company. Consequently, the simulation enables the comparison between the computed set of routes and the company's set of routes into different production's backgrounds.

In this sense, this chapter deals with the warehouse shipping and routing at SEAT, which can be seen as an one-product capacitated vehicle routing problem with deterministic demand in a car assembling company. On the one hand, the workstations' demands are stochastic in practice. On the other hand, in this chapter, the demand was simplified and treated as deterministic in the ILP. However, the stochasticity is considered and evaluated during the Monte Carlo Simulation.

Next, subsection 3.1.1 discusses the applied methodology.

3.1.1 Methodology

In this subsection, the overall methodology applied in this chapter is presented. The main purpose is to evaluate the performance of the input routes. So, there are some steps to follow, as described in figure 3.1. Each step is described in detail next.

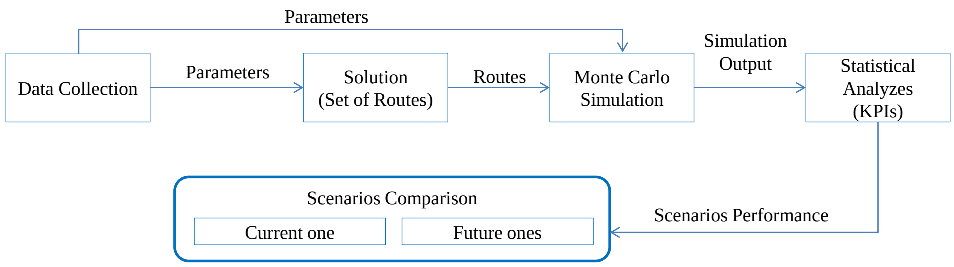


Figure 3.1: Methodology phases' interaction

First, it starts with the Data Collection process. The Data Collection is important to understand all aspects and processes of the problem. In addition, a statistical study is performed to evaluate the workstations orders, as discussed in chapter 1. Second, a set of feasible solutions is inserted. It may be either an output of an ILP model or the company's current solutions. The ILP model is presented in subsection 3.2. Third, the performance of the input routes is evaluated through a Monte Carlo simulation. The simulation procedure is in charge of analyzing how the routes work when facing different stochastic scenarios (discussed at subsection 3.2). Fourth, the performance of the routes is evaluated through several KPIs. These KPIs were defined based on strategic parameters set by the company. The fifth step is to prepare the conclusions of the tested scenarios, which regard to different demand levels. This methodology was designed after observing the decision process currently implemented in the company.

The remainder of this chapter is organized as follows. Section 3.2 presents the ILP model and the simulation method. Section 3.3 refers to the experiments performed, and section 3.4 presents the conclusions and describes future work.

3.2 The Solution Method

In the Optimization procedure, the routes are obtained by solving an ILP model in a deterministic environment. Next, these routes are tested through the Monte Carlo simulation that is based on stochastic scenarios. The company's current routes are evaluated through the same stochastic scenarios as well. Next, the ILP model and the Monte Carlo simulation are presented.

3.2.1 The Integer Linear Programming model

The ILP model of the current problem is an extension of the Asymmetric Capacitated Vehicle Routing Problem (ACVRP). So, the next paragraphs present data sets, parameters, variables, the objective function (OF), and constraints that were introduced in that ILP model.

The introduced data sets refer to the locations to supply ($n \in N$), where n = 0 represents the depot and the rest represent the workstations; The arc set ($a \in A$), in which arc $(ij) \in A$ represents the connection between the nodes ($i, j \in N$).

Next, the parameters are introduced; The fixed travel cost spent to go from node i up to node j (DC); The fixed cost of introducing a route (RC); The fixed cost of a free spot in the convoy (EC); The distance between nodes ($i, j \in N$) is (d_{ij}); The convoy's capacity (C); The maximum number of convoys is (m); The convoy's average speed (v); The time required to supply a material at the workstation or node ($tsup$); The average demand (D_i) of the node ($i \in N$), which is the average demand of a workstation during the considered time-horizon. A workstation's average demand is the sum of the total demand per the total of periods considered. As illustrated in figure 1.8, the total of periods is the ratio between the time-horizon per a considered time-window. In this work, the considered time-window is set to 60 minutes. Also, the workstations' average demands were considered based on the company's historical data.

Lastly, the decision variables are presented: the x_{ij} variable will be equal 1 if arc $(ij) \in A$ is activated, 0 otherwise. The U_i variable represents the load of a vehicle after visiting workstation $(i \in N)\backslash i \neq 0$. The model is presented next.

$$\min \sum_{i}^{N} \sum_{j\backslash(i\neq j)}^{N} (DCd_{ij}x_{ij}) + RC \sum_{j\backslash(j\neq 0)}^{N} x_{j0} + EC(\sum_{j\backslash(j\neq 0)}^{N} x_{j0}C - \sum_{i\backslash(i\neq 0)}^{N} D_i) \tag{3.1}$$

$$\sum_{i\backslash(i\neq j)}^{N} x_{ij} = 1 \qquad \forall j \in N\backslash\{0\} \tag{3.2}$$

$$\sum_{j\backslash(i\neq j)}^{N} x_{ij} = 1 \qquad \forall i \in N\backslash\{0\} \tag{3.3}$$

$$\sum_{i\backslash(i\neq 0)}^{N} x_{i0} \leq m \tag{3.4}$$

$$U_j - U_i + x_{ij}C \leq C - D_i \qquad \forall i \in N, j \in N\backslash\{i \neq j\} \tag{3.5}$$

$$D_i \leq U_i \leq C \qquad \forall i \in N\backslash\{0\} \tag{3.6}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in N, j \in N\backslash\{i \neq j\} \tag{3.7}$$

$$U_i \in \mathbb{Z}^+ \qquad \forall i \in N\backslash\{0\} \tag{3.8}$$

The equation 3.1 represents the Objective Function that aims to minimize the sum of the costs associated with the real problem, which are: the total distance of the routes, the total number of routes, and the cost related to a convoy that is not loaded fully. In this last case, each empty spot (i.e., without a box) represents a lost opportunity to the company. Also, these KPIs are aligned with others works from the literature, which already considered different variants of the Vehicle Routing Problem with Stochastic Demand (VRPSD). See [Juan et al. (2015)]. Then, the constraints 3.2 state that all the workstations must be attended. The constraints 3.3 state that all vehicles must leave the workstation after unloading. The constraints 3.4 ensure that the maximum number of convoys that departs from the depot is m. The constraints 3.5 and 3.6 are the sub-tour elimination constraints. These constraints impose both the connectivity of the solution and the vehicle capacity requirements. The constraints 3.7 state that variables x_{ij} are binaries. The constraints 3.8 state that variables U_i are integer and positive.

3.2.2 The Monte Carlo Simulation

In this chapter, the simulation evaluates the routes' performance by testing them through different scenarios. These scenarios were calculated based on the average and the standard deviation (SD) of a two-weeks workstations' demand (demand from Monday to Friday). Table 3.1 describes the seven scenarios tested. In scenario 0 (Historical Data), a set of routes is evaluated by applying the actual historical demand. Then, scenarios 1 to 6 correspond to the Monte Carlo simulation output. The demand for each workstation is randomly generated based on variations of the SEAT's actual demand.

Item	Standard Deviation Description	Average Demand
0	Historical data	Historical data
1	Low (↓ 5%)	Current
2	High (↑ 5%)	Demand
3	Low (↓ 5%)	Higher
4	High (↑ 5%)	Demand (↑ 5%)
5	Low (↓ 5%)	Lower
6	High (↑ 5%)	Demand (↓ 5%)

Table 3.1: Scenarios' description. The disclosed percentage is based on the company's historical data. As a result, the Monte Carlo simulation generates orders based on an assumed normal distribution, whose parameters are detailed in the table. For example, scenario four considers a normal distribution, in which both the SD and the demand are 5% higher than the company's actual values.

The demand for each one of 113 workstations was generated through the Monte Carlo method. A normal distribution was assumed to compute the workstations' demand. So, the average and SD of this Normal distribution were calculated based on the two-week historical data. By assumption, it is stated that the likelihood of a workstation asks more or fewer materials is equal. That is the reason that normal distributions were chosen. The implementation of this procedure was done through C++ code.

Then, for each proposed scenario, a time horizon of ten days are evaluated. Each day contains 45 periods of 60 minutes. These periods were established after removing all scheduled pauses in the production line. Also, the cumulative variation of 10 percent in the average demand is coherent to the actual level of production and corresponds to the planning objectives. Likewise, the cumulative SD variation was set up to 10% (the difference between the higher and lower SD) because a greater variety would be an unreal overestimated factor, considering the analyzed historical data.

So, the orders generated through the Monte Carlo simulation should be assigned to its respective route and the period when it must be supplied. Afterward, the supplying activity is simulated, considering a route's trajectory, a convoy's average speed, a material handling time, and the convoy's capacity. The system also considers those orders that are not attended at the correspondent period. In those cases, the orders will be supplied at the following period. Notice that the routes are fixed and backorders may occur due to lack of supplying capacity. In this chapter, orders that are not supplied during the simulation due to lack of capacity will be defined as backorders. The simulation's scheme is presented in figure 3.2.

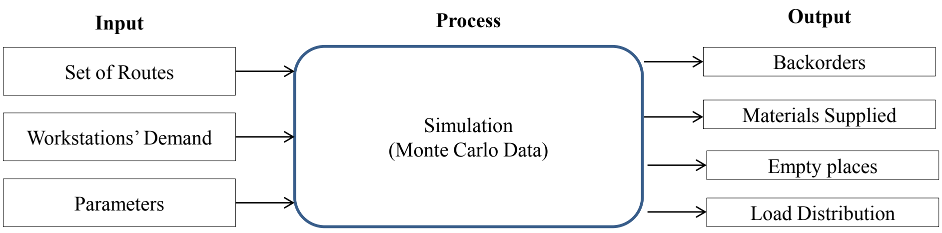


Figure 3.2: Simulation scheme

Then, the expected simulation's outputs are (i) the total of backorders, (ii) the total of materials supplied, (iii) the total of empty places (spots) in all convoys and, (iv) the cargo loaded distribution among the routes.

3.3 Experiments

Section 3.3 presents the experiments executed and the analysis of the results obtained. First, the ILP output is presented and compared to the company's current solution. Next, the simulated results are presented. Those results refer to the simulation of the scenarios presented in table 3.1.

3.3.1 ILP Output

The experiment was processed in a machine equipped with Intel i7 processor, 2.70GHz, 16GB RAM and Linux 64 bits Ubuntu 11.0.4. The program languages C++ and AMPL were used. The mathematical model was solved through the compiler GNU GCC and the software

CPLEX version 12.8.0. Time processing limit of 3,600 seconds was set for the CPLEX execution. Then, the best solution provided was considered and stated as the feasible proposed routes. The ILP's output and the company's solution are presented in table 3.2.

Item	Total of Routes	Distance Traveled (meters)	OF Costs
Current Routes	6	3,959.0	4,559.0
Proposed Routes	3	2,779.8	3,079.8

Table 3.2: ILP Solution and the current one comparison in terms of the number of routes and the sum of these routes' distances.

The ILP model achieved much better results in comparison to the current company's solution, as presented in table 3.2. The comparison is made in terms of the number of routes and the sum of the routes' distance. The simulation phase is responsible for providing KPI results for all solutions through the considered scenarios. Although the ILP solution's GAP is 19.5%, the objective functions' result is 3,084.16. The GAP is defined as the following equation: *(Upper Bound - Lower Bound)/Upper Bound*. Regarding the costs assigned for each objective function component, the Route's cost (RC) is defined as 100 monetary units, the distance's cost (DC) is stated as one monetary unit per meter, and the empty spot's cost (EC) is stated as one monetary unit as well.

The current Routes' results were obtained through the calculation of these results based on the costs stated in the last paragraph. So, regarding the performance of the company's KPIs, the first KPI refers to the total of routes needed to execute the warehouse shipping. The current set of routes presents six routes, and the optimized one presents three routes. So, the proposed routes are half of the current ones. The second KPI regards the total distance traveled during the studied period. The current set of routes presents a total of 3,959 meters, and the proposed one presents 2,779.8 meters, which is about 30% lower than the current one.

It is noteworthy mention the company evaluate the routes through a term called "Logistics group". It refers to a set of workstations that were clustered and create a Logistic group. By contrast, this work evaluates the workstations individually. As a result, it permits workstations from different logistics groups to be joined and compound one route.

3.3.2 Simulations Outputs

Before describing the simulations results, some premises are stated. First, a route's trajectory completion time is limited up to 60 minutes. Second, the total number of empty spots was calculated by summing all the empty spots in each convoy throughout the considered time-horizon. Moreover, if a route has not any material to supply in a period, then the total of empty spots will be zero for that period. It means the convoy stays in the warehouse during that period. The simulation results are presented in tables 3.3, 3.4 and 3.5.

Item	Scenario 0		Scenario 1	
	P.R.	C.R.	P.R.	C.R.
(I) Backorder	0%	0%	0%	0%
(II) Supplied	100%	100%	100%	100%
(III) E.Spots	98,266	198,043	139,248	310,529
OF cost	7,205	12,877	8,952	17,601

Table 3.3: Simulation output - Scenarios 0 and 1. The letter P.R. represents the proposed routes and the letter C.R. the current ones. The items I, II, and III represent the percentage of backorders, the percentage of attended demand, and the sum of empty spots, respectively. The percentage of the items I and II refer to its respective metrics and the total demanded during the simulation.

Item	Scenario 2		Scenario 3	
	P.R.	C.R.	P.R.	C.R.
(I) Backorders	0%	0%	0%	0%
(II) Supplied	100%	100%	100%	100%
(III) E.Spots	139,248	310,530	138,347	309,628
OF cost	8,928	17,601	8,890	17,563

Table 3.4: Simulation output - Scenarios 2 and 3. The letter P.R. represents the proposed routes and the letter C.R. the current ones. The items I, II, and III represent the percentage of backorders, the percentage of Attended demand, and the Sum of empty spots, respectively. The percentage of the items I and II refer to its respective metrics and the total demanded during the simulation.

The main conclusion regarding those experiments is that both sets of routes were able to supply all demand. That is an important observation since the number of proposed routes is significantly smaller than the number of actual routes. The reduced number of routes leads

Item	Scenario 4		Scenario 5		Scenario 6	
	P.R.	C.R.	P.R.	C.R.	P.R.	C.R.
(I) Backorders	0%	0%	0%	0%	0%	0%
(II) Supplied	100%	100%	100%	100%	100%	100%
(III) E.Spots	9137,793	309,654	141,123	311,681	140,549	311,395
OF cost	8,867	17,564	9,007	17,650	8,983	17,638

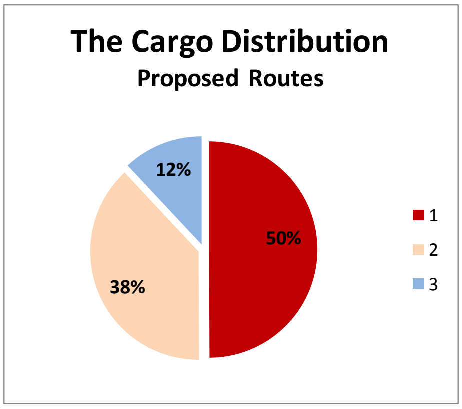
Table 3.5: Simulation output - Scenarios 4, 5, and 6. The letter P.R. represents the proposed routes and the letter C.R. the current ones. The items I, II, and III represent the percentage of backorders, the percentage of Attended demand, and the Sum of empty spots, respectively. The percentage of the items I and II refer to its respective metrics and the total demanded during the simulation.

to a cost reduction on equipment and personal. In addition, the total number of empty spots also reduced. The proposed routes presented nearly 45% less empty spots compared with the current routes. That output is another significant result because it represents a substantial improvement in the efficiency of the use of resources.

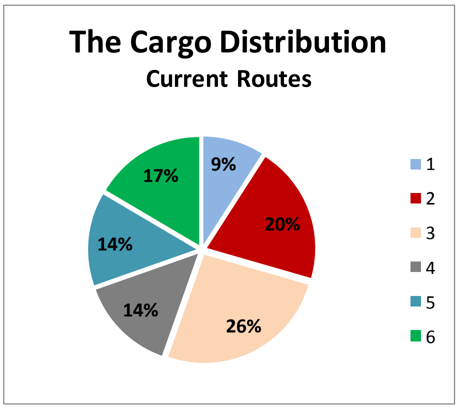
Regarding the load distribution among the routes, figure 3.3 illustrates the load distribution related to the worst-case scenario, which is the fourth one. This scenario represents both the higher demand and higher Standard Deviation (SD) levels. So, that scenario was selected to evaluate how a set of routes manages the load distribution between the routes. Consequently, figure 3.3 illustrates that the computed ILP solution does not handle that KPI properly because there is one route that is responsible for half of the workload. On the contrary, the current company's solution tackles better this issue. As a result, the logistics manager should evaluate the pros and cons of both solutions. Note that this indicator is measured in terms of the number of orders assigned to each route.

3.4 Conclusion

The main contributions of this chapter are summarized as follows: (i) presenting a case study about a real internal logistics routing problem in the car-assembling factory, (ii) designing an ILP model that provides suitable and feasible solutions, and (iii) presenting a Monte Carlo simulation method that evaluates the performance of a set of routes, considering a realistic and stochastic environment. Also, this chapter considered both real data and the company's KPI's, leading to



(A)



(B)

Figure 3.3: The workload distribution between the proposed routes and the current solution. This indicator is measured in terms of the number of orders assigned to each route. The letter A represents the results achieved by the proposed routes and the letter B the current ones. Moreover, each figure's number represents a different route.

interesting business insights for the SEAT Logistics department.

To sum up, this chapter studies and analyses a real case of a warehouse shipping and routing problem at a car-assembling factory. An ILP model for a deterministic version of the problem and a simulation procedure based on Monte Carlo simulation were proposed. The ILP model aims to provide feasible solutions or a set of routes, and the simulation's goal is to evaluate the performance of the routes on a realistic stochastic environment using the company's KPIs.

The ILP's solution overcame the current solution over the two main KPI's: Total of routes and routes' distance. The third KPI refers to the number of backorders. For this one, both ILP's routes and current's routes were able to deliver all the demand on time and without backorders because all orders were delivered in the considered time-horizon. Finally, the fourth KPI is the number of empty spots in convoy. The proposed set of routes presented a better performance on this KPI than the current one through the simulated scenarios. The total average number of empty spots for the new routes is about 45% lower than the current ones.

Another important aspect is the loaded cargo balance among the routes, which should be reviewed in future work due to the poor performance observed of the proposed routes. This aspect could be improved by including specific constraints on the model.

Therefore, on the one hand, it can be concluded that the proposed set of routes can be implemented in a real context. The applied methodology enables decision-makers to evaluate the performance of a mathematical model's output in a realistic context, via the Monte Carlo simulation phase. Consequently, a better knowledge of the strengths and the weakness of the mathematical model's solution are unveiled. Moreover, one of the main applications and benefits of this work is to enable the company to obtain better insights and to plan, more efficiently, when it launches a new car model, for instance.

On the other hand, that work is viewed as the first attempt to optimize a specific logistic flow inside an assembling workshop. A feasible solution was achieved. However, it has some limitations concerning the way that the orders variability are tackled. Perhaps, the premise that considers the workstations demands as average values is not the most suitable one. Also, the solution provided by the ILP model is not the optimal one. As a result, it also should be further evaluated in future work.

Moreover, future works may focus on developing strategies to improve the interface between the Optimization and the Simulation phases, by feeding optimization models' parameters with insights from the simulation phase, see [Osorio & Selvam (2017)]. That approach can be made using a Simheuristic, [Juan et al. (2015)]; [Grasas et al.(2016)], that integrates the optimization and simulation phase in a repeated cycle intending to improve the solution.

Furthermore, we could extend this work by considering the production forecast. These areas could help to plan the impact on that forecast in the logistics activities and, in particular, the warehouse shipping problem at a car manufacturer.

Chapter 4

THE IN-HOUSE LOGISTICS ROUTING PROBLEM

4.1 Introduction and problem statement

In this chapter, the internal logistics routing problem is further studied. That problem is viewed as an operational and strategic one because it is highly relevant to the company's business due to several reasons that are pointed next. First, it is directly connected with the activities that add value to the product. Second, it is a problem with high complexity, there are more than 120 workstations to supply in each production line, and each workstation has a singular demand behavior. Moreover, if the supply fails, the production may stop. A company that produces 2,400 cars daily cannot afford regular fails in the production line.

So, the main issue consists of designing the internal supply routes in a car-assembling factory, as illustrated in figures 1.7 and 1.9. Additionally, this problem can be seen as an extension of the one-product Capacitated Vehicle Routing Problem with stochastic demand. However, it is not the same problem.

The characteristics of the tackled problem are the following: (i) stochastic and unknown demand; (ii) self-ask-supply approach; (iii) long-term and fixed routes; (iv) drivers must return to the depot after concluding the route; (v) orders are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are allowed; (viii) each workstation is assigned to a route; (ix) fixed-customer-sequence definition; (x) capacitated vehicles; and (xi) homogeneous fleet. Therefore, to the best of the author's knowledge, all these assumptions give rise to a brand-new problem of the vehicle routing class. That problem is stated as the **In-house Logistics Routing Problem** (ILRP). Chapter 2 provides a comparison between the In-house Logistics Routing Problem and the related Vehicle Routing Problems (VRP).

Furthermore, figure 4.1 summarizes the main concepts of the ILRP. Note that figure 4.1 presents a scenario that considers two fixed routes, which are illustrated by the green and orange trajectories introduced in the workshop layout. Moreover, those routes must supply the workshops' orders, whose locations are illustrated by the colored circles placed in the workshop layout. Besides, observe that each workstation is placed above a specific route because a workstation is supplied by one route only. Also, at the bottom of the figure 4.1, there is a timeline, in which the workstations' orders are placed. Notice that those orders are clustered into periods. Then, the defined fixed routes are responsible for supplying all the period's orders. However, a workstation's orders tend to be unsteady, as observed in the figure. That approach may incur in backorders because there are periods, whose total number of placed orders surpass a route supplying capacity.

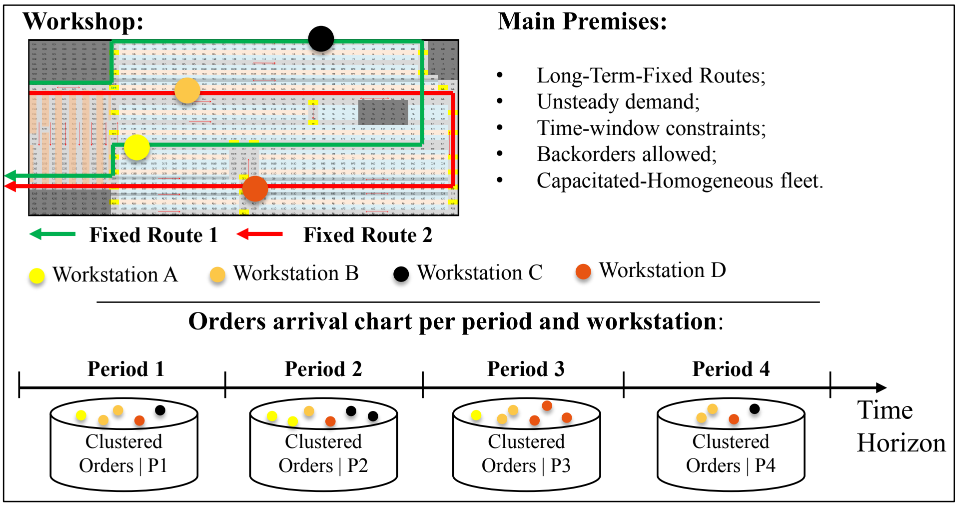


Figure 4.1: The In-house Logistics Routing Problem description.

To exemplify how the supply activity works, figure 4.2 presents a three-period example. In this example, one fixed route is considered, which is able to supply up to three SKU in each period. Also, figure 4.2 presents the Service-Quality-Level (SQL) Concept, which is defined by the ratio between the number of units supplied on-time per the total of orders. Then, a simulation of each period is executed, taking into account the stated premises. Note that backorders have priority over current period's orders. Also, a period's backorder is defined as a delayed order that was not supplied in previous periods. As a result, backorders are viewed as the consequence of the time-windows constraints violations.

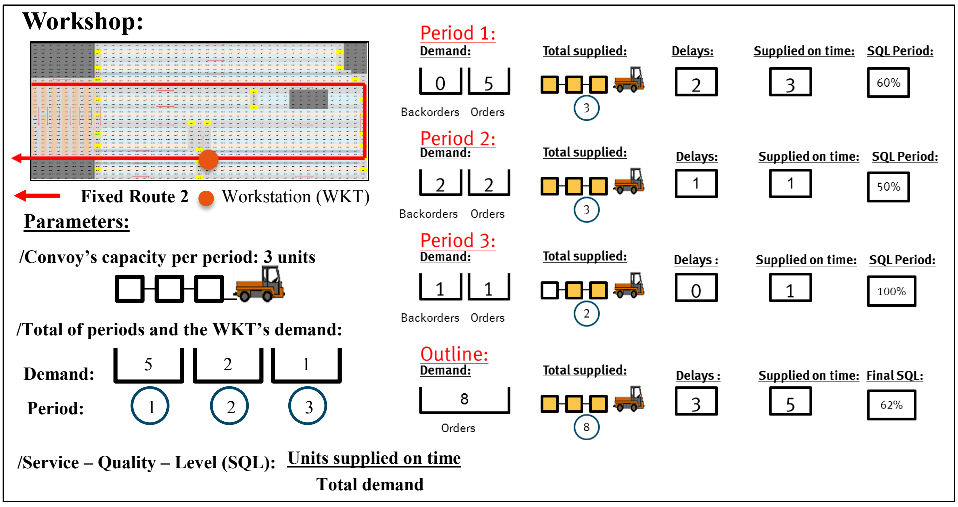


Figure 4.2: The In-house Logistics Routing Problem simulation.

As a result, three major objectives are faced in this chapter. Firstly, to propose a deterministic mathematical model based on Integer Linear Programming (ILP), which provides solutions to the described problem. Secondly, to present a simulation-based Iterated Local Search (SimILS) Metaheuristic capable of calculating good solutions for a large-scale and stochastic version of the cited problem. Finally, to apply these methods on a real data context and analyze the results.

Consequently, three major objectives are pursued that are translated into the following primary Key Performance Indicators (KPIs): (i) the number of routes; (ii) the total routes' distances; and (iii) the total volume of materials not supplied on time (backorders). All of these indicators are standardized under the same measure, a cost function defined by the company.

Also, the company considers other secondary KPIs, defined as (i) the total orders supplied; (ii) the total distance covered throughout the simulation; and (iii) the total of empty spots of the convoys that departed from the warehouse during the simulation. It is noteworthy to state that the secondary KPI are computed through a simulation procedure.

Also, note that the primary KPIs will be used to calculate the best supply routes. Consequently, the primary KPIs guide the optimization procedures. Meanwhile, both the primary and secondary KPIs will be used to evaluate the performance of different solutions through a simulation procedure over a realistic environment.

In this chapter, the SEAT's workshop is assumed to have more than 120 workstations. Each workstation has an unknown and unsteady demand, as illustrated by figure 1.10. So, the data evaluation was executed as the following. First, data from a considered time horizon was gathered. Then, all the data was distributed into different periods. Likewise chapter 3, each period is compounded by one hour effectively worked, in which the pauses were not considered. As a result, a total of 21 periods per day is assumed. So, if a scenario of 10 days is considered, a total of 210 periods will be generated, in which the orders of more than 120 workstations are placed.

The workstations' orders used in this chapter is a sample of the real data provided by the company. The provided orders refer to two different periods of the years 2017 and 2018. Each year corresponds to a data set. Next, each data set is separated into two clusters based on a time sequence. The first cluster (cluster 1) regards to the first half of the requests done, and its major purpose is to be the input data for algorithms, which calculate suitable solutions. Then, the second cluster (cluster 2) represents the requests done in the second half of the considered time-horizon. The cluster 2's purpose is to evaluate the cluster 1 's solution, but considering a different set of data, see figure 4.3. Note that the ILP is a deterministic formulation because the input data is already known (cluster 1). However, the ILRP presents stochastic orders actually. Therefore, the routes computed based on known orders are verified considering a brand-new data set, which is cluster 2. In this sense, estimated orders (cluster 1) are considered for computing a feasible solution to be proofed by unknown orders.

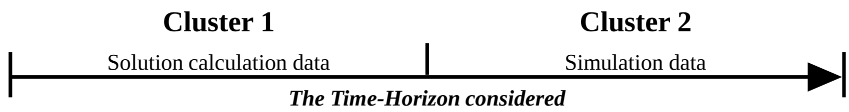


Figure 4.3: The data clustering scheme. The 1st cluster gives support for the routes optimization. Then, the 2nd cluster major purpose is to evaluate the previous solution obtained.

Consequently, the main goal of this work is to compute a solution to the ILRP, which provides a satisfactory set of fixed routes to cope with a stochastic system over an internal logistics context. The developed methodology has two phases. The first phase consists of calculating a set of fixed routes to handle the company's supplying activity. In this phase, the cluster 1 data is introduced. Moreover, there are two optimization approaches proposed: (i) an ILP model and (ii) a SimILS Metaheuristic. The ILP is known to provide-proofed optimal solutions. Also, the ILS has been successfully applied to complex Combinatorial Optimization problems, see [Lourenço et al.(2019)]. Additionally, the simulation aspect of the SimILS enables the introduction of stochastic data. In this phase, the main goal is to compute a solution that can handle further real scenarios.

In the second phase of the proposed methodology, the cluster 1's solution is evaluated. The computed set of routes is simulated over the cluster 2 data, whose orders are different from cluster 1's ones. Besides, cluster 1's solution is compared with the company's one through the simulation approach.

The remainder of this chapter is organized as follows. Section 4.2 presents the mathematical model. Next, section 4.3describes the SimILS method. Section 4.4 refers to the experiments performed, and section 4.5 presents the conclusions and describes future work.

4.2 The Integer Linear Programming model

In this section, the Integer Linear Programming (ILP) model of the deterministic version of the In-house Logistics Routing Problem (ILRP) is presented. This model is an extension of the Asymmetric Capacitated VRP model described in [Crainic & Laporte(2012)]. The main objective of the mathematical model is to find the optimal-fixed routes to be applied. Therefore, an important aspect of the model is the input data, in particular, how the workstations' orders are considered in the model.

As said in chapter 1, the workstations' orders are gathered through the SEAT's SAP system. Consequently, the considered orders are a sample of historical data. Then, the total demand of a workstation will be the sum of the orders places throughout that a specific time window. See figure 1.8 for further information about orders clustering. The details of the ILP model are detailed next.

The data sets introduced are the following: the set of locations to supply ($n \in N$), where n =1 represents the Depot and the rest represent the workstations; the arc set ($a \in A$). The periods set ($l \in L$), in which L represents the complete time horizon; the routes' frequency set ($r \in R$).

Next, the parameters are introduced; the convoy's capacity (C); the fixed travel cost spent to go from node ($i \in N$) up to node ($j \in N$) (MC); the fixed cost of introducing a route (RC); the fixed cost of a backorder (SC); the distance between nodes ($i, j \in N$) is (d_{ij}); the maximum number of convoys (K); one period's length (T); the time required to supply a material at the delivery point ($tsup$); the convoy's average speed (v); the maximum frequency a route can have (R); the demand (D_{il}) of the node ($i \in N$) at the period ($l \in L$), which is the demand of a workstation during a period considered l. Notice that deterministic data values, such as speed and a material's supplying time were defined by the company; and the considered workstations' orders were based on historical data.

