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A Methodology for Data-Driven Decision-Making in Last Mile Delivery Operations

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A METHODOLOGY FOR DATA-DRIVEN DECISION-MAKING IN LAST-MILE DELIVERY OPERATIONS

by

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ABSTRACT

Across all industries, from manufacturing to services, decision-makers must deal day to day with the outcomes from past and current decisions that affect their business. Last-mile delivery is the term used in supply chain management to describe the movement of goods from a hub to final destinations. This research proposes a methodology that supports decision making for the execution of last-mile delivery operations in a supply chain. This methodology offers diverse, hybrid, and complementary techniques (e.g., optimization, simulation, machine learning, and geographic information systems) to understand last-mile delivery operations through data-driven decision-making. The hybrid modeling might create better warning systems and support the delivery stage in a supply chain. The methodology proposes self-learning procedures to iteratively test and adjust the gaps between the expected and real performance. This methodology supports the process of making effective decisions promptly, optimization, simulation, and machine learning models are used to support execution processes and adjust plans according to changes in conditions, circumstances, and critical factors. This research is applied in two case studies. The first one is in maritime logistics, which discusses the decision process to find the type of vessels and routes to deliver petroleum from ships to villages. The second is in city logistics, where a network of stakeholders during the city distribution process is analyzed, showing the potential benefits of this methodology, especially in metropolitan areas. Potential applications of this system will leverage growing technological trends (e.g., machine learning in supply chain management and logistics, internet of things). The main research impact is the design and implementation of a

methodology, which can support real-time decisions and adjust last-mile operations depending on the circumstances. The methodology allows taking decisions under conditions of stakeholder behavior patterns like vehicle drivers, customers, locations, and traffic. As the main benefit is the possibility to predict future scenarios and plan strategies for the most likely situations in last-mile delivery. This will help determine and support the accurate calculation of performance indicators. The research brings a unified methodology, where different solution approaches can be used in a synchronized form, which allows researches and other interested people to see the connection between techniques. With this research, it was possible to bring advanced technologies in routing practices and algorithms to decrease operating cost and leverage the use of offline and online information, thanks to connected sensors to support decisions.

Dedicated to my family for their love and continuous support.

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CHAPTER 1: INTRODUCTION

Last-mile delivery is the term used in supply chain management to describe the movement of goods from a hub to final destinations. This research proposes a methodology that supports decision making for the execution of last-mile delivery operations in a supply chain. Across all industries, from manufacturing to services, decision-makers must deal day to day with the outcomes from past and current decisions that affect their supply chain. The result of the decisions and their consequences are reflected in the activities related to the flow and transformation of products or services in a specific market or business. So far, practitioners and academics agreed over the concept of supply chain management as the practice of handling flows of resources that link between different parties in a supply chain. The resources are information, material, products, services, and money (Mentzer et al. 2001). For example, for the manufacturing industry, it can include the process of manufacturing and distributing products, starting with the suppliers of raw materials or components, following with the various facilities; which include manufacturing plants, warehouses or distribution centers, and concluding with customers or final consumers(Shapiro, 2006), nowadays called last-mile delivery.

This research proposes a methodology to improve the performance of distribution operations, considering key factors such as better use of the heterogeneous fleet and efficient routing systems. For this purpose, this research effort concentrates on two case studies, a case study for maritime logistics delivery of fuel to villages and a case study for city logistics delivery to stores.

The maritime logistics case examines a maritime corporation's delivery of fuel. Specifically, it is concerned with the specialized fleet of vessels that reaches the remote parts of Western Alaska as they become accessible during the summer months. In the process of fuel delivery, the principal tankers hold fuel, where tankers and lighter vessels collect and supply the product.

The purpose of this first case is to analyze and implement the methodology to improve the decision process to determine the type of vessels and routes to deliver petroleum derives from ships to villages. This case study is characterized to allow split deliveries, where customers (villages in this case) can be attended for more than one vehicle (vessels). The objective is to minimize the total fleet satisfying clients' demands. In this case, the methodology is focusing on the use of optimization and simulation techniques to handle the problem. Deep reinforcement learning is introducing to determine the delivery process.

The case study for city logistics represents an emerging market where factors such as fragmentation, higher congestion, parking issues, and dense commercial areas combined with residential habitats are the main challenging factor for dispatchers. Therefore, this case is focusing on urban logistics, which analyzes the network of stakeholders during the city or urban distribution process, showing the potential benefits of this methodology, especially in understudied metropolitan areas from emerging markets. All these factors in towns affect the execution of daily last-mile operations and fulfillment of stores. Design methodologies to determine the same-day and next-day service are needed for manufacturers and retailers. Consequently, the use of highly effective decision support tools becoming more important for all stakeholders. These tools must be able to address strategic and operational decisions for multiple stakeholders (Taniguchi et al. 2012; Macharis et al. 2014)

This proposed work contributes to the research community by understanding the evolution of last-mile delivery logistics and define future trends of research and applications. This research creates a data-driven methodology to assess the behavior and interrelationships between last-mile stakeholders, like CPG (Consumer Packaged Goods) manufacturers, freight carriers, retailers (including Nano stores) and end consumers. Other stakeholder's behavior analysis as city administrators decisions are out of the scope, but it's expected that this methodology will allow to include other stakeholders for future investigation. This research project aims to have a sense of how multiple stakeholders face changes in the last-mile operation environment. Analytical techniques are used to represent and understand the logistics operations.

1.1 Background

Researches and industry managers have realized the need to improve the execution of daily transportation operations and noted how it had become a source of competitiveness growth and cost reduction. Routing planners struggle to accurately set and forecast delivery routes based on the day of the week, time, location, customer, and driver behavior. For example, in a city, high traffic, customers' location, buyer regret, lack of nearby parking, elevators out of service, and many other operational issues, all add cost, time and troublesomeness to this critical activity. Given the challenges transportation, supply chain managers, and city planners face with managing data complexity and prediction techniques; some gaps have been exposing in this research.

In this section, background in data-driven supply chain management is described, followed by the challenges in the integration between decision levels in a supply chain, a short discussion of hierarchical models for production systems and finally the issues addressed in last-mile delivery operations.

1.1.1 Data-Driven Analytics and Supply Chain Management

The decision-making in the context of supply chain management has been considered as a task performed depending on the kind of problem and decision time frame (planning horizon). For instance, decisions about process control in a factory must be taken for a short period (real-time) or on the contrary, arrangements that must deal with the configuration (facilities location) of the supply chain, should be taken for an extended period. Commonly, those decisions are divided into three main categories: strategic, tactical, and operational (Shapiro, 2006). The strategic level decisions are those that must be taken for long periods, years usually, for example, decisions about the supply network design. Tactical decisions are those for the medium term, months or weeks, like production plans. The third category is the operational level decisions; for short terms, like days or hours.

Thanks to the advance in technology and the internet of things with the use of sensors in industrial processes (automatic control), a new level of decision has been added to the classical view. The Execution Level sometimes also called *Control Level,* where decisions should be taken in near real-time (Darby et al., 2011). This level is characterized to handle possible disturbances that mandate to do rescheduling, rerouting, new vehicle dispatching, among other decisions (Montoya et al., 2010; Grossmann, 2012).

Table 1 brings an example of the primary issues and main objectives for each level of decision for a supply chain (Simchi-Levi et al., 2009).

Table 1:Decision Levels in a Supply Chain

Decision Level	Key Issues	Time Horizon	Main Objectives
Strategic	Network Design Distribution strategies Outsourcing Product Design	Years Months	Finance Sustainability
Tactictal	Production Sourcing Inventory Control Supply Contracts Inventory-Routing	Months Weeks	Resource Allocation Finance
Operational	Dispatching plan Scheduling	Days Hours	Support the execution
Execution	Vehicle dispatching Process Control Rerouting Sensing Delivery Rescheduling	Minutes Seconds	Avoid disturbances Manage unpredictive events Minimize costs Customer Service Level

Strategic decisions are made for long term impact. Some examples of strategic issues in a supply chain are:

- How many, when, and where should the production plants, and distribution centers be located?
- How should the products flow through the distribution network?

- How should be the configuration, size, capacity of fleet vehicles for the supply chain?

Tactical decisions are made for medium-term impact and are mainly applied to set operational goals. Balance the capacity with demand and the allocation of resources. Some tactical issues in a supply chain are:

- What is the optimal mix between private fleet and a third-party fleet?
- Which distribution center should serve each consumer center?
- What products and in what quantities should be produced in each plant and equipment?
- Which supplier, and in what quantities, should attend each plant?

Operational decisions are related to the execution level, such as programming of daily transport, manufacturing operations. Examples of decisions of operational issues in a supply chain are:

- Which are the most efficient modes of transportation?
- What are the best routes to serve customers?

Execution decision should be taken in a short period, (1 day). Plans have to be prepared to address problems, with a horizon of time of hours or minutes. This kind of situations mostly arises when anomalies exist, and a decision should be implemented. Gartner, whose is an advisory firm recognized worldwide, defines the focus of the supply chain execution as: *"Supply chain execution (SCE) is focused on execution-oriented applications, including warehouse management systems (WMSs), transportation management systems (TMSs), global trade management (GTM) systems and other* *execution applications, such as real-time decision support systems (for example, dynamic routing and dynamic sourcing systems) and supply chain visibility systems within the enterprise."* (Gartner IT Glossary, 2017).

Data analytics methodologies impact industrial and service operations. These schemes have been relevant for a wide selection of traditional engineering areas, such as the best performance defined by lean six-sigma initiatives, customer segmentation for resource optimization, pattern identification, classification strategies, and forecasts. The data analytics practice is divided into four main areas:

Descriptive Analytics: At this stage, descriptive statistics and data mining are commonly used to do segmentation, dimensionality reduction, and classification. Generally, large amounts of data are analyzed to discover patterns.

Visual Analytics: Information visualization enabled by dashboards to analyze and visualize the data to extract useful information. The methods of visual analysis combine descriptive and inferential statistical techniques with specific knowledge in engineering and systems management. The graphics can show accurate data to capture the behavior of a system and to understand its trends and cycles. The design of dashboards with business intelligence software to show the Key Performance Indicators (KPIs) is the trend across many organizations.

Predictive Analytics: Use techniques of classical linear and non-linear regression, simulation, regression trees, random forests, and neural networks. Analyze historical data to make estimations about future or unknown events. It is used for inventory management, customer and traffic behavior, among others.

Prescriptive Analytics: This stage of the analytics oversees the best course of action for a given situation. Techniques such as dynamic programming and stochastic modeling are widely used for supply chain management to demonstrate previous techniques, along with simulation (discrete, dynamic, agent base) and operations research (mixed integer programming).

A group of technologies deals with data analytics, which refers to the methods and techniques to extract patterns and new information from structured, semi-structured, and/or unstructured data. Figure 1 represents how the data flows across different stages throughout the different kinds of analytics paradigms.

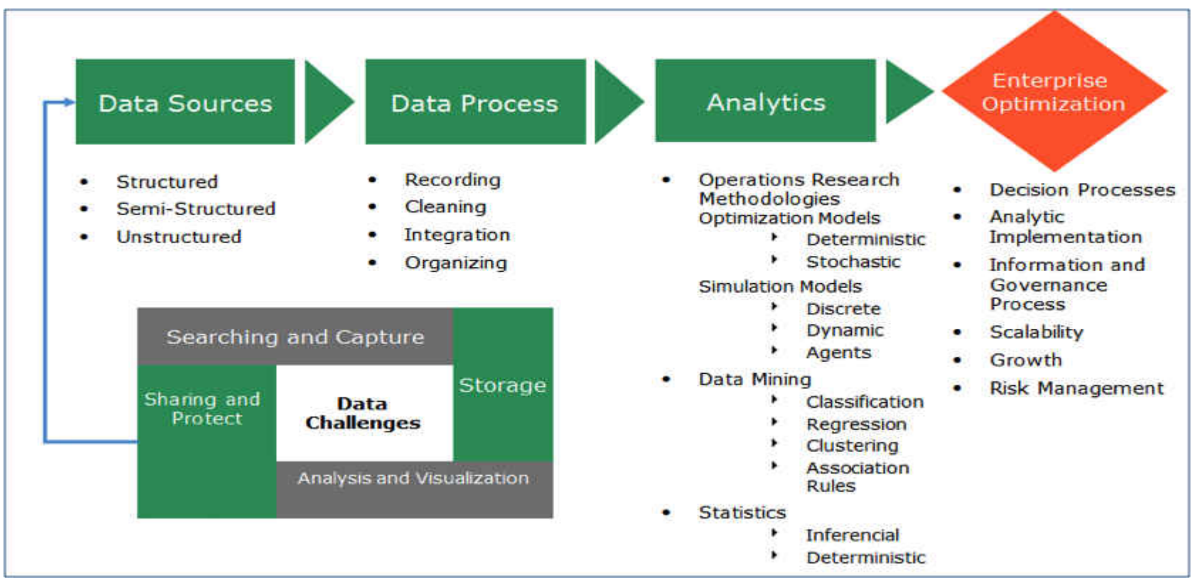

Figure 1: Data-Driven Enterprise Optimization.

Once the data is obtained, a process of cleaning, organizing, and storing starts, followed by analytics and implementation. These are tools that help handle data volume, diversity, and imprecisions and provide robust solutions. The techniques of data mining and predictive analytics help the enterprise make a better decision-making process. The main objective of these technologies and approaches is to extract valuable information (Insights) from the data, to support the decision-making process.

The scheme in Figure 2 depicts how the data goes through different stages, such as for example, preprocessing data with some statistical and data mining techniques to be prepared for a simulation-optimization modeling process. After the data and the analysis is done, a decision-making process is supported thanks to that process. A series of scenarios are listed at the end of the analysis to make the decision. Furthermore, with this analysis, data scientists can also discover causalities. Data analytics is not only used to identify patterns but also is used to understand what happened in the past and to have a solid base to apply predictive analytics and infer what can happen in the future.

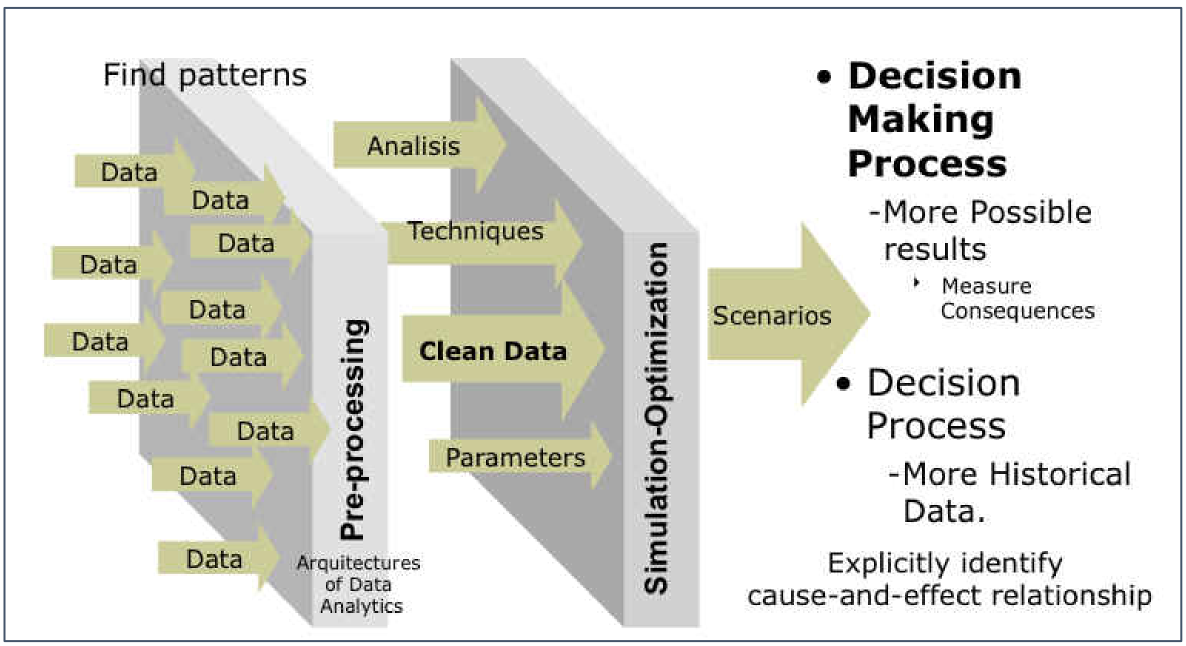

Figure 2: Example of Data analytics stages.