Finally, the decision variables are introduced: the x_{ijkr} variable will be equal 1 if arc $(i, j) \in A$ belongs to the route ($k \in K$) and has a frequency ($r \in R$) within a period, 0 otherwise; the y_{ikr} variable will be equal 1 if node ($i \in A$) is visited by vehicle ($k \in K$), which has a frequency ($r \in R$); the bc_{lk} represents the backorders inserted in the vehicle ($k \in K$) at the period ($l \in L$); the f_{kr} represents the frequency ($r \in R$) that a route ($k \in K$) has within one period time T. Finally, the add_k is the additional capacity that a route ($k \in K$) can receive. The ILP model is presented next:

$$\min \sum_{i}^{N} \sum_{j\backslash(i\neq j)}^{N} MCd_{ij} \sum_{k}^{K} \sum_{r}^{R} x_{ijkr} + \tag{4.1}$$

$$\sum_{k}^{K} \sum_{j\backslash(j\neq 1)}^{N} \sum_{r}^{R} RCx_{1jkr} + \sum_{l}^{L} \sum_{k}^{K} SCbc_{lk}$$

$$\sum_{r}^{R} f_{kr} \leq 1 \qquad \forall k \in K \tag{4.2}$$

$$\sum_{i\backslash i>1}^{N} y_{ikr} \leq f_{kr}|N| \qquad \forall k \in K, r \in R \tag{4.3}$$

$$\sum_{k}^{K} \sum_{r}^{R} y_{ikr} = 1 \qquad \forall i \in N\backslash i > 1 \tag{4.4}$$

$$\sum_{k}^{K} \sum_{r}^{R} y_{1kr} \leq K \tag{4.5}$$

$$\sum_{r}^{R} \sum_{i\backslash i>1}^{N} (D_{il}y_{ikr}) + bc_{(l-1)k} \leq \tag{4.6}$$

$$\sum_{r}^{R} (rCf_{kr}) + add_k + bc_{lk} \qquad \forall l \in L, k \in K$$

$$\sum_{j\backslash(j\neq i)}^{N} x_{ijkr} = y_{ikr} \qquad \forall k \in K, r \in R, i \in N\backslash i \neq 1 \tag{4.7}$$

$$\sum_{j\backslash(j\neq i)}^{N} x_{jikr} = y_{ikr} \qquad \forall k \in K, r \in R, i \in N\backslash i \neq 1 \tag{4.8}$$

$$\sum_{i,j\in S\backslash(j\neq i)}^{N} x_{ijkr} = |S| - 1 \qquad \forall S \subset N, k \in k, r \in R \tag{4.9}$$

$$add_k \leq C \qquad \forall k \in K \tag{4.10}$$

$$(\sum_{r}^{R} \sum_{j\backslash(i\neq 1)}^{N} (D_{il}y_{ikr}) + bc_{(l-1)k} - bc_{lk})tsup+ \tag{4.11}$$
$$\sum_{r}^{R}\sum_{i}^{N}\sum_{j\backslash(i\neq j)}^{N} r*(d_{ij}/v)x_{ijkr} \leq T \qquad \forall k \in K, l \in L$$

$$[T - (r+1)(\sum_{i}^{N}\sum_{j\backslash(i\neq j)}^{N} (d_{ij}/v)x_{ijkr}) \tag{4.12}$$
$$-(f_{kr}rCtsup)]/tsup \leq add_k \qquad \forall k \in K, r \in R$$

$$x_{ijkr} \in \{0,1\}, \mathbb{Z} \qquad \forall i,j \in A, k \in K, r \in R \tag{4.13}$$
$$y_{ikr} \in \{0,1\}, \mathbb{Z} \qquad \forall i \in N, k \in K, r \in R \tag{4.14}$$
$$bc_{lk} \in \mathbb{Z}^+ \qquad \forall l \in L, k \in K \tag{4.15}$$
$$f_{kr} \in \mathbb{Z}^+ \qquad \forall k \in K, r \in R \tag{4.16}$$
$$add_k \in \mathbb{Z}^+ \qquad \forall k \in K \tag{4.17}$$

The objective function (OF)(4.1) minimizes the sum of the costs related to the total distances covered by all the routes, the number of routes, and the costs related to the backorders of the route ($k \in K$) at a period ($l \in L$). The constraints (4.2) define the number of laps, or the frequency ($r \in R$), that route ($k \in K$) does during one period. Constraints (4.3) state the maximum number of nodes a route ($k \in K$) can visit, considering its frequency ($r \in R$). Constraints (4.4) state that each customer must be attended by only one route. Constraint (4.5) states that the depot must be visited by $|K|$ vehicles at most. Next, the constraints (4.6) define the number of backorder bc_{lk} of the route ($k \in K$) in the period ($l \in L$). The constraints (4.7) and (4.8) define that the vehicles that visit a node ($i \in N$) must depart from that location after the supplying activity. The constraints (4.9) are responsible for avoiding the sub-tours to happen. The constraints (4.10) state that the maximum additional capacity a route can receive is fewer or equal to C. The constraints (4.11) state that each route can last up to T minutes, taking into account the capacity, the supplying time, the distance, and the traveling speed. The constraints (4.12) define the maximum additional capacity a route can receive, based on the amount of time left in a period. Lastly, constraints (4.13), (4.14), (4.15), (4.16), and (4.17) define the domain of the variables.

Notice that the constraints (4.6), (4.10), and (4.13) aim to increase a convoy's capacity as much as possible. To do so, the constraints consider a rule called as **residual capacity**, which is explained as follows. A convoy's capacity is calculated through a function that has the following parameters: (i) convoy speed; (ii) period duration; (iii) time to supplied materials; and (iv) route's length. For example, suppose one scenario, in which a period has 60 minutes and a route's duration is about 21 minutes, including the supplying time to place all materials in the correct place. Consequently, the route can complete two trips within 60 minutes. If the convoy has its capacity limited to 4 orders per travel, the capacity will be equal to 8 as a result. Nevertheless, there are 19 minutes left to supply. So, we add to the capacity the exact number of orders the convoy is able to supply and back to the depot before finishing the current period. So, if the trajectory takes 12 minutes, the supplying procedure three minutes per order and there are 19 minutes left, the algorithm will be able to add two units more in the total capacity. As a result, the total capacity of this route will be ten units per period. That procedure enables the algorithm to come closer to real practice.

To obtain the solutions for this model, the AMPL language was used and solved by CPLEX 12.6.8, as explained in section 4.4.

4.3 The simulation-based Iterated Local Search

The Simulation-based Iterated Local Search (SimILS) Metaheuristic is based on the methodology proposed by [Grasas et al.(2016)]. In this section, a SimILS algorithm to solve the ILRP is presented. The reason to select the SimILS is due to the remarkable results of the ILS to solve Combinatorial Optimization Problems (COP), such as real problems, whose demand is unknown, see [Grasas et al.(2016)]. So, the SimILS is considered as an appropriate solution approach because it can handle with real-based problems. The algorithm 4 resumes the complete SimILS Metaheuristic developed.

Algorithm 4: The complete SimILS Algorithm

$(S_0)\leftarrow$ Generate_Initial_Solution
$(S^{'}) \leftarrow$ Execute the SimILS procedure $(S_0, W_{Priority\_routes\_weights})$
$(S^{*}) \leftarrow$ Execute the SimILS procedure $(S^{'}, W_{Priority\_SQL\_weights})$
Return Best_Sol(S^{*})

It is noteworthy to state that the objective function introduced in the SimILS is the same one introduced in the ILP (equation 4.1). Moreover, the complete algorithm 4 shows that the SimILS procedure is applied twice with different inputs and objectives; that is the reason it is called as completed. In the first phase, the method seeks a solution with a reduced number of routes. Indeed, a solution with a bigger number of routes than the current solution is not allowed by the company. As a result, the first phase calculates a solution $(S^{'})$ which is compounded by the fewer number of routes possible. Consequently, fictitious high weights are introduced on the routes' and the distances' terms, and low fictitious weight is assigned to the backorders one. It is done to force the reduction of the number of routes and the total routes' distance.

Afterward, the SimILS procedure is repeated, but based on the solution $(S^{'})$, which was previous computed, and different fictitious weights. The new weights are related to the Service-Quality-Level (SQL). The SQL is defined as the rate between the number of orders supplied at the correct period per the total of orders received during all considered periods. In this phase, the SimILS is forced to improve the backorders indicator without increasing the number of routes and the total routes' distance. As a result, the output solution is a trade-off between those three considered criteria, which are: (i) number of routes, (ii) sum of each route's distance, and (iii) total of backorders.

Next, the components that integrate the SimILS metaheuristic are described. The algorithm 5 resumes the structure applied, which can be divided as follows: (i) the initial solution, (ii) Local Search (Intra-route phase), (iii) Local Search (inter-route phase) (iv) the simulation phase, (v) the perturbation phase, and (vi) the stopping criterion.

Algorithm 5: The Sim-ILS Algorithm

1 $S_0 \leftarrow$ Generate_Initial_Solution (*sub-section 4.3.1)*
2 $S^* \leftarrow$ Local_Search_Intra_Routes (S_0) (*sub-section 4.3.2)*
3 $SimOF^* \leftarrow$ Simulation ($S^*, Weights$) and Let $S^{'} = S^*$
4 **while** $(it\_ils \leq it\_ils\_LIM)$ **do**
5     $S^{'} \leftarrow$ Local_Search_Inter_Route($S^{'}$) (*sub-section 4.3.3)*
6     $S^{'} \leftarrow$ Local_Search_Intra_Route($S^{'}$)
7     $SimOF^{'} \leftarrow$ Simulation ($S^{'}, Weights$) (*sub-section 4.3.4)*
8   **if** $(SimOF^* > SimOF^{'}) \wedge$
9     $(SQL(SimOF^*) < SQL(SimOF^{'}) \vee (it\_ils < it\_ils\_LIM/2))$ **then**
10   Let ($S^* \leftarrow S^{'}$) and Let ($SimOF^* \leftarrow$SimOF$^{'}$)
11   **end**
12   **if** $(it\_ils < it\_ils\_LIM)$ **then**
13   **if** $(it\_ils > it\_ils\_LIM/2)$ **then**
14             $S^{'} \leftarrow$ Perturbation ($S^*, Pert\_Service\_Level$)(*sub-section 4.3.5)*
15   **else**
16             $S^{'} \leftarrow$ Perturbation ($S^{'}, Pert\_Service\_Level$) (*sub-section 4.3.5)*
17   **end**
18   **end**
19     $it\_ils \leftarrow it\_ils + 1$
20 **end**
21 $SimOF^* \leftarrow$ Simulation (S^*, $Weights$) *and* **Return** ($SimOF^*$)

The main elements applied in algorithm 5 are introduced as follows: S_0 is stated as the initial solution; S^* is defined as the output solution of the Local Search Intra Routes moves (subsection 4.3.2) when the input solution is (S_0); $SimOF^*$ is the objective function value computed through the SimILS procedure.

Afterward, once the iterations phase is reached (line 4), the $S^{'}$ value is considered, which may receive the output solutions computed by the following procedures: (i) Local Search Inter Routes moves; (ii) Local Search Intra Routes moves (subsection 4.3.3); and (iii) the perturbation phase, lines 5, 6 and 14 (also 16) respectively of the algorithm 5. Moreover, there is one parameter applied that is the $Pert\_Service\_Level$, which is introduced at the Perturbation phase's description further ahead.

Note that a *Service level* is defined as a solution's capability of supplying the orders during the correct period. So, based on the number of orders received and the number of backorders, the service level value may be reached.

4.3.1 The Initial Solution

An initial feasible solution is obtained through a greedy algorithm, which each workshop's aisle is viewed as a route. So, on the one hand, the initial solution will have many routes. On the other hand, these routes are sequenced correctly. That is viewed as an advantage because the workstations are supposed to be visited in sequence. The initial solution is introduced through the method *Generate_Initial_Solution* in the algorithm 5.

4.3.2 Local Search phase (Intra-Route Neighborhood Search)

Next, an Intra-Route Neighborhood Search (Intra-RNS) is executed. In this work, the Intra-RNS consists of applying moves inside the same route in a similar way proposed by [Penna et al.(2013)]. In other words, one node (representing a workstation) or more nodes from a route are transferred to another position in the same route. [Penna et al.(2013)] define the *Or-optK* move, which refers to K adjacent nodes that are removed from a route and inserted in another position of the same route. Its computational complexity is $O(n^2)$. The purpose of the Intra-RNS application here is to verify any route's improvement opportunity. This procedure is executed through the method *Local_Search_Intra_Routes* procedure. The reader may observe that the Intra-RNS moves are applied in the algorithm 5 in lines 2 and 6.

4.3.3 Local Search phase (Inter-Route Neighborhood Search)

The Inter-RNS moves involve a set of nodes that moves between routes. In other words, one or more nodes from a route are transferred to another different route. These moves are also based on the [Penna et al.(2013)]'s work. In this work, the Inter-RNS moves that have a positive impact on the local search are the *Shift (1,0)* and the *k-Shift*. The *Shift (1,0)* selects a unique node and inserts it in any position of the new route. The *k-Shift* move consists in selecting a subset of consecutive nodes K from a route A and inserting them at the end of a route B.

In both moves, it must be checked the new route's capability to deliver the relocated demand, concerning the route's capacity. Notice that both Inter-RNS moves have the same computational complexity, which is $O(n^2)$.

Then, the moves' strategy is defined based on [Penna et al.(2013)]. However, a modification of the *k-Shift* movements is executed, which is called *k-Shift-complete*. Even though a solution's cost is still an important acceptance criterion here, there are two main differences between this work's approach and the *k-Shift* and *Shift (1,0)* ones. The first variance concerns the confrontation between demand and capacity. On the one hand, the *k-Shift-complete* permits backorders to happen. On the other hand, it will penalize the OF whenever it occurs. the previous moves do not allow backorders. The second difference regards the nodes relocation from the original route into a second one. The subset of K consecutive nodes is placed at all the possible locations of another route, including at the beginning and the end. By contrast, [Penna et al.(2013)] state the *k-Shift* places the transferred nodes at the end of a route only.

So, the *k-Shift-complete* is neither limiting the movement to a route's end location nor transferring only one node at each time. Regarding the acceptance criterion, the solutions' costs are considered as the main measure. It is computed as same as equation 4.1.

To conclude, the SimILS takes into account the best improvement strategy, whenever the local search phase is executed, because the problem is considered as a strategical one and the execution time is not a relevant issue. The reader may observe that the Inter-RNS moves are applied in the algorithm 5 line 5. An example of both Intra and Inter-RNS moves is illustrated in figure 4.4.

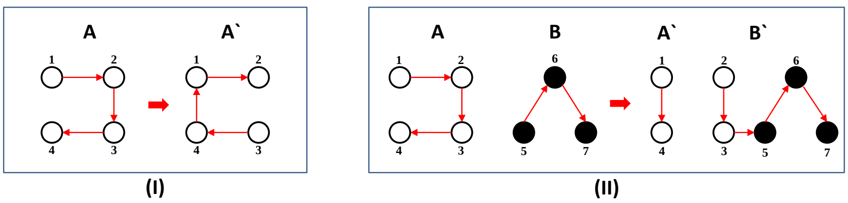


Figure 4.4: An Or-opt2 (I) and a 2-Shift-complete (II) moves examples.

4.3.4 Simulation Phase

One important aspect of SimILS is the simulation phase. In this subsection, the simulation procedure is defined as **Simulation(*Solution*, *Weights*)**, in which *Solution* refers to the input solution and *weights* refers to the OF's weights, which were described in section 4.2. So, to execute the simulation procedure, two main inputs are necessary, which are: (i) the fixed routes calculated in the Local Search phase, and (ii) the workstations' orders. Afterward, the simulation procedure discloses the results related to the primary KPIs, which are necessary calculate a solution's OF. Moreover, the secondary KPIs can also be calculated through the simulation. The later KPIs will be used as secondary criteria to evaluate a solution. The simulation structure is presented by algorithm 6. Note that the simulation procedure is entirely related to the example presented by figure 4.2.

Algorithm 6: The Simulation Algorithm

$S^* \leftarrow$ Input Solution (Fixed Routes)
for *(Route* $\in S^*$*)* **do**
  for *(p* $\in$ *Periods)* **do**
    Total_Backorders += Get_Back_Orders(Route, p)
    Total_Dist_Traveled += Get_Distance_Traveled(Route, p)
    Total_Supplied_Route += Get_Supplied(Route, p)
    Total_Empties_Route += Get_Empties(Route, p)
  end
end
Return ($SimOF^*$) Simulated OF and KPIs.

Here, all periods of the time horizon are considered. As a result, it is defined as the complete simulation ($Comp\_Sim$). The Comp_Sim has its advantages and drawbacks. On the one hand, it may lead to a high computational effort, depending on the time horizon's size. On the other hand, it permits a complete evaluation of the time horizon considered. Therefore, the algorithm could assess extensively the solutions calculated by the Local Search phase. In this sense, Comp_Sim is a suitable approach because the SimILS deals with a strategic problem. In other words, the company does not need to compute a new solution so often because the routes do not change regularly. As a result, an objective function value ($SimOF$) is set based on the Comp_Sim's output, as described in the Algorithm 5.

Then, the Algorithm 5 executes the Comp_Sim in three moments. The first one is placed at the beginning of the SimILS procedure to compute and save the $SimOF(Initial\_Solution)$. Next, the Comp_Sim is called after the LS phase to compute the $SimOF(Local\_Search)$. Finally, the Comp_Sim computes the $SimOF(Final\_Solution)$ to close the SimILS procedure. Note that the Comp_Sim is responsible for calculating a solution's objective function value.

To conclude the Comp_Sim description, the **residual capacity rule**, stated in subsection 4.2, is also considered here.

4.3.5 Perturbation Phase

The purpose of the Perturbation phase is to make a significant change in the current solution to start searching another space of feasible solutions. It can be resumed into two main points. Firstly, that technique must conduct the ILS to escape from an optimal local solution. Secondly, the Local Search should not easily undo the perturbation execution. By doing so, it will permit the ILS to go to a large search on the space of feasible solutions. The perturbation can be found in the algorithm 5 through the method **Perturbation(*Solution*, *Perturbation SQL*)**.

So, the perturbation procedure applied in this work is based on the Inter-route moves described in subsection 4.3.3. Considering previous experiments, the algorithm is set to run ten iterations during the perturbation phase. Moreover, it has the same Inter-route moves' structure except for two main differences.

First, on the one hand, the inter-RNS algorithm evaluates the solution's cost in order to decide if a new solution should be accepted or not. On the other hand, the perturbation procedure does not care about the solution's cost but the Service-Quality Level (SQL). So, a new route will be accepted in the solution as long as its SQL value is lower or equal to the defined SQL limit. As a result, the SQL is a relevant indicator because it avoids low-SQL solutions, which could produce poor results at the local search phase further ahead. In addition, there is another important criterion to take into account, which concerns the solution introduced in the perturbation procedure. It varies depending on the iteration that the SimILS algorithm is, see algorithm 5. So, the current solution ($S^{‘}$) will be the input up to the first half of the total of iterations. Afterward, the best solution found so far (S^{*}) will be introduced.

Then, the second divergence between the Local Search and the perturbation procedure refers to the way that the SQL is computed. So, the complete simulation is executed in the Inter-RNS algorithm, but a partial one ($Partial\_Sim$) is applied in the perturbation phase instead.

The Partial_Sim works over a single route only, which is the one created by the inter-RNS moves. The main idea is to perform a short simulation and reduce the computational effort during the simulations executions. So, a biased-random method was created to reduce the simulation iterations, in which all the periods are sorted in a decreasing manner, regarding its backorders values. So, the first item of the list will be the period that has the highest backorders value (likewise, the worst SQL result). That method was developed based on the work of [Grasas et al.(2017)].

Afterward, an item (period) of this list is randomly selected. The criterion to pick up one item is based on a geometrical distribution, which usually prioritizes the top-ranked values. Also, the total number of selected items is limited to one decimal part of the total of periods. As a result, the simulation will considered only a small subset of the total of periods. Moreover, the selected periods are likely to be the most disruptive ones, in terms of the number of backorders.

4.3.6 The SimILS Stopping Criterion

Concerning the stopping criterion, the main condition to interrupt the procedure is whenever the maximum number of iterations is achieved. The SimILS's maximum number of iterations value is presented in the appendix 4.7 at the end of this chapter.

4.4 Experiments

The methods described in previous sections are evaluated through two main computational experiments. The first experiment's main goal is to compare the performance between the ILP model and the SimILS algorithm. The second experiment aims to compare the performance between the SimILS algorithm and the company's actual solution.

The experiments were carried out on the Operational System Windows 7 Enterprise 64 bits, Intel Core i7-4810MQ, 2.80GHz, 8 cores and 16 GB of RAM as the maximum capacity. Moreover, the programming languages JAVA were used to build the SimILS. Also, the ILP was modeled through AMPL language and was solved by CPLEX 12.6.8.

4.4.1 The instances

An instance is defined as the number of orders that a set of workstations (WST) requires over a determined time-horizon. So, one instance differs from another regarding the following aspects: (i) the set of WST considered; (ii) the number of orders; and (iii) the time-horizon considered. Saturdays, Sundays, and holidays data were not included because it does not represent a typical working day. So, two sets of data were gathered. The data sets are divided into two categories, which are the small boxes (SB) orders category, and the large containers (LC) orders one. As described in the chapter 1, this work deals with a "one-product" problem that can tackle orders of SB and LC separately.

Next, for each SKU class, three groups of data were collected. The first group is called Test data, which is a particular subset compound by a selection of all the workshop's workstations and their respective orders throughout a considered time-horizon. By contrast, the second group considers all workstations that compound an assembly line, as well as their respective orders; in this case, five working days were used. Finally, the third group of data is like the second one (all workstations) but considering the demand during a larger time-horizon size one, in this case, four weeks.

Furthermore, those orders were collected over two different periods in the year, which refer to different production level and other intrinsic features. The orders were collected directly in the material management system of the company (SAP). The table 4.1 summarizes the instances' characteristics, and the data's details are presented in the table 4.7. Then, in the table 4.1, there are the following indications, concerning the data clustering strategy: (1) test data; (2) real data with five-days time horizon; and (3) real data with a four-weeks time horizon. Next, the **Item** column refers to the name of the instances; the **Material Type** refers to an instance's SKU class; the column **Days** refers to the instance's number of days; column **Period** represents the number of periods an instance considers; the **WST** refers an instance's total of workstations considered. The * marker highlights the real-world instances.

Class (Group)	Item	Material Type	Days	Periods	WSTs
Test Data(1)	1-3		5	105	10
	4-6		5	105	15
	7-9	Small Boxes	5	105	20
Real Data(2)	10*		5	105	123
Real Data(3)	11*		22	420	122
Test Data(1)	12-14		5	105	10
	15-17		5	105	15
	18-20	Large Containers	5	105	20
Real Data(2)	21*		5	105	127
Real Data(3)	22*		22	420	126

Table 4.1: The summary of the instances' structure.

As mentioned, two main experiments are performed in this chapter. Experiment 1 aims to evaluate the performance between the ILP model and the SimILS approaches through a subset of workstations and their respective demands. Figure 4.6 summarizes the main four steps of experiment 1. Note that the methods' performance is measured based on the Objective Function value (expression 4.1) and the computational time using the Test data class (1), which is presented in table 4.1.

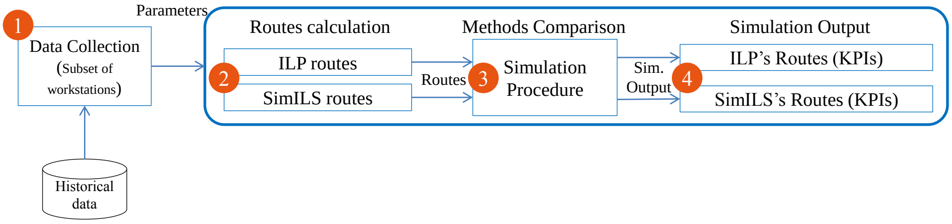


Figure 4.5: The ILRP experiment 1's scheme. A sample of the company's data is collected. Note that a subset of the total of workstations is considered. Then, the optimization methods are executed under the same input data. Next, the respective computed solutions and further premises are inserted in a simulation procedure. Finally, the simulated output are compared.

Afterward, experiment 2 is presented by figure 4.6, in which two phases are observed. Those phases represent the data set clustering idea illustrated by figure 4.3. In this sense, the first phase represents the cluster 1 application, in which the SimILS algorithm calculates fixed routes through the real historical data (2) and (3) presented in table 4.1. As a result, the first phase of experiment 1 is compound by the steps one, three, five, and six of the figure 4.6.

Later, the second phase of experiment 2 refers to the cluster 2 application over the real historical data (2) and (3). So, that phase is present by figure 4.6 through steps two, four, five, and six. Note that the solutions computed in step three are introduced in step four. Moreover, notice that the simulation procedure (algorithm 6) is applied to the current fixed solutions used in the company also. As a result, the purpose is to compare the SimILS solution with the company's current one. The table 4.2 resumes the experiments conducted.

Item	Method	Data
1	ILP vs. SimILS	Test Data (A subset of workstations)
2	SimILS_sol vs.Current_sol	Real Data (Phases 1 and 2)

Table 4.2: The experiments outline.

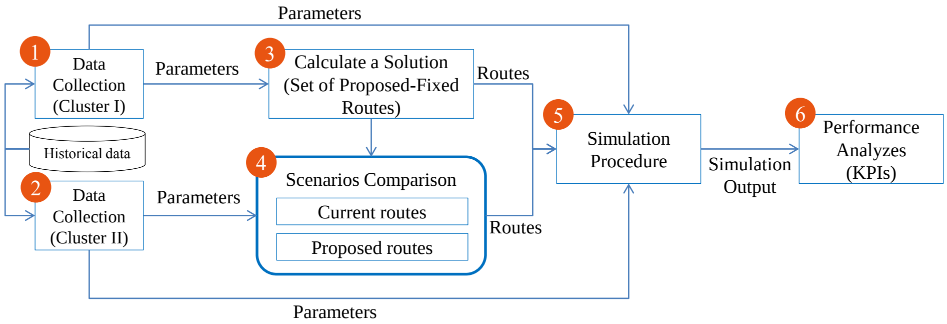


Figure 4.6: The data clustering scheme. The 1st cluster gives support for the routes optimization. Then, the 2nd cluster major purpose is to evaluate the previous solution obtained.

The Parameters

The parameters used in the experiments are both set by the company directly (e.g., cost values or vehicles capacity) and obtained via preliminary experiments (e.g.,total of iterations in the perturbation phase). The parameters used in the experiments are indicated in table 4.7. Moreover, a C++ code procedure was developed to build a distance matrix. That matrix presents the minimum distance from one workstation to the others, considering the workshop layout.

4.4.2 The Experiment 1

Experiment 1's goal is to compare the results provided by the ILP model and the SimILS. Once these methods have the same OF expression, they will be evaluated based on the OF values and computational time. The results related to the experiment 1 are presented in the tables 4.3 and 4.4.

So, a total of nine experiments were conducted regarding the ILP and the SB class. The ILP model found the optimal solution for four instances; feasible solutions with about 14.5% gap for two instances; and could not find any feasible solution for three instances. Likewise, nine ILP experiments were conducted for large containers. Then, the ILP model found the optimal solution for three instances; feasible solutions with about 20% gap for three instances, and could not find any feasible solution for three instances.

Concerning the SimILS's results, the algorithm was able to find feasible solutions for all tested instances. Precisely, two of these solutions were optimal ones, as proved by the ILP.

As a result, the ILP and SimILS methods were compared, taking into account the optimal solutions provided by the ILP. For those optimal solutions, the GAP between the methods' solutions has been smaller or equal than 5% for six out of seven optimal solutions found. Notice the $GAP = OF(ILP)/OF(SimILS) - 1$.

Even though the ILP model can manage to compute the better solutions in the easiest instances, the SimILS outperformed the ILS in the most complicated ones in a very short computational time. Notice also that the computer ran out of memory when running the ILP model for the larger instances (20 workstations). Consequently, no solution was computed in those cases. Therefore, the SimILS is able to provide very good results in short time making the SimILS a proper algorithm to deal with more complicated or real-world instances, like those applied in experiment 2.

4.4.3 The Experiment 2

Here, the objective is to compare the performance between the company's set of routes and the solutions computed through the SimILS procedure. To better explain those experiments, this section is divided into two parts. The first part refers to a solution calculation applying the cluster 1 concept, see 4.3. Then, the second part refers to solution evaluation through the simulation of cluster 1's solution over the cluster 2 data.

Solution Calculation Experiments - Cluster 1

As presented in section 4.1 and illustrated by figure 4.3, the complete-real data was distributed into two clusters. In experiment 1, only the instance's solutions gathered through cluster 1 are available. The table 4.5 presents both the results computed by the SimILS and the results provided by the simulation of the current routes provided by the company.

Item	WST	Method	OF Value	R.	Distance (m)	Back Orders	GAP cplex(%)	Time (sec)
1	10	ILP	**1459,8**	1	1359,8	0	0%	16
1	10	SimILS	1607,2	1	1507,2	0	-	6
$GAP_{met.}$			10%		11%	0%	-	
2	10	ILP	**1953,9**	1	1853,9	0	0%	12
2	10	SimILS	1956,3	1	1856,3	0	-	5
$GAP_{met.}$			0,1%		0%	0.1%	-	
3	10	ILP	**2308,9**	1	1853,9	355	0%	37
3	10	SimILS	2311,3	1	1856,3	355	-	6
$GAP_{met.}$			0.1%		0%	0.1%	-	
4	15	ILP	**1686,9**	1	1586,9	0	0%	2219
4	15	SimILS	1741,4	1	1641,4	0	-	6
$GAP_{met.}$			3%		3%	0%	-	
5	15	ILP	2020,4	1	1920,4	0	14%	7200
5	15	SimILS	2032,3	1	1932,3	0	-	6
$GAP_{met.}$			1%		1%	0%	-	
6	15	ILP	2247,18	1	2147,2	0	15%	7200
6	15	SimILS	2251,1	1	2151,0	0	-	5
$GAP_{met.}$			0.2%		0.2%	-	-	
7	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
7	20	SimILS	2357,2	1	2257,2	0	-	8
8	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
8	20	SimILS	2002,7	1	1902,7	0	-	11
9	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
9	20	SimILS	2247,2	1	2147,2	0	-	7

Table 4.3: The Summary of the small boxes Experiment 1's results. The bolded values represent optimal solutions. The (*) marker indicates that no feasible solution was provided. The R. refers to the number of routes. Also, the $GAP_{met.}$term refers to the comparison between the values computed by the ILP and SimILS. It is computed as $(ILP_{Value}/SimILS_{Value} - 1)$.

Item	WST	Method	OF Value	R.	Distance (m)	Back Orders	GAP cplex(%)	Time (sec)
12	10	ILP	**1100,4**	1	997,49	3	0%	16
12	10	SimILS	1150,4	1	1047,4	3	-	5
GAP$_{met.}$			5%		5%	0%	-	
13	10	ILP	**1317,2**	1	1217,2	0	0%	17
13	10	SimILS	**1317,2**	1	1217,2	0	-	7
GAP$_{met.}$			**0%**		0%	0%	-	
14	10	ILP	**1349,2**	1	1217,2	32	0%	34
14	10	SimILS	**1349,2**	1	1217,2	32	-	9
GAP$_{met.}$			**0%**		0%	0%	-	
15	15	ILP	1409,2	1	1132,2	177	13%	7200
15	15	SimILS	1293,9	1	1144,9	49	-	11
GAP$_{met.}$			-8%		1%	-72%	-	
16	15	ILP	1670,9	1	1493,9	77	26%	7200
16	15	SimILS	1509,4	1	1362,4	47	-	9
GAP$_{met.}$			-10%		-9%	-39%	-	
17	15	ILP	2126,3	2	1920,3	6	21%	7200
17	15	SimILS	1959,5	1	1765,5	94	-	7
GAP$_{met.}$			-8%		-8%	1467%	-	
18	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
18	20	SimILS	4756,5	1	1492,5	3164	-	10
19	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
19	20	SimILS	2658,5	1	2288,5	270	-	8
20	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
20	20	SimILS	4260,1	1	2537,1	1623	-	11

Table 4.4: The Summary of the Large Containers Experiment 1's results. The bolded values represent optimal solutions. The (*) marker indicates that no feasible solution was provided. The R. refers to the number of routes. Also, the $GAP_{met.}$term refers to the comparison between the values computed by the ILP and SimILS. It is computed as $(ILP_{Value}/SimILS_{Value} - 1)$.