The value creation thanks to the use of analytics is demonstrated in several cases (Brynjolfsson et al., 2011) when a company can obtain detailed information regarding its performance in detail and a convenient manner. (Monitoring and Visualization). ii) When an organization can utilize resources more efficiently as products and services are targeted to meet specific needs through customizable actions. (Optimization, Simulation modes, Hybrid modeling) and iii) When human force is replaced or supported by algorithms. (Artificial Intelligence)

1.1.1.1 Dynamic business metrics

Analytics support the main three objectives of a company, such as revenue, risk, and profitability. Figure 3 presents some dynamics business metrics that can be achieved in an organization. The main groups of indicators are in technology, revenue, risk, and profitability.

The construction of dynamic business metrics can be achieved throughout the detailed analysis of the business. Nowadays, a lot of companies are invested in data analytics (Rivera, 2014). The current techniques, methodologies, and architectures of data analytics are affecting how the organizations can measure their inputs and outputs. Analytics can support the construction of these indicators in terms of computational times and managing the information (Groschupf et al., 2013).

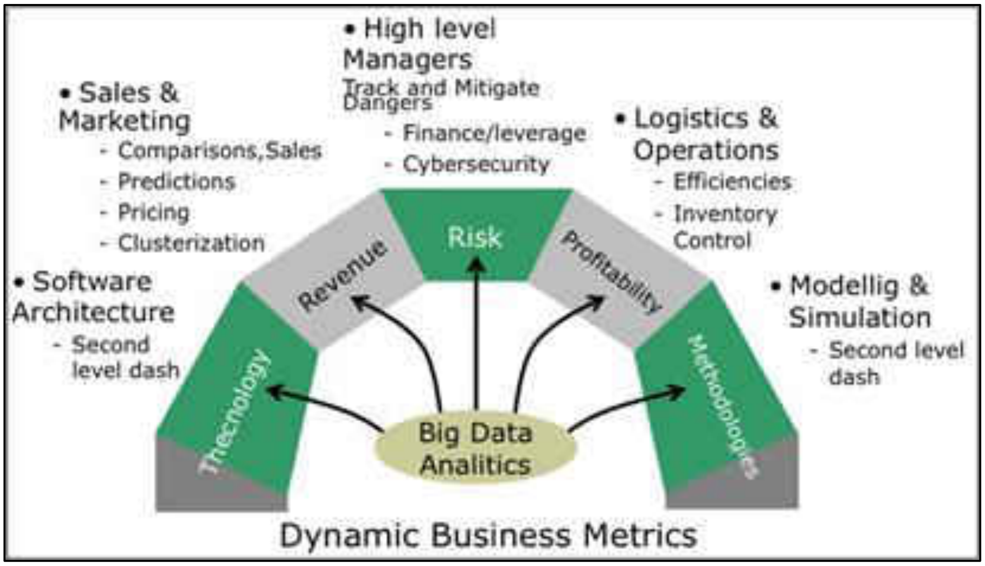

Figure 3: Business Metrics.

In conclusion, analytics help organizations increase revenue, speed time to market, optimize its workforce, or realize other operational improvements. (Morgan, 2015). Data analytics is named as a scientific paradigm for discoveries (Hey et al., 2009). Optimization, simulation, and machine learning models or analytics aim to give the necessary base to handle complex problems in terms of scalability and the amount of data and sources. (Bell et al., 2009; Chen et al., 2014).

1.1.2 Challenges for integration between decision levels in a supply chain

Nowadays, the integration between decision levels is one of the main concerns in academia and industry. Substantial process in this endeavor has been more notable in the execution and operations levels.

The primary application area has been in the manufacturing industry (Chu et al. 2015). In Figure 4, Dias and Lerapetritou (2017), depict an example of the different stages from the execution process to the supply chain management. Each of which is represented considering the time horizon and the opportunity for optimization.

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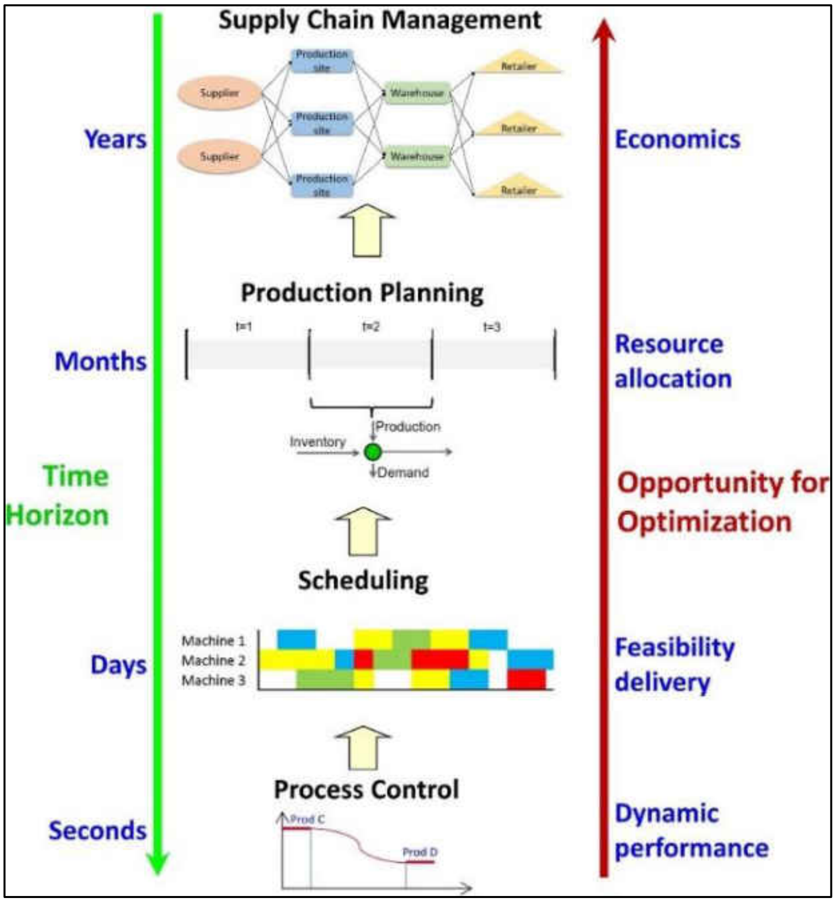


Figure 4: Decision Making in supply chains. Source: Dias et al., 2017.

Measuring the impact of the operational decisions throughout the supply chain is one of the challenges many companies encounter. Holding better methodologies to support the coordination between the execution and the other levels helps to reach benefits for the organization.

The decisions usually follow a policy, a previous plan, and a schedule. At times in the execution phase, decisions should be made under an uncertain environment, due to unforeseen events and in a short time. Decision-makers have struggled to find ways to predict the most likely variations and analyze various possible conditions. Figure 5 depicts a learning process between the original plans and the deviations in the execution process.

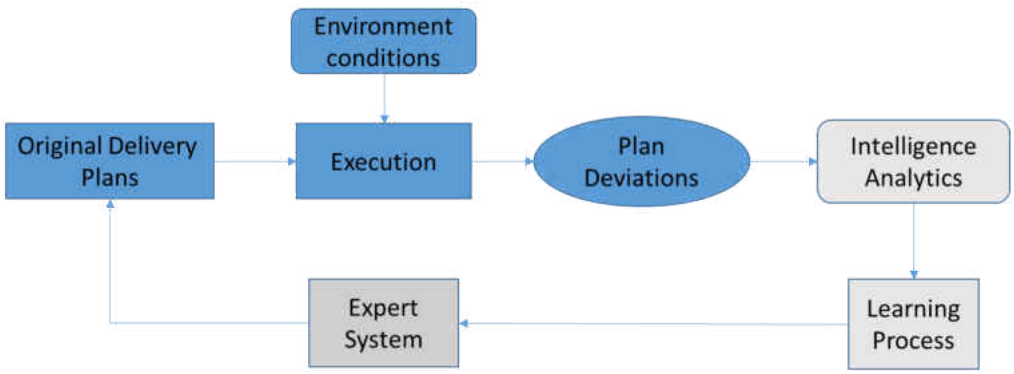


Figure 5: Learning process in last-mile delivery.

Scenario planning approaches are the most common tools to support the decision instead of just with mental models. Consequently, having better tools to make predictions that support the decisions and synchronization between the plans and the execution throughout the different functional areas in a supply chain, helps to decrease the vagueness in making decisions under uncertain situations. This is the future's state of the art for supply chain management operations.

Furthermore, the availability of technology and information in near real-time provides excellent opportunities for businesses across all industries to offer a better experience for their customers. However, it also comes along with challenging problems such as ineffective forecasting methods for customer behavior prediction, responsiveness to market changes, and inadequate infrastructures, among others.

1.1.3 Hierarchical Models in Production Systems Supply Chains

The decisions in a supply chain are expected to be organized hierarchically between the strategic, tactical, and operational levels. However, in practice, this is not the rule. One of the challenges many companies face is the lack of design integration of the operational decisions throughout the supply chain (Shah, 2005). Figure 6 depicts a comparison between service and manufacturing supply chains.

Hierarchical structures have been proposed mainly for production in manufacturing systems. Usually, the different decision levels are organized depending on the impact, purposes, and planning horizon.

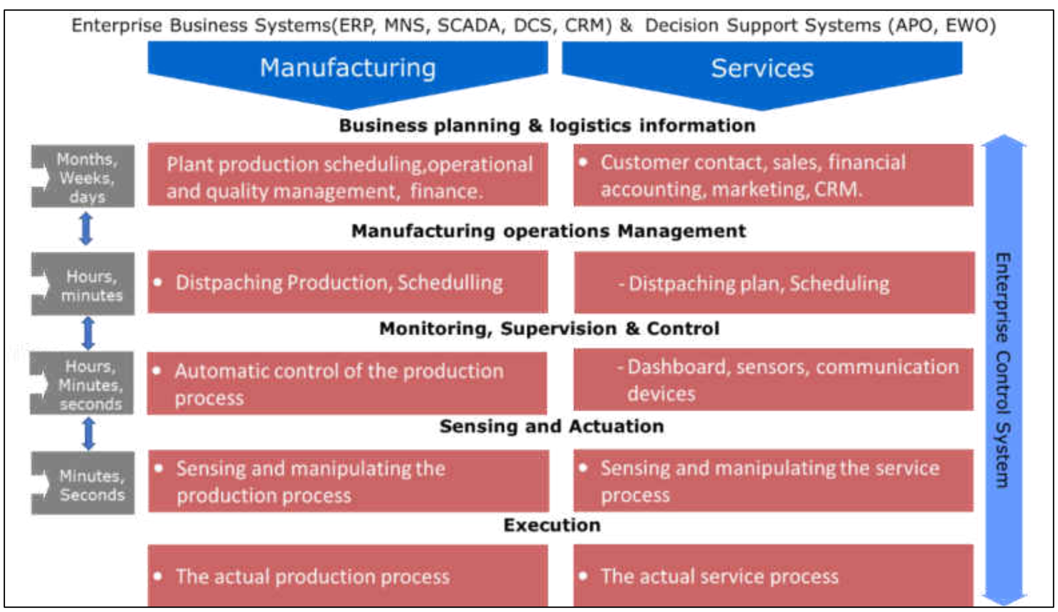


Figure 6: Hierarchical model for production systems in manufacturing and service supply chains.

It is based on the hierarchical model proposed by the International Society of Automation (ISA), (Scholten, 2007). The upper layer deals with the strategy and tactical decisions, where the decision should be taken for the long and medium-term. It is followed by and connected with the manufacturing operations which set the activities to meet the final product. It is under medium and short time and is mainly under operative decision level in a supply chain. Finally, it's the sensing and execution levels where automatic control systems, dashboards, and communication systems support the operation. Allowing data integration and flow of information. Systems like ERP's Enterprise Resource Planning, Manufacturing Execution Systems, (MES), Supervisory Control and Data Acquisition -SCADA. With more analytic oriented systems such as Advance Planning Optimization APO and Enterprise-Wide Optimization EWO methodology (Chu et al. 2015).

The systems mentioned above and the interaction between the different layers allows for the gathering and analysis of information in short periods. Going uphill from the execution level with the results of the actions to the management level and downward transferring instructions to do the activities. Having better methodologies to support the coordination between the execution levels helps reach benefits for the organization. The decisions are addressed from decision-makers in strategic levels to the operative ones, going through the tactical levels. It has been demonstrated that better decisions are supported for the use of feedback practices which flows in the opposite direction (Van et al., 2007), after the analysis of this feedback the system can make better decisions.

A more specific example of the hierarchical model is presented by Chu et al. 2015 (Figure 7.) The authors recreate different decisions structured in a hierarchy structure for the typical manufacturing industry. In the high level represent the configuration of the supply chain, which is the strategic level. The next level should be defined as production quantities by the planning period. A scheduling plan should accompany this process. Finally, in the last two levels, the authors display the feedback control system with a dynamic optimization model.

The decision support systems and the transactional information technologies allow the flow of information between the different layers. However, the software design along with modeling and optimization methods is a highly active research area for decision-making systems that can capture the experience and learnings between the different decision levels (Grossmann, 2005; Chu et al., 2015).

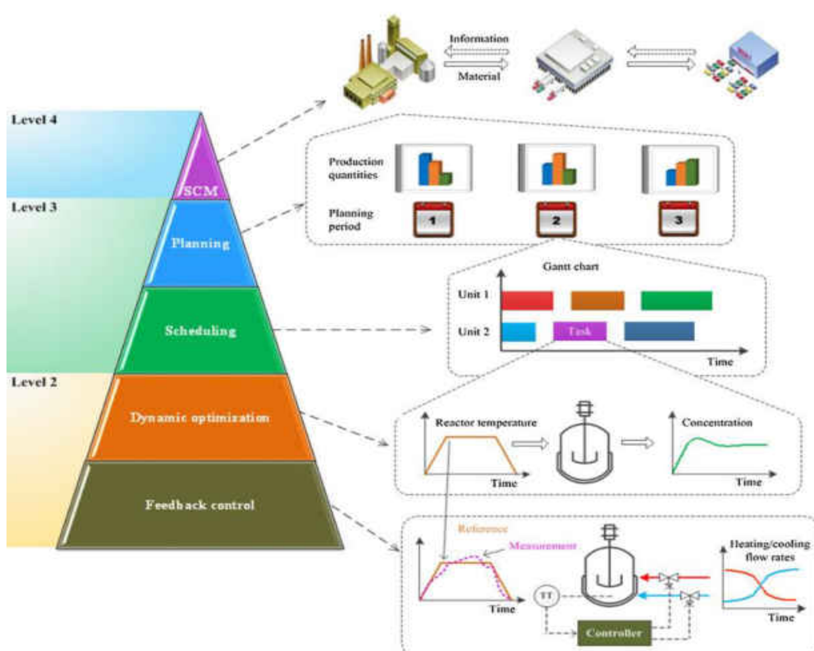


Figure 7: Hierarchical structure in the manufacturing industry. Source: Chu et al., 2015.

It is common for the chemical and energy industry to use hierarchical methodologies. The service industry has been adopting these practices during the last years. For instance, challenges in transportation and logistics aim to reduce the low performance in delivery strategies which are linked to non-forecasted uncertainties (on consumers' and drivers' behavior) and inappropriately managed delivery processes.

The lack of shared information distorts visibility among suppliers, retailers, and logistics operators, affecting quick gains in logistics and obstruct effective horizontal collaboration to forecast the performance of the operations accurately. Consequently, if the prediction is below the real outcome, it will cause higher costs, (Example: lost sales) and increase uncertainty, risks. On the other hand, if the prediction is above that of the real requirement, resources will be poorly planned and will also increase costs.

The literature review in chapter two digs into scopes, model formulations, solution approach, and implementation strategies have been used to face the challenges in the execution process in the supply chain and specifically in last-mile operations. Additionally, some examples are described. Most of them are in the manufacturing process. This research is aimed to bring a methodology which allows the integration of different levels of the decision in time and process in a supply chain, and it is focused on the execution level.

1.2 Last-Mile Delivery Operations

The term used in supply chain management to describe the movement of goods from a hub to final destinations is Last-Mile (Figure 8). The execution of last-mile delivery operations in a supply chain is just as important as the operation success at any point of the supply chain. “Last-mile logistics is the least efficient stage of the supply chain and comprises up to 28% of the total delivery cost” (Ranieri et al., 2018). Therefore, the search for improvement techniques represents a considerable challenge for the corporate and academic community.

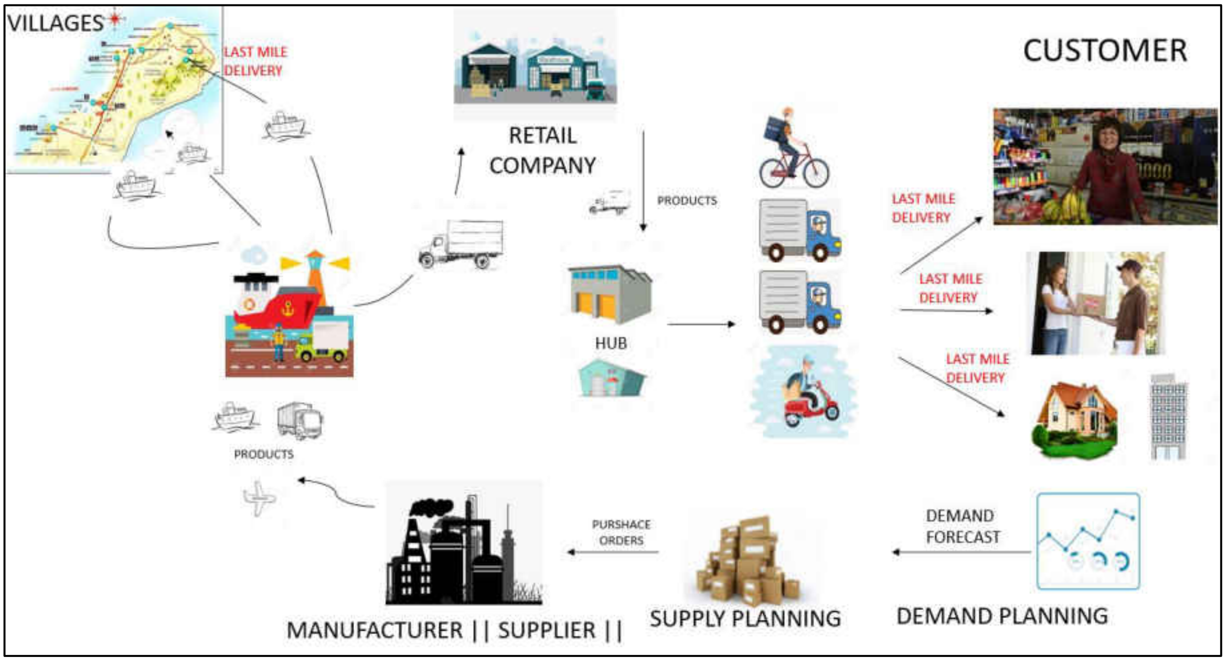


Figure 8: Last Mile Stage in the Supply Chain

With the constant positive economic growth of cities around the world, the need for material movement is increasing quickly. When analyzing how stores are switching to a just-in-time stock system (Nuzzoloa et al., 2018), it is possible to relate it to the increase of orders being made to vendors, therefore increasing the work activity of delivery companies. With that, more delivery vehicles will be on the streets; that, together with the unstoppable increase of the range on heavy traffic hours in big urban areas, magnifies issues such as pollution and traffic itself, consequently, affects the quality of life the population. Therefore, the necessity of better methodologies to handle this situation is a must for involved stakeholders.

Concerning the main problems affecting the city's logistics (CL), the synergy between the main stakeholders, such as customers, delivery companies and city governments, should be understood and analyzed to reduce the negative effects the delivery process would cause (Ananda et al., 2016). This synergy is related to how the process occurs in a city environment and how it creates good or adverse events. One way to observe it is by going to the beginning of the process which is the order being made; it ultimately causes goods being transported inside of the city, therefore one more truck occupying road area and polluting the area. From that point, the analysis should focus on how to reduce that impact to the minimum while providing the best service to the clients, that being by reducing the time the trucks spend on streets.

The focus of the stakeholder analysis is kept as taking into account the interests among all of the active participants of the process (Anand et al., 2012). The point of this analysis is to define another challenge as being the maintenance of the process for reaching all stakeholders objectives, as they are distinct and sometimes differ in magnitude and importance (Van Heeswijk et al., 2016).

With the increasing application of optimization of processes inside of smaller companies around the globe, they have been reducing the size of their stocking areas; which is a benefit, as the newly regained area can be now used for other purposes. The issue is that the prediction of usage of those goods needs to be improved in a way that the just-in-time system needs to be applied (Nuzzoloa et al., 2018). The impact of the increasing rate of that system directly hits the volume and speed requirements for the delivery companies. Therefore, even more, vehicles will have to be in the streets.

The use of innovative methods for the delivery of goods is nowadays faced with a variety of factors to be considered. These factors include cost reductions, services levels, and the environment itself where concerns exist regarding pollution of the air, noise pollution, traffic, and mobility issues. (He et al., 2019).

This research effort considers the state of the art methodologies for supply chain / last-mile operational strategies, having into account the existence of routing software applications and intelligent solutions that can account for the suitability, risks, limitations, and restrictions of the existing urban freight transportation systems.

1.3 Problem Statement

Nowadays, across industries, managers are struggling to find ways to close the gap between strategy and execution. Generally, a strategic problem is habitually solved without considering operational and implementation levels. Commonly because issues are considered and addressed sequentially and individually, therefore, due to the complexities that can arise in the execution process (unpredicted events, perturbations, changes in human behavior) when the problems occur at this level, the resolution should be made under the conditions established by the strategic and tactical levels. This may result in inefficiencies across the system.

Under the idea of widespread efficiency, the understanding of different decision making of stakeholders is challenging. Currently, the manufacturing industry appears to be more mature in this endeavor. On the other hand, the design and implementation of an integrated scheme for the service industry, like transportation and logistics, is a complex mission.

Important factors remain to be solved. Such as dynamic address behavior from humans and the environment besides the common unstable conditions from logistics operations. Predictive and normative hybrid techniques must be designed and used to support the execution process and adjust plans according to changes in critical factors according to a set of potential scenarios.

Data-driven analytics might be an essential step to understand critical issues, build proper measurement systems, predict the evolution of systems, and lead stakeholders to reinvent their strategies, policies, and technology. Hybrid modeling approaches can improve execution operations through optimization and agent-based modeling, among other techniques. In consequence, it can leverage a methodology driven by the possibility of integrating different decision layers.

1.4 Research Questions

Given the challenges identified in the problem statement, the research questions for this research are:

a) Is there a way to translate and contextualize the characteristics of last-mile operations in their different stakeholder's decision making, to create useful insights and predictions and identify the possible consequences in the execution operation?

b) Is it possible to develop a methodology that leverages better coordination between different stakeholders, to enable optimization and better forecasting on the execution of operations? And lastly,

c) Could this methodology be developed to combine the analytic models with emerging technologies and applications to solve the business and the industrial characteristics of last-mile delivery operations simultaneously?

1.5 Research Contribution

The main contribution of this research is to provide a decision methodology to analyze and capture the information involved in different areas of last-mile delivery to reach integrated solutions for decision making in functional areas.

Through the analysis of the information systems, sensors information, optimization, and simulation-optimization-ML (machine learning) models are projected to translate data and contextualize information, between devices and systems on an execution network.

The proposal is different from the existing literature and contributes to the research community by integrating characterization and prediction of stakeholders' behavior in supply chain operations; using machine learning, dynamic and stochastic techniques to forecast behaviors, trends and performance.

The goal is to integrate methods which support decisions in the decision-making levels.

The methodology is designed with three main objectives:

- Propose a comprehensive and scalable methodology to model and integrate different decision-making levels in terms of operational and management decisions.
- Design a model-based decision-making methodology, which can capture and learn from the activities across different time and space scales in last-mile operations.
- Identify the research gaps and future research on this topic.

Last-mile operations require accurate and realistic simulation virtual environments that enable risk-free training and testing of learning agents. These simulations need to be much more sophisticated than collections of scenarios. It should also be able to capture the complexity of dynamic environments and agents' behaviors, including those that have a low probability of occurrence. We are proposing a methodology that allows virtual environments (simulations) to interact with learning agents.

The methodology proposes hybrid modeling and self-learning procedures to iteratively test and adjust the gaps between the expected and real performance. This methodology supports the process of making effective decisions promptly, optimization models and machine learning models are used to support execution processes and adjust plans according to changes in conditions, circumstances, and critical factors. All of which can be anticipated via scenario planning and dynamic models. The methodology architecture intends to leverage and synchronize technological trends, such as the internet of things in supply chain networks by considering the use of complementary approaches.

This research proposes a potential technology solution for enabling and improving near real-time decision-making process in logistics operations. It also contributes to the development of a methodology and architecture for leveraging operations research management techniques and machine learning tools to define requirements for an application methodology.

The methodology is designed to create warning systems and, together with mathematical models, support more effective delivery processes and proactive, dynamic decision-making during the execution stage considering real-time data.

Moreover, it is also proposed that the contributions from this methodology can be extended by other researchers or industry actors to drive the adoption and potential standardization of an open real-time solution paradigm within the logistics/supply chain operations.

1.6 Document Outline

Chapter 1 defined the background about decision-making in supply chains and went over the main definitions and challenges, to provide the contextual information and terminology that are significant to this work. The different sections describe the traditional and current methodologies followed by the tendencies in technology and methods. At the end of the chapter is focusing on the last-mile operations context the opportunities to understand and analyze the integrating decisions on different stakeholders, the problem definition, the research questions, and the research contribution are described. Chapter two is focused on the literature review. Due to the extensive research in supply chain management (since the 1980s), only sources from the last decade are referenced, and it is emphasized on the study at the execution level and last-mile research tendencies. This chapter highlights the main characteristics and the main challenges that should be solved. Chapter three describes the proposed methodology and each of the steps to be followed to tackle the last-mile delivery operations. Chapter four presents two case studies for logistics operations; and chapter five states conclusions and future research.

CHAPTER 2: LITERATURE REVIEW

This literature review has three main objectives. First, to provide the contextual knowledge to analyze the execution level in a supply chain. Here is where the outcomes from the previous level decisions are revealed. Secondly, to bring an overview and detect challenge s and opportunities for the hierarchical Integration of decision-making in supply chains (Gutierrez et al., 2011). Third, to identify the advances and challenges in transportation and logistics such as a vehicle-dispatching problem for the delivery of goods in a city. Therefore, this literature review aims to provide a comprehensive background to discover research gaps that could be feasibly addressed by the proposed methodology.

2.1 The methodology of the Literature Review

The articles were gathered mainly from the engineering literature database; Ei Compendex. The search was aimed at finding implementation strategies, solution approaches, and scopes of decision-making strategies. Most of the revised articles were quantitative oriented. The next Figure depicts a mental map of the search. Keywords such as analytics, agent-based simulation, hybrid methods, hybrid modeling, artificial intelligence, dynamic optimization, dynamic routing, and control and integration, were used. One or more combinations of those keywords were specified under main topics such as supply chain management, supply chain execution, and last-mile delivery.

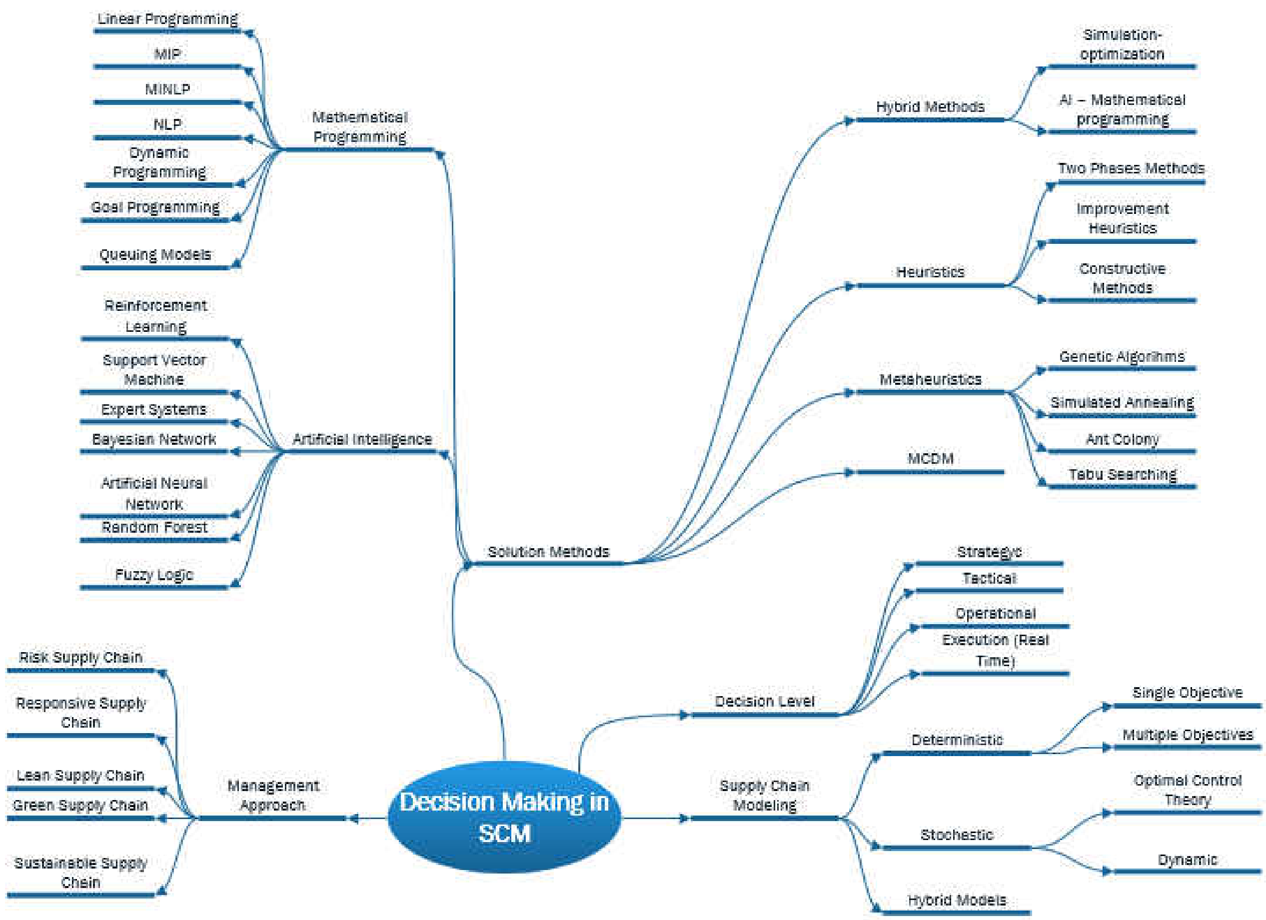


Figure 9: Mental map for decision-making tools in Supply Chain Management.