Item	M. Type	Clt	Routes' Class	OF	Routes (units)	Distance (meters)	Back Orders	T. Supplied	T. Emp. Spots	T. Traveled	Time (sec)
10	SB	1	Current	13.650,49	4	5.800	3.850	11.761	4.923	330.857	1
10	SB	1	SimILS	9.387,34	4	4.722	665	11.783	5.209	273.984	122
GAP$_{met.}$				-31%	-	-19%	-83%	0%	6%	-17%	
11	SB	1	Current	325.703,12	4	3.912	317.791	50.981	20.876	911.764	1
11	SB	1	SimILS	188.375,84	4	5.223	179.152	52.862	6.105	1.064.024	547
GAP$_{met.}$				-42%	-	34%	-44%	4%	-71%	17%	
21	LC	1	Current	18.506,60	6	8.313	4.194	3.152	275	1.052.110	1
21	LC	1	SimILS	11.482,32	6	5.214	268	3.256	504	768.700	137
GAP$_{met.}$				-38%	-	-37%	-94%	3%	83%	-27%	
22	LC	1	Current	210.550,79	6	6.862	197.689	13.222	1.240	3.394.932	1
22	LC	1	SimILS	82.677,43	6	5.221	71.456	14.680	1.143	3.270.752	784
GAP$_{met.}$				-61%	-	-24%	-64%	11%	-8%	-4%	

Table 4.5: The summary of the experiments 2's result - cluster 1. The first column refers to a instance's item and the second refers to the Material type. The LC means Large Containers and SB means Small Boxes. The third column refers to the cluster. The fourth column indicates the solution's origin. The fifth column depicts the OF's value. The sixth column presents the number of routes. The seventh column refers to the sum of all the solution's routes distance. The eighth column points out the backorders. The ninth column presents the total of orders attended. The tenth column refers to the total of empties spots. The eleventh column presents the total distance traveled. Finally, the twelfth column refers to the computational time. Also, the $GAP_{met.}$term refers to the comparison between the values computed by the ILP and SimILS. It is computed as $(Current_{Value}/SimILS_{Value} - 1)$.

Solution Evaluation Experiments - Cluster 2

To conclude the experiment 2's executions, the second phase of tests was conducted. Here, the goal is to evaluate the solution computed before (cluster 1) into a new set of data (cluster 2). As a result, both SimILS solutions and the company's current solution are simulated based on the cluster 2 data basis. Table 4.6 presents the results.

Regarding the analysis of the results, the SimILS method outperformed the company's solutions. It can be confirmed by each OFâs indicators. Moreover, the secondary KPIs were improved in most of the cases as well. Even though the number of routes is the same for each instance, the reader may notice that the SimILS's solutions presented a better OF values in all tested instances. The difference between the SimILS routes and the company's ones relies on two premises. The first premise concerns with how the high/low turnover materials are faced. That premise is explained next. As an assumption, a single workstation is split into two workstations whenever it receives both classes of materials; in other words, low and high turnover materials. Likewise, the company does the same strategy in their current analysis. Also, the company prefers routes that join workstations, which receive materials with related consumption rate.

On the contrary, this work did not take it into account to compute solutions. As a result, materials with different consumption rates are allowed to be mixed in the same route in this work. The reader may notice that our approach may avoid two routes to visit the same workstation. The second premise concerns the workstations clustering as well, but focus on its locations instead. The company usually does not merge workstations from different areas, or aisles, in the same route. By contrast, this work did not take into account any clustering limitation rule.

Item	M. Type	Clt	Routes' Class	OF	Routes (units)	Distance (meters)	Back Orders	T. Supplied	T. Emp. Spots	T. Traveled	Time (sec)
10	SB	2	Current	14.018,49	4	5.800	4.218	8.642	3.303	235.034	1
10	SB	2	SimILS	9.612,34	4	4.722	890	8.773	3.251	192.253	1
GAP$_{met.}$				-31%	-	-19%	-79%	2%	-2%	-18%	
11	SB	2	Current	206.902,12	4	3.912	198.990	51.763	20.455	908.962	1
11	SB	2	SimILS	146.387,44	4	5.223	137.165	52.681	5.278	1.046.986	1
GAP$_{met.}$				-29%	-	34%	-31%	2%	-74%	15%	
21	LC	2	Current	17.273,60	6	8.313	2.961	2.961	210	757.375	1
21	LC	2	SimILS	11.442,32	6	5.214	228	2.416	352	559.594	1
GAP$_{met.}$				-34%	-	-37%	-92%	-18%	68%	-26%	
22	LC	2	Current	153.324,79	6	6.862	140.463	13.404	1.250	3.439.588	1
22	LC	2	SimILS	46.669,43	6	5.221	35.448	14.606	1.097	3.247.471	1
GAP$_{met.}$				-70%	-	-24%	-75%	9%	-12%	-6%	

Table 4.6: The summary of the experiments 2's result - cluster 2. The first column refers to a instance's item and the second refers to the Material type. The LC means Large Containers and SB means Small Boxes. The third column refers to the cluster. The fourth column indicates the solution's origin. The fifth column depicts the OF's value. The sixth column presents the number of routes. The seventh column refers to the sum of all the solution's routes distance. The eighth column points out the backorders. The ninth column presents the total of orders attended. The tenth column refers to the total of empties spots. The eleventh column presents the total distance traveled. Finally, the twelfth column refers to the computational time. Also, the $GAP_{met.}$term refers to the comparison between the values computed by the ILP and SimILS. It is computed as $(Current_{Value}/SimILS_{Value} - 1)$.

4.5 Conclusion

This chapter considers a real problem in a real car-assembling company that consists of finding the best supply routes from the warehouse to workstations, which are located along an assembly line. These routes are maintained fixed for an extensive period. Meanwhile, demand is unknown. The objective is to find routes that are cost-efficient and do not lead to delays in production. To the best of the author's knowledge, a brand-new problem to the VRP literature is presented, which is called the **In-house Logistics Routing Problem**. That problem is compound by a set of premises stated as follow: (i) the stochastic and unknown demand; (ii) the self-ask-supply approach; (iii) the long-term and fixed routes; (iv) the driver must return to the depot after concluding the route; (v) requests are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are allowed; (viii) each customer is assigned to a route; (ix) the fixed-customer-sequence definition; (x) capacitated; and (xi) homogeneous fleet.

So, both an ILP model to a deterministic version of the problem and a SimILS algorithm were proposed to calculate suitable fixed routes. Also, a comparison between these two approaches was performed, and the conclusion is that the SimILS obtained excellent solutions, in particular for the larger instances.

Another experiment that compares the solutions obtained by the SimILS with the actual company solution was conducted, using large and real data (historical data). For those cases, the SimILS obtained the best overall results, considering the objective function values and computational time. Moreover, taking into account the KPIs presented by the company, the SimILS presented better performance than the company's solutions in all the real-world instances evaluated.

As a result, it is possible to state that this work presents a valuable methodology to be applied to any car-assembling company. Indeed, the methodology and results received positive and valuable feedback from the company's experts, who found it novel and interesting. So, the third conclusion refers to the remarkable contribution to the company, as depicted by the results presented.

As future work, methods that are able to solve large instances of the In-house Logistics Routing Problem should be explored, such as the branch-and-cut procedure and lagrangean relaxation. Moreover, extensions of the SimILS and the simulation procedure may be improved by adding a more realistic aspect, such as the traffic on the assembly-lines, the use of a different type of vehicles and self-guided automatic vehicle.

Finally, concerning the real application, it would be quite interesting studying the introduction of alternatives systems that do not count with the logistics operator as the one responsible for placing orders but an automatic-placing-order system. That study should also evaluate the most suitable management procedure to regulate the logistics flows based on that new scenario.

Data	Application	SimILS Parameters	
		1st phase	2nd phase
Number of Iteration	ILS	8	8
Number of Iteration	LS	8	8
Fictitious Weight	Route	1,000	1,000
Fictitious Weight	Distance	100	1
Fictitious Weight	Backorders	0.08	1
Max K-value	The LS moves	10 nodes	
Convoy Speed	All cases	7 km/h	
Convoy Capacity	Large Boxes	4	
Convoy Capacity	Small Boxes	48	
Placing a Large SKU	Large Boxes	2.69 min	
Placing a Small SKU	Small Boxes	0.66 min	

Table 4.7: Chapter 4 - Appendix A: Summary of the SimILS's parameters structure.

Chapter 5

ASSESSING IN-HOUSE LOGISTICS FLOWS

5.1 The internal logistics routing management system

The objective of this chapter is to analyze the current company's scenario and to propose three alternative ones for the company's Internal Logistics Routing Management (ILRM) system. The three scenarios refer to Internal Logistics alternatives that are evaluated through Operational Research methodologies, which are seen as supportive tools. The main target is to reduce the number of backorders. Therefore, that chapter conducts an assessment of the ILRM system in a car-assembling company.

So, the first alternative scenario considers variables routes using the actual placing-orders system (the logistics operator is responsible for placing the orders); the second one uses variable routes but considering that the demand is given by automatic-ordering system; the third alternative scenario also considers variable routes dependent on the demand but using a forecast demand obtained by the Manufacturing Resource Planning (MRP) system.

To proceed with that analysis, a set of methods based on Operations Research were developed, which are: (i) a data analysis to understand the demand behavior; (ii) an **Integer Linear Programming** (ILP) model to compute feasible solutions for each alternative scenario; (iii) a metaheuristic that consists of an **Iterated Local Search** (ILS) algorithm to solve the large-scale realistic instances; and (iv) a Simulation procedure to evaluate the performance of the scenarios in a realistic environment using real data.

As a result, this chapter presents interesting problems in a car-assembly company as well as it proposes an ILP model and an ILS algorithm that evaluate a real case in SEAT company. This proposed methodology can be applied and extended to any car-assembling company.

The remainder of this chapter is organized as follows. Section 5.2 presents the internal-logistics routing management system and the methods applied to make the analysis of the considered scenarios. Section 5.3 describes data analysis. Section 5.4 presents the mathematical model. Next, section 5.5 describes the ILS algorithm to solve the routing problem for large-scale applications. Section 5.6 describes the simulation algorithm responsible for evaluating the company's current solution. Section 5.7 reports the computation experiments and its results. Finally, section 5.8 presents the conclusions and describes future work.

5.2 The internal logistics routing management system

An internal logistics routing management (ILRM) system controls the delivery of the orders from the warehouse towards the assembling line. This work considers four ILRM systems, which are the SEAT's current one and three alternatives systems. The three new scenarios are defined as follows: (i) variable routes and current orders, (ii) variable routes and automatic-ordering system and (iii) variable routes and forecasted orders. Therefore, four possible scenarios of ILRM system are discussed. These scenarios differ from themselves regarding the routing and order concepts, as shown in figure 5.1.

Concerning the routing concepts, two classes are considered, which are the**fixed routing** and the **variable routing**. In other words, fixed-routing management considers scenarios where the routes are always the same for an extended period, which is similar to a public-buses routes. In this case, the manager must decide which set of routes is the most suitable one to supply all the materials for a long-term horizon, e.g., months. By contrast, the variable-routing management enables to rebuild a set of routes periodically, according to the workstations' demands. Moreover, the manager must decide the frequency that those routes will be updated.

Regarding the ordering concepts, three possibilities are considered in this work. The first possibility considers the actual system of the company, in which the logistics operator visits the workstations each time the route is executed and decide if orders should be placed or not. The second possibility refers to an ordering system based on an automatic-placing-orders system (automatic one). Lastly, there is a possibility that considers a forecast demand system obtained by the Manufacturing Resource Planning (MRP) system (forecasted orders). The company actual orders are taken into account to develop these three ordering systems.

So, for the first system (current order one), the company's historical demand is analyzed. For the automatic-placing-orders system, the company's historical demand is considered to propose an automatic system that places orders steadily. Finally, the real-orders provided by the company are taken into consideration to propose a forecasted based order procedure. Each scenario is explained next.

Orders / Routes	Current Orders	Automatic-Orders System	Forecasted Orders
Variable Routes	Variable routes and current orders scenario (2)	Variable routes and automatic-orders system scenario (3A)	Variable routes and forecasted orders scenario (3B)
Fixed Routes	Current scenario (1)	N/A	N/A

Figure 5.1: The proposed scenarios outline. The "N/A" term means the scenario is not considered.

5.2.1 The Current System - Scenario 1

The current scenario is represented by fixed-routes management and the historical orders premises. As stated before, the fixed-route approach does not allow the managers to adapt the routes in the short-term horizon. Also, the logistics operator is the one responsible for placing orders. That approach is defined as the **self-ask-supply order approach**. This scenario is defined as follows: (i) self-ask-supply order approach; (ii) stochastic and unknown demand because the demand depends on the behavior of the logistic operator; (iii) long-term and fixed routes; (iv) drivers must return to the depot after concluding the route; (v) requests are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are allowed; (viii) each workstation is assigned to a specific route; (ix) capacitated vehicles; and (x) homogeneous fleet.

The self-ask-supply order approach may increase the order's variability because the logistic operator has the autonomy to decide if an order should be placed or not. This scenario is similar to the In-house Logistics VRP proposed in chapter 4, which employs a mathematical formulation and a Simulation-based Iterated Local Search algorithm to provide feasible solutions for a real-case application. However, chapter 5 introduces an additional realistic characteristic. The logistics operators do not need to visit all the workstations during a circuit. It is considered that a logistics operator knows the workstations' average consumption. As a result, he/she is allowed to not visit all the workstations during its trajectory, which can be viewed as a short-cut procedure.

5.2.2 The Variable Routes and Current Orders System - Scenario 2

The variable routes and current orders scenario is defined by variable-routes management and the historical orders premises. Consequently, the ILRM system enables the routes to be changed at each considered period. A period could be seen as a 60 minutes time-window range, for example. Also, the company's real orders are clustered into a set of periods, likewise the current scenario.

As a result, in each period, a set of routes is computed to supply all the orders assigned to that period. This scenario is defined as follows: (i) stochastic and unknown demand; (ii) self-ask-supply approach; (iii) variable routes; (iv) the driver must return to the depot after concluding the route; (v) orders are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are not allowed; (viii) capacitated vehicles, and (ix) homogeneous fleet.

Also, this scenario may be classified as the **traditional VRP** because the routes are calculated at the beginning of each period when the demand is disclosed. In practice, a period's demand corresponds to the clustered orders that were placed in the previous period. Also, the computed routes are kept fixed during the whole period but not during the whole planning time horizon. So, that scenario is evaluated through an ILP formulation and an ILS Metaheuristics that are able to compute feasible solutions. These methods are presented in sections 5.4 and 5.5 respectively.

5.2.3 The Variable Routes and Automatic-Orders System - Scenario 3A

The next scenario considers the variable routes and an automatic-orders system. It means the routes may vary at each period depending on the demand. However, an alternative ordering system is considered. The alternative system places the orders automatically instead of the logistics operator, and it works as follow. First, the historical demand data is considered to simulate how the automatic ordering system would work because it is not an actual system. Then, after computing those automatic orders, it is evaluated the impact of introducing an automatic-placing-orders system.

So, to compute the automatic orders, each workstation's ordering frequency is reached through the real data. As a result, an estimation of the real workstations' consumption can be obtained.

Next, orders are created based on that estimation and clustered into periods. The orders are now expected to be more stable because they are controlled through an algorithm that stores and evaluate all the workstations' consumption data. So, the unsteady orders' behavior is reduced considerably.

To sum up, this scenario is defined as follows: (i) the driver must return to the depot after concluding the route; (ii) requests are made throughout the time-horizon; (iii) variable routes; (iv) time-window constraints; (v) backorders are not allowed; (vi) capacitated vehicles; and (vii) homogeneous fleet. This scenario fits the **Periodic VRP** because the customer's orders are allocated in periods, see [Campbell & Wilson(2014)]. A VRP is solved at the beginning of each period considering the actual workstations' consumption obtained throughout an automatic-placing-orders system. Likewise scenario 2, that scenario is evaluated through the ILP formulation and the ILS Metaheuristics that are able to compute feasible solutions for scenario 3 as well.

5.2.4 The Variable Routes and Forecasted Orders - Scenario 3B

The variable routes and forecasted orders scenario is based on the previous scenario presented in subsection 5.2.3. However, no orders are placed instead. Consequently, this scenario is considered as a step further because it considers the assumption that there is no need for placing orders. The workstations' consumption information may be gathered through the company's production scheduling and the Manufacturing Resource Planning (MRP), which is the methodology applied to compute the materials and resources needed to deliver a production schedule. As a result, that scenario may be interpreted as the **Inventory Routing Problem** (IRP). Therefore, following the concepts stated by [Coelho et al.(2013)], this scenario is defined as follow: (i) finite time horizon, (ii) single products, (iii) many-to-many structure, (iv) multiple routing, (v) Order-up-to-level inventory policy, (vi) lost sales not allowed, (vii) homogeneous-fleet composition, and (viii) multiple-fleet size. According to the authors, the parameters (iii) many-to-many structure and (v) Order-up-to-level inventory policy are not observed together usually.

5.3 Demand data analysis

In order to conduct the demand data analysis, the first step is to understand the demand behavior. It is an essential step as the orders are the basis for evaluating the different scenarios.

To illustrate how the data is managed in this work, a five-days data collection is taken into account, as an example. Next, those five-days orders are clustered into different periods. So, the following periods' sizes are considered: 60, 120, and 180 minutes. Notice that bigger periods are not feasible because the logistic operator will be supposed to forecast more than three-hours materials consumption. Furthermore, there are cases, in which a workstation's buffer capacity is smaller than three-hours consumption. Therefore, this will lead to frequent stock-outs.

Figure 5.2 illustrates the five-days orders clustered in the 60, 120 and 180 minutes time-periods. The reader may notice that there is not a clear demand's pattern for each considered time period. Furthermore, the deviation is quite high regarding the smallest period, which is 60 minutes one.

Figure 5.2: The orders placed throughout a five-days time horizon. All workshop's workstations were considered. The orders were clustered into periods of 60, 120, and 180 minutes. The lines' bullets represent the exact moment when an order was placed.

In the current scenario, the company assigns the orders to fixed routes and executes the supply of these orders following the FIFO premises. Consequently, that approach allows backorders to happen because the routes have a limited capacity, and the orders have a significant variability, as shown in figure 5.2. Usually, the production does not stop due to backorders because each workstation has a small buffer, as said in chapter 1. A workstation's small buffer is a company's premise by the way.

For the remaining scenarios (2, 3A and 3B), one relevant decision to be made is to identify the most suitable periods' size to recalculate the routes. So, the main criteria to take into account when making a decision refer to the number of routes and backorders that each option will imply. So, the methods to solve those questions are discussed in sections 5.4 and 5.5.

5.3.1 The automatic-placing-orders process

Since the company's historical data only reflects the orders placed by the logistics operators, the subsequent data analysis' is relevant to develop a methodology that represents an automatic-placing-orders system. That automatic system's purpose is to reduce the orders dispersion throughout the time-horizon. The automatic-placing-orders systems are supposed to send orders through lots of sensors placed in strategical locations throughout the assembly line. So, to reproduce that automatic-placing-orders system, a three-step strategy is developed. Figure 5.3 illustrates that strategy.

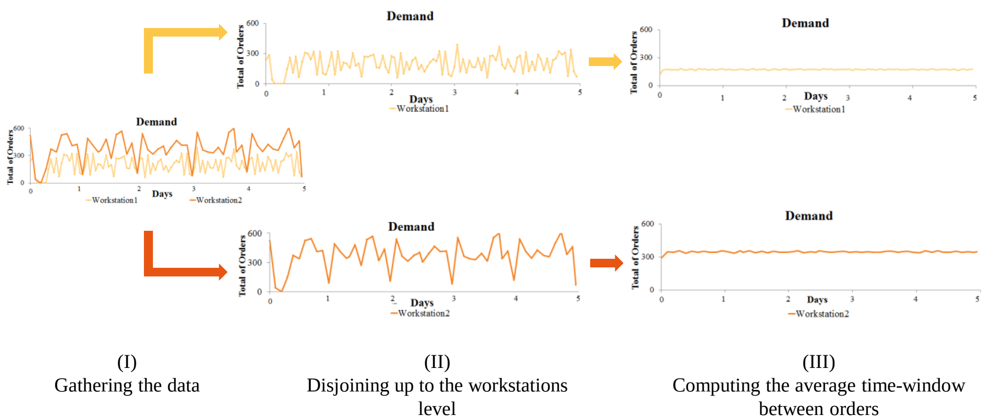


Figure 5.3: Creating the automatic-placing-orders processes.

The first step is the **data collection**, which was presented previously in this section. Next, the second step is **disjoining the data into workstations level**. Consequently, a workstation's consumption rate may be observed, as well as further workstation's metrics, such as the maximum and minimum time windows between two orders; the average time window between two consecutive orders; and its standard deviation as well. Besides, three premises are considered at this point. First, each workstation's order is view in terms of Stock-Keeping-Unit (SKU), and the replenishing will be always a SKU's total capacity. Second, the gathered real-historical-orders data reflects an unsteady ordering procedure. Then, neither the maximum nor the minimum time window between two consecutive orders can be considered. The minimum time window may be a consequence of an excess of orders and the maximum time window may be a consequence of a buffer created previously. As a result, the average time window between two consecutive orders is considered to develop the automatic-placing-orders pattern that smooths the demand. Third, the production level and the products' mix must be the same along the considered time-horizon. As a result, the average ordering ratio of each workstation may be inferred as illustrated by phase (iii) **Computing the average time window between orders** in figure 5.3. The figure 5.4 represents an automatic-ordering-system behavior.

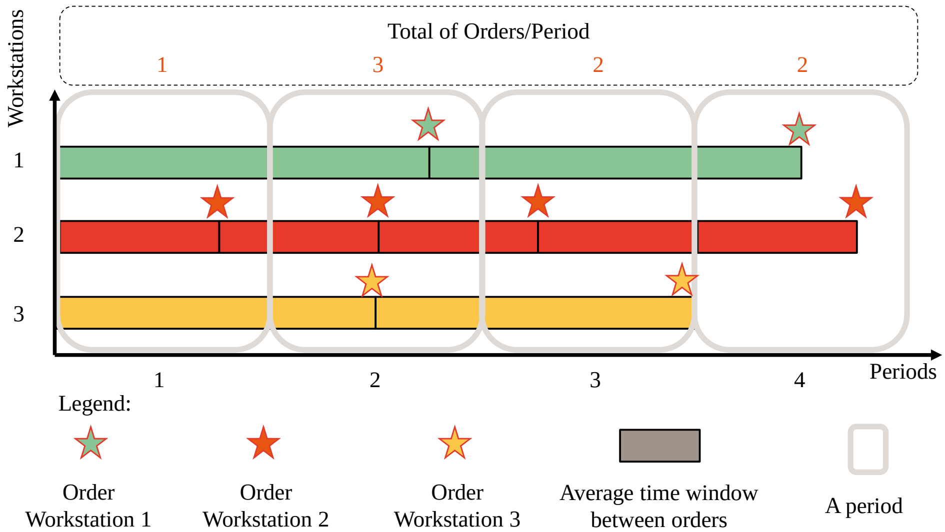


Figure 5.4: Computing the average time window between two consecutive orders.

5.3.2 The forecasting-orders data process

Next, the process that computes the forecasted orders is introduced. The forecasted orders represent a MRP based system, which is a further step regarding the automatic-orders process because no order is placed.

Instead, the demand can be forecasted based on the company's MRP. In practice, it will be the consequence of the collaboration between the production and logistics teams.

Consequently, for each cars-production schedule, the required materials are set, and the time-window between visits may be defined for each workstation. As a result, the company can reach the step (iii) of the figure 5.3 as soon as the production schedule is stated. In this case, there is no need for placing orders. To guarantee some management insurance and reduce the probability of running out materials, due to any production causality, one may introduce some checking and standard procedures across the line, which are responsible for verifying the level of materials in the workstations, for instance. It is entirely related to the IRP scenario that is described by chapter 2.

To conclude, the scenario 3B is not implemented currently. As a result, the automatic-placing-orders procedure, described in sub-section 5.3.1, is replicated to reproduce the forecasted orders. This procedure presented in scenario 3A is able to manage to compute a suitable set of forecasted orders, taking into account the premises described in the previous paragraph.

5.4 The Integer Linear Programming model

In this section, the Integer Linear Programming (ILP) model that solves the deterministic version of the Periodic VRP is presented. It is applied in scenarios 2 (current orders, variable routes), 3A (automatic orders, variable routes) and scenario 3B (forecasted orders, variable routes), see section 5.2. This model is an extension of the Asymmetric Capacitated VRP model described in [Crainic & Laporte(2012)]. The main objective of the formulation is to find the optimal set of routes for each period of the considered time horizon. Therefore, an important aspect of the model is the input data, in particular how the workstations' orders are considered in the model. As discussed in section 5.3, the considered orders are samples of the historical data gathered during a selected time-horizon. So, the real demand of each workstation is considered and allocated into time-periods, i.e., the real orders of one day are clustered into one-hour periods, for instance. The details of the ILP model are detailed next.

The data sets introduced are the following: The set of locations to supply ($n \in N$), where n =1 represents the Depot and the rest represent the workstations; The arc set ($a \in A$). The periods set ($l \in L$); The routes' frequency set ($r \in R$).

Next, the parameters are introduced; the convoy's capacity (C);

the fixed travel cost spent to go from node i up to node j (MC); the fixed cost of introducing a route (RC); the distance between nodes ($i, j \in N$) is (d_{ij}); the maximum number of convoys in one period (K); One period's length (T); the time required to supply a material at the delivery point ($tsup$); the convoy's average speed (v); the maximum frequency a route can have (R); the demand (D_{il}) of the node ($i \in N$) at the period ($l \in L$), which is the demand of a workstation during a period considered l. It is noteworthy to highlight that the deterministic data values, such as speed and a convoy's capacity were defined by the company; and the considered workstations' orders were based on historical data.

Finally, the decision variables are presented: the x_{ijkrl} variable will be equal 1 if arc ($i, j \in A$) belongs to the route ($k \in K$) and has a frequency ($r \in R$) within the period ($l \in L$), 0 otherwise. We state the route's frequency as the number of times a route can be started and concluded within a period. The y_{ikrl} variable will be equal 1 if node ($i \in A$) is visited by vehicle ($k \in K$), which has a frequency ($r \in R$) during the period ($l \in L$). The f_{krl} represents the frequency that a route ($k \in K$) has within the period ($l \in L$). Finally, the add_{kl} is the additional capacity that a route ($k \in K$) can receive during the period ($l \in L$). The ILP model is presented next:

$$\min \sum_{i}^{N} \sum_{j\backslash(i \neq j)}^{N} MCd_{ij} \sum_{l}^{L} \sum_{k}^{K} \sum_{r}^{R} x_{ijkrl} + \sum_{l}^{L} \sum_{k}^{K} \sum_{j\backslash(j \neq 1)}^{N} \sum_{r}^{R} RCx_{1jkrl} \quad (5.1)$$

$$\sum_{r}^{R} f_{krl} \leq 1 \qquad \forall k \in K, l \in L \quad (5.2)$$

$$\sum_{i\backslash i>1}^{N} y_{ikrl} \leq f_{krl}|N| \qquad \forall k \in K, r \in R, l \in L \quad (5.3)$$

$$\sum_{k}^{K} \sum_{r}^{R} y_{1krl} \leq K \qquad \forall l \in L \quad (5.4)$$

$$\sum_{k}^{K} \sum_{r}^{R} y_{ikrl} \leq 1 \qquad \forall i \in N\backslash i > 1, l \in L \quad (5.5)$$

$$\sum_{k}^{K} \sum_{r}^{R} y_{1krl} \leq D_{il} \qquad \forall i \in N\backslash i > 1, l \in L \quad (5.6)$$

$$\sum_{i\backslash i>1}^{N} D_{il} = \sum_{i\backslash i>1}^{N} D_{il} \sum_{k}^{K} \sum_{r}^{R} y_{ikrl} \qquad \forall l \in L \quad (5.7)$$

$$\sum_{j\backslash(j\neq i)}^{N} x_{ijkrl} = y_{ikrl} \qquad \forall k \in K, r \in R, i \in N\backslash i \neq 1, l \in L \quad (5.8)$$

$$\sum_{j\backslash(j\neq i)}^{N} x_{jikr} = y_{ikrl} \qquad \forall k \in K, r \in R, i \in N\backslash i \neq 1, l \in L \quad (5.9)$$

$$\sum_{i,j\in S\backslash(j\neq i)}^{N} x_{ijkrl} = |S| - 1 \qquad \forall S \subset N, k \in k, r \in R, l \in L \qquad (5.10)$$

$$\sum_{r}^{R} \sum_{j\backslash(i\neq 1)}^{N} D_{il} y_{ikrl} tsup + \sum_{r}^{R} \sum_{i}^{N} \sum_{j\backslash(i\neq j)}^{N} r * (d_{ij}/v) x_{ijkrl} \qquad (5.11)$$
$$\leq T \qquad \forall k \in K, l \in L$$

$$[T - (r+1)(\sum_{i}^{N} \sum_{j\backslash(i\neq j)}^{N} (d_{ij}/v) x_{ijkrl}) - \qquad (5.12)$$
$$(f_{krl} rCtsup)]/tsup \leq add_{kl} \qquad \forall k \in K, r \in R, l \in L$$

$$add_{kl} \leq C \qquad \forall k \in K, l \in L \qquad (5.13)$$
$$x_{ijkrl} \in \{0,1\}, \mathbb{Z} \qquad \forall i, j \in A, k \in K, r \in R, l \in L \qquad (5.14)$$
$$y_{ikrl} \in \{0,1\}, \mathbb{Z} \qquad \forall i \in N, k \in K, r \in R, l \in L \qquad (5.15)$$
$$f_{krl} \in \mathbb{Z}^{+} \qquad \forall k \in K, r \in R, l \in L \qquad (5.16)$$
$$add_{kl} \in \mathbb{Z}^{+} \qquad \forall k \in K, l \in L \qquad (5.17)$$

The objective function (5.1) minimizes the sum of the costs related to the total distances covered by all the routes and the number of routes, for each period the period ($l \in L$). The constraints (5.2) define the number of laps, or the frequency ($r \in R$), that a route ($k \in K$) does during the period ($l \in L$). Constraints (5.3) state the maximum number of nodes a route ($k \in K$) can visit during the period ($l \in L$). Constraints (5.4) state that the depot must be visited by $|K|$ vehicles at most during the period ($l \in L$). Constraints (5.5) state that each workstation must be attended by only one route at most, during the period ($l \in L$). Then, constraints (5.6) and (5.7) ensure that only the workstations that have placed orders at the period ($l \in L$) will be visited during the period ($l \in L$). The constraints (5.8) and (5.9) define that, for each customer i, the vehicle that visits it must enter and leave during the period ($l \in L$). The constraints (5.10) are responsible for avoiding the sub-tours to happen. The constraints (5.11) state that each route can last up to T minutes during the period ($l \in L$), taking into account the capacity, the supplying time, the distance, and the traveling speed. The constraints (5.12) define the maximum additional capacity a route can receive, based on the amount of time left in the period ($l \in L$). The constraints (5.13) state that the maximum additional capacity a route can receive during the period ($l \in L$) is fewer or equal to C. Lastly, constraints (5.14), (5.15), (5.16), and (5.17) define the domain of the variables.

Note that the **residual capacity rule**, which aims to increase a convoy's capacity is also applied in this model. The constraints (5.12) and (5.13) are responsible for introducing and regulating that rule in this chapter. The complete description of the residual capacity rule can be found in section 4.2. Also, notice that the ILP presented in this chapter considers that none backorder is allowed.