This literature review is split up into subject areas to address the core problem statement of hierarchical integration between levels that confirm a supply chain in an organization (Figure 10). The first two sections cover the integration methods mainly for Tactical, Operational, and Execution levels and discuss characteristics of modeling approaches and solution algorithms. The motivation of the second section is mostly over the practices in data analytics, showing some industrial cases using operations research techniques in the industry.

Figure 10: Ei Compendex searching method.

The third section focuses on delivery logistics, which is the executive level in services companies and determines what state of the art is in that area. Due to the particular interest in the industry and their challenges, and opportunities in the service industry, the vehicle dispatching task was chosen. The fourth section summarizes the conclusions of this review and determines a research gap to justify the proposed methodology.

2.2 Integration of Operational and Execution Level

Practitioners and academics have reported the benefits of the integrated method. Nie at coauthors in 2012, has published that decreases in net profit can be up to 40% for the use of a sequential approach against integrated methods (Nie et al., 2012). The performance of the systems is improved and reveals better coordination between decision-makers.

Most of the solution approaches that aim to have an integrated method use principles of system engineering by modeling different decision levels at the same time. A formal methodology widely known in the manufacturing industry is called: Enterprise-Wide Optimization (EWO). The method integrated optimization models with management science mainly for uses in chemical companies. (Grossmann, 2005). The next table lists the main challenges found in the literature.

Table 2: Challenges for integrated decision levels

Challenge	Characteristic
Heterogenety	Dynamic models and Logical Restrictions
Uncertainty	Control system always worl online in a closed loop
Multi-scale	Time integration between diferent time scales.
Implementation	Large computational time to solve it
Large Scale	Multiple dynamic models
Combination	Two or more challenges to solve

Preceding literature review in this topic discusses the theory, the models, applications, methods, and methodologies. Most of them are about production scheduling and routing problems.

For instance, Harjunkoskia and coauthors in 2014, discuss in-depth the production scheduling problems and describe in detail the strengths and weaknesses of the models (Harjunkoskia et al., 2014). Harjunkoski presented a more narrowed work; where the author is more interested in industrial environments; he depicted the hurdles for deploying scheduling solutions, some relations with ongoing technological transition were considered (Harjunkoski, 2016).

The integration between control (execution level) and scheduling (operative Level) have been reported as the key for successful operational processes in the reduction of costs (Baldea and Harjunkoski, 2014) and the advantages of sharing information between decision levels (Harjunkoskic et al., 2009).

Regarding methodology and solution approaches, Grossmann did an excellent job explaining the concept of Enterprise-Wide Optimization (EWO). The process industry is susceptible to issues of coordination. EWO allows optimization of the operations of supply (planning), manufacturing (scheduling) and distribution (real-time optimization) activities at the same time, to reduce costs and inventories. Furthermore, it highlights the necessity of deterministic and stochastic linear and nonlinear optimization models among IT tools) to support supply chain operations and bring customer satisfaction. (Grossmann, 2005, Varma et al., 2007). Other approaches include the Integration of methodologies and software platform, which allows for the modeling of integrated design for scheduling and control problems. (Pistikopoulos and Diangelakis, 2016).

Sahinidis in 2004 presents a review centered on the techniques and methodologies to handle uncertainty considerations to reduce the gap between models and real-world industries (Sahinidis, 2004). The Chu and You proposed a bi-level program to manage uncertainty in the integration of planning and scheduling. In the model, the upper level solves the planning problem, and the in the lower level it solves the scheduling problem. Considerations on disturbances are also taken into account (Chu et al., 2012). Similar approaches have been presented. For example, Koller & Ricardez proposed a dynamic optimization methodology to understand the implications of design and control on scheduling decisions (Koller and Ricardez-Sandoval, 2017). Finally, under the topic of uncertainty, a detailed taxonomy of different types of uncertainty faced by scheduling algorithms and its relevance on executing production schedules are presented in 2005 (Aytug et al.,2005).

Some examples of integration between operational planning and control are segmented into two different problems: scheduling and routing problem. There could be other problems attended by researchers worldwide. However, the main is related below.

Harjunkoskia et al., 2014, have attended scheduling problems which include a control stage; Engell and Harjunkoski, 2012; Baldea et al., 2014; Pistikopoulos et al., 2016; and Chu and You, 2012; Munawar, 2005 to name a few.

On the other hand, for the service industry routing problems has been attended by Subramanyam et al., 2017, with a multi-period vehicle routing problem allowing for customer service requests which are received dynamically over the planning horizon. The decision-making process is analyzed as a multi-stage robust optimization problem with binary recourse decisions.

The techniques applied to solve scheduling problems, the most common are mixed-integer dynamic optimization (MIDO) (Chu and You, 2012), recourse-based stochastic programming, robust stochastic programming, probabilistic programming, fuzzy programming, and stochastic dynamic programming (Gutierrez et al. 2008; Sahinidis, 2004).

Other applications based on hybrid models (HM) and Artificial Intelligence (AI) have been used to attend scheduling and control problems. It is the case of a Hybrid Mathematical Programming Discrete-Event Simulation Approach for Large-Scale Scheduling Problems, proposed by Castro et al., 2011; or the inputs of Chu et al., 2015, related with an integrated problem into a bi-level program.

Also, some applications and extension of Control Theory (CT), have been studied by Ivanov et al., 2012. The author describes essential issues and perspectives that delineate dynamics in supply chains, where the identification of Control Theory to production, logistics, and SCM in the period from 1960 to 2011; Years before, Branicky et al., 1998., introduced a mathematical model of hybrid systems as interacting collections of dynamical systems, evolving on continuous-variable state spaces and subject to continuous controls and discrete transitions.

The use of artificial neural networks (ANNs) has been successfully applied to solve a variety of problems for decades ago (Ruiz et al, 2007). As is the case of Sabuncuoglu and Gurun, 1996, who proposes a new neural network approach to address the single machine mean tardiness scheduling problem and the minimum makespan job shop scheduling problem. Li and Jayaweera (2015), present in their study: “Reinforcement learning aided smart-home decision-making in an interactive smart grid,” a Markov decision process (HM-MDP) model for customer real-time decision making. Specifically, they proposed a Q-learning algorithm, which is used under the approximate dynamic programming (ADP) approach. Van Tongeren and coauthors presented another Q-Learning approach in 2007. Their work focuses on the description of each of the echelons in a supply chain as an agent that can sequentially take decisions and learn over the time the best policies (Van Tongeren et al., 2007)

Parallel to work mentioned above, Li et al., 2015, presents a methodology which takes into account real-time decisions in a smart electricity grid. In this case, the solution is to focus on ensuring grid-stability and Quality-of-Service (QoS). This methodology was based on Machine Learning applications. McDonnell et al. have proposed another learning approach to improve decision-making in a hierarchical manufacturing environment, 2005. In this case, a reinforcement learning approach is employed for specifying the payoffs in reconfiguration games through capturing the effects of a sequence of reconfiguration decisions. Therefore, in the long run, the "machine-level controller" can learn the results of past decisions, and improve its decision-making process in manufacturing during the time (McDonnell et al., 2005).

Recently, a work focused on the human process of decision making under supply chain management circumstances was done by De Maio et al., 2016, they presented a methodology to support and trace social decision-making activities when different decision-makers have to find a consensus to select a most promising alternative to follow. The method takes into account theory of fuzzy logic and also uses a Reinforcement Learning algorithm to learn the weight of the decision-makers through the analysis of past process executions considering context and performances of business processes for the Consensus Model. In the same way, Apak et al., 2013, presents A Decision-Making Model for the Evaluation of Supply Chain Execution and Management Systems. This work presents a fuzzy logic-based approach oriented to integrate the Fuzzy Analytic Hierarchy

Process to weigh the decision criteria and the Fuzzy Technique. Also, according to Long, 2017, the complicated microstructures, macro emergencies, and dynamic evolutions in a supply chain network pose challenges to solving operational problems for the network's performance improvement. In this work, long proposes a methodology of data-driven decision making for supply chain networks based on Agent-based modeling to recreate the dynamics in a supply chain network and to verify the solutions generated for the decision-agents. Other authors also support their research with ABS, for example, Ta et al., 2005, developed a multi-agent approach for supply chain management for the operational level which integrates planning, execution, and supervising. In this study, task allocation and performance for supply chain management were attended.

Mathematical programming and Artificial Intelligence methods are used mainly for execution problems. Uncertainty in planning, scheduling, and control are the primary concerns. Some works were found to attend operations and execution problems such as scheduling and rescheduling, routing and rerouting, and other real-time optimization problems. However, applications that include strategic and operation-execution decision level are still developing.

Another point to highlight is the AI applications are used mainly to support real-time optimization and decision support systems. On the other hand, models based on fuzzy and multi-criteria extensions, have been used to model human considerations, uncertainty, and vagueness on decision-making processes across supply chains operations.

2.3 Data-Driven Decision Making in Supply Chains

Data analytics is not only used to identify patterns, but it is also used to understand previous occurrences and to have, and solid base to apply predictive analytics and infer what can happen in the future. Hazen (2014) determines how important the quality of the data is, to manage a supply chain and its use in business analytics. In his research, he states four essential characteristics: 1) the accuracy of the data is essential in order to have error-free data, 2) timelines to have up-to-date analysis, 3) consistency to have data presented in the same format, or at least by groups (structured, unstructured and semi-structured) and finally 4) completeness to check if there is missing data or there is the necessary data.

For many organizations, much of this data is scattered among numerous kinds of software on different applications, sometimes in different geographies and in many different formats instead of being consolidated. In the last decades, it has been a concern for many organizations to know how to gain more insight and protect their information at the same time. This issue has always been essential to align the organization with its mission and vision.

In the last three decades, it has been an increasing tendency for companies to seek the incorporation of business analytics into their business model pursuing economic, environmental, social, and government benefits. (Sanchez, 2014) The objective of these tendencies is to maximize profitability and minimize externalities (Miller et al.,, 2014) in order to optimize the use of scarce resources and promote waste reduction (Blanco, Sheffi, 2015) some of them through mathematical models using simulation and optimization techniques (Sterman, 2012) (Rabelo, Hughes, 2005).

A survey of 560 enterprises Chen et al., (2014) shows how the use of analytics techniques and the big data technology represents advantages for the improvement in business, above 50% are agree that with these techniques operational efficiency can be achieved (Gutierrez et al., 2016).

Nowadays, with big data tools, a new application is rising to support the process of traditional modeling and simulation processes. With these, it is possible to obtain data for initialization of the models, set up scenarios, and evaluate the results of these models (Tolk, 2015). Operations research has been playing an essential role in this field, mainly in the formulation and solution of many big data and data mining problems (Olafsson et al., 2008).

Data mining uses optimization techniques to resolve problems that arise in the presence of large amounts of data and their corresponding optimization models (Xanthopoulos et al., 2012). Data mining optimization is a big field of work for many organizations; due to their need to extract useful information for their processes. Optimization and Simulation models are extensively used for these organizations, but they can be better exploited in terms of their usefulness. Recent research demonstrates that optimization techniques work efficiently for data challenges and optimization processes (Olafsson, 2008; Sanders, 2014).

Simulation processes also have an essential role in creating and assessing scenarios of real problems. In this case, it is possible to recreate more data and usability.

Machine Learning is also used extensively in the industry. It is a set of algorithms that have information about datasets and can generate information/rules from this data to construct inferences and predictions (Xanthopoulos et al., 2012).

For example, one of the growing concerns with the energy crisis caused by environmental contamination and decreasing petroleum storages has lead governments and companies to build and implement sustainable projects to find alternative energy sources as the best option to achieve independence from fossil fuels. One result of this has been the diminishing environmental impact generated by their production and use. To reach this, it is necessary to understand and have a baseline of almost all the operations in an organization (Pirachican et al., 2009; Montoya et al., 2014; Blanco et al., 2015).

Therefore, the challenge is to implement efficient systems that support these technologies and inform communities about the impacts of their actions (Eccles et al., 2012). The use of mathematical models has been crucial to understanding the possible scenarios and results for their use.

Many companies follow their business analytics initiatives through their supply chain, where they focus on minimizing costs, optimizing scarce resources, and maximizing the profit. Also, by implementing techniques to improve and create products, processes, and business models, taking into account their impact on the environment and society (Canon et al., 2014).

Goetschalckx et al., (2002) And Shapiro (2004) present a review of the technical literature for the optimization of supply networks and its multiple areas of application. The mathematical optimization models have been applied to a series of process industries, including the fruit industry (Masini et al., 2009; Gutiérrez et al., 2007), food distribution (Ahumada and Villalobos, 2009; Rong et al., 2011), petrochemical industries, (Lababidi et al., 2004), pharmaceutical Industries (Papageorgiou et al., 2001), (Shah 2004) and the steel Industry (Gutiérrez et al., 2003) among others.

Another successful area where analytics support the decision-making process is in the oil industry (Alfonso et al., 2007; Gutierrez et al., 2011). Walls (2004) states that to improve performance and the decision-making process, the managers need to be aligned with the project portfolio to know and apply risk-management techniques as well as improve their policies to determine how to use the optimization portfolio outcomes (Walls, 2004).

Neiro and Pinto (2004) proposed a general methodology for modeling an oil supply network by the connection of three basic models: A model for the supply of crude oil, a model for the operation of the refinery, and a model for the oleoducts. They used mixed integer nonlinear programming. Papageorgiou (2009) presents an interesting critical review of methodologies for decision-making at process industry supply chains, including the presence and effects of uncertainty and business/financial and sustainability aspects.

In the energy industry, Bai et al., (2011), analyze the planning of biofuel refinery locations by incorporating the impact of traffic congestion into the routing and the delivery of raw material and the product in the biofuels supply chain. Kim et al., (2011a) include the selection of fuel conversion technologies, capabilities, biomass locations, and transport logistics when maximizing an objective function for a global benefit.

In Huang et al.,(2010), the authors developed a model, which integrates the spatial and temporal dimensions for the strategic planning of future bioethanol supply chain systems, minimizing the cost of the entire chain. Parker et al., (2010) developed a model that determines the optimal locations, types of vehicles and sizes of biorefineries while maximizing profits through the biofuels supply and demand chain from the site of production of raw materials to the fuel terminal. The resources considered include crops and residues sustainability.

Recently in the journal Knowledge-Based Systems, the author Long Q, (2017), discusses a data-driven methodology for decision making in supply chains. It has into account data-granularity, business analytics, and the four basic dimensions for decisions in supply chains (Knowledge, time, information, and material flows). An experiment is done under the agent-based simulation paradigm. The next Figure represents his proposal.

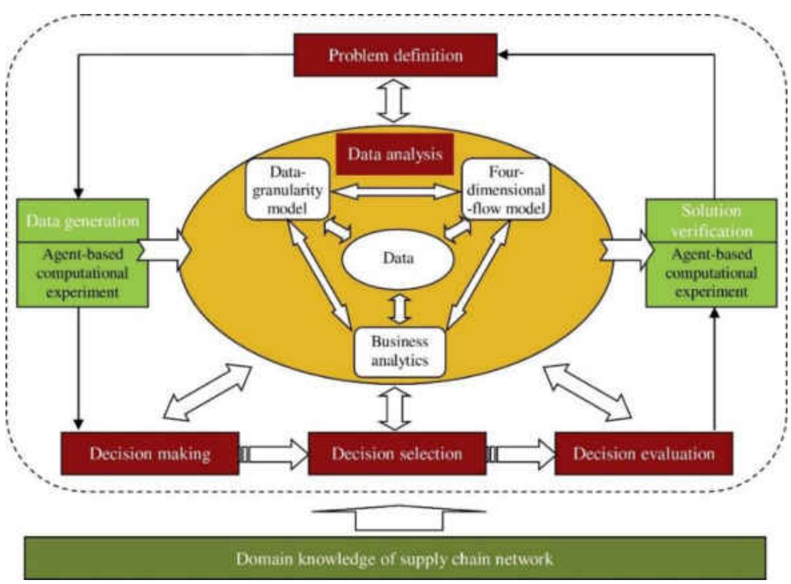


Figure 11: Data-Driven for SCM. Source: Long, 2017.

Martinsuo (2013) stated that in business, there are uncertainties and unforeseen events that add complexity to the project portfolio management. On the other hand, the updating practices and changes among their projects make day-to-day operations become challenges for the managers. In conclusion, Martinsuo states that the art of project portfolio management is like a negotiation or bargain to deal with multiple variables that could affect project development.

2.4 Last-mile Execution Level in Transportation and Logistics.

Urban distribution is responsible for 13% of the undesired congestion and 25% of urban emissions worldwide. It also accounts for 28% of total transportation costs (Roca-Riu et al., 2012). Therefore, the industry, government, and academia seek to improve the performance of urban operations. However, urban distribution is a complex challenge given that it depends on multiple stakeholders that change delivery services (manufacturers and distributors) increase demand (consumers) and very environmental and traffic regulations (public sector) (Anand et al.,2012; Kim et al.,2015). Despite being a growing research field, there is a significant opportunity on understanding how (planned and unplanned) changes in city infrastructure (e.g., parking spaces and roadways), use of novel technologies, as well as the evolution of the urban logistics ecosystems, drives high-performance strategies in urban distribution topics.

For instance, the growing size of e-commerce, now representing business of US$97 billion (National Retail Federation, 2017), is re-scaling and changing supply chain operations. Nowadays, last-mile services account for 53% of shipment costs due to a higher frequency of small, personalized orders. Consequently, the use of highly effective decision support systems is becoming more critical for all stakeholders. These systems must be able to address strategic and operational decisions for multiple stakeholders (Taniguchi et al., 2012, Macharis et al., 2014) through a set of additional, integral tools such as simulation, optimization, agent-based modeling, predictive tools, etc. These systems must also monitor and control operations by measuring their performance through multiple key performance indicators (e.g., costs, time).

Building a generic system that integrates metrics, various decision levels, multiple stakeholders, and supplementary techniques is a huge challenge (Anand et al., 2012; Macharis et al., 2014). Furthermore, current proposals have focused on developed, mature environments that possess different characteristics for growing, developing contexts. Despite complex interactions and dynamic behaviors among various stakeholders are present in both cases, the evolution of the latter is more dependent on a set of features related to urbanization, socioeconomic changes, accessibility and retailing footprint (Mejía et al., 2017) and not just technologically driven as the former. These characteristics hinder or boost the performance of planning and execution of urban distribution strategies. For example, poor infrastructure adds more complexity to urban distribution due to the lack of alternative routes, inaccessibility to specific regions and increasing congestion to the most distant, densely populated areas (Blanco, 2013). There are just a handful of studies in developing countries that characterize urban logistics operations, but they do not address dynamic decision making. Also, there are no discussions regarding a platform composed of various complementary methodologies to analyze, tailor urban distribution for these countries to keep profitable operations and improve performance (Joerss et al.,2016;)

One of the primary growth drivers for last-mile activities is consumer behavior (Kim, 2015). Consumer profiles have become more diverse and dependent on a large quantity of physical and internet-based retail channels.

Furthermore, consumers seek more delivery, payment, and merchandising options to acquire their services and products. This increases the material flow in fragmented distributions to meet just-in-time shipments and avoid having stockouts to serve demanding consumers.

On the other hand, cash and information flows must be synchronized to prevent wrong shipping orders from shippers (e.g., supplier, retailer) and returning them from small retailers and end consumers. These consumers are located in fast-growing metropolitan areas with poor infrastructure where companies perform millions of deliveries (Gutierrez et al., 2009, 2010a; Garza et al., 2011); therefore, using effective logistics strategies becomes a priority (Blanco and Fransoo, 2013). Nano stores represent a huge part of this fragmented retailing landscape.

A second driver that impacts efficiency in last-mile operations is related to driver decisions and expertise. Those components might shape value-added activities, react to customer requests, and overcome poor infrastructure. Therefore, driver behaviors influence logistics performance and help explain the gap between plans and real distribution operations (e.g., routes, schedules). Thus, including drivers' knowledge into decision-making models and data-driven analytics will allow for synchronizing information technologies with human experience to reach better time, service level, profit, etc. (Mahmassani, 2005).

A third driver widely studied topic comes from geographic location and how it impacts the distribution performance. Methods that find the best routes to visit multiple users subject to distinct constraints such as capacity, fixed schedules, density and city topology have been widely documented in the vehicle routing problem (VRP) (Pillac et al.,2013) and in city logistics models (Kim et al.,2015; Taniguchi et al.,2012).

The Heterogeneous vehicle routing problem with time windows is a class of the Vehicle Routing Problem (VRP) in which the capacity of the vehicles can be different (when is equal is called homogeneous fleet) and time windows are asking by the customers. There are many sources of research literature (theory and real-world solutions) on the VRP and its many classes; to point out some of them: Toth and Vigo. (2014), Cordeau et al. (2007), Golden et al. (2008), and Laporte (2009).

Dynamic fleet and vehicle routing management is a promising avenue that has studied changing traffic, demand variants (Pillac et al., 2013). Recently, agent-based modeling integrated methodologies for various stakeholders (i.e., supplier, logistics operators, retailers, and city planners) in urban logistics (Anand et al., 2016), land use and transportation (Adnan et al., 2016).

In the search for the best method to get close to the analysis and application of a systematic improvement to last-mile delivery, there is the exploring of the division of all people involved into those that can take decisions, and those who are participants or the actions of it are already pre-defined. For the first case, there are the urban consolidation center operators, the carrier employees, and the shipping company employees. Isolating them, it becomes easier to apply further studies and verify what is possible to be done in terms of decision-making to improve the system (Van et al., 2016).

The idea of pick-own-parcel stations, where customers are notified that their delivery arrived, and they can go and pick their packages have been presented some failures caused by the receivers themselves, such as not showing up after a few days. Although it would reduce the costs for the delivery companies (if they do not reduce their prices), it would not solve some other problems, as even more vehicles will be in the streets, creating even more traffic than using delivery trucks (Wanga et al., 2016).

Together with it, there is an extensive list of approaches currently being applied in that system analysis. They might be demand or supply models – which are models in which the choices are either based on the agents given the transportation network or where the states of that transportation network can be reproduced, respectively - and demand-supply models, that includes computer simulation software modeling, especially agent-based simulation (ABS) (Basingab et al., 2017; Nagadi et al., 2018; Nuzzoloa et al., 2018).

Other previous approaches include only the geographic positioning of the urban consolidation centers to reduce the distance of traveling by the delivery vehicles only. It does not get to the point to analyze traffic situations or a variety of things that directly impacts on the delivery system. Other methods apply probability and statistics to calculate shortest paths based on the client's location, but they are aggregate the same issues as the other one (Van et al., 2016).

The focus on agent-based simulation is to define and uses a limited environment and creates behaviors and interactions based on probabilities inputted by the modeler/user (Nuzzoloa et al., 2018), and then use this to solve last-mile delivery logistics problems.

On ABS, the agent can decide options that create the most efficient outcome, as well as understanding what is desirable and wanted by the simulation operator, therefore increasing the "focus" on walking towards an acceptable end goal. These decisions are most of the times limited by policies inserted by the user of the modeling software to create a system as close as possible to the real-world environment (Van et al., 2016). The inputs must fulfill a set of necessities that will feed the pre-analysis of the simulation. It includes all the relationships between agents, including how they interact with each other (Macal & North, 2005). The point is to assure that the interactions will be acceptable and will be performed to help the simulation.

The growth in the distribution of goods in multimodal transportation planning always has been relevant for the industrial and economic growth of society. Specifically, for urban areas where the challenge to tackle the dynamics in these areas call for strategy development. The last-mile distribution uses the techniques and models for vehicle routing. Historical evolution of the solution approaches and trends are summarized in the following Figure 12.

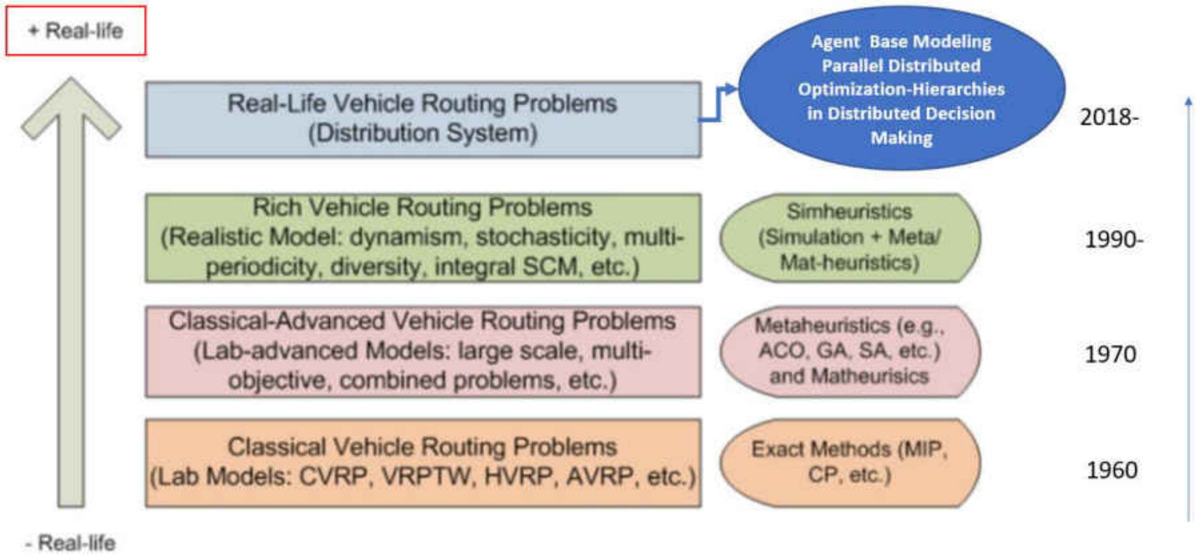


Figure 12: Solution trends in vehicle routing problems (Adapted: Caceres et al. 2014).

2.5 Literature review discussion

Mathematical optimization and simulation models have widely studied each of traditional supply chain decision levels (strategic, tactical, and operational). However, most of the solution approach for the possible issues at each level, only focus on a single level isolated from others. In consequence, the methods for solving different problems in a supply chain are commonly applied sequentially. When a high-level issue is resolved, the outcome is transmitted to the other levels as a parameter. This solution approach is repeated for each level. Finally, the solutions are assembled to form a complete solution. In part, this is a common practice for the difficulties in the implementation stage (Chu et al., 2015).

On the other hand, the possible issues that can appear in one of the supply chain levels are related to each other. (Simchi-Levi et al., 2009). Data-driven approximations have been used to handle the integration of solutions. (Long, 2017).

To address dynamic behavior and unstable conditions from logistics operations, hybrid techniques must be used to support the delivery process and adjust plans according to changes in critical factors according to a set of potential scenarios. Data analytics might be a first step to understand critic issues, build proper measurement systems, predict the evolution and lead stakeholders to reinvent their strategies, policies embracing technology and a data-driven culture (Hey et al., 2009; Brynjolfsson et al., 2011).

As described in the literature review, there has been an increase in research on the integration between execution and operative and tactical planning. Nowadays, these practices span mainly across in-process production industries. Different methodologies and perceived benefits of the integration are documented, despite the similar systematic challenges and characteristics faced in their respective complex and dynamic environments. Generally, the studies that were further along with demonstrating the benefits of hierarchical integration have achieved it at both the strategical and organizational levels, which require feedback learning processes to learn from past behaviors, mistakes, and disturbances to deliver a better understanding of the decision process.

2.5.1 Visual Analytics about the Literature Review

A continuation of a short resume about some statistics in the literature review. To detect the number of journals for different analysis, a 0-1 matrix was built. The next Figure 13 presents an example of the matrix.