The AMPL language is used to solve the presented ILP model. Also, it is solved through CPLEX 12.8. As discussed further ahead, the ILP formulation is suitable for small instances. For the large or the real-world instances, a Metaheuristic was developed, and it is presented in the next section.

5.5 Routing Problem and Large-scale applications

Even though the ILP formulation is able to provide feasible solutions, its performance tends to fall as larger instances are introduced. As a result, to deal with large-scale applications, or the companies ones, a metaheuristic is proposed to compute feasible solutions, which are applied to scenarios 2, 3A and 3B.

So, the developed metaheuristic is an Iterated Local Search (ILS) based on the methodology proposed by [Lourenço et al.(2019)]. The reason to select the ILS is due to its remarkable results solving COP, as presented previously. The algorithm 7 resumes the ILS Metaheuristic developed.

Algorithm 7: The ILS Algorithm

1 $S_{complete} \leftarrow \emptyset$
2 **for** $(p \in Periods)$ **do**
3     $S_{0p} \leftarrow$ Generate_Initial_Solution (*sub-section 5.5.1)*
4     $S_p^* \leftarrow$ Local_Search (S_{0p}) (*sub-section 5.5.2)*
5     $S_p^{'} \leftarrow$ An empty solution of period (p)
6   **while** *(it_ils $\leq$ it_ils_LIM)* **do**
7         $S_p^{'} \leftarrow$ Local_Search($S_p^{'}$) (*sub-section 5.5.2)*
8   **if** *(S_p^*>$S_p^{'}$)* **then**
9   Let ($S_p^* \leftarrow S_p^{'}$)
10   **end**
11         $S_p^{'} \leftarrow$ Perturbation ($S_p^{'}$) (*sub-section 5.5.3)*
12         $it\_ils \leftarrow it\_ils + 1$
13   **end**
14     $S_{complete}^{p} \leftarrow S_p^*$
15 **end**
16 **Return** $S_{complete}$

The algorithm 7 is executed for each considered period, as indicated by line 2. Moreover, the algorithm 7's structure is resumed in four steps, as follows: (i) Initial Solution; (ii) Local-Search phase and Acceptance Criterion; (iii) Perturbation phase; and (iv) Stopping Criterion. Besides, the main elements applied are introduced as follows: $S_{complete}$ is defined as the complete final solution, in which each period's solutions is inserted; the S_{0p} is stated as a period's initial solution; S_p^* is a period's current best solution. Afterward, once the iterations phase is reached, at line 6, the $S_p^{'}$ value is considered. The $S_p^{'}$ receives the output solutions computed by the local search procedure, at lines 5, 7, and at the perturbation phase, at line 11. Next, each ILS's step is explained.

5.5.1 The Initial Solution

Likewise the the SimILS algorithm presented in chapter 4, an initial feasible solution is obtained through a greedy algorithm, in which each workshop's aisle is viewed as a route. In addition, the workstations are supposed to be visited in sequence. By doing so, the input solution will be one that the routes' workstations are sequenced adequately. This initial solution is introduced through the method *Generate_Initial_Solution* in the algorithm 7, which generate a period's initial solution S_{0p}, at line 3. Next, a further second greedy algorithm is introduced, which aims to aggregate the created routes S_{0p}. The criterion to merge two routes is the cost and the number of backorders. If the resultant solution has a fewer cost and there is no backorder, a second initial solution S_{02} is generated. It is stored and will be useful further ahead in the perturbation phase presented at sub-subsection 5.5.3. Note that the second procedure is not considered by the former SimILS algorithm.

5.5.2 The local search phase and the acceptance criterion

Next, the local search phase is executed. It consists of applying moves inside the same route, called as Intra-Neighbourhood-Search (Intra-NS), in a similar way proposed by [Penna et al.(2013)] and described in chapter 4 in subsection 4.3. In other words, one node (representing a workstation) or more nodes from a route are transferred to another position in the same route. For further information about the local search moves applied here, see subsection 4.3.

Furthermore, the Inter-Neighbourhood-Search (Inter-NS) is also considered. It involves a set of nodes that move between routes. In other words, one or more nodes from a route are transferred to another route. These moves are also proposed by [Penna et al.(2013)]. For further information about the local search moves applied here, see subsection 4.3.

In both moves, the new route's capability to supply the relocated demand is checked. To do so, the new route's capacity and its resultant number of orders are evaluated. Again, according to [Penna et al.(2013)], both Intra-NS and Inter-NS moves presented have the same computational complexity, which is $O(n^2)$.

Regarding the acceptance criterion, a solution's cost is viewed as the main measure. Also, a solution's cost is calculated as same as represented in equation 5.1 in section 5.4. To conclude, the best improvement strategy is taken into account whenever the local search phase is executed. Moreover, the execution time has not shown to be a major issue during the experiments' phase. The reader may observe that the local search moves are applied in the algorithm 7 in lines 4 and 7.

To conclude the local search description, note that the **residual capacity rule**, which was defined in section 5.5, is also considered in this in the proposed ILS algorithm. That procedure enables the algorithm to come closer to real practice. Besides, it is represented by constraints 5.12 and 5.13 in section 5.4 as well.

5.5.3 Perturbation Phase

The purpose of this phase in the ILS method is to make a significant change in the current solution to start searching another space of feasible solutions. As described in previous chapters, that procedure must conduct the ILS to escape from an optimal local solution. By doing so, it will permit the ILS to go to a comprehensive search on the space of feasible solutions. The perturbation can be found in the algorithm 7 through the method **Perturbation(*Solution*)** at line 11.

The perturbation procedure applied in this work is based on the inter-routes moves described in sub-subsection 5.5.2. The perturbation procedure is presented in algorithm 8.

Algorithm 8: The perturbation phase

Let ($S^{'} \leftarrow$ Current Solution) and Let ($S^{*} \leftarrow$ Best Solution)
//$it\_ils\_LIM(x\%)$ indicates the reached percentage of the total iterations
if $(it\_ils = it\_ils\_LIM(50\%))$ **then**
  Let ($S^{'} \leftarrow S_{02}$)
end
if $(it\_ils \leq it\_ils\_LIM(25\%))$ *or* $((it\_ils > it\_ils\_LIM(50\%))$ *and* $(it\_ils \leq it\_ils\_LIM(75\%)))$ **then**
  $S^{'} \leftarrow$ Perturbation ($S^{'}$) (*//Input the current solution*)
end
if $(it\_ils > it\_ils\_LIM(25\%)$ *and* $(it\_ils < it\_ils\_LIM(50\%))$ *or* $((it\_ils \geq it\_ils\_LIM(75\%)))$ **then**
  $S^{'} \leftarrow$ Perturbation (S^{*}) (*//Input the best solution*)
end

Then, the perturbation phase is split into four parts, which concerns to the achieved number of iterations, and is illustrated by figure 5.5.

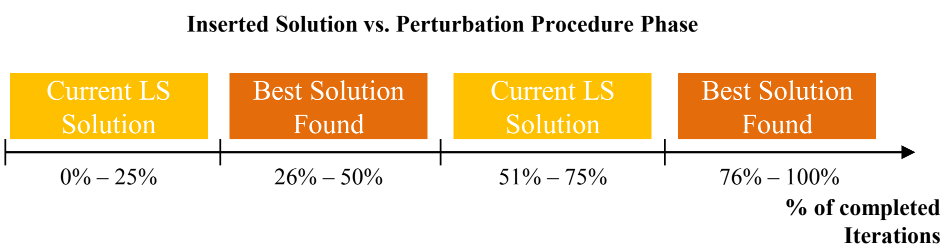


Figure 5.5: The figure illustrates the introduced solution in the perturbation procedure, which regards to the number of iterations reached.

So, the first and the third part will receive the last solution found, as presented in the algorithm 8 at line 6. On the contrary, the second and the fourth parts will receive the best solution found so far, as indicated in line 9. Whenever the half of a period's total iterations is achieved, a new initial solution S_{02} is introduced. Note that the S_{02} was defined in sub-section 5.5.1. Also, the perturbation algorithm is iterated ten times. This structure was achieved after the execution of a set of experiments.

Also, the perturbation algorithm is quite similar to the local search one, but there is one main difference instead. On the one hand, the local search algorithm evaluates both (i) a solution's cost and (ii) the absence of backorders to decide if a new solution should be accepted or not. On the other hand, the perturbation does not care about a solution's cost, but the number of backorders generated. So, if a new route presents none backorder, it will be accepted as a new route of the new solution.

So, the algorithm 8 presented the general perturbation procedure that is applied during an ILS iteration. It indicates which solution to input depending on the ILS's iteration. Additionally, the algorithm 9 is presented to introduce the perturbation calculation procedure itself. Notice that the algorithm 8 refers to the **Perturbation(*Solution*)** procedure that is found in algorithm 8 in lines 7 and 10.

Algorithm 9: The perturbation pseudo-code

Get S' (*The Solution to be perturbed*)
Set S^* (*The Solution after the perturbation*)
for ($it \leq it\_lim\_Perturbation$) **do**
    $S^* \leftarrow$ Local_Search (S') (*The Intra-RNS and Inter-RNS*)
    if *(S^* has none backorders)* **then**
        Let ($S' \leftarrow S^*$)
    end
end
Return S^*

5.5.4 The ILS-Stopping Criterion

Concerning the stopping criterion, the condition established to interrupt a procedure is related to the number of iterations. Thus, the algorithm breaks when the algorithm achieves the maximum number of iterations set, as stated in line 6 in the algorithm 7. The ILS's maximum number of iterations value is presented in the appendix B 5.7.

5.6 The current-routes simulation

In this section, the simulation procedure defined as the **current-routes simulation** is presented. It is applied to evaluate the scenario 1 or the company's ILRM system. Notice that in scenario 1, the routes are fixed for all time horizon and do not vary depending on the demand, which is similar to the simulation example described by figure 6 in chapter 4. To be able to compare this scenario with the three alternatives ones, the company's routes need to be simulated in a realistic environment. Note that other scenarios do not require the simulation, because the KPIs have already been calculated through the ILS algorithm.

To run this procedure, the following inputs are necessary: (i) the company's current routes; (ii) the historical orders; (iii) the company's deterministic data; and (iv) the definition of the periods' sizes. Afterward, the input data is simulated to obtain the statistics related to the primary KPIs. Then, a realistic objective function is calculated, which is the same one presented in the ILP model in section 5.4. Therefore, the main KPIs of the objective function are the number of routes and the total of all the route's trip distance.

The secondary KPIs are also available through the simulation and can be used to evaluate a solution. These secondary KPIs are (i) total of backorders; (ii) total distance traveled; (iii) total of orders supplied; and (iv) total of empties spots in each convoy's departure. An empty spot is a free spot in the convoy that could be filled with an order. For example, a convoy whose capacity is four units, and it is loaded with three units results in one empty spot. Besides, note that backorders are computed here because the simulation refers to the current company's scenario, in which backorders are likely to happen.

So, the algorithm 10 presents the current routes' simulation, and the following notation is presented. The complete solution ($S^p_{complete}$) contains each period's solution. Therefore, each period has its solution, which is defined by (S_p^*).

Algorithm 10: The current-routes simulation

Get $S^p_{complete}$ (*The Solution to be Simulated*)
Cluster the historical data (*To sort the orders chronologically*)
for ($p \in Periods$) **do**
  $S_p^* \leftarrow$ Input Solution ($S^p_{complete}$)
  for *(Route* $\in S_p^*$*)* **do**
    Eliminate the route's nodes with null demand
    $S_p^* \leftarrow$ Local_Search (S_p^*) (*The Intra-NS only*)
    Collect the route's Objective Function and KPIs
  end
end

In that algorithm, the historical orders are clustered into the considered periods, as described in section 5.3. Regarding the solution analysis, on the one hand, the routes will be the same for each period. On the other hand, the algorithm withdraws each node that has not any order assigned to it. That procedure enables a route to become more efficient in terms of distance and time. Also, an Intra-RNS is executed to certify that each route is distributed properly. Afterward, the objective function is computed as well as the secondary KPIs.

5.7 Experiments

To evaluate the scenarios described in section 5.2, four main computational experiments are presented. Each experiment is defined as follows: The first experiment has as the main goal to compare the performance between the ILP model and the ILS algorithm. The second experiment aims to assess the company's current internal logistics routing management (ILRM) system through the simulation method (algorithm 10). Then, the third and fourth experiments apply the ILS algorithm to compute the proper routes for the SEAT's ILRM system. These experiments are presented in table 5.1.

Exp.	Method	Data Applied	Scenario
1	ILP vs. ILS	Test Data	-
2	Current-routes simulation	Real Data (2) and (3)	1
3	ILS variable routes	Real Data (2) and (3)	2
4	ILS variable routes	Real Data (2) and (3)	3(A and B)

Table 5.1: The ILRM system experiments outline.

The experiments were carried out on the Operational System Windows 7 Enterprise 64 bits, Intel Core i7-4810MQ, 2.80GHz, 8 cores and 16 GB of RAM as the maximum capacity. Moreover, the programming languages JAVA were used to build the ILS. Also, the ILP was modeled through AMPL language and was solved by CPLEX 12.8.0.

5.7.1 The instances

An instance is stated as the number of orders that a set of workstations (WST) requires over a determined time horizon. So, one instance differs from another regarding the following aspects: (i) the SKU class; (ii) the set of WST considered; (iii) the number of orders placed; (iv) the time-horizon considered; and (v) the periods' size.

Saturdays, Sundays, and holidays data were not included because they do not represent a typical working day. Therefore, two sets of data were gathered. Each one refers to a SKU class, which are the small boxes (SB) and the large containers (LC). For each SKU class, three groups of data were collected. The **first group** is called Test data, which is a particular subset compound by a selection of all the real workshop's workstations and their respective demands throughout the considered time horizon. The **second group** refers to the set of all workstations that compound an assembly line and their respective demand during a short time horizon; in this case, five working days. The **third group** of data is like the second one (all workstations are considered) but considering a larger time-horizon size, in this case, four weeks.

Moreover, those orders were collected over two different periods in the year. As a result, instances of different production levels and other intrinsic features were considered. The orders data was collected directly in the material management system of the company, which is the commercial software SAP. The table 5.2 summarizes the instances' characteristics. The data is available in the data set proposed by [Fabri (2019)], which can be found in the Mendeley plataform. In the table 5.2, the instances are classified into three groups: (i) test data; (ii) real data with smaller time-horizon size; and (iii) real data with larger time-horizon size. The second column (*Item*) refers to the name of the instances, and *WST* represents the number of workstations considered. Also, there are indications related to the types of materials (small boxes and large containers), the number of periods considered in the historical data, and the periods' size considered. The * marker highlights the real-world and complete instances.

The parameters used in the experiments are either directly set by the company, as cost values and vehicles capacity, or defined via pre-

Class (Group)	Item	SKU Type	Total of Periods	Period's size (hour)	WSTs
Test Data(1)	1-2-3		10-50-100	1	5
	4-5-6		10-50-100	1	10
	7-8-9	SB	10-50-100	1	15
Real Data(2)	10*-14*		105-55-35-30-15	1-2-3-4-8	123
Real Data(3)	15*-19*		441-231-147-126-63	1-2-3-4-8	122
Test Data(1)	20-21-22		10-50-100	1	5
	23-24-25		10-50-100	1	15
	26-27-28	LC	10-50-100	1	20
Real Data(2)	29*-33*		105-55-35-30-15	1-2-3-4-8	127
Real Data(3)	34*-38*		441-231-147-126-63	1-2-3-4-8	126

Table 5.2: The summary of the instances' structure.

liminary experiments as the setting data related to the algorithm. The distance matrix between the workstations was computed by the author based on the workshop layout and through a C++ procedure. The parameters used in the experiments are indicated in the appendix B 5.7. The experiments are summarized in table 5.1.

5.7.2 The Experiment 1

Experiment 1's goal is to compare the results provided by the ILP model and the ILS algorithm. These methods are evaluated based on objective function values and computational time. The results related to the experiment 1 are presented in the tables 5.3 and 5.4.

Regarding the achieved results, the ILP model found the optimal solution in five out of nine SB instances; among the four instances left, feasible solutions were obtained for two of them with 12% gap and 3% gap, respectively. Besides, the ILP model could not find any feasible solution for two instances.

For the LC instances, the ILP model found the optimal solution in six out of nine LC instances; it got feasible solutions up to 9% optimally gap for one instance, and it could not find any feasible solution for two instances.

Concerning the ILS's results, the algorithm was able to find feasible solutions for all instances of both SB and LC SKU classes. Besides, the ILS computed the optimal solution for six out of 18 instances, as proved by the ILP.

As a result, it can be stated that the ILS presented a satisfactory performance. It is concluded comparing the ILS's results and the ILP's optimal solutions. The GAP between the methods' solutions has never been bigger than 6%, for those instances that the ILP proofed the optimality.

Although the ILP model can manage to compute the better solutions in the easiest instances, the ILS outperformed the ILP in the most complicated ones in a shorter computational time. Notice also that when running the ILP model for the larger instances (15 workstations) the computer ran out of memory. Consequently, no solution was computed in those cases. Therefore, the ILS is able to provide excellent results in short time, which makes the ILS a proper algorithm to deal with more complicated or real-world instances, like those applied in experiments 3 and 4.

5.7.3 The Experiment 2

Experiment 2 aims to compute the performance of the company's set of routes through the simulation procedure defined by algorithm 10. This algorithm is applied to real data (2) and (3). Moreover, experiment 2 obtains results for the **scenario 1** described in sub-section 5.2.1. Also, three clustering possibilities are evaluated, in which the orders are assigned to periods with the following sizes; 60 min, 120 min, and 180 min. The experiment 2's results are disclosed in tables 5.5 and 5.6.

5.7.4 Experiment 3

Experiment 3's goal is to compute routes for an ILRM system defined by variable routes and the company's current orders. These characteristics represent the **scenario 2**, which is described in subsection 5.2.2. The purpose is to understand the consequences of computing variable routes in a non-steady orders context. The algorithm 7 is responsible for computing these routes. Tables 5.5 and 5.6 present the results.

5.7.5 Experiment 4

Experiment 4's goal is to compute routes for an ILRM system defined by variable routes and an automatic-placing-orders system context. It is defined as the **scenarios 3A and 3B**, which are described in subsections 5.2.3 and 5.2.4, respectively. The experiment's motivation is to understand the benefits of introducing an automatic-placing-orders system that smooths the orders' placement. The algorithm responsible for computing these routes is the 7 one, as well. Tables 5.5 and 5.6 present the results. The discussion of the results of these last 3 experiments is presented in the following subsection 5.7.6

Item	WST	Per.	Met.	OF Value	Routes	Distance (m)	G_{cplex} (%)	Time (sec)
1	5	10	ILP	**4,177.64**	4	3,777.64	0%	0
1	5	10	ILS	**4,177.64**	4	3,777.64	-	0
G				0%	-	-	-	
2	5	50	ILP	**36,953.44**	37	33,253.44	0%	1
2	5	50	ILS	37,055.73	37	33,253.44	-	0
G				0.3%	-	-	-	
3	5	100	ILP	**76,470.61**	77	68,770.61	0%	4
3	5	100	ILS	76,739.19	77	69,039.19	-	0
G				0.4%	-	-	-	
4	10	10	ILP	**5,454.35**	77	4,954.35	0%	0
4	10	10	ILS	5,551.21	77	5,051.21	-	0
G				2%	-	-	-	
5	10	50	ILP	50,613.87	43	46,313.87	3%	7,200
5	10	50	ILS	51,933.94	43	47,633.94	-	0
G				3%	-	-	-	
6	10	100	ILP	**105,449.17**	92	96,249.17	0%	282
6	10	100	ILS	108,481.09	92	99,281.09	-	0
G				3%	-	-	-	
7	15	10	ILP	15,931.65	12	14,731.65	12%	7,200
7	15	10	ILS	16,940.26	12	15,740.26	-	0
G				6%	-	-	-	
8	15	50	ILP	(*)	(*)	(*)	(*)	(*)
8	15	50	ILS	81,720.32	50	76,720.32	-	3
9	15	100	ILP	(*)	(*)	(*)	(*)	(*)
9	15	100	ILS	160,378.14	100	15,740.26	-	6

Table 5.3: The summary of the SB SKU Experiment 1's results. The bolded values represent optimal solutions. The (*) marker indicates that no feasible solution was provided. Also, the Gterm refers to the comparison between the values computed by the ILP and ILS. It is computed as $(ILP_{Value}/ILS_{Value} - 1)$.

5.7.6 The large-scale experiment's results

One of the main objectives of this work is to evaluate the new proposed scenarios and compare them to the actual one. Tables 5.5 and 5.6 resume the results of experiments 2, 3 and 4. The results achieved are discussed next.

Considering that the routes are divided into SB and LC categories, the results will be described taking into account the SB and LC results separately, as well. Furthermore, the major indicators to take into account to decide on a scenario to another are: (i) the maximum number of routes; (ii) the number of backorders; (iii) the total distance traveled, in this order of importance.

So, regarding the SB experiments, ten sets of experiments were carried out in total (items 10-19 from table 5.2) that represents 26 individual experiments. Thus, the results are evaluated comparing those ten instances items, see table 5.2.

Even though the scenario 2 achieved excellent overall results, such as solutions' costs (five out of ten), none backorders reported and the best solutions in terms of distance covered (six out of ten), it is not a suitable solution. It is explained by the variability of the number of routes from one period to another. As a result, some periods requires much more resources than others. That makes the system's management quite complex and expensive. Moreover, scenario 1 achieved good solutions' costs as well (three out of ten). However, that scenario incurs in a lot of backorders (six out of six). That is why it is discarded. Finally, that scenario 3A has the best overall results as well as suitable management procedures. First, it presents the best performance regarding the maximum number of routes (ten out of ten). Second, there are no backorders reported. Third, it computes solutions with good performance in terms of distance covered (four out of ten). Therefore, concerning the main performance indicators and the company's management premises, the most suitable scenario is the 3A one.

Then, regarding the LC experiments, ten sets of experiments were carried out in total (items 29-38 from table 5.2) that represents 26 individual experiments. So, the results are evaluated comparing those ten instances items, as well. The scenario 3A has the best overall results. First, it presents the best performance regarding the maximum number of routes (nine out of ten) and the solutions' costs (six out of ten). Second, there are no backorders reported. Third, it computes solutions with good performance in terms of distance covered (three out of ten). Therefore, concerning the major performance indicators and the company's management premises, the most suitable scenario is the 3A one. Scenario 2 also achieved excellent results, such as the best solutions' distance covered (seven out of ten). However, it achieved solutions with high variability in terms of the number of routes, as well as the SB context. Moreover, scenario 1 also must deal with a high number of backorders that makes it not the best system to choose.

Concerning the decision of choosing the best time-window size to cluster all orders. For this question, it is observed that there is not the right answer because it is a trade-off between solutions' costs and management procedures.

According to the tables 5.5 and 5.6, the best period size would be the 480 minutes, or a shift one, because it incurs in the best KPIs' results (instances 19 and 38). By contrast, the managers in charge of that decision should evaluate the consequence of retaining and joining all the order placed in a 480 minutes range. Notice that the orders placed in one period must be delivered in the next period only. As a result, concerning the evaluated company's context, it is recommended the scenario 3A with 60 minutes of period size as a first implementation. Even though the 60 minutes size does not represent the best solutions' costs, it enables to correct the routes more frequently and avoid longer-term failures. Further ahead, alternatives periods' sizes could be evaluated, and its implementation analyzed further.

Also, scenario 3A (experiment 4) is viewed as the most suitable one. Moreover, notice that scenario 3A is entirely related to scenario 3B, as described in section 5.3.2. It is because the automatic-placing-orders systems may represent the forecasted demand obtained by the Manufacturing Resource Planning (MRP) system. So, the placed orders would be quite similar for both scenarios. As a result, experiment 4 represents both scenarios 3A and 3B. Therefore, scenario 3B is also a suitable alternative to be implemented.

To conclude that subsection, the instance number 30 is taken into account to illustrate the number of routes and the number of orders calculated in this instance, see figures 5.6 and 5.7.

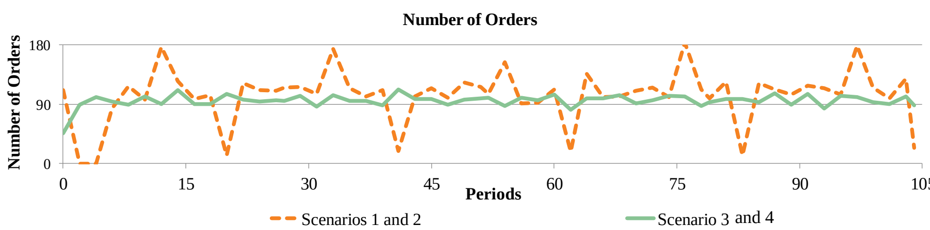


Figure 5.6: The number of orders applied for scenarios 1, 2, 3A, and 3B, regarding instance number 30.

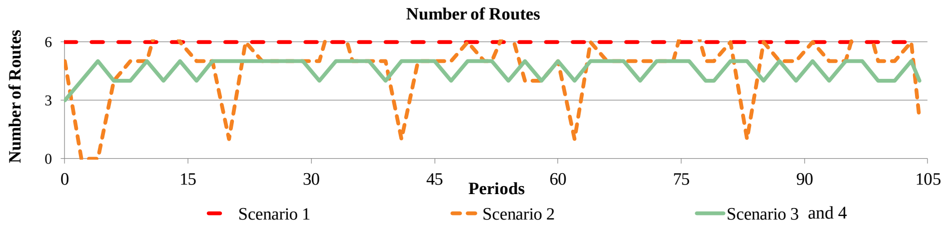


Figure 5.7: The number of routes applied for scenarios 1, 2, 3A, and 3B, regarding instance number 30.

5.8 Conclusion

In this chapter, a real problem in a real car-assembling company was considered. That problem consists of finding the most suitable internal logistics routing management (ILRM) system in charge of both placing orders and deliver them. A total of four scenarios were discussed, which cover the current company's system and three alternatives systems. To summarize, the first scenario represents the current company's approach. The second scenario considers variables routes using the company's actual orders. The third one computes variable routes through an automatic ordering system. Finally, the fourth one also considers variable routes dependent on the demand but using a forecast demand obtained by the Manufacturing Resource Planning (MRP) system.

These scenarios were evaluated through Operations Research-based methodologies, which are: (i) an ILP model; (ii) a Metaheuristics; and (iii) a simulation procedure. Besides, a class of IRP, which is uncommon to be evaluated in the literature, was approached. That is represented by the scenario 3B, which is described in subsection 5.2.4.

Also, this work proposes an ILP model for a deterministic version of the Periodic VRP, as well as an ILS algorithm to calculate variable routes to internal logistics routing management systems. A comparison between these two approaches was performed and concluded that the ILS obtained outstanding solutions, in particular for the real-world instances. It was considered the objective function values and computational time as a comparative basis. Therefore, the ILS presented a better performance than the company's solutions in all the real-world instances evaluated.

Regarding the ILRM system scenarios, scenario 3B is the recommended one. That is the one defined by variable routes and the forecasted orders system. Even though it may be challenging to integrate the logistics and production to work together and work at the workstations' consumption rates, it will imply in the same benefits pointed to the experiment 4 (scenario 3A), but without any complex automatic-placing-orders system implementation. Moreover, for those conservative managers, who may view that alternative as a risky one due to the lack of checking procedures in the assembly line, the introduction of checkpoints along the assembly line is suggested. These checkpoints will verify the level of materials in the workstations.

Furthermore, it is also recommended scenario 3A, which is the variable route and automatic-placing-orders system. It may ensure an online control of each workstation. However, it could require a significant initial investment to introduce the automatic-placing-orders system. Figure 5.8 summarizes the advantages and challenges of each scenario described in this work.

Scenario	Advantages	Challenges
1	• The number of routes is steady. • No need for routes computing and order placing systems.	• Lack of routes' flexibility. • Deal with backorders. • It may incur in higher battery consumption
2	• There are periods with a reduced number of routes. • None backorders.	• Deal with the high variability of the number of routes. • Implementing the routes computing system.
3	• The number of routes is steady and flexible. • The best trade-off between solutions' costs, stability, and battery consumption. • None backorders.	• Implementing both the routes computing and automatic placing-orders systems.
4	• The number of routes is steady and flexible. • No need for an automatic placing-orders system. • The cheapest alternative, in terms of implementation of supportive systems. • None backorders.	• The integration between Production and Logistics teams. • Implementing the methodology of forecasting demand. • Ensure the workstations consumption level.

Figure 5.8: The summary of the scenarios' conclusions.

As a result, it is stated that this work presents a valuable methodology to be applied to any car-assembling company. Indeed, the presented methodology and results were presented to the company's experts, and they found it novel and interesting. Concluding, this work refers to the remarkable contribution to the company, as depicted by the results presented.

As future work, methods to optimally solve large instances of the presented ILP should be explored, such as the branch-and-cut procedure. Moreover, extensions of the ILS and the simulation procedure may be improved by adding a more realistic aspect, such as the traffic on the assembly-lines, the use of a different type of vehicles and self-guided automatic vehicle.

Finally, concerning the real application, would be quite useful for studying the interaction between the flows that compound the logistics activities inside an assembly line. One suitable alternative to achieve such level of analysis would be a simulation model based on a Discrete-Event-Simulation. That model is able to evaluate the assembly lines' aisles and the introduced logistics flows. So, the major objective would be to identify the main bottlenecks in the assembly line under the logistics perspective.

Item	WST	Per.	Met.	OF Value	Routes	Distance (m)	G_{cplex} (%)	Time (sec)
20	5	10	ILP	**3,533.24**	6	2,933.24	0%	0
20	5	10	ILS	**3,533.24**	6	2,933.24	-	0
G				0%	-	-	-	
21	5	50	ILP	**17,479.91**	30	14,479.91	0%	0
21	5	50	ILS	**17,479.91**	30	14,479.91	-	0
G				0%	-	-	-	
22	5	100	ILP	**33,472.93**	57	27,772.93	0%	1
22	5	100	ILS	**33,472.93**	57	27,772.93	-	0
G				0%	-	-	-	
23	10	10	ILP	**4,311.03**	6	3,711.03	0%	4
23	10	10	ILS	**4,311.03**	6	3,711.03	-	0
G				0%	-	-	-	
24	10	50	ILP	**31,645.39**	44	27,245.39	0%	44
24	10	50	ILS	32,627.02	48	27,827.02	-	1
G				3.1%	-	-	-	
25	10	100	ILP	**62,839.74**	87	54,139.74	0%	1,556
25	10	100	ILS	63,082.27	87	54,382.27	-	2
G				0.4%	-	-	-	
26	15	10	ILP	7,797,09	10	6,797.09	9%	7,200
26	15	10	ILS	7,746.68	10	6,746.68	-	0
G				-0.6%	-	-	-	
27	15	50	ILP	(*)	(*)	(*)	(*)	(*)
27	15	50	ILS	42,194.62	54	36,794.62	-	2
28	15	100	ILP	(*)	(*)	(*)	(*)	(*)
28	15	100	ILS	85,098.06	107	85,098.06	-	4

Table 5.4: The summary of the LC SKU Experiment 1's results. The bolded values represent optimal solutions. The (*) marker indicates that no feasible solution was provided. Also, the Gterm refers to the comparison between the values computed by the ILP and ILS. It is computed as $(ILP_{Value}/ILS_{Value} - 1)$.