ID	Autho	Year	Title	Journal	Requirement	Production	Scheduling	Distribution	Transportation	Demand	Literature Review	IT	Strate	Tactic	Operational	Execu	DETERMINIST	STOC	Math Programming	AI	Sim-O	AI-Mat
1	Ahum	2009	Application	European Journal of Operational Research							1						0	0	1	0		
2	Adnan	2016	SimMobility: A Multi-scale Integrated Agent-based Simulation Platform					1	1				1	1						1		
3	Anand	2012	Citylogistics modeling efforts: Trends and gaps-A review					1	1		1											
4	Apak,	2013	A decision	International Jo	1			1	1				1				0	0	0	1		
5	Ayug,	2005	Executing	European Journal of Operational Research			1				1						0	0	0	0		
6	Bai Y.	2011	Biofuel refin	Transportation Research Part B: Methodological				1	1								1	0	1	0		
7	Balde	2014	Integrated	Computers & Chemical Engin		1	1				1				1	1	0	0	0	0		
8	Blanco	2015	EcoGrowth:	MIT-ESD. ESD-WP-2015-03									1	1			0	0	0	0		
9	Blanco	2013	Reaching 50 million nanostores: Retail distribution in emerging megacities.																			
10	Branic	1998	A unified fra	IEEE transactions on automatic control,													0	1	0	0		1
11	Bryejo	2011	Strength in	SSRN 1819486													0	0	0	0		
12	Castro	2011	Hybrid math	Industrial & Engineering Chemistry Resea			1								1		1	1	0	0	1	
13	Chen,	2014	Data-intensi	Information Sciences							1						0	0	0	1		
15	Chu, Y	2015	Model-base	Computers & Chemical Engin		1	1				1				1		1	0	1	0		
16	Chu, Y	2015	Integrated	Computers & Chemical Engin		1	1								1	1	1	0	1	0	1	1
17	Darby	2011	RTO: An ov	Journal of Process Control							1					1	0	0	0	0		
18	De Ma	2016	A framework	Knowledge-Based Systems.									1				0	0	0	1		
19	Dias,	2017	From proce	Computers & Chemical Engin		1	1				1			1	1		0	0	0	0		
20	Eccles	2013	A Tale of Tw	Journal of Applied Corporate Finance									1				0	0	0	0		
21	Engel	2012	Optimal ope	Computers & Chemical Engineering			1								1	1	1	1	0	1	1	
22	Garcia	2015	Supplychai	Computers & Chemical Engin		1	1	1	1	1	1		1	1	1		0	0	0	0		
23	Goetsc	2002	Modeling an	European Journal of operation		1		1	1	1	1		1	1			0	0	0	0		
24	Grosd	2013	The Guide T	Datameer Whitepaper													0	0	0	0		
25	Gross	2005	Enterprise-w	WileyInterScience		1		1						1	1		1	0	1	0		
26	Gross	2012	Advances in	Computers & Chemical Engin		1	1	1							1		0	1	1	0	1	
27	Gutiér	2010	Planificació	Revista Facultad de Ingeniería		1		1	1						1		1	0	1	0		
28	Harjun	2016	Deploying s	Computers & Chemical Engineering			1	1						1	1		0	0	0	1		
29	Harjun	2014	Scope for in	Computers & Chemical Engin		1	1				1				1	1	0	0	0	0		
30	Harjun	2009	Integration	Computers & Chemical Engin		1	1								1	1	0	1	0	0		
31	Hazen	2014	Data quality	International Journal of Produ		1		1	1	1			1				0	0	0	0		
32	Hey, T	2012	The Fourth	E-Science and Information Management									1				0	0	0	0		
33	Huang	2010	Multistage	Transportation Research Part E: Logistics and Transportation Review										1			1	0	1	0		
34	Ivanov	2012	Applicability	Annual Reviews in control		1	1								1		0	1	0	0		
35	Kim, G	2015	Citywide routing problem (CityVRP): A review. IEEE Transactions on Intelligent Transportation Systems.																			
36	Koller	2017	A Dynamic	Computers & Chemical Engin		1	1							1	1		0	1	1	0		
37	Labab	2004	Optimizing	Industrial & Eng	1		1								1		0	1	0	0		
38	Li, D.	2014	Rainbrain	Green Energy and Systems Conference (IGESC)													0	0	0	1		
40	Li, Z.	2009	Integrated	Computers & Chemical Engineering			1								1	1	1	0	1	0		
41	Long,	2017	Data-driven	Knowledge-Based Systems										1	1		0	1	0	0	1	
42	Macha	2014	A stakeholder-based multicriteria evaluation framework for city distribution. Research in Transportation Business & Management.																			
43	Mahm	2005	Transportation and traffic theory flow, dynamics and human interactio					1	1	1			1	1						1		
44	Masin	2009	Optimal ope	Optimization in	1			1					1	1			1	0	0	0		
45	McDo	2005	A learning	International journal of produc		1	1								1	1	0	0	0	1		
46	Mejia	2017	A structural estimation model to analyze the evolution of retail channels in emerging countries.																			
47	Mente	2001	Defining su	Journal of Busi	1			1		1			1				0	0	0	0		
48	Monto	2015	Conceptual	Production Planning and Con		1		1		1			1	1			0	0	0	0		
49	Munar	2005	A multilevel	Industrial & Engineering Chem		1	1								1	1	0	1	0	0		
50	Neiro	2004	A general m	Computers & Chemical Engin		1			1					1	1		1	0	1	0		
51	Nie, Y	2012	Integrated s	AIChE Journal		1	1								1		0	1	1	0		
52	Olafss	2008	Operations	European Journal of Operational Research									1	1	1		0	0	0	0		
53	Papag	2001	Strategic Su	Industrial & Engineering Chem		1		1		1			1	1			1	0	1	0		
54	Papag	2009	Supplychai	Computers & Chemical Engin		1		1		1			1	1			1	0	1	0		
55	Parker	2010	Developme	Biomass and Bioenergy		1		1					1	1			1	0	1	0		
56	Pillac,	2013	A review of dynamic vehicle routing problems.								1		1									
57	Pistik	2016	Towards th	Computers & Chemical Engin		1	1						1	1			1	0	1	0		
58	Rabel	2005	Sustaining	Journal of Engineering and Technology Management						1			1	1			0	1	0	0		
59	Roca-	2012	An evaluation of urban consolidation centers through logistics syste					1	1				1									
60	Rong,	2011	An optimiza	International Journal of Produ		1								1			1	0	1	0		
61	Sabur	1996	A neural ne	European Journal of Operational Research			1								1		1	0	0	1		
62	Sahin	2004	Optimization	Computers & Chemical Engineering							1		1	1			0	0	0	0		
63	Sanch	2014	Integrating sustainability issues into project management									1	1				0	0	0	0		
64	Sande	2014	*Big Data Dr*	1. Pearson Education.								1					0	0	0	0		
65	Scholt	2007	The road to	Isa		1						1	1	1	1		0	0	0	0		
66	Shah	2004	Pharmaceu	Computers & Chemical Engineering			1	1				1		1	1		0	1	1	0		
67	Shah,	2005	Process ind	Computers & Chemical Engineering													0	0	0	0		
68	Shapi	2006	Modeling the supplychain.					1	1					1	1		0	0	1	0		
69	Shapi	2004	Challenges of strategic supplychain planning and modeling														0	0	0	0		
70	Simch	2009	Designing a	Computers & Chemical Engineering									1				0	0	0	0		
71	Subra	2017	Robust Multi-Period Vehicle Routing under Customer Order Uncertai					1	1					1	1	1	0	1	1	1		
72	Ta, L.	2005	A multi-age	Proceedings. 2005 IEEE		1	1							1	1	1	0	0	1	1		
73	Tanig	2012	Emerging techniques for enhancing the practical application of cityl					1	1				1	1			1					
74	Tolk, A	2015	The Next Ge	Summer Simulation Multiconference 2015								1	1	1			0	1	0	1		
75	Troldb	2014	Assessing	Renewable and Sustainable Energy Reviews													0	0	0	0		
76	Van T	2007	"Q-learning	IEEE International Conference on Systems			1	1				1	1	1			0	0	0	1		
77	Varma	2007	Enterprise-w	Computers & Chemical Engin		1	1				1				1		0	0	1	0		
78	Walls	2004	Combining	ournal of Petroleum Science & Engineering.								1	1	1			1	0	0	1		
79	Xanth	2012	*Robust data*	Springer Science & Business Media													0	0	0	1		

Figure 13: Example Matrix 0-1 for Journal classification.

The next Figure identifies the top five journals for publications. As a number one and with an essential difference versus the others is the journal: Computers & Chemical Engineering. This is due, most of the research is for processes in manufacturing. It is followed by the European Journal of Operations Research, the Industrial & Engineering Chemistry Research and the International Journal of Production Economics.

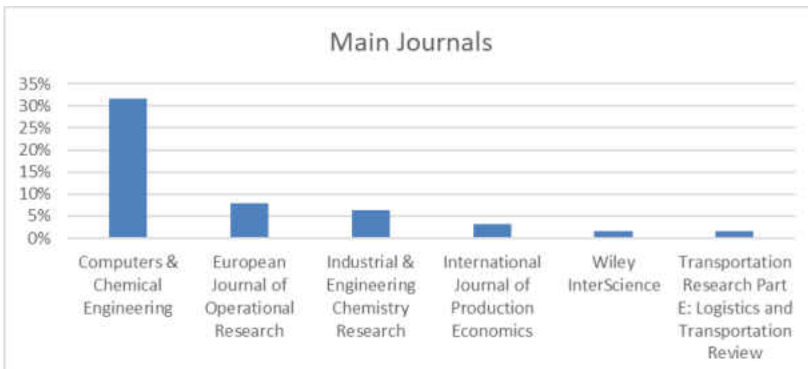


Figure 14: Top 5 journals.

Next Figure is a big picture of the journals where the literature review was collected.

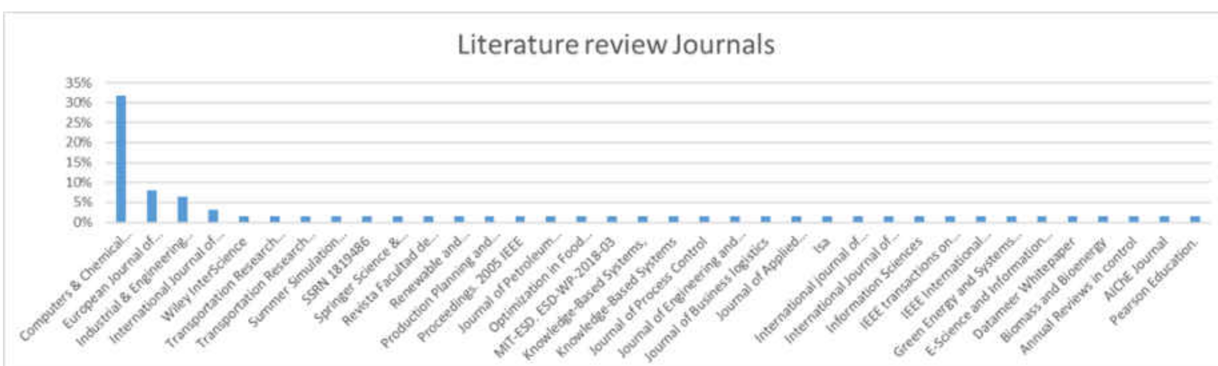


Figure 15: Names of Publication Journals.

The following Figure depicts the techniques used for the solution; it should be noted the use of mathematical programming during all years. On the other hand, also, it is important to highlight the absence of artificial intelligence works between 2005 and

2012. The publications in 2005, probably were research made with 2-3 years previously. Almost a decade, where these techniques were not used in advertisements. However, since 2012, the number of books is increasing. In 2015 more variety of publications, where the use of the four approaches are reported.

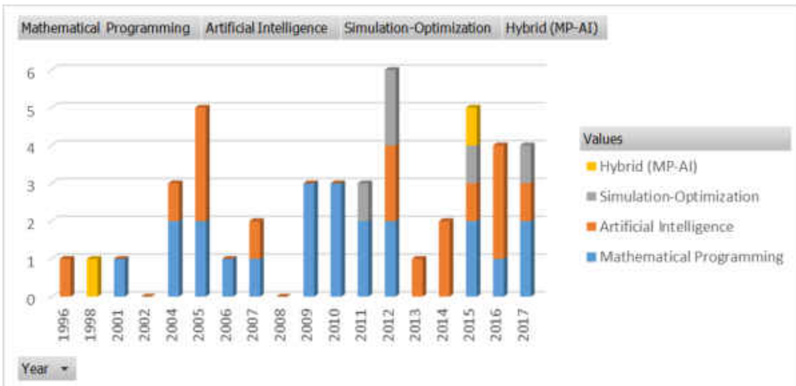


Figure 16: Solution method reported.

About the execution process in supply chains, the next Figure represents the reported applications in scheduling, production planning, and transportation management.

Figure 17: Type of application.

Most of the applications are in scheduling and production, around 80%. The next Figure represents the application by percentage.

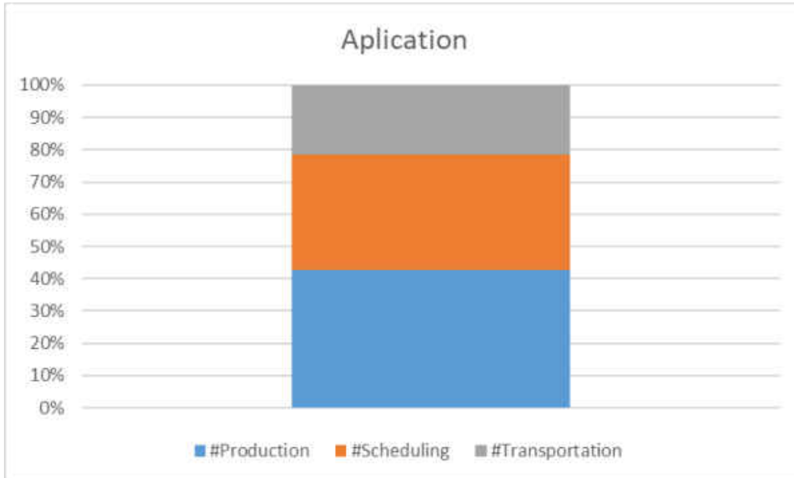


Figure 18: Percentage of Type of application.

The next two Figures show the type of decision level. The most predominant are Tactical and Operative. The execution level has small participation, around 10% against the operational with an approximate 25%.

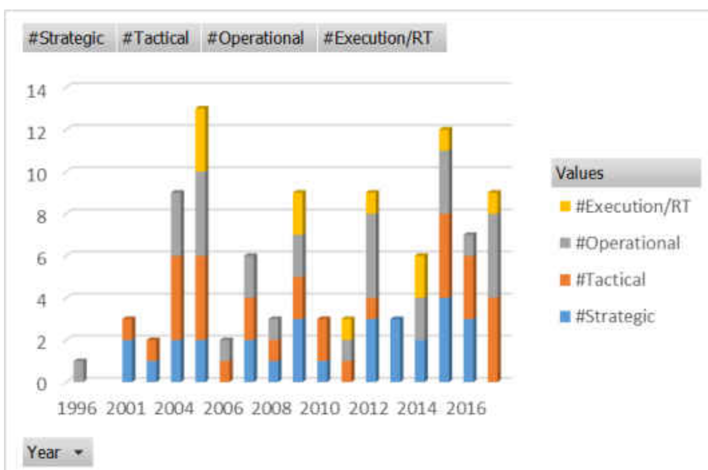


Figure 19: Decision Level in the supply chain.

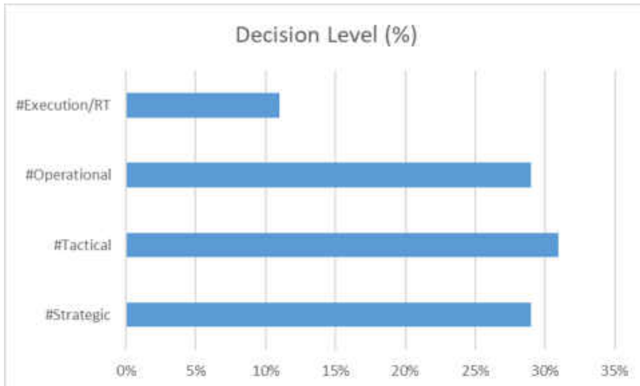


Figure 20: Percentage Decision Level in the supply chain.

Finally, to sum up, the next Figure shows the number of papers per exciting topic and the following table is showing a table with the identified GAPS from the literature.

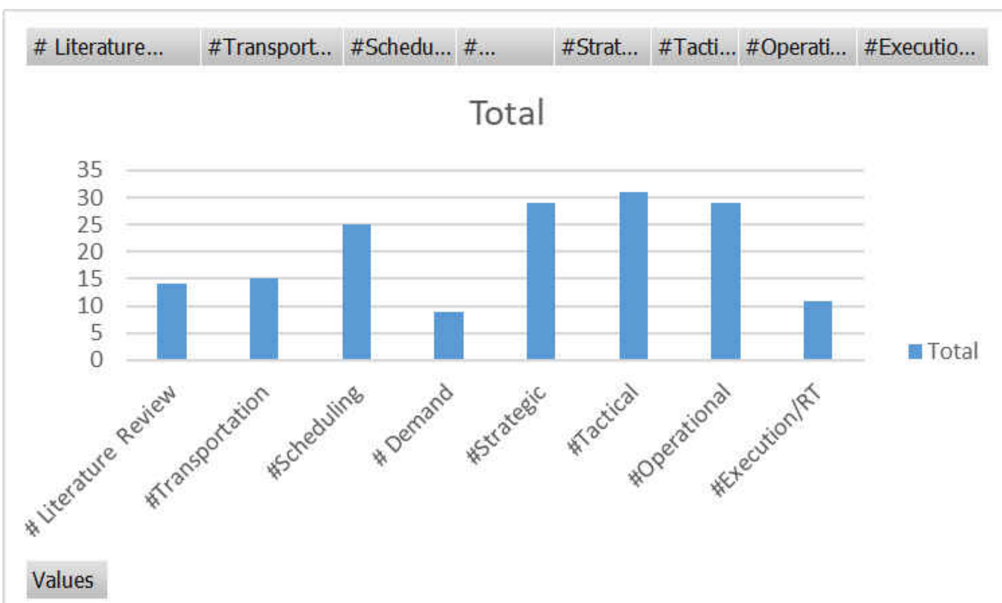


Figure 21: Main Topics in the literature review.