I.	E.	OF Value	Cost Per.	M. R.	R. (Uts)	T. Sup.	B.	T. Emp	Trav. P.(m)	Proc. (sec)
10	2	4,507,047	42,924	4	395	20,547	3,779	8,256	8,780	82
10	3	**4,501,578**	42,872	7	402	20,547	-	11,033	7.050	589
10	4	4,715,301	44,908	4	419	18,218	-	12,209	6,049	3,998
11	2	2,383,686	43,340	4	208	20,547	1,820	6,958	14,109	213
11	3	**2,316,067**	42,110	6	206	20,547	-	9,012	12,010	4,137
11	4	2,334,270	42,441	4	207	19,083	-	9,636	11,886	8,921
12	2	1,557,189	44,491	4	136	20,547	2,123	8,992	20,512	203
12	3	1,504,610	42,989	6	134	20,547	-	7,573	17,078	4,160
12	4	**1,436,351**	41,039	4	127	18,220	-	8,158	16,845	7,684
13	3	**1,184,716**	39,491	7	105	20,547	-	8,395	20,062	4,055
13	4	1,212,621	40,421	4	107	20,835	-	7,960	22,081	7,588
14	3	637,237	42,482	4	56	20,547	-	9,424	42,642	4,000
14	4	**591,755**	39,450	4	52	20,835	-	7,151	43,256	4,837
15	2	**17,671,405**	40,071	4	1,610	108,514	29,026	28,060	6,754	659
15	3	20,136,547	45,661	11	1,857	108,514	-	52,778	6,422	8,546
15	4	19,266,988	43,689	4	1,763	95,079	-	54,110	6,653	73,888
16	2	**9,375,251**	40,586	4	853	108,514	20,139	37,068	11,641	1,454
16	3	10,093,791	43,696	8	927	108,514	-	39,049	10,129	23,515
16	4	10,117,435	43,798	4	923	99,605	-	47,778	10,645	44,098
17	2	**6,073,949**	41,319	4	552	108,514	21,577	41,322	17,284	1,101
17	3	6,715,634	45,685	9	617	108,514	-	30,810	15,479	16,597
17	4	6,433,192	43,763	4	587	95,079	-	36,740	15,224	26,773
18	3	**5,138,631**	40,783	10	470	108,514	-	31,436	18,073	16,999
18	4	5,532,133	43,906	4	504	108,673	-	40,139	20,444	23,155
19	3	**2,559,889**	40,633	6	234	108,514	-	28,745	35,770	14,628
19	4	2,752,616	43,692	4	252	108,673	-	39,955	37,355	15,544

Table 5.5: The summary table of the experiments 2, 3, and 4 regarding the SB. The first column refers to instances' items. Then, the next columns present the experiments (E.), the OF, costs per period, maximum of routes in one period, instance's total of routes, the orders supplied, the total of backorders, the total of free spots in each convoys' departure, the average distance covered per period and the computational time. The bolded OF value represents an instance's best value.

I.	E.	OF Value	Cost Per.	M. R.	R. (Uts)	T. Sup.	B.	T. Emp	Trav. P.(m)	Proc. (sec)
29	2	6,540,724	62,293	6	588	5,670	658	1,972	16.517	11
29	3	5,726,599	54,539	11	529	5,670	-	945	11,929	276
29	4	**5,330,844**	50,770	6	490	5,011	-	920	11,261	345
30	2	3,474,148	63,166	6	309	5,670	417	2,410	32,699	25
30	3	2,877,858	52,325	8	265	5,670	-	1,111	22,502	697
30	4	**2,757,777**	50,141	5	253	5,249	-	1,116	22,037	1,097
31	2	2,305,580	65,874	6	204	5,670	561	3,056	52,184	46
31	3	1,933,952	55,256	9	178	5,670	-	1,296	35,308	948
31	4	**1,763,448**	50,384	5	162	5,015	-	1,234	31,677	1,505
32	3	**1,458,842**	48,628	9	134	5,670	-	1,272	40,235	1,160
32	4	1,545,908	51,530	5	142	5,751	-	1,700	42,409	1,844
33	3	**762,750**	50,850	5	70	5,670	-	1,690	82,227	1,523
33	4	773,966	51,598	5	71	5,751	-	1,751	83,549	1,783
34	2	26,025,245	59,014	6	2,429	30,183	6,148	8,940	13,086	87
34	3	26,167,575	59,337	12	2,454	30,183	-	2,807	11,806	2,145
34	4	**24,885,138**	56,429	7	2,320	26,403	-	3,577	11,596	4,836
35	2	13,836,652	59,899	6	1,284	30,183	4,806	13,196	25,220	112
35	3	13,532,374	58,582	10	1,263	30,183	-	4,255	23,636	3,872
35	4	**12,976,102**	56,174	6	1,202	27,663	-	3,744	24,509	8,477
36	2	8,972,787	61,039	6	830	30,183	5,038	16,312	39,848	162
36	3	9,029,160	61,423	11	842	30,183	-	5,140	37,108	4,520
36	4	**8,243,240**	56,076	6	762	26,403	-	3,940	37,187	9,332
37	3	**6,886,625**	54,656	11	641	30,183	-	5,633	43,044	5,179
37	4	7,036,361	55,844	6	650	30,191	-	4,563	49,245	12,129
38	3	3,623,168	57,511	8	336	30,183	-	7,293	91,676	6,713
38	4	**3,492,228**	55,432	6	322	30,191	-	4,418	99,140	10,175

Table 5.6: The summary table of the experiments 2, 3, and 4 regarding the LC. The first column refers to instances' items. Then, the next columns present the experiments (E.), the OF, costs per period, maximum of routes in one period, instance's total of routes, the orders supplied, the total of backorders, the total of free spots in each convoys' departure, the average distance covered per period and the computational time. The bolded OF value represents an instance's best value.

Data	Application	ILS Parameters Values
Number of Iteration	ILS	8
Number of Iteration	LS	8
Fictitious Weight	Route	10,000
Fictitious Weight	Distance	1
Max K-value	The LS moves	10 nodes
Convoy Speed	All cases	7 km/h
Convoy Capacity	Large Boxes	4
Convoy Capacity	Small Boxes	48
Placing a Large SKU	Large Boxes	2.69 min
Placing a Small SKU	Small Boxes	0.66 min

Table 5.7: Chapter 5 - Appendix B : Summary of the ILS's parameters structure.

Chapter 6

INTERNAL LOGISTICS FLOWS SIMULATION

6.1 Introduction

The motivation to study the Internal Logistics Flow (ILF) in an assembly line come from the study of a real case based on SEAT S.A., which expressed the importance of analyzing assembly lines focus on the internal logistics processes.

Even though the ILFs represent relevant activities in assembly lines studies, companies have dedicated more effort to evaluate production activities than the internal logistics ones. Consequently, most of the assembly line simulations focus on the product point of view, evaluating machines failures, cycle times, and lines' throughput, see [Negahban & Smith (2014)] and [Semini et al.(2006)]. The logistics processes are introduced in the analyses as the procedures responsible for delivering materials. By contrast, the logistics flows observed in the workshop are not the focus on those simulations studies.

To analyze the ILF, the Simulation methodology presented by [Banks et al.(2005)] was considered. Also, according to [Tako & Robinson(2012)], simulation is a suitable methodology to face logistics problems. Among the Simulation methodologies, there are three approaches to be highlighted: the System Dynamics, Agent-based Modelling, and Discrete Event Simulation (DES), as discussed in chapter 2. Also, simulation models have been extensively used to deal with logistics problems, as observed in [Tako & Robinson(2012)], [Hillier & Lieberman (1995)] and [Banks et al.(2005)]. In the Logistics field, most of the simulation studies focus on external logistics. Those studies that focus on assembly lines are focused on the production point of view because they consider aspects such as the production flow in the assembly line and machines interruptions.

To sum up, in this chapter, the main goal is to propose a simulation model to evaluate and analyze the internal logistics activities in an assembly line of a car-manufacturing company. A DES model is developed through the Plant Simulation software as well as an analysis of the internal logistics in SEAT is performed. So, to evaluate the internal logistics flows, two main KPIs are stated by the company, which are related to the logistics flows' performance and the assembly line's aisles utilization. Moreover, three scenarios are evaluated based on the actual system, the introduction of autonomous vehicles and applying a transit flow policy. The results indicated the main aspects and areas of the assembly line that contribute to a disruption of the logistics operations. Notice that the proposed DES concepts can be applied whenever a new scenario occurs or even in other industries that rely on assembly lines. As a result, in the end, a set of best practices are disclosed for bench-marketing purposes.

Note that there some characteristics that differ the automotive industry from other manufacturing industries, regarding a DES model development. First, to conduct a DES study over an entire assembly line, a significant amount of data is required. Usually, the automotive industry does not disclose that required data. Second, the DES's complexity is significant in terms of the number of processes. There are many processes to be considered because many types of internal logistics flows are introduced into the model. Third, there are the workstations' orders to take into account. In SEAT, one assembling line can produce more than 600 cars each day. Considering that a car is assembled with more than 2,500 materials, in those workstations, the scope of the DES model is quite significant. By contrast, a DES model developed for the automotive industry is completely applicable to other industries because we assume that many relevant concepts and procedures have already been considered. Consequently, businesses that share similar concepts, but on a smaller scale, can take advantage of this work as well.

The remainder of this chapter is organized as follows. Section 6.2 describes the case-study tackled in this chapter. Section 6.3 presents the developed simulation model and the experiments result. Finally, section 6.4 concludes the paper.

6.2 The Internal Logistics Flows Simulation in assembling lines

In this chapter, the main goal is to identify the highest logistics flows bottlenecks in the system, which are those aisles that are more collapsed in terms of traffic. It can be achieved through an Internal Logistics Flows (ILF) simulation focus on the company's assembly line.

The ILF study is a relevant issue for companies, in particular for those that tackle scenarios with high variable demand. A proper ILF simulation study enables a company to carry on analysis of the followings items: (i) flows' bottlenecks; (ii) layout evaluation; and (iii) introduction of new premises such as the input of traffic new rules or a new product. Consequently, this approach is highly recommended whenever there are changes in the operation of the assembly lines and production plannings, such as the introduction of a new layout.

Next, it is presented the main processes related to the supplying activities in SEAT. It is quite related to those explained in chapter 1. So, first, non-regular logistic flows are presented in figure 6.1. In other words, those logistics flows whose departure from the warehouse towards the assembly line is not periodical. Later, those flows with periodical departure are presented through figure 6.1. Notice that these processes were considered for the development of the DES model

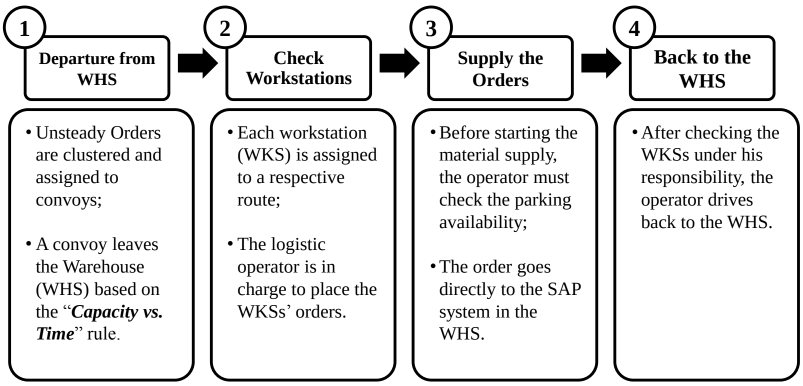


Figure 6.1: The summary of the processes of a non-regular departure logistic flow.

There are four main steps to be considered in figure 6.1 that are: (i) departure from the warehouse (WHS); (ii) check workstations; (iii) supply workstations; and (iv) return back to the WHS. Each step is explained in detail in chapter 1.

Concerning the convoys' departure frequency, notice that it depends on the material consumption rate. Consequently, materials with non-uniform consuming rates are delivered not periodically as well. Then, the convoys that have these material assigned to them depart under demand. On the contrary, some materials are requested regularly. So, those materials are assigned to another class of convoys. As a result, it is stated that there are two main classes of convoys, those with non-regular departure and those with regular departures. The processes for those logistics flows that have a regular departure from the WHS (for example every 15 minutes) is presented figure 6.2.

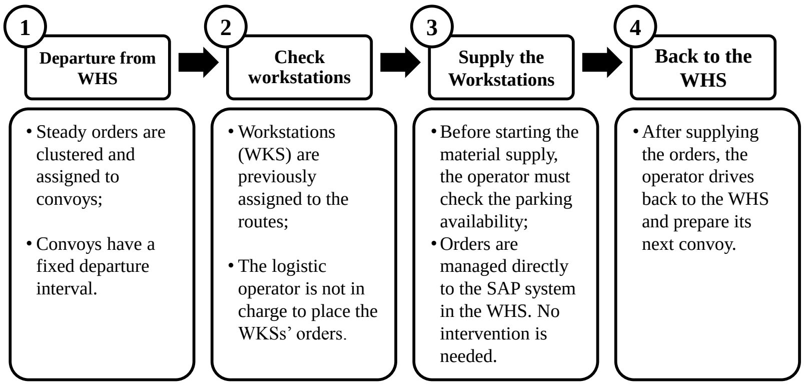


Figure 6.2: The summary of the processes of a regular departure logistic flow.

The processes represented in figure 6.2 are quite similar to those in the non-regular departure. On the one hand, the routes are divided into SKU classes, and the routes do not share supplying locations. On the other hand, the materials supplied here are viewed as steady ones because its consumption rate is well defined. Therefore, there is no need to ask the logistics operator to place orders because SAP rules the orders. Figure 6.2 presents the main components of these regular departure routes.

Then, all classes of flows are tested through an assembly-line simulation model. That model was developed based on classical simulation models methodologies stated by [Banks et al.(2005)] and [Brooks & Robinson (2001)], which can be resumed into five steps: (i) problem formulation; (ii) model construction; (iii) data collection; (iv) experiments; and (v) validation. Figure 6.3 summarizes the main procedures to take into account.

As presented in subsection 2.4, most of the works in the literature prioritize the manufacturing issues and consider the body-shop phase when car-assembling lines are evaluated. So, this work provides a set

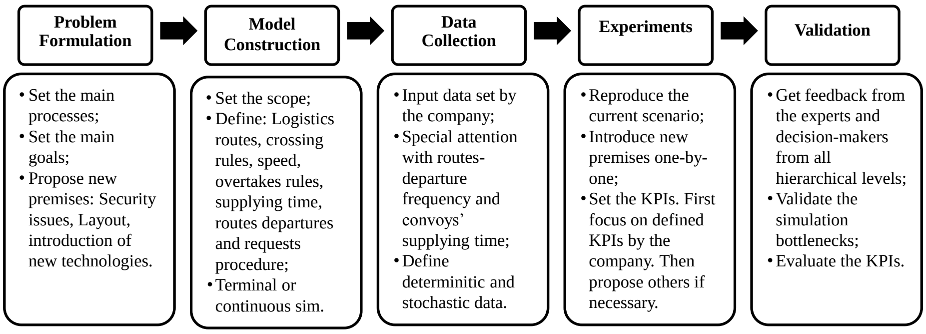


Figure 6.3: The classical simulation modeling framework and the best practices over an DES assembly-line model construction.

of best practices for those who develop DES models centered on ILF analysis.

Next, it is presented a simulation model that copes with the ILF processes faced in SEAT.

6.3 The Simulation Model Description

In this section, the DES model applied to the ILF of two car-assembly lines, which is motivated by the application in SEAT. The DES model developed in this work is defined as a terminating simulation model, as stated by [Banks et al.(2005)]. Besides, it follows the concept of the building blocks design. According to [Valentin et al.(2003)], building blocks are suitable for logistics environments because there are processes that repeat over the model. As a result, routines were developed to the users drag and drop them in the frame. Furthermore, some parameters of the model are done through excel tables that can be filled previously by the user. Then, to better explain the model's concepts, the simulation model is presented through the framework illustrated by figure 6.3.

6.3.1 Problem Description

The first step concerns the **problem description**. It is compound by three main phases: (i) set the main processes; (ii) set the main goals; and (iii) propose new premises, such as a new layout and the introduction of new technologies. So, the main processes have already been presented in the last section by figures 6.1 and 6.2. So, the main goal of this work is identifying the logistics flows' bottlenecks through a simulation model that considers a company's workshop. Also, evaluating the consequences of introducing a set of established premises, such as layout, convoys' speed, and workstations' demands. Finally, the new premises evaluated are the introduction of an autonomous vehicle and a single flow traffic policy. As stated in chapter 1, that model does not consider the content of the supplied boxes and containers but the number of SKU units a route must deliver.

6.3.2 Model Construction

The second framework's step is the **model construction**. The problem is modeled through The DES model's. To provide a better understanding of the model and set its scope, it is presented the main model's concepts as follows: (i) layout; (ii) traffic flow; (iii) non-regular routes departure; (iv) supplying activity; and (v) KPIs report.

The first concept is the **layout** one that is defined by the aisles' and intersections' rules. Here, the main traffic rules are stated, such as overtaking permissions, intersection priorities, and workstations' location. Figure 6.4 illustrates the layout developed through the Plant Simulation software. The dimensions of the studied workshop are nearly 350 meters in width by 60 meters in height. Moreover, it contains two assembly lines that can process more than 1.300 cars per day.

The workshop is divided into two main parts, with different logistics operations. The left-hand part contains verticals aisles as the majority, and it is called Supermarket. Next, the right-hand part has horizontal aisles as a majority and is viewed as the assembly line zone. Notice that both of these areas are considered in this chapter because both of them must receive materials through the logistics flows. However, the supermarket is also a location from where logistics flows depart.

Second, to set the traffic rules in all the workshop' areas, **traffic flow** concepts were developed. These concepts or rules are responsible for defining items such as routes' directions, routes departure, and a convoy's decision whether an overtaking is possible or not.

The third concept regards the **non-regular convoys departures** that are called as supplying routes. It concerns the logistics flows that are in charge of supplying the materials with variable consumption rate. The workstations' consumption or orders are available in the company's SAP system. So, the author introduced in the model those orders that refer to real-historical data. Therefore, the workstations' demands are the main component of the variability of the DES model. Figure 6.5 illustrates how orders are placed along five days considering one workstation.

Next, a routine was built that is in charge of assigning requests to the respective convoys. By definition, a workstation's orders must

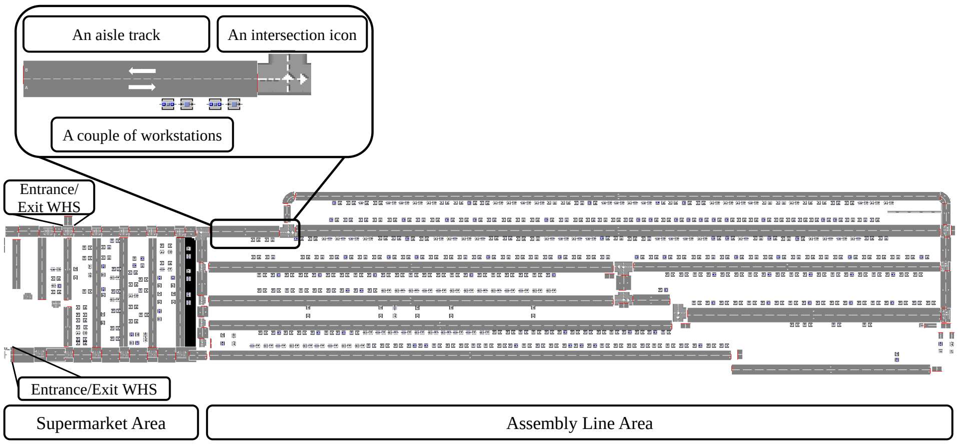


Figure 6.4: The layout of the studied workshop. It is compound by the aisles (tracks) and the workstations (grey dots). Besides, there are two main parts. The left-hand part that contains verticals aisles is called Supermarket. Next, the right-hand part that contains long horizontal aisles is viewed as the assembly line zone.

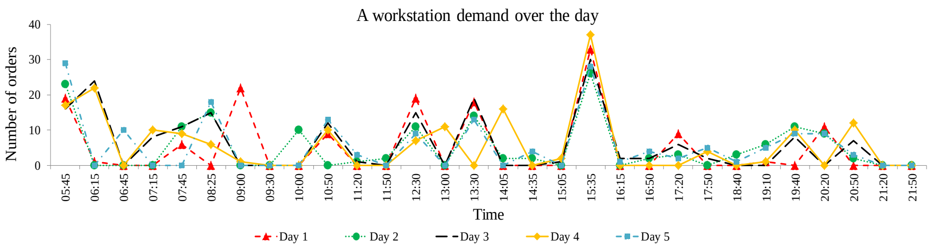


Figure 6.5: The demand behavior of a workstation throughout five consecutive days.

be assigned by a unique and pre-established convoy. The departure is allowed either whenever a time-limited is reached or the number of orders assigned is equal to the convoy's capacity. Notice that each convoy is unique and refers to a specific route.

The fourth concept is the **supplying activity**. It is important because it provides information about how the unloading activity may interfere on both aisle's traffic and over workstations areas. Particularly, for those workstations that receive both LC and SB materials from more than one convoy. Figure 6.6 illustrates two convoys supplying their workstations.

Finally, the last concept concerns the **KPI reporting**. To report the KPIs, the model collects the data generated throughout the simu-

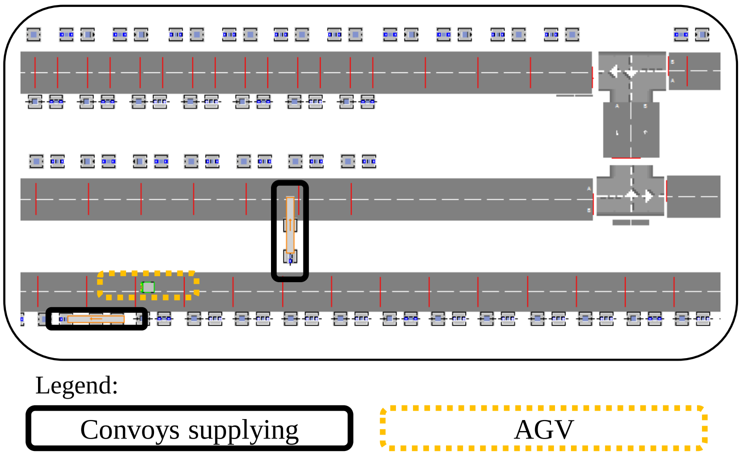


Figure 6.6: A piece of layout that shows two convoys supplying their respective workstations.

lation. That data refers to the convoys' and aisles' information, orders' information and interferences data, such as overtaking and logistics flows' interruptions.

To conclude the subsection, it is stated that the developed DES model shares some concepts with the Agent-Based modeling based on the premises stated by [Macal & North (2010)]. On the one hand, it is stated that each vehicle, or agent, is a modular and uniquely identifiable individual. Besides, it is assigned attributes to each vehicle such as name, route's tracks, workstations to be visited, and departure time. Moreover, those vehicles interact with other vehicles dynamically, as it is observed in the interference data collection. As a result, the vehicles have a sort of protocol for interactions with other vehicles. On the other hand, the vehicles cannot learn and adapt their behavior completely, for example, deciding to change the routes' trajectory due to huge traffic congestion. In this sense, it is assumed that the proposed model incorporates some concepts of the agent-based simulation. However, it is a DES model.

6.3.3 Data Collection

The third step of the framework is **data collection**, which was briefly cited in the last step (Model Construction). So, to carry on this study, the real data provided by the SEAT was considered. Deterministic parameters were defined by the company, such as speed, capacity, and time spent to deliver the material at the correct place. Concerning to the models' input data, the table 6.1 is presented. It contains the main parameters applied in this work.

Data	Value
Supplying Average Time LC	2.69 min
Supplying Average Time SB	0.66 min
Convoy's Average Capacity LC	4 units
Convoy's Average Capacity SB	48 units
Convoy's Average Speed	7 km/h
AGV Convoy's Average Speed	4 km/h
Number of workstations	154 units
Number of assembly Lines	2 lines
One replication simulation Period	One day (2 shifts)
Warm-up Period	15 minutes
Time-slot for Supplying routes	30 minutes
Number of days applied	Five days

Table 6.1: Summary of the parameters' structure. Notice that LC means Large Containers and SB means Small Boxes.

The orders of 154 workstations are delivered through four main logistics flows, which are presented by table 6.2 and defined as follows: (i) supplying route; (ii) cycle route AGV; (iii) cycle route operator; and (iv) JIT.

To summarize table 6.2, the supplying routes refer to the convoys that deliver materials whose consumption rate is not regular, e.g., the workstation described by figure 6.5. By contrast, the remaining logistics flows receive materials with regular consumption rate. Therefore, all of them follow a systematic departure routine that is defined as regular departures. Among those flows, there are the "cycle routes AGV" and "cycle routes Operator" that are conducted by an AGV and a logistics operator, respectively. Finally, there are the JIT flows that are executed by outsourced employees.

Logistics Flow	Main Characteristics
Supplying route	Non-regular departure; Overtaking allowed; 17 Routes
Cycle routes AGV	Regular departure; Overtaking not allowed; 4 Routes
Cycle routes Operator	Regular departure; Overtaking allowed; 2 Routes
JIT	Regular departure; Overtaking allowed; 5 Routes

Table 6.2: Summary of logistics flows applied.

As stated in subsection 6.3.2, the demand assigned to the supplying-routes category is the main variable component introduced in the model.

Table 6.3 present a summary of that data according to the supplying routes only.

R.	Mat.	Line	D1	D2	D3	D4	D5	Confidence Interval $LB \leq \mu \leq UB$	p-value
1	LC	1	243	247	277	287	279	$241 \leq \mu \leq 291$	25
2	LC	1	112	115	129	138	135	$110 \leq \mu \leq 140$	15
3	LC	1	211	210	239	236	230	$208 \leq \mu \leq 242$	17
4	LC	1	163	158	191	180	199	$156 \leq \mu \leq 200$	22
5	LC	1	243	231	277	275	285	$233 \leq \mu \leq 291$	29
6	SB	1	8	9	14	11	9	$7 \leq \mu \leq 13$	3
7	SB	1	67	60	72	68	63	$60 \leq \mu \leq 72$	6
8	LC	1	36	37	51	55	44	$33 \leq \mu \leq 55$	11
9	SB	2	57	55	67	73	77	$54 \leq \mu \leq 78$	12
10	SB	2	306	328	352	328	343	$309 \leq \mu \leq 353$	22
11	LC	2	89	79	93	106	103	$81 \leq \mu \leq 107$	13
12	LC	2	241	279	286	320	301	$249 \leq \mu \leq 321$	36
13	LC	2	225	209	259	277	285	$210 \leq \mu \leq 292$	41
14	LC	2	164	177	189	200	190	$167 \leq \mu \leq 201$	17
15	SB	2	189	200	221	234	220	$190 \leq \mu \leq 234$	22
16	SB	2	244	250	289	280	263	$241 \leq \mu \leq 289$	24
17	LC	2	56	62	62	71	69	$56 \leq \mu \leq 72$	8

Table 6.3: The summary of the applied variable demand. The first, second, and third columns refer to a route-identification item, a route's load type and the assembling line assigned, respectively. The five-days demand is presented throughout columns four to eight. The ninth column represents the confidence interval, concerning the route's five-days demand. The LB and UB refer to the lower bound and upper bound values of the CI, respectively. The last column presents the p-value applied to the confidence interval, which is defined as 5%.

The reader may observe that the table 6.3 contains a confidence interval (CI) study among the five-days demand sample. It represents the measure of error because the μ is defined as the average value computed through the sample. As a result, it is an estimated value of the population average μ_*. Consequently, μ has an error that is measured through the CI.

To identify that error, it is introduced the CI construction procedure state by [Banks et al.(2005)]. Besides, in that case, the average and the standard deviation is not known for all the population, but the sample only. Assuming that each sample's elements are normally distributed, the equation approached is the following:

$$CI = \mu \pm t_{\alpha/2,n-1}\frac{S}{\sqrt{n}} \tag{6.1}$$

In equation 6.1, it is considered that μ value represents the sample's average, S value represents the standard deviation of that sample, n is the total number of sample's elements, and $t_{\alpha/2,n-1}$ is the quantile of the t distribution with n-1 degrees of freedom that cuts off $\alpha/2$ of the area of each tail. So, setting the α value equal to 5%, the probability of the demand fits a CI is 95%.

6.3.4 Experiments and validation

As said, the main objective of this chapter is to analyze the logistics flows' bottlenecks through a simulation model. That model considers the company's workshop and evaluates the consequences of introducing all parameters and demands previous presented. So, table 6.4 presents the three scenarios considered. The objective is to evaluate these new scenarios and contrast them with the actual system.

Scenario	Main Purpose
A - Current company's scenario.	Collect the current metrics.
B - Introduction of autonomous AGVs.	Enable an AGV to overtake by itself.
C - Introduction of a single flow policy.	One flow aisles whenever possible.

Table 6.4: Scenarios evaluated through the simulation.

The first scenario aims to compute the current system's metrics. The second scenario evaluates the introduction of an autonomous-AGV concept that permits an AGV to overtake other vehicles by itself and without any external support. The purpose is to evaluate how these robots will affect the level of interferences in the workshop. Lastly, the third scenario refers to the introduction of a single flow policy. So, the workshop's aisles will have a single flow whenever it is possible. Then, for each scenario, five experiments were executed, one for each considered day, see table 6.3. Moreover, scenarios B and C were defined based on the company's suggestions and discussions. The model was built on the Plant Simulation software (version 13) developed by Siemens.

As explained, that model integrates the workshop layout, the logistics flows, the workstations' demand and further premises defined by the company. For each scenario, the model was executed five times and, at each time, a different set of demands were introduced. Besides, the simulation time was set as one day-processing time, and two shifts within a day were considered. As mentioned, the introduced demand presents different values along the days and different levels over a single day, see figure 6.5 and table 6.3. However, all other parameters, such as speed and convoys' capacity were maintained.

Afterward, the experiments' results were evaluated under the company's KPIs. These KPIs concerns to the routes and aisles utilization. Considering the performance of the routes, each route was observed individually based on the following indicators: (i) total of backorders; (ii) backorders' duration; (iii) trip's duration; and (iv) a route's trip distance. Notice that backorder is defined as a material that was supplied later than its due date.

Then, regarding the aisles' performance, the following indicators were considered: (i) total of interferences; (ii) interferences' duration; and (iii) total of vehicles. Interferences are actions that disturb a convoys' trajectory. In this sense, an interference may be an overtaking or breaking at the intersections, for instance. Furthermore, the interferences are classified into five groups defined as follows: (i) overtake; (ii) blocked AGV; (iii) waiting before the intersection; (iv) overtake with both vehicles moving; and (v) overtaking not allowed.

The computed KPIs are presented in tables 6.5, 6.7 and 6.6. Also, these tables present the results of the scenarios A, B, and C. Notice that the KPIs are computed after 15 minutes of warm-up or simulated minutes.

Table 6.5 presents the results related to aisles' performance. Each line represents a different workshop's aisle. So, for each aisle and each scenario, the total of interferences are indicated. Moreover, it presents the length those interferences last and the total of vehicles that passed through that aisle along the day. As said, five experiments are executed per scenario. So, each experiment was replicated just once because the variability is linked to a day's orders only. Also, to present the aisles' results properly, the main ones were selected to expose the results. The criteria to select an aisle was based on its average number of interferences throughout the simulation.

In addition to table 6.5, figures 6.7 and 6.8 are presented. These figures illustrate heat-maps layouts based on the number of interferences. Moreover, the following reference is considered to build these heat maps: blue color, or the absence of geometric symbols, is set if the number of interferences is fewer o equal to 4; yellow, or squares icons, for total of interferences values between 5 and 15; red, or circles, applied for total of interferences values bigger than 15.

The reader may notice that the conflicting areas are placed where there are higher workstations concentrations. Usually, these areas re-

Aisle	Total Interf. (units) Scenarios			Duration Interf. (min) Scenarios			Total vehicles (units) Scenarios		
	A	B	C	A	B	C	A	B	C
1	143	139	151	14	5	23	613	618	636
2	126	132	91	7	8	4	439	445	379
3	92	93	103	4	4	9	414	421	330
4	68	68	58	3	3	3	529	525	503
5	44	45	51	2	2	2	515	520	335
6	40	47	90	2	2	3	332	338	532
7	17	18	15	3	3	2	588	592	569
8	7	8	6	1	1	1	1031	1050	943
9	6	6	6	1	1	1	647	659	594
10	6	7	4	1	1	1	659	672	656
11	6	6	6	1	1	1	558	566	627

Table 6.5: The summary of the aisles' result throughout the three considered scenarios. It is sorted in a decreasing fashion, according to the number of interferences. Only aisles with a relevant number of interferences were selected. Note that the values of each column refer to the average results computed through the simulation of the five-days data.

ceive all kinds of logistics flows. Also, the workshop's entrance and exit points are viewed as complicated ones. For example, the aisle number 7 receives the main entrance and exit doors to the assembling line. Therefore, many logistics flows must pass by there.

To continuing the interferences analyses, table 6.6 indicates the main types of interferences. Moreover, for each type, the average value found through the simulations and the respective scenario are presented.

Table 6.6 suggests that the main disturbing item is the overtake one. Indeed, the convoys must overtake themselves on many occasions, such as whenever slower AGVs are ahead, and a workmate is parked supplying materials. Also, blocked AGV has significant values in scenarios A and C because the current AGVs are able neither to overtake nor to take decisions. Consequently, it must interrupt its trajectory frequently. On the contrary, scenario B enables the AGV to overtake other vehicles. As a result, the interferences related to blocked AGV were significantly reduced, as well as the interferences' average duration. Moreover, scenario B does not contribute to minimizing the total of interferences, as observed in figure 6.7. However, the interferences, in that case, tend to be quicker. It is explained by the fact that the

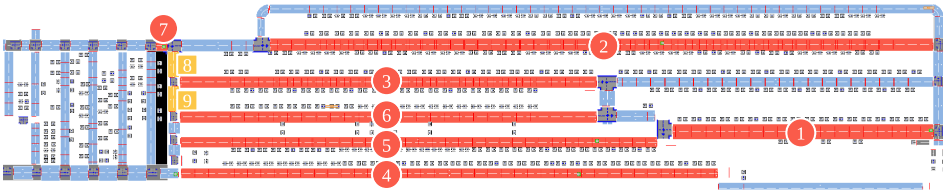


Figure 6.7: A heat map based on the workshop's layout and the number of interferences computed through the simulation of the scenarios A and B. Notice that the level of interferences is quite similar in both scenarios. However, those scenarios' interferences are not the same ones, as observed in table 6.6.

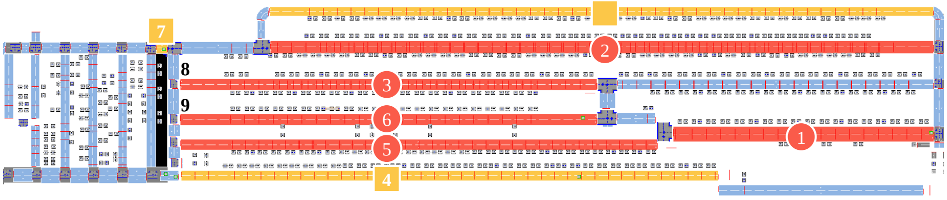


Figure 6.8: A heat map based on the workshop's layout and the number of interferences computed throughout the scenario C.

blocked AGV cases were replaced by the overtakes ones. The overtakes interferences are faster than blocked AGV ones.

Regarding the impacts of scenario C, on the one hand, that approach contributes to increasing the total number of interferences because the number of overtakes increases as well. On the other hand, it decreases the number of overtakings when both vehicles are moving, which is representative due to security reasons. Moreover, according to table 6.5, the total of vehicles that pass through those aisles is reduced. In many situations, a vehicle goes back to the warehouse through the same aisle where it was. That is counted as two vehicles by the system. It explains the high level of vehicles in scenarios A and B. Moreover, notice in figure 6.8 that aisles number 7 has reduced the number of interferences due to the application of scenario C.

Concerning the routes' evaluation, table 6.7 presents the results related to the introduced logistics flows. So, it is reported for each route the following indicators: (i) the total of backorders; (ii) the sum of the length the backorders last; (iii) routes' trip duration; and (iv) a route's trip distance. Once again, it is assigned to each route its average value of each scenario.

Notice that the considered routes are the supplying ones, which are the ones that must supply materials with variable consumption rate.

Interferences	Scenarios A	B	C
	Interferences (units)		
Overtake	402	465	475
AGV Blocked	67	0	64
Waiting before the Intersection	69	62	64
Overtake with both vehicle moving	47	50	5
Overtaking not allowed	1	1	1

Table 6.6: Summary of the average number of interferences found during the experiments. Note that the values of each column refer to the average results computed through the simulation of the five-days data.

Route	Mat.	Total Backorders (units) Scenarios			Backorders Duration (min.) Scenarios			Trip Time (min.) Scenarios			Trip (meters) Scenarios		
		A	B	C	A	B	C	A	B	C	A	B	C
1	LC	169	170	125	10	11	10	11	11	10	500	500	500
2	LC	30	30	21	3	3	1	10	10	4	443	443	431
3	LC	146	146	118	11	11	6	11	11	8	647	647	635
4	LC	43	43	55	2	2	3	8	8	9	624	624	624
5	LC	200	200	161	24	24	11	11	11	9	711	711	711
6	SB	0	0	0	4	4	3	7	7	8	711	711	711
7	SB	0	0	0	1	1	1	7	7	6	647	647	635
8	LC	2	2	1	1	1	1	7	7	4	443	443	431
9	SB	0	0	0	1	1	1	6	6	6	555	555	550
10	SB	0	0	0	1	1	1	5	5	5	488	488	488
10	LC	0	0	0	0	0	0	0	0	0	488	488	488
11	LC	6	6	8	1	1	1	6	6	6	488	488	488
11	LC	0	0	0	0	0	0	0	0	0	352	352	352
12	LC	201	201	191	15	15	13	10	10	10	384	384	384
13	LC	199	199	179	26	26	19	13	13	13	633	633	633
14	LC	78	78	69	5	5	3	9	9	8	616	616	616
15	SB	0	0	0	1	1	1	13	13	15	1298	1298	1252
16	SB	0	0	0	1	1	1	4	4	4	753	753	753
17	LC	0	0	0	1	1	1	10	10	10	352	352	352

Table 6.7: The summary of the logistics flows' results through the simulation of the three considered scenarios. Only the supplying routes were considered, which refers to those routes with non-periodical departure. Note that the values of each column refer to the average results computed through the simulation of the five-days data.

Concerning table 6.7's results, the first general analysis one may do is that the considered routes are not balanced. In other words, there are some logistics operators that received more load than others. As a result, the reassignment of the workstations into the routes should be considered. Besides, the SB routes are better to execute their tasks than the LC ones. Indeed, the LC routes presented the major overall backorders values because the demand for LC is also higher.

Moreover, the reader can observe that scenarios A and B are quite similar because the autonomous AGVs does not improve the performance of other vehicles. Notice that the AGV routes are not considered here because they supply materials with steady consumption rate only.

By contrast, scenario C do incur on a reduction of the level of backorders as well as a reduction on the backorders duration for most of the routes. It is explained because the routes were reorganized in such a way that the distance of their trips became a little shorter. Also, the routes were able to complete a trip faster than before, as presented by table 6.7. Note that the routes' reconfiguration was necessary to adapt them to the new layout's flows found in scenario C.

Regarding the model's validation, the model structure and the computed results have been exposed to the company's employees. They found them interesting and wondering about introducing it as a supportive methodology to evaluate logistics flows in other areas as well, for example, the Warehouse. It was noticed that the graphical tools, such as the heat maps, are good options to promote a model validation.

To conclude, the author suggests that scenario C should be tested in practice because of its overall performance in reducing the number of backorders. Also, it is a cheaper scenario than the autonomous AGV one. However, scenario C requires a higher effort to organize all the routes' trajectories and processes because it impacts on many of them.

Also, the following managerial insights may be interpreted based on the previous results: (i) workshop areas that receive a high number of workstations are likely to be defined as a conflicting one; (ii) shorter routes may implicate in a fewer number of backorders as well as the average duration a backorder last. So, the longer a route is and the more workstations it receives, a higher level of backorders it will have; (iii) single-flow aisles may increase the traffic security because it minimizes both the number of overtakes with two moving vehicles and the chance of frontal accidents; (iv) the introduction of autonomous AGV supports the ILF to become more fluid because there are not issues regarding blocked AGV. However, the number of overtakes in the workshop will increase; (v) heat-maps are a suitable tool to present results to stakeholders because these maps are straightforward and widely accepted by them.

6.4 Conclusions

This chapter tackled a real-world case study that faces the internal logistics operations in a workshop, which contains two assembly lines in a car-manufacturing company.

Also, an ILF simulation based on a DES model to evaluate the workshop' aisles and the introduced logistics flows. The major objective was to identify the main bottlenecks in the assembly line under the logistics perspective, such as the flows' obstructions or interferences.

The study was carried out in a real car-assembling company, considering real data and the actual assembly-lines operations. Also, two further scenarios were evaluated. The first scenario introduced autonomous AGVs that can overtake other vehicles. The second one referred to a one flow policy in the company's workshop aisles. The results exposed which aisles are overused, the disturbs among the logistics flows, and the logistics flow's performance, regarding the total of backorders, trips duration, and the routes' length in terms of distances and time.

As a result, this chapter contributes to both the literature and the industry by providing a DES model whose objective is to assess the ILFs in a car-assembling workshop. To the best of the author's knowledge, the simulation literature lacks of studies that integrate more than one class of ILFs to evaluate how a workshop can absorb all the traffic. Therefore, a set of best practices for bench-marketing purposes was presented for those who want to develop DES models centered on ILFs analysis. Focusing on real operations, it was proposes a set of managerial insights related to ILFs in assembling lines that can impact on the efficiency of the logistics operations.

To conclude, the study was presented to the company's employees that found it interesting and useful. They observed that it may be extended to the warehouse's flows as well, which could be viewed as future work. Concerning further applications, it would be useful to introduce the concepts developed for external logistics into internal logistics, such as drivers' behaviors. Also, methods should be introduced to support the company to compute those routes, such as the metaheuristic that faces combinatorial optimization problems presented in chapters 4 and 5. Later, those routes may be introduced and tested in a similar DES model.

Chapter 7

APPLYING LAGRANGEAN RELAXATION TO SOLVE THE FLOW SHOP SCHEDULING PROBLEM WITH PRECEDENCE CONSTRAINTS, RELEASE DATES AND DELIVERY TIMES

This chapter is based on the following publication:

Fabri, M., Ramalhinho, H. (2019)The Lagrangean Relaxation for the Flow shop Scheduling Problem with Precedence Constraints, Release Dates and Delivery Times. *Journal of Advanced Transportation.*

7.1 Introduction and problem statement

Several manufacturing companies sort their processes in a sequential fashion. The sequenced standard follows the concept that each process has its suppliers and clients, which may be represented by previous and successor processes, respectively. That concept may be interpreted as a Flow Shop one [Pinedo (2016)].

In the Flow Shop methodology, each process may be viewed as a single or a set of machines. Then, each machine is responsible for executing a specific task. Furthermore, all the jobs must follow the same sequence of machines. So, after a job completes a task in a machine, it must join a queue at the next machine. Also, the tasks must be executed under some constraints, such as release dates or resources availability.

In this chapter, a real-world problem, inspired in the SEAT activities, is presented. It is equivalent to the Flow shop problem with precedence constraints, release dates, and delivery times. Precisely, three final processes of a company's production flow are considered, which are the Checking, Loading, and Departing processes.

Therefore, the studied problem is stated as the Flow shop problem with precedence constraints, release dates, and delivery times with the objective function of minimizing the makespan. That problem is defined as a strongly NP-hard problem [Lourenço .(1996)]. Figure 7.1 summarizes the processes of interest.

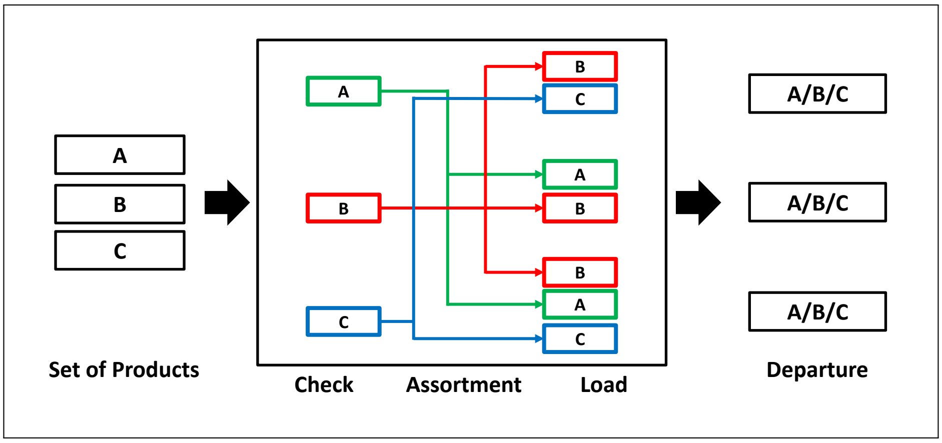


Figure 7.1: The outbound processes' scheme

As disclosed in chapter 1, SEAT is able to produce up to 2.400 cars (products) each day. Notice that these products are not all the same because the products are customized according to the client's demands. So, after the manufacturing phases, each product is assigned to a cluster.

A cluster is represented by the letters A, B, and C in figure 7.1. Regularly, a cluster is compound by a set of products that are similar to each other, such as a car model. Also, each cluster must pass by a quality control process to avoid sending poor-quality products to the final clients. The control consists of evaluating each product individually. As a result, the operator receives a list of clusters to be checked.

Then, each cluster is scheduled and checked one by one. Notice that the time spent at each cluster may vary according to the type of the products that compound the cluster as well as the found failures.

In contrast, some products do differ from themselves, and that is the reason that justifies the clustering procedure at the checking phase. So, the company avoids mixing different products in the same cluster in that first phase.

After the checking phase, an established cluster is fragmented. In other words, the products that compound that cluster are placed in a waiting zone and assorted according to its destinations. So, after a truck's load has already been wholly sorted in the waiting area, the related dispatching truck is authorized to get inside the marquee. Therefore, a truck is not allowed to get inside te marquee before all its cargo have already been sorted in the waiting zone.

So, it can be assumed that each outgoing truck has a precedent-jobs list. Then, after the truck's arrival, the operators start to load the truck. The loading task is concluded after an amount of time, which may vary according to the truck type, the cargo, and the required paperwork. In this work, it is assumed that there is one team in charge of loading the trucks. As a result, the trucks will be loaded one by one.

Finally, the last process is the Departure one. Here the truck departs from the company towards the client's location. Notice that it is not considered to evaluate which route the truck driver should do, but the average duration to reach the clients' locations instead.

Therefore, the checking and the loading process were modeled as machines. So, the checking process is defined as the Machine 1 (M1) and the loading process as Machine 2 (M2). Moreover, it is stated that the main objective is to minimize the maximum date when a client receives its products. As a result, this problem is tackled as the two-machine Flow shop Scheduling problem with precedence constraints, release dates, and delivery times.

Moreover, the described problem is modeled as a time-indexed formulation, which is based on the discretization of the time horizon. This kind of formulation is known to provide tighter linear relaxation bounds. However, the model presents a high number of variables. See [Cota et al.(2016), Souza & Wolsey (1992), Van den Akker et al. (2000)].

To sum up, this chapter faces two primary objectives. The first is to present a suitable model to cope with the Flow shop problem with precedence constraints, release dates, and delivery times. The second goal is to solve the proposed model problem through an appropriated decomposition method. Here, an Integer Linear Programming

(ILP) model on time-indexed variables is presented. Additionally, a Lagrangean Relaxation (LR) is proposed to obtain both upper and lower bounds. The sub-gradient method was chosen to conduct the convergence of the LR. See [Vanderbeck & Wolsey (2010)].
The paper is organized as follows. Section 7.2 presents the developed ILP model. Section 7.3 describes the Lagrangean Relaxation. Next, section 7.4 discusses the computational experiments and results. Finally, the 7.5 concludes the chapter.

7.2 The Integer Linear Programming model

The two-machine Flow shop Scheduling problem with precedence constraints, release dates, and delivery times are set as $(F2|prec, r_j, q_j|Dmax)$, based on the notation presented by [Pinedo (2016)]. In other words, the described problem aims to solve a scheduling problem, whose target is to minimize the date when the last product will be delivered to the client. Also, as stated before, the checking and departing processes are viewed as a machine each. Moreover, there are a set of constraints to take into account. These constraints state that the machines are not allowed to work with more than one job at the same time. Also, all jobs must be executed only once. Besides that, there is a precedence list that must be respected. That precedence list enables a job to be processed in machine 2. The mathematical model of this formulation is presented next.

The term $F2$ means that there are two machines in sequence. The terms $(prec, rj, q_j)$ mean that there are three classes of constraints applied, which are: the precedence, the release dates, and the delivery times ones, respectively. Finally, the D_{max} term refers to the objective function, which minimizes the latest date a client receives its products.

Moreover, the $(F2|prec, r_j, q_j|Dmax)$ can be described as follows. Consider a set $J^1 = \{1, \ldots, n\}$ of jobs to be processed on the first machine M_1, which correspond to the clusters to be processed at the first machine. Likewise, consider a set $J^2 = \{1, \ldots, m\}$ of jobs to be processed on the second machine M_2, which correspond to outgoing trucks to be loaded at the loading process. The processing time of a job j at a machine i is denoted by p_{ij}, which corresponds to the time for processing a cluster at the M_1. The precedence constraints imply that for each job (truck) $j \in J^2$ is associated a nonempty set $S_j \subseteq J^1$ such that j can only be processed in M_2 after all clusters belonging to S_j have been processed in M_1. Furthermore, it considers the delivery time d_j for each job $j \in J^2$. It corresponds to the time required to deliver the job $j \in J^2$ to its final client. The delivery time data refers to the time spent in transit. As a reference, the reader may consider that the delivery time is related to the time spent from the factory location to a range of destinations, such as another European country or even a country in North Africa.

So, the problem consists of finding a sequence of clusters in J^1 to be processed in M_1 and a sequence of the jobs in J^2 to be processed in M_2 to minimize the maximum date when a client receives its job. In other words, the target is to minimize D_{max}, which is equivalent to the latest time that one client receives its products.

So, it is proposed a time-indexed model, which is based on a time-discretization of the planning horizon into a set $T = \{0, \ldots, h\}$ of periods. Time-indexed formulations have been shown in the literature to be likely to provide better LP-relaxation bounds than other formulations for scheduling problems, see [Cota et al.(2016), Souza & Wolsey (1992), Van den Akker et al. (2000)]. Continuing, it is defined two binary variables: x_{jt} (resp. y_{jt}) assumes value 1 if a job $j \in J^1$ (resp. $j \in J^2$) starts its processing in M_1 (resp. M_2) in period $t \in T$, and 0 otherwise. Also, the integer variable D_{max}, which is the maximum time when the last client receives its products. The proposed ILP formulation for that version of the $(F2|prec, r_j, q_j|Dmax)$ is presented as follows:

$$\min D_{max} \tag{7.1}$$

$$\sum_{t=0}^{h-p_{1j}} x_{jt} = 1 \qquad \forall j \in J^1 \tag{7.2}$$

$$\sum_{t=0}^{h-p_{2j}} y_{jt} = 1 \qquad \forall j \in J^2 \tag{7.3}$$

$$\sum_{t=0}^{h-p_{2j}} t y_{jt} - \sum_{t=0}^{h-p_{1k}} (t + p_{1k}) x_{kt} \geq 0 \qquad \forall j \in J^2, \forall k \in S_j \tag{7.4}$$

$$\sum_{j \in J^1} \sum_{s=\max(0;t-p_{1j}+1)}^{t} x_{js} \leq 1 \qquad \forall t \in T \tag{7.5}$$

$$\sum_{j \in J^2} \sum_{s=\max(0;t-p_{2j}+1)}^{t} y_{js} \leq 1 \qquad \forall t \in T \tag{7.6}$$

$$D_{max} \geq \sum_{t=0}^{h-p_{2j}} (t + p_{2j} + d_j) y_{jt} \qquad \forall j \in J^2 \tag{7.7}$$

$$x_{jt} \in \{0,1\} \qquad \forall j \in J^1, \forall t \in T, t \leq h - p_{1j} \tag{7.8}$$
$$y_{jt} \in \{0,1\} \qquad \forall j \in J^2, \forall t \in T, t \leq h - p_{2j} \tag{7.9}$$
$$D_{max} \in \mathbb{Z}^+ \tag{7.10}$$

The objective function (7.1) minimizes the time of reception of the last job. It is equivalent to the biggest value possible of $(t+p_{2j}+d_j)y_{jt}$, in which t represents the initial processing time of the job ($j \in J^2$). Constraints (7.2) (resp. (7.3)) state that each job $j \in J^1$ (resp. $j \in J^2$) has to be started exactly once at M_1 (resp. M_2). In other words, one job must be processed only once by either the machines. The precedence constraints (7.4) ensure that a job $j \in J^2$ cannot be processed at M_2 before all jobs in S_j have been completed at M_1. Further explanation could be find in figure 7.2. Constraints (7.5) (resp. (7.6)) state that machine M_1 (resp. M_2) can handle at most one job at any time period. Consequently, the M1 and the M2 are not able to process more than one job at the same time. Next, the D_{max} value is established by constraints (7.7). The D_{max} value represents the makespan of the delivery time. Lastly, constraints (7.8), (7.9) and (7.10) define the domain of the variables.

7.3 The Lagrangean Relaxation

The proposed method to get the $(F2|prec,rj, q_j|Dmax)$ problem solved is the Lagrangean Relaxation (LR). The LR is applied to the previous ILP model. The precedence constraints (7.4) that couple the scheduling on machines M_2 and M_1 are relaxed in the LR approach. Figure 7.2 illustrates a scheduling, which is not feasible to constraints (7.4).

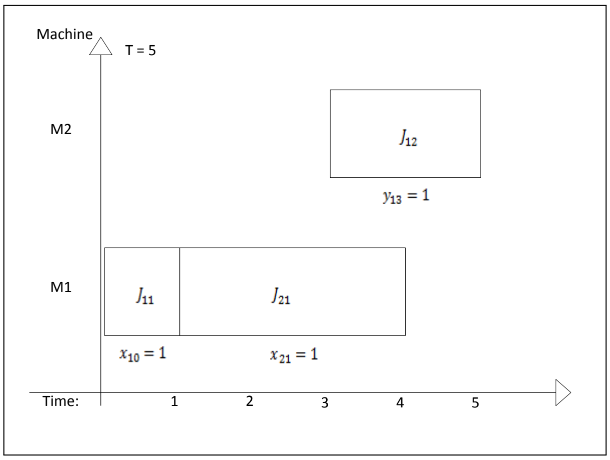


Figure 7.2: Scheduling violating the precedence constraints 7.4.

In this example, job 1 (J_{11}) processed by M_1 begins its processing at $t = 0$, so, $x_{10} = 1$, and job 2 (J_{21}) processed by M_1 begins its processing at $t = 1$, so, $x_{21} = 1$. Considering $S_1 = \{J_{11}, J_{21}\}$ as the predecessors of job 1 (J_{12}) processed by M_2, it can only start its processing at $t = 4$. However, in this example, J_{21} begins its processing at $t = 3$, $y_{13} = 1$, and not at $t = 4$ as expected, violating the precedence constraints.

Let $\lambda_{jk} \geq 0$, $j \in J^2$, $k \in S_j$, be the Lagrangean multipliers associated with constraints (7.4). The Lagrangean multipliers are equivalent to the dual variables associated with each relaxed constraint placed in the objective function, see [Vanderbeck & Wolsey (2010)]. If a job is scheduled in M_2 before one of its predecessor has been completed, the objective function will be penalized in the Lagrangean subproblem L(λ) as follows:

$$L(\lambda) = \min D_{max} + \sum_{j \in J^2} \sum_{k \in S_j} \lambda_{jk} \left(\sum_{t=0}^{h-p_{1k}} (t + p_{1k}) x_{kt} - \sum_{t=0}^{h-p_{2j}} t y_{jt} \right) \quad (7.11)$$

s.t. (7.2), (7.3), (7.5), (7.6), (7.7), (7.8), (7.9) and (7.10).

The subgradient algorithm is used to solve the Lagrangean dual $\max\{L(\lambda) : \lambda \geq 0\}$. The resulting model allows decomposing the Lagrangean subproblem into one smaller subproblem $L(\lambda)_x$ in M_1.

Notice that the subproblem $L(\lambda)_x$ is the total weighted completion time scheduling problem on one machine. The completion of a job $k \in J^1$ is weighted by the sum of penalties applied on all jobs to be scheduled on M_2, which have job k among their predecessors. Setting $w_k^1 = \sum_{j \in J^2 : k \in S_j} \lambda_{jk}$, $k \in J^1$, subproblem $L(\lambda)_x$ is written as follows:

$$L(\lambda)_x = \min \sum_{k \in J^1} w_k^1 \sum_{t=0}^{h-p_{1k}} (t + p_{1k}) x_{kt} \quad (7.12)$$

s.t. (7.2), (7.5), and (7.7).

Subproblem $L(\lambda)_x$ can be solved by the weighted shortest processing time first rule, in which jobs are sorted in decreasing order of $\frac{w_k^1}{p_{1k}}$. The proof is stated in [Pinedo (2016)]. So, an UB can be inferred based on the jobs sequenced on the M1 because it is possible to calculate the release dates of the jobs on the M2. The UB is discussed next.

In order to obtain a valid UB for the $(F2|prec, rj, q_j|Dmax)$ problem, let $\bar{x}_{kt}$, ($k \in J^1$; $t \in T$), be an optimal solution of subproblem $L(\lambda)_x$ for a given value of the Lagrangean multipliers.

On the one hand, considering a schedule on M_2 that the starting time t_j of each job $j \in J^2$ satisfies $t_j \geq \max_{k \in S_j}\{\sum_{t=0}^{h-p_{1k}} (t + p_{1k})\bar{x}_{kt}\}$. Consequently, that schedule is viewed as a feasible solution and provides an UB for the $(F2|prec, rj, q_j|Dmax)$ problem.

On the other hand, the problem defined in the last paragraph is viewed as the Total Weighted Completion Time Scheduling Problem on one machine with release dates, which is a NP-Hard problem [Lenstra (1977)]. Thus, it is proposed a Lagrangean heuristic that consists of solving the subproblem $L(\lambda)_x$ in M_1, for a given value of the Lagrangean multipliers. Later, the approximation algorithm proposed by [Phillips et al. (1998)] is applied to the resulting problem with release dates in M_2.

In the first step, the approximation algorithm allows preemption to get an optimal schedule with the remaining weighted shortest processing time first rule. In the second step, jobs are nonpreemptively scheduled in the same order of their completion times. The algorithm produces, in $O(n)$ time, a nonpreemptive schedule. The produced non-preemptive schedule increases the total weighted completion time by a factor of 2, at most, regarding a preemptive schedule. As a result, a UB is obtained.

After computing the UB, a valid LB value is required to run the subgradient algorithm. As said in chapter 2, the subgradient algorithm is responsible for solving the LR procedure. So, the goal is to obtain the biggest LB value possible for each iteration of the subgradient algorithm. In this problem, a LB value corresponds to a solution that do not consider the constraints 7.6, which are relaxed. These constraints regard to the availability of the M2. As a result, the M2 is able to process more than one job at the same time. Afterward, a relaxed value of the Dmax is necessary, which means a valid LB. The Dmax can be evaluate as the biggest term of $(r_j + p_{2j} + d_j)y_{jt}$, $j \in J^2$, in which r_j represents the initial processing time of the job ($j \in J^2$). Note that the M2 availability is not viewed as an issue. The relaxed Dmax is computed following a rule that is introduced next.

To calculate the date a client will receive its products, the first step is to assign a minimum release date r_j value for each job $j \in J^2$, which is defined as $r_j = \sum_{k \in S_j} p_{1k}$. Then, it is added to the r_j value the respective processing time in the M2 (p_{2j}). Next, it is summed the delivery time required to deliver the products the client's location (d_j). Afterward, the computed values are sorted in a decreasing fashion. As a result, it is assigned the biggest value found to the D_{max} variable.

Notice that it is equivalent to the relaxation of the constraints (7.6). Additionally, constraints (7.4) were maintained to compute the released dates. In this sense, the computed value is a valid LB. The figures 7.3 and 7.4 depict examples of valid UB and LB solutions, respectively.

Therefore, notice that the complete formulation of the subproblem $L(\lambda)$ (equation 7.11) was not used to execute the LR because the ob-

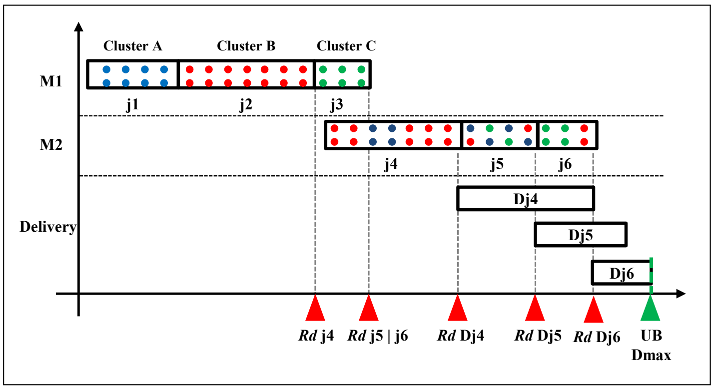


Figure 7.3: An Upper Bound solution example. The red triangles represent the release dates for each job. Furthermore, the green triangle represents the UB value.

jective function of the Lagrangean dual was not completely considered to obtain the bounds. Instead, the sequence calculated on M1 was considered. So, this work took advantage of the LR and the subgradient method structures to obtain valid UB values.

Moreover, the LB values were computed following a greedy rule based on the three components: (i) the minimum release date regarding each job $j \in J^2$; (ii) the processing time in the M2; and (iii) the delivery time. Afterward, both UB and LB values were introduced to the subgradient algorithm to pursuit its convergence. In this sense, that approach may be referred to as an adaptation of the LR method. The figure 2.1 illustrates the conditions to the method achieves the optimality.

7.4 Experiments

In this section, the computational results on random instances are presented as follows. The instances are divided into two groups: (i) small processing-time jobs, and (ii) long processing-time jobs. In the first (resp. second) group processing times are drawn from the uniform distribution between 1 and 10 (resp. 10 and 100). The number n of jobs in J^1 is set to 5, 10, 20, 40, and 60, and the number m of jobs in J^2 is set to $0.6n$, $0.8n$, n, $1.2n$, and $1.4n$.

The set S_j of predecessors of a job $j \in J^2$ is a random subset of J^1 with cardinality $|S_j|$ drawn from the uniform distribution between 1 and $(n-1)$. In the following tables, an instance is identified by $n - m - np - g$, where np is the maximum number of predecessors a job in J^2 can have, and g is the processing-time group. Regarding

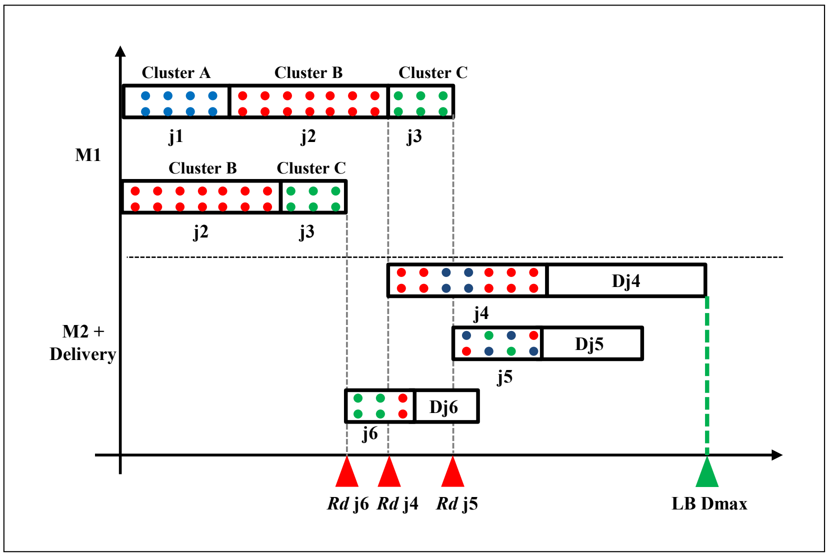


Figure 7.4: A Lower Bound solution example. The red triangles represent the release dates for each job. Furthermore, the green triangle represents the LB value. The figure depicts how the minimum release date (Rd) is computed for each $j \in J^2$. Notice that the placed jobs are not necessary processed at the same time in M1. The figure illustrates how to compute the release dates for each job $j \in J^2$, concerning its precedence list in M1.

the delivery times, it is calculated in terms of the uniform distribution between 100 up to 1,000 and from 1,000 up to 5,000 for elements of Group 1 and 2, respectively. The reader may interpret each slot of time as 10 minutes in the real world. Moreover, the author believes that this set of data represents quite well the studied processes and its variability, as well.