2.6 Summary and Research Gap

After the review, gaps were identified. Exact, heuristic and hierarchical algorithms have been studied and proposed to solve the delivery of goods, but a fast and reliable solution for real-world applications for organizations is still an inspiring task. The impact of dynamic conditions is significant for last-mile operations and forces most of the time, dispatchers to reschedule or adjust their decisions. Once the data is analyzed is possible to use it to make predictions about the behavior of the stakeholders; for this research, they are also called “agents.”

A methodology which can do an integration of different decision levels, considering the dynamic complexities of the stakeholders and the dimensions of a real-world organization and learning from the experience has yet to be developed. Solutions still need to be researched for essential factors such as human behavior and the environment besides the common conditions from logistics operations. Predictive and prescriptive hybrid techniques must be designed to support the execution process and adjust plans to changes. Approaches show different methods but do not have into account the learning process from the stakeholders and the dynamism of the environment. With this gap, the research question was refined.

2.6.1 Potential Benefits of this Methodology

The main potential benefit that is extracted from the previous analysis are:

- Learning from the experience and simulations can bring more and better efficiencies for service in supply chains and specifically in last-mile operations.

- The methodology supports the design and analysis of key performance indicators.
- Use of hybrid models to manage last-mile delivery operations in urban contexts and improve the execution phase in the supply chain.
- Representation of stakeholders’ behavior involved in the delivery of goods.
- The hierarchical methodology can bring a reduction of cost in the overall operation.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Description of Research Methodology

This research methodology aims to establish the necessary steps to address last-mile delivery operations efficiently. The flow chart (Figure 22) describes the steps and actions followed in this research.

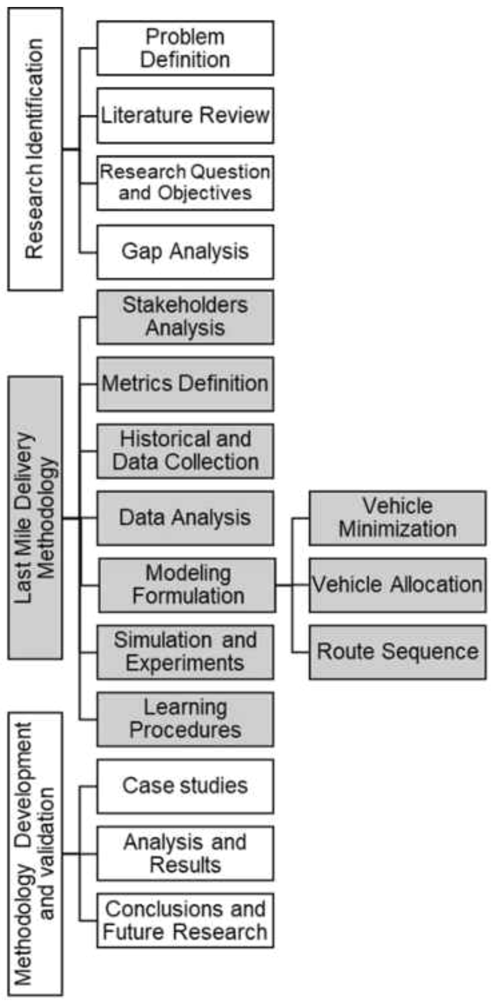


Figure 22: High-Level Research Methodology.

3.1.1 Research Identification and Gap Analysis

The research started with the problem definition and preliminary questions on how decisions influence at each of the levels of a supply chain with emphasis on last-mile delivery. A literature review was performed. This was cover in Chapters 1 and 2.

After the review, gaps were identified. Deterministic models are, in general, not entirely appropriate for real-world applications. Exact, heuristic, and hierarchical algorithms have been studied and proposed to solve the delivery of goods, but a fast and reliable solution for real-world applications for organizations is still an inspiring task. The background research for this topic entailed both journals and personal experience in academia and corporations. These have been allowed the interaction with stakeholders in the logistics and technological environments in addition to active attendance and participation at conferences, webinars, and workshops. The subject matter expertise in supply chain operations helped shade the current state of the art and its main challenges. The theory provided the engineering/research skillset to define the main components of the proposed methodology.

The impact of dynamic conditions is significant for last-mile operations and forces most of the time dispatchers to reschedule or adjust their decisions. Once the data is analyzed is possible to use it to make predictions about the behavior of the stakeholders; for this research, they are also called "agents."

A methodology with the architecture and tools able to do an integration of different decision levels, considering the dynamic complexities of the stakeholders and the dimensions of a real-world organization and learning from the experience has yet to be developed. Solutions still need to be researched for essential factors such as human behavior and the environment besides the common unstable conditions from logistics operations. Predictive and normative hybrid techniques must be designed to support the execution process and adjust plans to changes. Approaches show different methods but do not have into account the learning process from the stakeholders and the dynamism of the environment. With this gap, the research question was refined. A continuation is described as the last-mile delivery methodology and its principals' components.

3.2 Last-mile Delivery Methodology

Researches and industry managers have realized the need to improve the execution of daily transportation operations and noted how it had become a source of competitiveness growth and cost reduction. Routing planners struggle to accurately set and forecast delivery routes based on the day of the week, time, location, customer, and driver behavior. High traffic in urban areas, customers location, buyer regret, lack of nearby parking, elevators out of service, and many other operational issues, all add cost, time and troublesomeness to this critical activity. Given the challenges transportation, supply chain managers, and city planners face with managing data complexity and prediction techniques; some gaps have been exposing in this research.

3.2.1 Stakeholders analysis

Traditionally the literature mentions four stakeholders for city logistics: shippers, freight carriers, administrators, and clients (Taniguchi et al. 2011). These stakeholders have distinct behaviors to pursue different objectives. For instance, cost reduction is a common interest of profit maximizers like shippers, carriers, and money savers like consumers; while administrators are more aware of traffic congestion, accidents, and environmental problems. Table 3 presents a short description of each player in urban logistics with the respective goals, measurement indicators, and their characteristics in certainty and variability.

Table 3: Stakeholders of last-mile delivery decisions

			Data Analysis	Certainty		Variability		Literature Source
Stakeholder	**Description**	**Objective/Goals**	**Data Measurement**	**Deterministic**	**Probabilistic**	**Static**	**Dynamic**	
City Goverments	Local, state and city governments. Decision Makers	Better traffic	Traffic regulations	x		x		Alho et al. 2017; Rathore et al. 2016; Mahmassani. 2005.
		Control Environment	CO2 emissions.	x			x	
		Infrastructure Investment	Low/High emission areas					
		Land Use	Traffic congestion - flow		x		x	
		Road Safety	Type of use (residential, business)	x		x		
			Truck Weight limits per zone	x		x		
Inhabitants	Workers, kids (School), eldery population, regular pedestrians.	Minimize traffic congestion and accidents. Some externalities like pollution or noise	Additional travel time				x	Anad et al. 2012
			# of Accidentes				x	
			Pollution					
Carriers	Transporters, warehouse companies, 3PLs	Customer service	Transportation Cost	x		x		Kin et al. 2017
		Meet time windows	Fuel Consumption	x		x		
		Reduce costs	Driver Infractions		x		x	
			% Rejections		x		x	
			Capacity Utilization		x		x	
			Travel times		x		x	
			Number and % Fleet Use		x		x	
Shippers	Manufacturers, wholesalers, retailers	Customer service	Capacity Utilization	x			x	Taniguchi et al. 2012
		Reliability of transport	Driver Infractions		x		x	
		No damage in products	% Fleet Use		x		x	
		No delays	Service Cost					
		Increase safety	% OTIF (On time-In full)		x		x	
			% Rejections		x		x	
Customer and Consumers	The customer is who buys products from businesses, the consumer uses the business products (Can be a customer)	Obtain what they look for.	Frequency		x		x	Macharis et al. 2014
		Time, quantity and price	Locations	x			x	
		time windows	Time windows	x			x	
			Number of Returns		x		x	
			Meet the demand		x		x	

This analysis focus on quantitative metrics, such as time, quantity, performance, and rates. Once the performance system is created, and the interrelations are understood; the parameters can be used to make decisions for multiple stakeholders under the different circumstance and the respective levels. Consequently, the system should assess performance and compare solutions in real time to adjust strategies to meet goals and requirements. This capability would depend on the most likely scenarios to reduce delays, lost sales, costs, risk, and poorly planned resource allocation. Thus, near real-time decision making predictive tools under uncertain situations becomes a state-of-the-art tool to link forecasted performance with the execution of the operations.

This is a complex problem with a variety of situations. For example, Table 4 shows anomalies that can occur during the execution of the route. There is a list of possible offline and online actions (Hentenryck et al. 2009). Once one or more of these anomalies happen, the previous order must adjust depending on the conditions (signals of the environment).

Table 4: Possible anomalies and actions in the distribution of goods in a city.

Possible Anomaly/Disruption	**Action Off-Line**	**Action On-Line. Rules**	**Literature Sources**
New customer order arise during the day	Previous Profile Demand per customer	Hold the truck in the zone where the order are likely to arrive	Powell et al, 2005. Ichoua et al, 2006. Van et al, 2009. Pillac et al, 2012. Fleischmann et al, 2014.
	Identification of zones where customer are likely to order	Identify available cars in the zone.	
Customer Cancel the order during the Day	Previous Profile Demand per customer	Re-Scheduling a Car in the zone	
The customer is not in the delivery location	Customer Profile	Reschedule for same day or different day	
The customer don't pay the delivery			
Product rejection			
Theft of merchandise			
Vehicle accident	Driver Profile		
Via in construction(road closures)	Alternative routes	Rerouting	
Traffic Jam			

It is known that we must be able to measure a process to improve it (Drucker, 2012). Data accessibility eases monitoring improvements but devising the right performance measurement system supports an effective decision-making process. Nevertheless, choosing the most suitable performance indicators is not trivial because they differ among stakeholders, processes, and even depending on the stage of the decision.

Therefore, their configuration becomes essential to evaluate progress comparing a baseline case (i.e., reference level) with pre-defined objectives to various alternative scenarios. This also helps to track the improvements in current logistics operations and shape decisions under uncertain environments and diverse potential situations to guarantee better performance (Giaglis et al. 2004).

3.2.2 Simulation Environment

A simulation software environment is used to represent the behavior of stakeholders and driver's total delivery time, which is divided into two main components: uncertain service time at customer locations and uncertainty travel time on roads. Simulations have the potential to be used with the associated variables. The city also has different characteristics, depending on the zone. Travel times to go from one customer to another depends on the routes, the velocity, and the order of the visiting for each vehicle (Kim et al., 2016).

3.2.3 Stakeholders in the Simulation Environment

For this research, three main agents are studied and applied in the simulation: drivers, customers, and the city.

3.2.3.1 Driver-Vehicles

The vehicle agent is the agent of the driver. The velocity affects the travel time directly. Uncertain travel times are modeled as random variables (VanWoensel et al. 2008) usually; the information is condensed to stochastic travel times per path between the nodes and represented by a probability distribution. Burr, Weibull, Gamma, lognormal are classic distributions used in this case (Susilawati et al. 2013; Gómez et al. 2015; Groß et al. 2015). These distributions show a positive skew meaning that values indicate the significant amount of the density being below the mean value and the tail with low probability. Another characteristic of the drivers is the same person who does the delivery; he/she must park the car, go walking until the address "knock the door" and deliver the product. This set of activities can be called "service activities" and has a related: service time. In the literature, it is common to find service time modeled with triangular or normally distributed (Errico et al. 2016). Also, it is essential to point out the influence of the customer in this service time (Souyris et al. 2013).

3.2.3.2 Customers

The customers shopping behavior can change depending on the time of the year. Usually, companies detect two main seasons: valley and peak demands. The modeling of this is generally made through the analysis of historical data (Erera et al. 2009). During the season, the normal or uniform probability distribution is usually used to set up the number of orders per day (Secomandi, 2000). The geographical location where the demand showed up is modeled often through uniform distribution per zones and time of the year (Bertsimas et al., 1991).

Examples of the type of customers in a city are mom and pop stores, supermarkets, residents (townhouses or buildings), etc.

3.2.3.3 City

Uncertainty environment in a city due to changes in travel times for roads infrastructure or weather conditions, parking availability are some of the factors that incorporate challenging decisions or policies to meet customer demands and time windows. Which directly affects the services levels and operational costs when policies need to be updated and adapted with the information received from the environment. Table 5 depicts what can affect the estimated time of arrival in a city considering certainty and variability in their occurrence.

Table 5: Characteristics that affect the estimated time of arrival of goods in a city.

KPI's Characteristics							
Feature		**Certainty**		**Variability**		**Literature Source**
		Deterministic	**Probabilistic**	**Static**	**Dynamic**	
Traffic	Day/Hour		x		x	**Mahmassani, 2005**
	Weather		x		x	
	Infrastructure	x		x		
Location	Density	x		x		**Alho et al. 2017; Velasquez et al. 2017**
	Parking zone	x			x	
	Topology	x		x		
	Geography	x		x		
Driver	Expertise	x			x	**Toledo et al. 2007**
	Performance	x			x	
Customer	Time Windows	x			x	**Macharis et al. 2014**
	Locations	x			x	
	Building Specs.	x		x		
	Security	x		x		
	Delivery inst.	x			x	

The quality of the data directly affects the effectiveness of the models where it is used to make decisions. At the same time the correct identification of variability in the data trough probability distributions, and aligned with changes on time, for example during peak or valley traffic times in a city, determine a more realistic approximation to the reality and the quality of the outputs in the models.

3.2.4 Metrics for the distribution operation

Last-mile operations comprise a wide variety of logistics processes, but they are mainly linked to four main pillars: customer behavior, staff (driver) behavior, geographical issues, and congestion conditions. Metrics such as estimated time of arrival (ETA), cost to serve, service level, among other KPIs linked to logistics are closely related to distribution procedures. Figure 23 highlights some characteristics of these indicators. There are two main groups: i) Travel issues that are affected by traffic conditions, location characteristics and vehicle driver performance (geographic and external non-controllable elements) (Montoya et al., 2009) and ii) service issues that influence mainly by consumer and driver behavior (human factors).

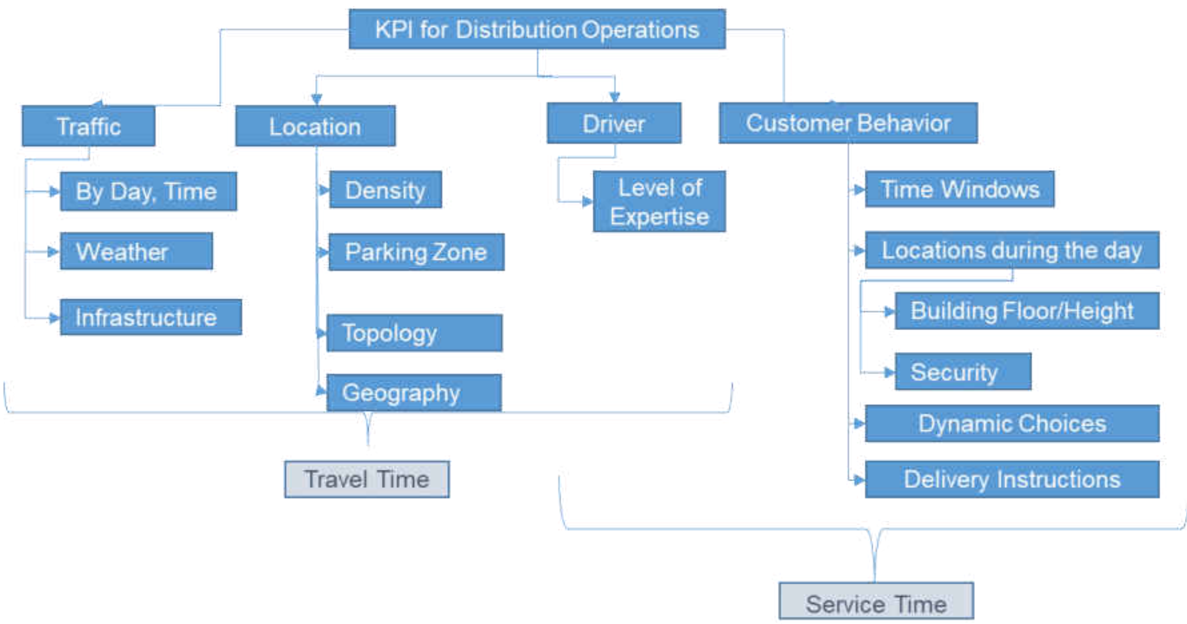


Figure 23: KPIs for last-mile delivery operations.