Table 7.1 summarizes the structure of the generated instances. The first column shows the instances' Groups. The second and third columns show the possible values for the number of jobs in J^1 and J^2, respectively. The fourth and the fifth columns show the uniform distribution intervals from which $|S_j|$ and the processing times are drawn, respectively. The sixth column refers to the time spent in transit to deliver the products to the final clients. The last column shows the identification, where one instance is generated for each value of m in the second column.

The experiments were carried out on the Operational System CentOS 7.x x86_64 with 27 compute nodes, 720 cores, and 7.4 TB of RAM as the maximum capacity. It is noteworthy that only one node was applied to proceed with the calculations. As a result, none parallel approach was used. Moreover, the programming languages C and C++

G	n	m	$\|S_j\|$	p_j	d_j	Identification
	5	3-4-5-6-7	U(1,4)	U(1,10)	$\mathrm{U}(10^2, 10^3)$	$5 - m - 4 - 1$
	10	6-8-10-12-14	U(1,9)	U(1,10)	$\mathrm{U}(10^2, 10^3)$	$10 - m - 9 - 1$
1	20	12-16-20-24-28	U(1,19)	U(1,10)	$\mathrm{U}(10^2, 10^3)$	$20 - m - 19 - 1$
	40	24-32-40-48-56	U(1,39)	U(1,10)	$\mathrm{U}(10^2, 10^3)$	$40 - m - 39 - 1$
	60	36-48-60-72-84	U(1,59)	U(1,10)	$\mathrm{U}(10^2, 10^3)$	$60 - m - 59 - 1$
	5	3-4-5-6-7	U(1,4)	U(10,10^2)	$\mathrm{U}(10^3, 5,000)$	$5 - m - 4 - 2$
	10	6-8-10-12-14	U(1,9)	U(10,10^2)	$\mathrm{U}(10^3, 5,000)$	$10 - m - 9 - 2$
2	20	12-16-20-24-28	U(1,19)	U(10,10^2)	$\mathrm{U}(10^3, 5,000)$	$20 - m - 19 - 2$
	40	24-32-40-48-56	U(1,39)	U(10,10^2)	$\mathrm{U}(10^3, 5,000)$	$40 - m - 39 - 2$
	60	36-48-60-72-84	U(1,59)	U(10,10^2)	$\mathrm{U}(10^3, 5,000)$	$60 - m - 59 - 2$

Table 7.1: Summary of the instances.

were used with compiler GNU GCC, and CPLEX 12.6.8. was used to solve the ILP models.

So, the first results reported concerns to the ILP model experiments, which is solved through the software CPLEX with a time limit of 7,200 seconds. Tables 7.2 and 7.3 show the results for the instances which CPLEX obtained lower and upper bounds within the time limit. Also, these tables show the Lagragean Relaxation's results regarding the same instances and metrics

The results related to the Group 1's instances are presented in table 7.2. Next, the results related to the Group 2's instances are presented in table 7.3. Then, tables 7.2 and 7.3 present the following data for each instance: a instance's identification, the final upper (UB) and lower (LB) bounds obtained within the time limit, the percentage gap, and the time in seconds. The Linear Relaxation bounds are presented in the subsequent table 7.4, along with results for the LR, as well. The percentage gap is computed as $\frac{(UB-LB)}{UB}$. The dash symbol "-" in the tables means that a method did not finish within the time limit.

Regarding the results, the mathematical model is able to obtain the optimal solution for 16 instances of Group 1 and only nine instances for Group 2. Furthermore, the CPLEX was not able to provide neither a feasible UB nor a LB for the most complicated instances of Group 2. By contrast, the LR was able to compute valid bounds for all instances. Indeed, the LB values were verified to be the same as the optimal solutions in 21 out of 50 opportunities. Moreover, LR's GAP values were smaller than 5% in 28 out of 50 opportunities. To conclude, the maximum time spent by the LR to complete the method was 61 seconds, and it was observed for the most complicated instance.

Furthermore, it is presented two figures that illustrate the applica-

Group 1 Instances								
	Integer Model CPLEX				Lagrangean Relaxation			
Instance	LB	UB	G. (%)	Time (sec)	LB	UB	G. (%)	Time (sec)
5-3-4-1	**794**	**794**	0	0	794	799	1	0
5-4-4-1	**671**	**671**	0	0	**671**	**671**	0	0
5-5-4-1	**842**	**842**	0	0	842	852	1	0
5-6-4-1	**801**	**801**	0	0	801	812	1	0
5-7-4-1	**901**	**901**	0	0	901	905	1	0
10-6-9-1	**939**	**939**	0	1	939	955	2	0
10-8-9-1	**983**	**983**	0	5	983	989	1	0
10-10-9-1	**1,002**	**1,002**	0	10	996	1,024	3	0
10-12-9-1	**1,001**	**1,001**	0	2	1,001	1,013	1	0
10-14-9-1	**906**	**906**	0	0	906	916	1	0
20-12-19-1	**926**	**926**	0	28	926	953	3	0
20-16-19-1	**962**	**962**	0	24	954	984	3	0
20-20-19-1	**1,048**	**1,048**	0	43	1,048	1,125	7	0
20-24-19-1	**1,082**	**1,082**	0	51	1,082	1,096	1	0
20-28-19-1	**1,100**	**1,100**	0	189	1,1	1,167	6	0
40-24-39-1	**1,012**	**1,012**	0	2,332	1,006	1,085	7	0
40-32-39-1	1,096	1,159	5	7,200	1,144	1,266	10	0
40-40-39-1	1,084	1,128	4	7,200	1,092	1,26	13	1
40-48-39-1	1,074	1,146	6	7,200	1,116	1,251	10	1
40-56-39-1	1,051	1,126	7	7,200	1,069	1,155	7	2
60-36-59-1	1,184	1,288	8	7,200	1,233	1,324	7	2
60-48-59-1	1,16	1,505	23	7,200	1,225	1,259	3	3
60-60-59-1	1,194	1,58	24	7,200	1,268	1,381	8	4
60-72-59-1	1,195	1,618	26	7,200	1,289	1,442	10	5
60-84-59-1	1,118	1,100,843	99	7,200	1,283	1,502	14	7

Table 7.2: Results for the ILP model running CPLEX with a time limit of 7,200 seconds. The GAP is defined as $(UB - LB/UB)$ and represents by "G.". Results depicted for Group 1's instances. The bolded LB and UB values represent an instance's optimal solution.

Group 2 Instances								
	Integer Model CPLEX				Lagrangean Relaxation			
Instance	LB	UB	G. (%)	Time (sec)	LB	UB	G. (%)	Time (sec)
5-3-4-2	**4,630**	**4,630**	0	1	4,630	4,66	1	0
5-4-4-2	**3,222**	**3,222**	0	12	**3,222**	**3,222**	0	0
5-5-4-2	**3,222**	**3,222**	0	26	3,222	3,305	2	0
5-6-4-2	**4,855**	**4,855**	0	26	4,840	4,959	3	0
5-7-4-2	**4,954**	**4,954**	0	21	4,954	5,09	3	0
10-6-9-2	5,271	5,272	0.001	7,200	5,221	5,317	2	0
10-8-9-2	**4,289**	**4,289**	0	52	**4,289**	**4,289**	0	0
10-10-9-2	**5,080**	**5,080**	0	3,138	5,080	5,123	1	0
10-12-9-2	**4,802**	**4,802**	0	70	4,802	4,865	1	0
10-14-9-2	**5,151**	**5,151**	0	157	5,151	5,22	2	0
20-12-19-2	5,398	6,124	12	7,200	5,921	6,003	1	1
20-16-19-2	5,248	5,824	10	7,200	5,697	5,963	4	1
20-20-19-2	5,394	5,726	6	7,200	5,726	6,124	6	2
20-24-19-2	5,313	7,033	24	7,200	5,581	6,201	1	2
20-28-19-2	5,647	7,328	23	7,200	6,067	6,617	8	3
40-24-39-2	5,928	7,941	25	7,200	6,281	7,296	14	6
40-32-39-2	-	-	-	7,200	6,025	7,132	15	7
40-40-39-2	-	-	-	7,200	7,296	7,989	9	12
40-48-39-2	-	-	-	7,200	6,562	8,227	20	15
40-56-39-2	-	-	-	7,200	7,111	7,976	11	17
60-36-59-2	-	-	-	7,200	7,349	8,144	10	16
60-48-59-2	-	-	-	7,200	8,101	9,839	18	34
60-60-59-2	-	-	-	7,200	7,572	9,609	21	43
60-72-59-2	-	-	-	7,200	7,150	9,905	28	45
60-84-59-2	-	-	-	7,200	7,388	10,302	28	61

Table 7.3: Results for the ILP model running CPLEX with a time limit of 7,200 seconds. The GAP is defined as $(UB - LB/UB)$ and represents by "G.". Results depicted for Group 2's instances. The bolded LB and UB values represent an instance's optimal solution.

tion of the sub-gradient algorithm when solving the Lagrangean Sub-problem. The first figure represents a scenario that the optimal solution was achieved and the other figure represents a scenario that the convergence was not achieved, figures 7.5 and 7.6, respectively.

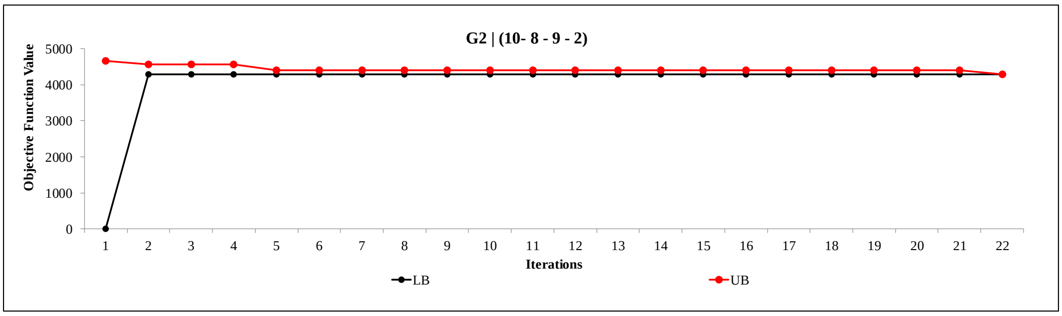


Figure 7.5: The instance G2 | (10-8-9- 2) did converge its LB and UB values. As a result, both UB and the LB computed are considered optimal solutions.

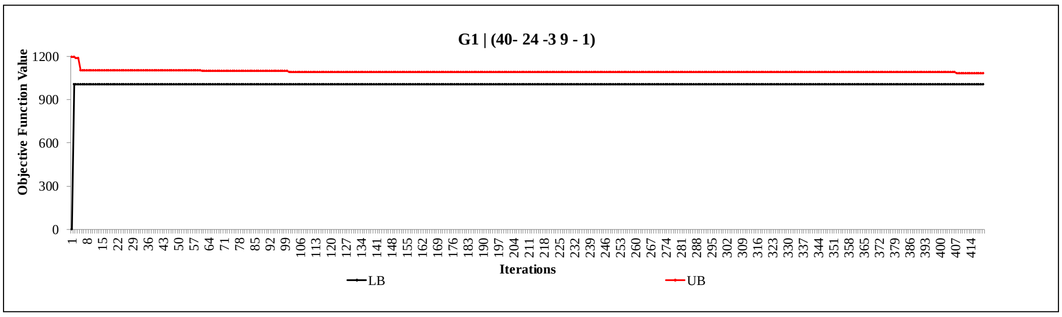


Figure 7.6: The instance G1 | (40-24-39- 1) did not converge its LB and UB values. As a result, neither UB nor the LB computed are considered as optimal solutions.

Next, the results obtained with the linear relaxation of the ILP model are reported. Also, the results based on the proposed Lagrangean Relaxation (LR) are presented as well. The time limit was set as 7,200 seconds for both experiments.

Table 7.4 shows the results for instance of the Groups 1 and 2. Results obtained with Linear relaxation are shown from the second to the third columns and from the eighth to the ninth columns. Moreover, the LR results are shown from the fourth to the sixth columns and from tenth to the twelfth columns. The first column presents the instance, the second column refers to the Linear Relaxation solution, and the third column presents the computational time in seconds. Then, the Lower bound of te RL is presented in the next column, following by the ratio between both lower bounds found, and finally the LR's computational time. Afterward, the same structure repeats for instances of Group 2. The dash symbol "-" in the tables means that a method did not finish within the time limit.

For both Groups of instances, the results show a common pattern. The LR provided either equal or better LB result than linear relaxation for all out of the 50 instances. Also, the CPLEX was not able to compute a valid LB for the four most complicated instances, which refer to the Group 2 ones. As a result, LR outperformed the Linear Relaxation for all out of 50 instances. Furthermore, the LR provided valid LB for the four most complicated instances. By contrast, The Linear relaxation was not able to compute valid LB for those instances within 7,200 seconds of computing time.

As previously mentioned, instances of Group 2 were generated with longer processing times than those of Group 1, c.f., Table 7.1. As a result, those instances present a much larger time-horizon, increasing the number of variables drastically. This fact has a significant impact on the performance of the methods.

Group 1 Instances						Group 2 Instances					
	Linear Relaxation		Lagrangean Relaxation			Linear Relaxation			Lagrangean Relaxation		
Instance	LB	Time (sec)	LB^*	(LB^*/LB)	Time (sec)	Instance	LB	Time (sec)	LB^*	(LB^*/LB)	Time (sec)
5-3-4-1	788	0	794	1 %	0	5-3-4-2	4,620	0	4,630	0 %	0
5-4-4-1	666	0	671	1 %	0	5-4-4-2	3,139	0	3,322	6 %	0
5-5-4-1	840	0	842	0 %	0	5-5-4-2	3,144	0	3,322	6 %	0
5-6-4-1	795	0	801	1 %	0	5-6-4-2	4,824	0	4,840	0 %	0
5-7-4-1	895	0	901	1 %	0	5-7-4-2	4,903	4	4,954	1 %	0
10-6-9-1	932	0	939	1 %	0	10-6-9-2	5,092	9	5,221	3 %	0
10-8-9-1	966	0	983	2 %	0	10-8-9-2	4,228	7	4,289	1 %	0
10-10-9-1	985	0	996	1 %	0	10-10-9-2	4,815	25	5,080	6 %	0
10-12-9-1	995	0	1,001	1 %	0	10-12-9-2	4,777	1	4,802	1 %	0
10-14-9-1	905	0	906	0 %	0	10-14-9-2	5,028	36	5,151	2 %	0
20-12-19-1	909	1	926	2 %	0	20-12-19-2	5,394	60	5,921	10 %	1
20-16-19-1	941	2	954	1 %	0	20-16-19-2	5,247	100	5,697	9 %	1
20-20-19-1	1,009	4	1,048	4 %	0	20-20-19-2	5,393	97	5,726	6 %	2
20-24-19-1	1,044	6	1,082	4 %	0	20-24-19-2	5,300	207	5,581	5 %	2
20-28-19-1	1,046	5	1,100	5 %	0	20-28-19-2	5,646	229	6,067	7 %	3
40-24-39-1	978	10	1,006	1 %	0	40-24-39-2	5,927	231	6,281	6 %	6
40-32-39-1	1,066	10	1,144	7 %	0	40-32-39-2	5,940	332	6,025	1 %	7
40-40-39-1	1,060	15	1,092	3 %	1	40-40-39-2	6,211	596	7,729	24 %	12
40-48-39-1	1,064	15	1,116	5 %	1	40-48-39-2	6,067	719	6,562	8 %	15
40-56-39-1	1,045	26	1,069	2 %	2	40-56-39-2	6,181	760	7,111	15 %	17
60-36-59-1	1,135	28	1,233	9 %	2	60-36-59-2	6,546	724	7,349	12 %	16
60-48-59-1	1,118	40	1,225	10 %	3	60-48-59-2	-	7,200	8,810	- %	34
60-60-59-1	1,173	75	1,268	8 %	4	60-60-59-2	-	7,200	7,757	- %	43
60-72-59-1	1,174	100	1,289	10 %	5	60-72-59-2	-	7,200	7,715	- %	45
60-84-59-1	1,162	112	1,283	10 %	7	60-84-59-2	-	7,200	7,738	- %	61

Table 7.4: Results obtained with the linear relaxation and the LR on instances of Groups 1 and 2. The LB^* values refer to the Lower Bounds provided by the Lagrangean Relaxation. Likewise, LB values refer to the Lower Bounds computed by the Linear Relaxation.

7.5 Conclusion

In this chapter, a two-machine Flow shop Scheduling problem with precedence constraints, release dates, and delivery time was considered. Moreover, the problem's objective is minimizing the time a client receives the last job.

Also, an adaptation of the Lagrangean relaxation (LR) approach was proposed, which presented the best overall results. On the one hand, the LR has obtained the optimal solution only in three out of 50 instances. On the other hand, the LR outperformed the CPLEX for the most complicated instances. The LR was able to compute feasible solutions for all instances within 61 seconds of computing time, which is remarkable for an applied problem. Even though the ILP provided the optimal solution for 26 instances, those optimal solutions were achieved only for the easier instances.

Therefore, the work presents an alternative way for companies that must schedule their activities in a flow shop fashion. Besides, the activities described in that work may be adapted for a range of other scenarios. As a result, the methodology presented is a contribution to the companies that must schedule their processes, in particular, in the outbound area.

As future works, a metaheuristic that provides better UB and LB should be investigated. It could support to achieve better solutions for large instances.

Chapter 8

CONCLUSION

According to the World Economic Forum, the automotive sectors will receive more innovation in the next 20 years than there has been in the past 100 years [World-Economic-Forum (2016)]. The author hopes that this thesis contributes to supporting that affirmative to become real.

In this thesis, the automotive sector is the main scope. All the developed methods were done based on that industry. Precisely, the logistics concepts were considered with particular focus on the in-house or internal logistics processes of a car-assembling company in Spain.

So, several problems were tackled in this thesis, which regards to routes calculation and alternatives internal logistics management systems evaluations. Moreover, Monte Carlo simulations and a discrete-event simulation (DES) model were developed to consider real issues the problems assessments. As presented throughout the thesis, the results were validated by the company's experts, who found the methodology novel and interesting.

So, the developed methods were introduced in this thesis throughout the chapters 3 to 7. These chapters are summarized in the next section. Later, final remarks are presented considering this industrial Ph.D.

8.1 Main contributions and future research

Chapter 3 presented the first attempt to optimize a specific logistic flow inside an assembly workshop of this work. A feasible solution, or a set of internal logistic routes, was obtained through an Integer Linear Programming (ILP) model, and its solution was compared with the current solution through a Monte Carlo Simulation. The proposed solution achieved excellent performance in terms of the KPIs set by the company. However, it has some limitation to deal with the orders variability.

Chapter 4 is a step further in comparison to the previous one. Here the orders' stochastic property is the main issue to deal with. Consequently, the In-house Logistics Routing Problem and a Simheuristic based on Iterated Local Search (ILS) were presented. These methods have in common an objective function that aims to minimize the total of routes applied, the distance covered by those routes and the number of backorders. Moreover, the new methods were more realistic than the previous one because the company's historical orders were considered individually. As a result, chapter 4 presented a more robust approach than the previous chapter. However, high levels of backorders was still observed in the new proposed solutions. Concluding, the results show that the high number of backorders is related to the current ordering system procedure, which is based on the logistics operators assumptions.

Chapter 5 provided to SEAT feasible alternatives to improve its logistics activities by reducing the number of backorders. Then, that chapter conducted an assessment of Internal Logistics Routing Management (ILRM) systems in a car-assembling company. So, the company's current ILRM system was evaluated, and new scenarios were suggested. The first new scenario considers variables routes using the current ordering system. The second scenario uses variable routes that are computed based on the placed orders. Also, an automatic ordering system is introduced. The third alternative scenario also considers variable routes that depend on the demand but using forecasted demand obtained through the Manufacturing Resource Planning (MRP) system. To evaluate and optimize these scenarios, an ILP model and an ILS algorithm were developed to calculate those variable routes. Furthermore, a simulation procedure is presented to evaluate the company's current set of routes. Then, a comparison between all scenarios was executed. From the optimization point of view, the ILS was able to reduce the total distance covered throughout the considered time horizon, and none backorders were generated. Finally, the advantages and challenges of each scenario were presented. As a result, this chapter presented interesting problems in a car-assembly company, proposed an ILP model and an ILS algorithm, and evaluated a real strategical case in SEAT company. This proposed methodology can be applied and extended to any car-assembling company.

Chapter 6's main goal was proposing a simulation model to evaluate and analyze the internal logistics activities in the SEAT's assembly line. A DES model was developed through the Plant Simulation software as well as an analysis of the internal logistics in SEAT was performed. So, to evaluate the internal logistics flows, two main KPIs were stated by the company that were: the logistics flows' performance and the assembly line's aisles utilization. Moreover, three scenarios were evaluated based on the following premises: (i) actual system; (ii) introduction of autonomous vehicles; and (iii) applying a transit flow policy. The results indicated the main aspects and areas of the assembly line that contribute to a disruption of the logistics operations and should be considered to be improved. It was concluded that the proposed DES concepts could be applied whenever car manufacturer companies need to evaluate new premises, or even in other industries that rely on assembly lines. In the end, a set of best practices were disclosed for bench-marketing purposes.

Chapter 7 presents a methodology to support a company in the automotive business on scheduling the jobs on its final processes. These processes are: (i) checking the final product and (ii) loading the dispatch trucks. These activities are inspired in common procedures found in the outbound area of any manufacturing company. The problem faced is defined as the Flow shop problem with precedence constraints, release dates, and delivery times. The major objective is to minimize the latest date a client receives its products. The chapter presented a time-indexed integer mathematical model to compute feasible solutions for the presented problem. Moreover, a Lagrangean Relaxation procedure was introduced to compute valid Lower and Upper Bounds. The executed experiments were inspired by the company's premises. As a conclusion, the results showed that the proposed methodology was able to compute feasible solutions for all the instances tested. For the more complicated instances, the Lagrangean Relaxation approach was able to calculate better bounds in a shorter computational time than the Mathematical problem.

Then, back to the research question proposed in section 1.3, which was: *what is the best approach to deal with the in-house supplying routes design, regarding a car-assembly company scenario?* So, as a conclusion, it can be stated that this work presents a suitable approach to deal with the in-house supplying routes design in a car-assembly background. Furthermore, the three main objectives stated in section 1.3 were fulfilled. These affirmatives can be verified based on the discussions and results disclosed at each chapter, as well as the company's feedback concerning the presented methodologies. As a result, the main thesis' contributions are stated based on the research objectives presented in section 1.3.

- This thesis provides useful methods to be applied to the internal logistics approach. Indeed, the developed methods are not limited to a car-assembly company only, but any manufacturing company that shares similar concepts.

- A brand-new Vehicle Routing Problems was presented, which is defined as **Internal Logistics Routing Problem** (ILRP). The ILRP fits appropriately to the internal logistics flows evaluation over a manufacturer company.

- Novel Integer Linear Problems (ILP) formulations were presented. Those formulation are able to provided optimal solutions for the ILRP.

- Novel Metaheuristics algorithms were presented. Also,those algorithms are able to provided excellent feasible solutions for the ILRP.

- A discrete-event-simulation model was developed to tackle the Internal logistics flows evaluation over an assembly line, which is an important topic not covered adequately by the literature. Therefore, a set of best practices for bench-marketing purposes was presented for those who want to develop DES models centered on ILFs analysis, as well as a set of managerial insights related to ILFs in assembly lines that can impact on the efficiency of the logistics operations.

As a result, this work provides a new methodology to deal with real manufacturing assembly lines. Precisely, novel applications were conducted over a car-manufacturing company, as presented before. By contrast, there are many further opportunities observed and much research to be explored. As a result, future research is presented regarding the chapters' discussions. Later a final remark is stated in the next section.

- Future works applied to chapter 4 should explore methods to solve optimally large instances of the In-house Logistics Routing Problem, such as the branch-and-cut procedure and lagrangean relaxation. Moreover, extensions of the SimILS and the simulation procedure may be improved by adding a more realistic aspect, such as the traffic on the assembly-lines, the use of a different type of vehicles and self-guided automatic vehicle.

- The chapter 5 should be extended by developing methods to solve optimally large instances of the presented ILP, such as the branch-and-cut procedure. Likewise chapter 4, extensions of the ILS and the simulation procedure may be improved by adding a more realistic aspect, such as the traffic on the assembly-lines, the use of a different type of vehicles and self-guided automatic vehicle.

- Extensions of the chapter 6 may concern further applications of the developed DES, it would be interesting to introduce those concepts developed for external logistics into internal logistics, such as drivers' behaviors. Also, further methods should be introduced to support the company to compute those routes, such as the metaheuristics developed in chapters 4 and 5 that faces combinatorial optimization problems. Later, those routes may be introduced and tested in a similar DES model.

- Related to the last chapter 7, future works may focus on metaheuristics that provide better UB and LB. It could support to achieve better solutions for large instances.

8.1.1 Research in Progress

Besides the future work presented above, there are some practical applications that have been carried on in parallel to those topics presented so far. Then, the next paragraphs present the research in progress that is viewed as extensions of the methodology presented up to now.

So, the research in progress concerns to those applications related to the warehouse mainly. Precisely, the warehouse's issues refer to the aisles' traffic and the convoys setup mainly.

Regarding the traffic in the warehouse's aisles, a DES-based model was developed. That model considers some of the premises presented in chapter 6, because it executes a simulation under the logistics point of view, as well as the simulation modeling framework illustrated by figure 6.3. However, the warehouse is the main area of interest instead of an assembly area.

The warehouse simulation model (WSM) was developed through the Plant Simulation software, as the DES model presented in chapter 6. The major interest is to evaluate the current traffic of each aisle. Also, the main warehouse's flows were considered. Figure 8.1 represents the simulation model scheme, in which each process and logistics flow were introduced.

Afterward, the WSM was executed and its results validated by the company's expert. The results were compiled and resume through figure 8.2. In that figure, the reader may observe the average number of vehicles that pass through each specific part of the aisles. The graphic below presents the number of vehicles for each considered part of the warehouse.

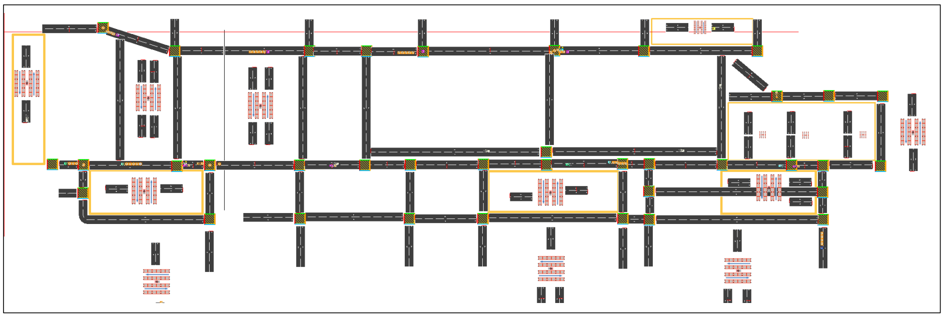


Figure 8.1: The WHS Simulation scheme. The layout description can be consulted in figure 8.2.

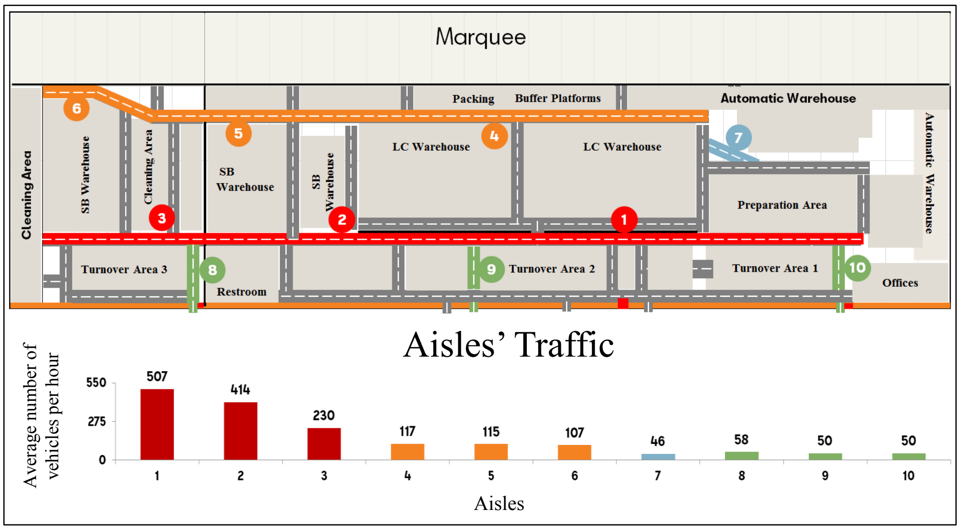


Figure 8.2: Warehouse traffic evaluation. The figure represents the warehouse layout. Each inserted number refers to a specific area of interest. The chart presents the average number of vehicles that pass through these areas per hour.

As a preliminary conclusion, it can be stated that the red aisles absorb most of the warehouse's traffic. Indeed, it represents the actual scenario observed in the practice. As a result, that model can be further applied by introducing new premises and alternatives to evaluate the consequences of new scenarios.

Moreover, further studies were conducted to evaluate alternatives approaches to prepare the convoys in the warehouse. These convoys are related to the supplying routes discussed in chapter 1. So, the target is to understand the most suitable procedure to organize the platforms that receive Larger Containers (LC). Note that there are different platforms because there are LC with different dimensions.

So, the study's scope deals with an area called *Preparation Area*. That area receives both empty platforms, which come back from the assembly line, and LC that was extracted from the WHS through picking processes. The goal is to assign the LC to the right platform as soon as possible. Consequently, the Preparation Area must receive the right platforms to receives the LCs. Considering that a limited area is available, the managers must take into account which set of platforms is the most suitable one to be placed in the Preparation Zone.

As mentioned, that is a research in progress. On the contrary, two preliminary results can be disclosed. The first result concerns the current platforms necessity. Figure 8.3 presents a Pareto chart that presents the platform consumption, regarding an one-day orders sample. It is observed that more than 75% of the orders can be allocated into two classes of platforms.

As a result, it is quite useful to evaluate how these platforms should be organized for those scenarios presented in chapter 5, which considers variable routes. Consequently, the figure 8.4 illustrates the platform consumption, regarding a scenario with variable routes and an automatic-ordering system. That is represented by scenarios three and four, which were presented by chapter 5.

Next steps could extend the data range from one day to several days. Also, propose different strategies to allocate those platforms in the Preparation Area.

Notice that the developed methodologies could be applied in several applications in the company, which is the target of any industrial Ph.D. Therefore, a set of measures were taken to promote that integration between the research and the application. The next section presents these measures.

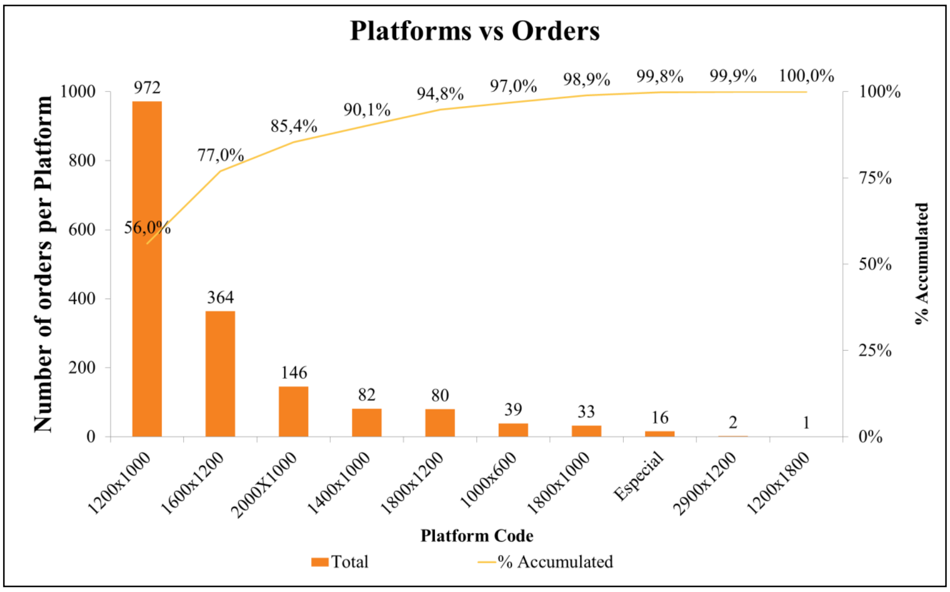


Figure 8.3: The current platforms consumption graph. Note that the Platform code refers to a platform's dimension over a centimeter basis.

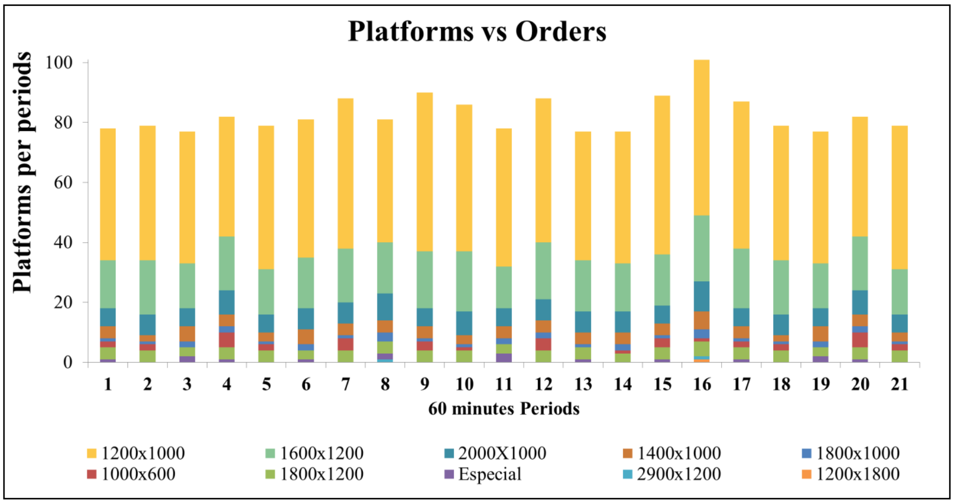


Figure 8.4: The platforms consumption graph. Note that the Platform code refers to a platform's dimension over a centimeter basis

8.2 The Industrial Ph.D. remarks

This thesis is the result of an Industrial Ph.D. So, most of the methods described in this work should be available to SEAT for further applications. Also, to explain how this research was conducted during the three years of the project, a methodology framework was created and presented to the company. Figure 8.5 illustrates that methodology.

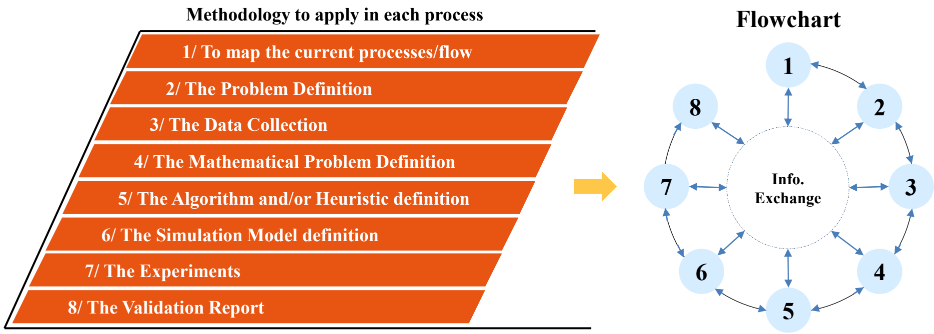


Figure 8.5: A methodological framework that resumes the approach in this thesis. Notice that the phases may be connected between themselves.

Regarding the practical point of view, a set of interfaces were developed to support applications of the methods. In particular, those methods related to the simulation of an input solution, and the developed metaheuristics (ILS and SimILS) applications presented in chapters 4 and 5.

These interfaces were programmed through JAVA code, as well as the Metaheuristics. As a result, the methods were embedded in a set of interfaces that are viewed as a tool. Consequently, a manual was written to provide more information about the tool's functions. Moreover, another manual was created to support the creation of further simulation models, based on the concepts and functionalities developed and described in chapter 6.

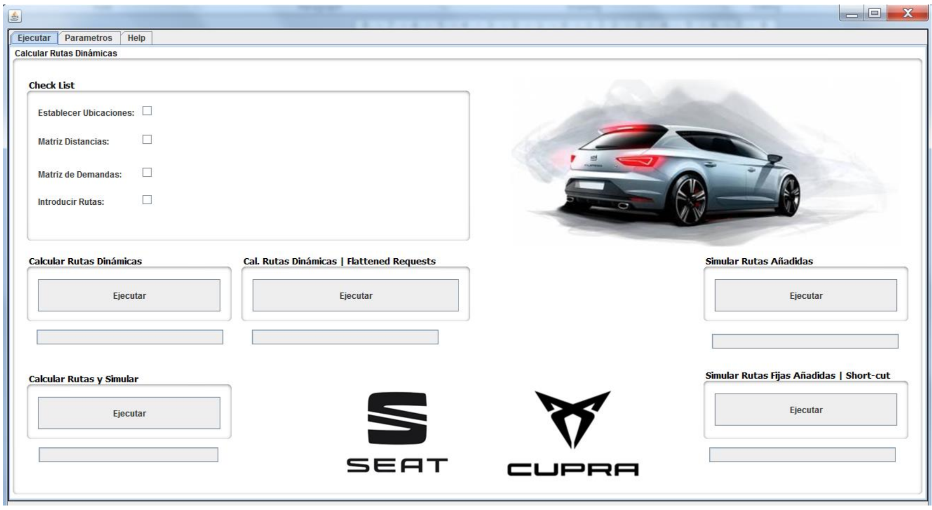


Figure 8.6: An interface to execute the SimILS, ILS and a Simulation procedure over an input solution. Also a checklist that refers to the required data.

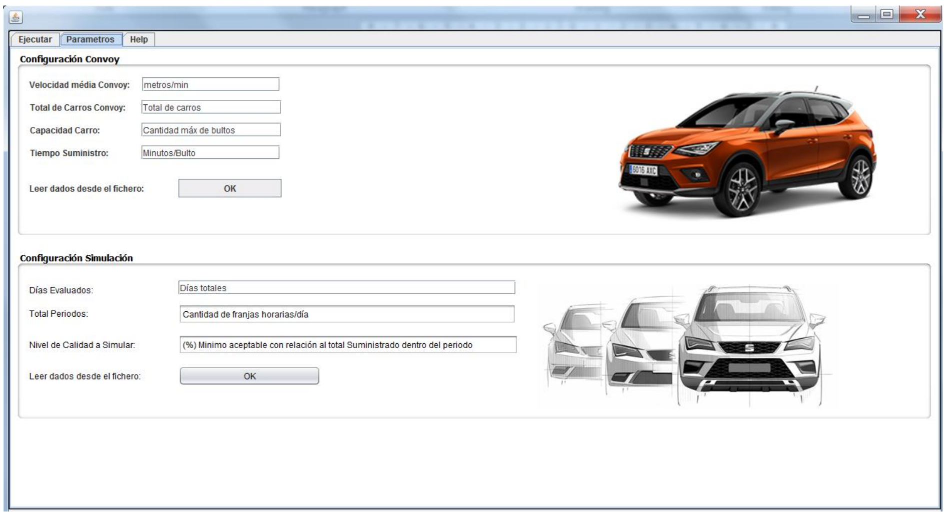


Figure 8.7: An interface that the users can introduce data by themselves, such as the convoys' average speed.

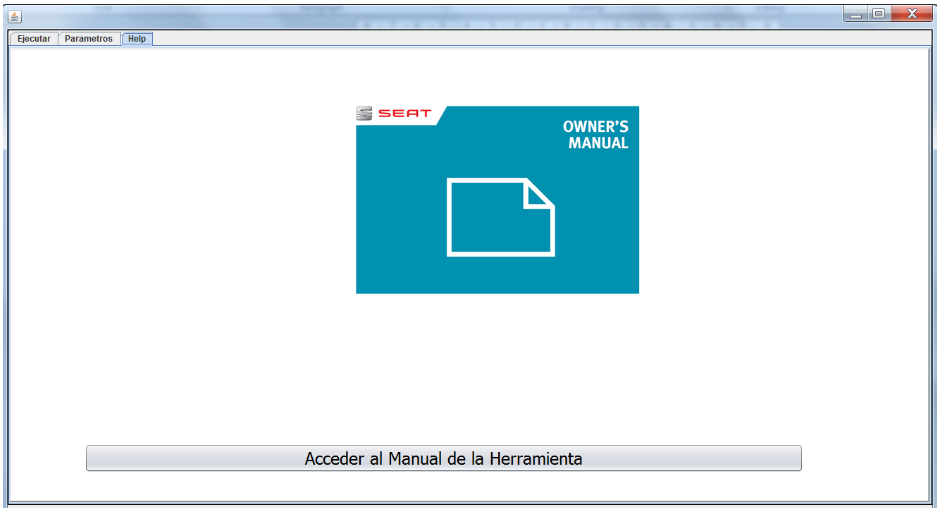


Figure 8.8: The last interface from which the user can access the interface's manual.

Bibliography

[Atieh et al. (2016)] Atieh, A. M., Kaylani, H., Al-abdallat, Y., Qaderi, A., Ghoul, L., Jaradat, L., Hdairis, I. (2016). Performance improvement of inventory management system processes by an automated warehouse management system. *Procedia Cirp, 41*, 568-572.

[Adulyasak, & Jaillet(2015)] Adulyasak, Y., Jaillet, P. (2015). Models and algorithms for stochastic and robust vehicle routing with deadlines. *Transportation Science, 50*(2), 608-626.

[Albareda et al.(2014)] Albareda-Sambola, M., FernÃ¡ndez, E., Laporte, G. (2014). The dynamic multiperiod vehicle routing problem with probabilistic information. *Computers Operations Research, 48*, 31-39.

[Altmeier et al., (2019)] Altmeier M., Bauer H., Becker M., & Simon M. (2019, June) Capturing value in machinery and industrial automation as market dynamics change. Retrieved August 30, 2019. *https://www.mckinsey.com/industries/advanced-electronics/our-insights/capturing-value-in-machinery-and-industrial-automation-as-market-dynamics-change*

[Banks et al.(2005)] Banks, J., Carson, I. I., Nelson, B. L., & Nicol, D. M. (2005). *Discrete-event system simulation.* Pearson.

[Beasley (1993)] Beasley, J. E. (1993, May). Lagrangian relaxation. In *Modern heuristic techniques for combinatorial problems* (pp. 243-303). John Wiley Sons, Inc.

[Bertsimas(1992)] Bertsimas, D. J. (1992). A vehicle routing problem with stochastic demand. *Operations Research, 40*(3), 574-585.

[Bianchi et al. (2006)] Bianchi, L., Birattari, M., Chiarandini, M., Manfrin, M., Mastrolilli, M., Paquete, L., Rossi-Doria, O., & Schiavinotto, T. (2006). Hybrid metaheuristics for the vehicle routing problem with stochastic demands. *Journal of Mathematical Modelling and Algorithms, 5*(1), 91-110.

[Bonabeau (2002)] Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences, 99*(suppl 3), 7280-7287.

[Boschetti et al. (2009)] Boschetti, M. A., Maniezzo, V., Roffilli, M., & Röhler, A. B. (2009, October). Matheuristics: Optimization, simulation and control. In *International Workshop on Hybrid Metaheuristics* (pp. 171-177). Springer, Berlin, Heidelberg.

[Braekers et al.(2016)] Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers & Industrial Engineering*, 99, 300-313.

[Brooks & Robinson (2001)] Brooks, R. J., & Robinson, S. L. (2001). *Simulation and Inventory Control (Texts in Operational Research).* Palgrave Macmillan.

[Campbell & Wilson(2014)] Campbell, A. M., & Wilson, J. H. (2014). Forty years of periodic vehicle routing. *Networks, 63*(1), 2-15.

[Caridade et al. (2017)] Caridade, R., Pereira, T., Ferreira, L. P., Silva, F. J. G. (2017). Analysis and optimisation of a logistic warehouse in the automotive industry. *Procedia Manufacturing, 13*, 1096-1103.

[Carson & Maria (1997)] Carson, Y., & Maria, A. (1997, December). Simulation optimization: methods and applications. In *Proceedings of the 29th conference on Winter simulation* (pp. 118-126). IEEE Computer Society.

[Chwif & Medina (2006)] Chwif, L., Medina, A. C. (2006). *Modelagem e simulação de eventos discretos*. Afonso C. Medina.

[Coelho et al. (2016)] Coelho, V. N., Grasas, A., Ramalhinho, H., Coelho, I. M., Souza, M. J., Cruz, R. C. (2016). An ILS-based algorithm to solve a large-scale real heterogeneous fleet VRP with multi-trips and docking constraints. *European Journal of Operational Research, 250*(2), 367-376.

[Coelho et al.(2013)] Coelho, L. C., Cordeau, J. F., Laporte, G. (2013). Thirty years of inventory routing. *Transportation Science, 48*(1), 1-19.

[Cordeau et al. (2002)] Cordeau, J. F., Gendreau, M., Laporte, G., Potvin, J. Y., Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research society, 53*(5), 512-522.

[Cota et al.(2016)] Cota, P. M., Gimenez, B. M., Araújo, D. P., Nogueira, T. H., de Souza, M. C., Ravetti, M. G. (2016). Time-indexed formulation and polynomial time heuristic for a multi-dock truck scheduling problem in a cross-docking centre. *Computers Industrial Engineering, 95*, 135-143.

[Crainic & Laporte(2012)] Crainic, T. G., Laporte, G. (Eds.). (2012). *Fleet management and logistics*. Springer Science & Business Media.

[Cristina Farrés (2017)] Cristina Farrés (2017, May 27) Seat confia su sistema de navegación a la aplicación estrella de Google, Waze. Retrieved August 30, 2019. *https://cronicaglobal.elespanol.com/business/seat-waze-saba_72933_102.html*

[Ĉujan (2016)] Cujan, Z. (2016). Simulation of production lines supply within internal logistics systems. *Open Engineering, 6*(1).

[Dantzig & Ramser (1959)] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science, 6*(1), 80-91.

[Dolors (2019)] Dolors Álvarezs (2019, April 24) Seat lamenta la rigidez de Barcelona y centra el 'car sharing' en Madrid. Retrieved August 30, 2019. *https://www.lavanguardia.com/economia/20190423/461819077859/seat-alquiler-coches-dias-horas-madrid.html*

[Fabri (2019)] Fabri, Marcelus (2019), Dataset for car-assembling-line: Workstations' distance matrix and demands. *Mendeley Data*, V1, doi: 10.17632/9jgb8m9xfv.1

[Faget et al.(2005)] Faget, P., Eriksson, U., Herrmann, F. (2005, December). Applying discrete event simulation and an automated bottleneck analysis as an aid to detect running production constraints. In *Proceedings of the 37th conference on Winter simulation* (pp. 1401-1407). Winter Simulation Conference.

[Feo & Resende (1989)] Feo, T. A., Resende, M. G. (1989). A probabilistic heuristic for a computationally difficult set covering problem. *Operations research letters, 8*(2), 67-71.

[Ferràs-Hernández et al.(2017)] Ferràs-Hernández, X., Tarrats-Pons, E., Arimany-Serrat, N. (2017). Disruption in the automotive industry: A Cambrian moment. *Business Horizons, 60*(6), 855-863.

[Fischetti & Lodi (2003)] Fischetti, M., Lodi, A. (2003). Local branching. *Mathematical programming, 98*(1-3), 23-47.

[Francis et al.(2007)] Francis, P., Smilowitz, K., Tzur, M. (2007). Flexibility and complexity in periodic distribution problems. *Naval Research Logistics (NRL)*, 54(2), 136-150.

[Gagliardi at al.(2007)] Gagliardi, J. P., Renaud, J., Ruiz, A. (2007, December). A simulation model to improve warehouse operations. In *Proceedings of the 39th conference on Winter simulation: 40 years! The best is yet to come* (pp. 2012-2018). IEEE Press.

[Gendreu & Potvin (2019)] Gendreau, M., Potvin, J. Y. (Eds.). (2019). *Handbook of metaheuristics* (Vol. 3). New York: Springer.

[Gendreau et al.(1996)] Gendreau, M., Laporte, G., Séguin, R. (1996). Stochastic vehicle routing. *European Journal of Operational Research, 88*(1), 3-12.

[Glover & Laguna (1997)] Glover, F., Laguna, M. (1997). General purpose heuristics for integer programming Part I. *Journal of Heuristics, 2*(4), 343-358.

[Glover et al. (1996)] Glover, F., Kelly, J. P., Laguna, M. (1996, November). New advances and applications of combining simulation and optimization. In *Proceedings of the 28th conference on Winter simulation* (pp. 144-152). IEEE Computer Society.

[Glover (1986)] Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers operations research*, 13(5), 533-549.

[Glover (1977)] Glover, F. (1977). Heuristics for integer programming using surrogate constraints. *Decision sciences, 8*(1), 156-166.

[Gottfredson, Stricker & Tsang, (2018)] Gottfredson M., Stricker K. & Tsang R. (2018, November 28) A Triple Threat to Automakers: Recession, Demographics and Disruption. Retrieved August 30, 2019. *https://www.bain.com/insights/a-triple-threat-to-automakers-recession-demographics-and-disruption/*

[Grasas et al.(2017)] Grasas, A., Juan, A. A., Faulin, J., de Armas, J., Ramalhinho, H. (2017). Biased randomization of heuristics using skewed probability distributions: a survey and some applications. *Computers Industrial Engineering*, 110, 216-228.

[Grasas et al.(2016)] Grasas, A., Juan, A. A., Lourenço, H. R. (2016). SimILS: a simulation-based extension of the iterated local search metaheuristic for stochastic combinatorial optimization. *Journal of Simulation, 10*(1), 69-77.

[Groër et al.(2009)] Groër, C., Golden, B., Wasil, E. (2009). The consistent vehicle routing problem. *Manufacturing service operations management, 11*(4), 630-643.

[Hillier & Lieberman (1995)] Hillier, F. S., Lieberman, G. J. (1995). *Introduction to operations research*. McGraw-Hill Science, Engineering Mathematics.

[Horta et al. (2016)] Horta, M., Coelho, F., Relvas, S. (2016). Layout design modelling for a real world just-in-time warehouse. *Computers industrial engineering, 101*, 1-9.

[Jozefowiez et al. (2002)] Jozefowiez, N., Semet, F., Talbi, E. G. (2002, September). Parallel and hybrid models for multi-objective optimization: Application to the vehicle routing problem. In *International Conference on Parallel Problem Solving from Nature* (pp. 271-280). Springer, Berlin, Heidelberg.

[Juan et al. (2015)] Juan, A. A., Faulin, J., Grasman, S. E., Rabe, M., & Figueira, G. (2015). A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. *Operations Research Perspectives, 2*, 62-72.

[Juan et al. (2013)] Juan, A. A., Faulin, J., Jorba, J., Caceres, J., & MarquÃ¨s, J. M. (2013). Using parallel distributed computing for real-time solving of vehicle routing problems with stochastic demands. *Annals of Operations Research, 207*(1), 43-65.

[Juan et al. (2011)] Juan, A. A., Faulin, J., Jorba, J., Riera, D., Masip, D., & Barrios, B. (2011). On the use of monte carlo simulation, cache and splitting techniques to improve the clarke and wright savings heuristics. *Journal of the Operational Research Society, 62*(6), 1085-1097.

[Koç et al. (2016)] Koç, Ç., Bektas, T., Jabali, O., Laporte, G. (2016). The fleet size and mix location-routing problem with time windows: Formulations and a heuristic algorithm. *European Journal of Operational Research, 248*(1), 33-51.

[Koç et al. (2016)] Koç, Ç., Bektas, T., Jabali, O., Laporte, G. (2016). Thirty years of heterogeneous vehicle routing. *European Journal of Operational Research, 249*(1), 1-21.

[Laporte (2009)] Laporte, G. (2009). Fifty years of vehicle routing. *Transportation Science, 43*(4), 408-416.

[Laporte (2000)] Laporte, G., Gendreau, M., Potvin, J. Y., Semet, F. (2000). Classical and modern heuristics for the vehicle routing problem. *International transactions in operational research, 7*(4â5), 285-300.

[Lenstra (1977)] Lenstra, J. K., Kan, A. R., Brucker, P. (1977). Complexity of machine scheduling problems. In *Annals of discrete mathematics* (Vol. 1, pp. 343-362). Elsevier.

[Levy & Bodin(1988)] Levy, L., Bodin, L. (1988). Scheduling the postal carriers for the United States postal service: an application of arc partitioning and routing. Vehicle Routing: methods and studies. Studies in Management Science and Systems-Volume 16. *Publication of: Dalctraf.*

[Lima & Ramalhinho(2017)] Lima, M.F., & Ramalhinho, H. (2017, December). Designing internal supply routes: A case study in the automotive industry. In *2017 Winter Simulation Conference (WSC)* (pp. 3358-3369). IEEE.

[Lin et al.(2018)] Lin, D., Lee, C. K. M., Lau, H., Yang, Y. (2018). Strategic response to Industry 4.0: an empirical investigation on the Chinese automotive industry. *Industrial Management Data Systems, 118(3)*, 589-605.

[Longo (2011)] Longo, F. (2011). Operational strategies and internal logistics costs analysis in a real warehouse based on modeling simulation. *International Journal of Computer Science Issues (IJCSI)* , 8(4), 39.

[Lourenço et al.(2019)] Lourenço, H. R., Martin, O. C., Stützle, T. (2019). Iterated Local Search: Framework and Applications. In *Handbook of Metaheuristics* (pp. 129-168). Springer, Cham.

[Lourenço .(1996)] Lourenço, H. R. (1996) Sevast'yanov's algorithm for the flow-shop scheduling problem, *European Journal of Operational Research* 91, pp. 176-189.

[Ludavicius & Ali(2014)] Ludavicius, E., Ali, A. (2014). Modeling and simulation of automotive engine sub-assembly for production improvement. In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (pp. 2040-2049).

[Klug (2013)] Klug, F. (2013). The internal bullwhip effect in car manufacturing.*International Journal of Production Research, 51*(1), 303-322.

[Macal & North (2010)] Macal C. M. & North M.J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4*(3), 151-162.

[Martínez-Barberá & Herrero-Pérez (2010)] Martínez-Barberá, H., & Herrero-Pérez, D. (2010). Autonomous navigation of an automated guided vehicle in industrial environments. *Robotics and Computer-Integrated Manufacturing, 26*(4), 296-311.

[Mason et al. (2003)] Mason, S. J., Ribera, P. M., Farris, J. A., & Kirk, R. G. (2003). Integrating the warehousing and transportation functions of the supply chain. *Transportation Research Part E: Logistics and Transportation Review, 39*(2), 141-159.

[Mehami et al. (2018)] Mehami, J., Nawi, M., Zhong, R. Y. (2018). Smart automated guided vehicles for manufacturing in the context of Industry 4.0. *Procedia Manufacturing, 26*, 1077-1086.

[Michalos (2010)] Michalos, G., Makris, S., Papakostas, N., Mourtzis, D., Chryssolouris, G. (2010). Automotive assembly technologies review: challenges and outlook for a flexible and adaptive approach. CIRP *Journal of Manufacturing Science and Technology, 2*(2), 81-91.

[Miller et el. (1960)] Miller, C. E., Tucker, A. W., Zemlin, R. A. (1960). Integer programming formulation of traveling salesman problems. emphJournal of the ACM (JACM), 7(4), 326-329.

[Moin, & Salhi(2007)] Moin, N. H., Salhi, S. (2007). Inventory routing problems: a logistical overview. *Journal of the Operational Research Society, 58*(9), 1185-1194.

[Muñuzuri et al. (2005)] Muñuzuri, J., Larrañeta, J., Onieva, L., & Cortés, P. (2005). Solutions applicable by local administrations for urban logistics improvement. *Cities, 22*(1), 15-28.

[Negahban & Smith (2014)] Negahban, A., Smith, J. S. (2014). Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems, 33*(2), 241-261.

[Novoa, & Storer(2009)] Novoa, C., Storer, R. (2009). An approximate dynamic programming approach for the vehicle routing problem with stochastic demands. *European journal of operational research, 196*(2), 509-515.

[Osorio & Selvam (2017)] Osorio, C., Selvam, K. K. (2017). Simulation-based optimization: achieving computational efficiency through the use of multiple simulators. *Transportation Science, 51*(2), 395-411.

[Patchong et al.(2003)] Patchong, A., Lemoine, T., Kern, G. (2003). Improving car body production at PSA Peugeot Citroen. *Interfaces*, 33(1), 36-49.

[Pelliccione et al.(2017)] Pelliccione, P., Knauss, E., Heldal, R., Ãgren, S. M., Mallozzi, P., Alminger, A., Borgentun, D. (2017). Automotive architecture framework: The experience of volvo cars. *Journal of systems architecture, 77*, 83-100.

[Penna et al.(2013)] Penna, P. H. V., Subramanian, A., & Ochi, L. S. (2013). An iterated local search heuristic for the heterogeneous fleet vehicle routing problem. *Journal of Heuristics, 19*(2), 201-232.

[Phillips et al. (1998)] Phillips, C., Stein, C., Wein, J. (1998). Minimizing average completion time in the presence of release dates. *Mathematical Programming, 82*(1-2), 199-223.

[Pinedo (2016)] Pinedo M.L. (2016). *Scheduling: theory, algorithms, and systems*,Springer.

[Poon et al. (2009)] Poon, T. C., Choy, K. L., Chow, H. K., Lau, H. C., Chan, F. T., Ho, K. C. (2009). A RFID case-based logistics resource management system for managing order-picking operations in warehouses. *Expert Systems with Applications, 36*(4), 8277-8301.

[Roman-Verdugo (2014)] Roman-Verdugo, O. (2014). Diagnóstico de Flujo del Área de Carrocerías de la Planta Ford de estampado y ensamble de Hermosillo, Sonora, México. *Produção em Foco*, 4(2).

[Ribino et al.(2018)] Ribino, P., Cossentino, M., Lodato, C., Lopes, S. (2018). Agent-based simulation study for improving logistic warehouse performance. *Journal of Simulation, 12*(1), 23-41.

[Ruiz-Torres & Nakatani (1998)] Ruiz-Torres, A. J., Nakatani, K. (1998, December). Application of real-time simulation to assign due dates on logistic-manufacturing networks. In *1998 Winter Simulation Conference. Proceedings*(Cat. No. 98CH36274) (Vol. 2, pp. 1205-1210). IEEE.

[Sachan & Datta (2005)] Sachan, A., & Datta, S. (2005). Review of supply chain management and logistics research. *International Journal of Physical Distribution Logistics Management, 35*(9), 664-705.

[Schaller (1997)] Schaller, R. R. (1997). Moore's law: past, present and future.emph IEEE spectrum, 34(6), 52-59.

[Seebacher et al. (2015)] Seebacher, G., Winkler, H., Oberegger, B. (2015). In-plant logistics efficiency valuation using discrete event simulation. *International Journal of Simulation Modelling, 14*(1), 60-70.

[Semini et al.(2006)] Semini, M., Fauske, H., & Strandhagen, J. O. (2006, December). Applications of discrete event simulation to support manufacturing logistics decision-making: a survey. In *Proceedings of the 38th conference on Winter simulation* (pp. 1946-1953). Winter Simulation Conference.

[Sniezek & Bodin (2006)] Sniezek, J., Bodin, L. (2006). Using mixed integer programming for solving the capacitated arc routing problem with vehicle/site dependencies with an application to the routing of residential sanitation collection vehicles. *Annals of Operations Research, 144*(1), 33-58.

[Solomon (1987)] Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations research, 35*(2), 254-265.

[Souza & Wolsey (1992)] Sousa, J. P., Wolsey, L. A. (1992). A time indexed formulation of non-preemptive single machine scheduling problems. *Mathematical programming, 54*(1-3), 353-367.

[Tako & Robinson(2012)] Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision support systems, 52*(4), 802-815.

[Toth & Vigo(2002)] Toth, P., & Vigo, D. (Eds.). (2002). *The vehicle routing problem.* Society for Industrial and Applied Mathematics.

[Valentin et al.(2003)] Valentin, E. C., Verbraeck, A., & Sol, H. G. (2003). Advantages and disadvantages of building blocks in simulation studies: A laboratory experiment with simulation experts. In *Proceedings ESS* (pp. 141-148).

[Van den Akker et al. (2000)] Van den Akker, J. M., Hurkens, C. A., Savelsbergh, M. W. (2000). Time-indexed formulations for machine scheduling problems: Column generation. *INFORMS Journal on Computing, 12*(2), 111-124.

[Vanderbeck & Wolsey (2010)] Vanderbeck F., Wolsey L. A.(2010). Reformulation and decomposition of integer programs. *50 Years of Integer Programming 1958-2008*. Springer, Berlin, Heidelberg, pp. 431-502, 2010.

[Vansteenwegen et al. (2009)] Vansteenwegen, P., Souffriau, W., Berghe, G. V., Van Oudheusden, D. (2009). Iterated local search for the team orienteering problem with time windows. *Computers Operations Research, 36*(12), 3281-3290.

[Vavrík et al. (2017)] Vavrík, V., Gregor, M., Grznár, P. (2017). Computer simulation as a tool for the optimization of logistics using automated guided vehicles. *Procedia engineering, 192*, 923-928.

[Velandia et al.(2016)] Velandia, D. M. S., Kaur, N., Whittow, W. G., Conway, P. P., West, A. A. (2016). Towards industrial internet of things: Crankshaft monitoring, traceability and tracking using RFID. *Robotics and Computer-Integrated Manufacturing, 41*, 66-77.

[Vis (2006)] Vis, I. F. (2006). Survey of research in the design and control of automated guided vehicle systems. *European Journal of Operational Research, 170*(3), 677-709.

[Wang & Chang (2015)] Wang, H. F., Chang, C. M. (2015). Facility layout for an automated guided vehicle system. *Procedia Computer Science, 55*, 52-61.

[Wilding et al.(2012)] Wilding, R., Wagner, B., Gligor, D. M., Holcomb, M. C. (2012). Understanding the role of logistics capabilities in achieving supply chain agility: a systematic literature review. *Supply Chain Management: An International Journal.*

[Wolsey (1998)] Wolsey, L. A. (1998). *Integer programming.* Wiley.

[World-Economic-Forum (2016)] World-Economic-Forum. (2016). World Economic Forum White Paper. Digital Transformation of Industries: In collaboration with Accenture.

[Zhou & Peng (2017)] Zhou, B., Peng, T. (2017). Scheduling the inhouse logistics distribution for automotive assembly lines with just-in-time principles. *Assembly Automation, 37*(1), 51-63.