3.2.5 Definition and development of steps for the last-mile methodology

Many types of research have proposed different methods to handle the vehicle routing problem. The solutions are usually divided into three types: exact, heuristic, and hierarchical approaches. However, there is not a complete methodology to handle dynamic environments and stakeholder behaviors.

Techniques from descriptive statistics, machine learning techniques (prediction), and optimization methods (prescription) are used to reduce operational gaps in the execution process for the last-mile delivery operations.

This proposed methodology has five main steps. Figure 24 shows every activity and how they are linked to each other.

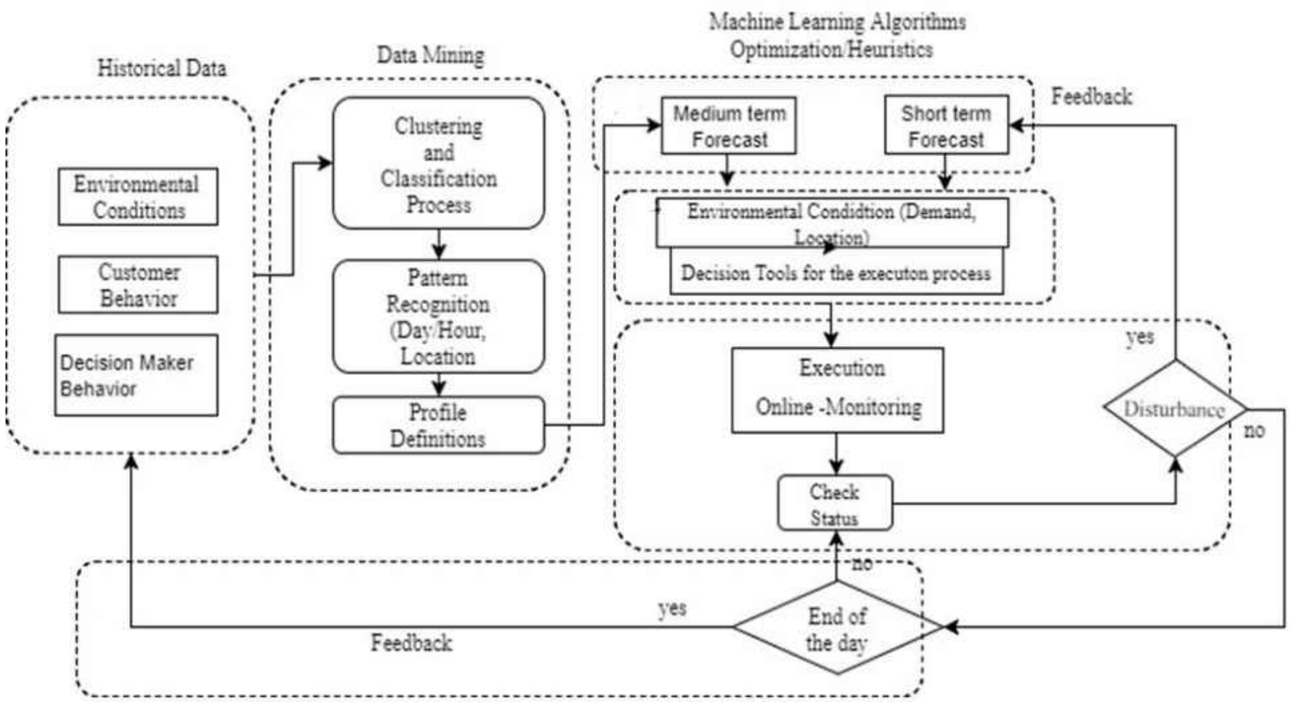


Figure 24: Last-mile Methodology description.

The first step is the storage of historical data and data collection from the delivery operations. The second is data analysis and clustering. Third, the modeling process and their approaches to solving the routes. Then simulation models and experiments over the founded routes. Finally, step five, we propose learning procedures to capture the experience from past deliveries and the conditions of the agents and can handle last-mile operations with efficiency. Figure 25 show the road map for each of the steps, linked with the main outcomes, methods and interrelationships.

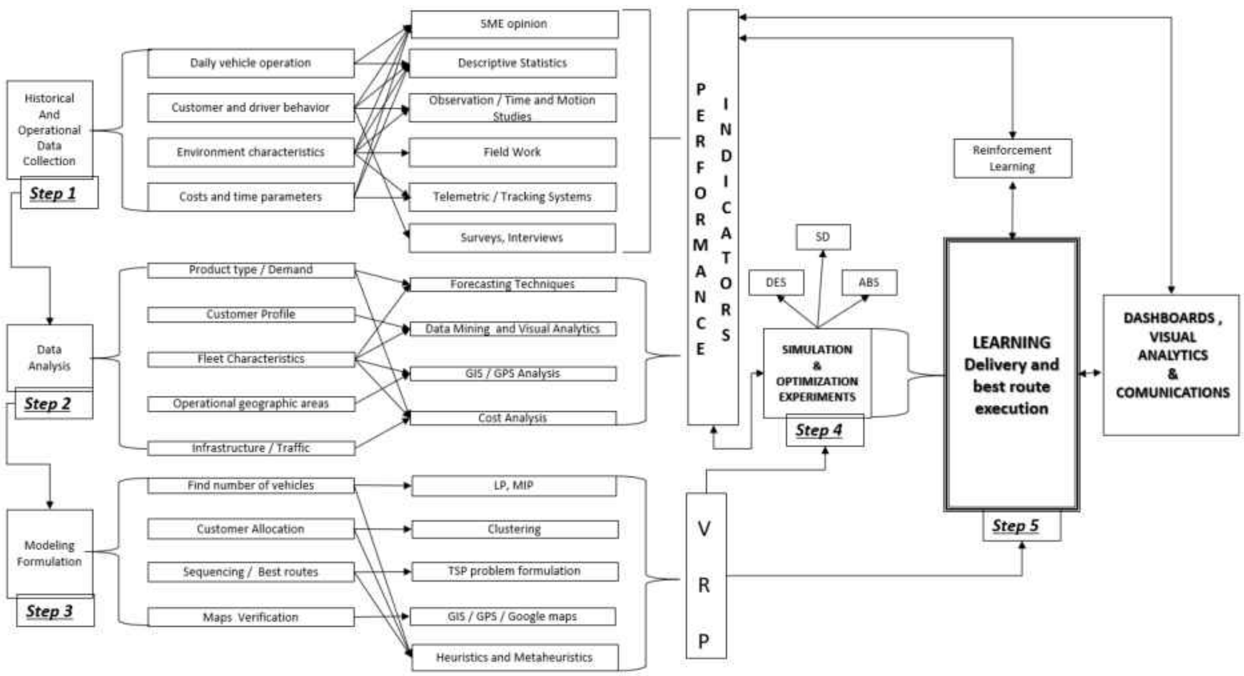


Figure 25: Last-Mile Methodology: methods map and interrelations

3.2.5.1 Step 1: Historical and data collection.

It is essential to get data from the daily vehicle operation, like customers behavior (service time and locations), characteristics of the environment of the process (zone of the city, parking, infrastructure, population density, etc.) and of course all the associated costs and time parameters (probability distributions in velocity, parking and service time). These data are used as input in the proposed models.

Once all the execution has been made, performance indicators feed the databases, to improve the algorithms and decisions.

3.2.5.2 Step 2: Data Analysis

Transportation managers have been identifying the importance of having some sense of future demand and type of products to plan their resources. With this in mind, we propose to have clarity in the following aspects: the variety of customers, demand per type of customer, characteristics of zones in the city, and customer assignation for each vehicle.

In this second step, data is analyzing by using data mining techniques to detect patterns and identify current significant variables. In this way, for example, customer profiles can be grouped. For last-mile operations is essential to create a geographical analysis to identify operation areas. Usually, the last-mile delivery process starts with cluster allocation. These clusters are defined based on the characteristics of the customer (demand, time window, etc.) and the availability of resources. This process identifies the areas and regions where requests are made with different characteristics, like the type of infrastructure, velocity during peak and valley times, and parking time.

3.2.5.3 Step 3: Modeling Formulation

The modeling formulation is designed to improve operations and set up potential actionable scenarios to respond immediately to changes (short term) and create a set of strategies to react under diverse circumstances (medium term). For example, in a vehicle-dispatching operation, all predictive models are based on elements from the drivers such as delivery locations, traffic conditions, possible routes, and behaviors/preferences.

The decision-making part oversees the use of heuristics and optimization tools to define actions in operations. A continuation of the general mathematical model, to support the plan for resources is described.

The Heterogeneous vehicle routing problem with time windows is a class of the Vehicle Routing Problem (VRP) in which the capacity of the vehicles can be different (when is equal is called homogeneous fleet) and time windows are asking by the customers. There are many sources of research literature (theory and real-world solutions) on the VRP and its many classes; to point out some of them: Toth and Vigo. (2014), Cordeau et al. (2007), Golden et al. (2008), and Laporte (2009). The following model depicts similar equations to the ones proposed by the literature.

This model allows a decision maker to define a vehicle routing to serve a set of nodes *N* that represent customers, from a depot *{0}*. Each link between a pair of nodes *(i, j)* represents an arc *A.* Based on these features, the vehicle routing problem (VRP) might be summarized in a graph *G= (N, A).* An example is shown in the next chapter to illustrate how the proposed model works in a hypothetical case based on real data.

This model allows a decision maker to define a different fleet size and vehicle routing to serve a set of customers. Symmetric costs for distances are assumed, and the costs are dependent on the vehicle type. Let G= (N, A) be a graph where N= {0} U {1, n}

U {n+1}. C= {1, n} is the set of customers and {0} and {n+1} represent the depot. K= {k1, K2…*K*} is the set of different vehicle types. $A \subseteq NxN$ Are the possible edges between the set of nodes. Some edges that are excluded include *(i, i),(i,0),(n+1,i)* where $i \in N$.

Main assumptions of this model:

- Time windows to serve the customers.
- Limited amount of vehicles type.
- Aggregate demand (no differentiation in products. It can be assuming weight and volume)
- Average speed
- All products are aggregated into a single category based on weight

Index

- $i, j \quad nodes/customers$
- $K \quad vehicle\ type\ k$

Parameters

- cap_k *capacity vehicle type k (weight)*
- $c_{(k)}$ *operational costs of vehicle k, based on operational cost per hour*
- $d_{(i)}$ *demand node i (demand)*
- $d_{(i,\ j)}$ *distance between nodes (customers).*
- $s_{(k)}$ *average speed of vehicle k*
- $tv_{j,k}$ *The vehicles k allowed in node j {1 is allowed, 0 Otherwise}*
- $infw_i$ *Lower limit for time window for customer i*

- *upw_i Upper limit for time window for customer i*

Variables

- *Z objective function*
- *$Y_{(i,j,k)}$ product (weight) transported through the arch (i-j) in vehicle type k*
- *$X_{(i,j,k)}$ 1 if the vehicle k travels the arc (i-j) and 0 if the vehicle k does not travel the arc (i-j)*
- *$VK_{(k)}$ quantity of vehicles type k*
- *$Q_{(i,j,k)}$ quantity of product transported from node i to node j in vehicle k*
- *U auxiliary variable which determines the order of the vehicle k visit node i, (* a maximum quote is recommended, the upper limit (number of vehicles plus one))*
- *E(n,k) Instant when vehicle k enters into node i*
- *S(n,k) Instant when vehicle k goes out from node i*

Equations

$$Z = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} ((C_k * (S_k)^{-1} * X_{i,j,k} * d_{i,j}) + \sum_{k \in K} V_k * FCOST_k) \quad (1)$$

$$\sum_{k \in K} \sum_{j \in N} X_{i,j,k} = 1 \qquad \forall i \in N \quad (2)$$

$$\sum_{i \in N} X_{i,j,k} = \sum_{i \in N} X_{j,i,k} \qquad \forall j \in N, k \in K \quad (3)$$

$$\sum_{i \in N} \sum_{k \in K} Y_{i,j,k} - \sum_{i \in N} \sum_{k \in K} Y_{j,i,k} = D_j \qquad \forall j \in N \quad (4)$$

$$\sum_{j \in N} \sum_{k \in K} Y_{i0,j,k} = \sum_{i \in N} D_i \quad (5)$$

$$\sum_{k\in K}\sum_{i\in N} Y_{i,i0,k} = 0 \qquad \forall i \in \boldsymbol{N} \tag{6}$$

$$Y_{i,j,k} \leq X_{i,j,k} * CAP_k \qquad \forall i \in N, j \in N, k \in K \tag{7}$$

$$\sum_{j\in N} X_{i0,j,k} = VK_K \qquad \forall k \in K \tag{8}$$

$$\sum_{j\in N} X_{i0,j,k} = \sum_{i\in N} X_{i,i0,k} \qquad \forall k \in K \tag{9}$$

$$U_{i,k} - U_{j,k} + |N| * X_{i,j,k} \leq |N| - 1 \tag{10}$$

$$x_{i,j,k} \leq y_{i,j,k} * Tv_{i,j,k} \tag{11}$$

$$y_{i,j,k} \leq MaxLoad_j \quad \forall i \in N, j \in N, k \in K \tag{12}$$

$$e_{j,k} \geq s_{i,k} + \left[\frac{dist_{i,k}}{aSpeed}\right] * x_{i,j,k} + \left[x_{i,j,k} - 1\right] * bm \quad \forall i,j,k \in IJK \tag{13}$$

$$s_{i,k} = e_{j,k} + \left[\left(\sum_{i,j,k\in IJK} y_{j,i,k} - \sum_{i,j,k\in IJK} y_{i,j,k}\right)/lrate\right] \tag{14}$$

$$e_{i,k} + devEnt_{i,k} \geq infw_i * \left[\sum_{i,j,k\in IJK} x_{j,i,k} - bm\left[1 - \sum_{i,j,k\in IJK} x_{j,i,k}\right]\right] \tag{15}$$

$$s_{i,k} - devSal_{i,k} \leq uppw_i * \left[\sum_{i,j,k\in IJK} x_{i,j,k} - bm\left[1 - \sum_{i,j,k\in IJK} x_{ij,k}\right]\right] \tag{16}$$

$$X_{i,j,k} \in \{0,1\} \tag{17}$$

$$Y_{i,j,k} \in R^{+} \tag{18}$$

Equation (1), *the* objective function considers fixed and variable costs of the vehicles. The vehicle cost in \$/hr is multiplied by the inverse of the speed, hrs mile, to yield a charge per mile. This multiplied by the distance, and $X_{i,j,k}$ yield the cost for a specific route in vehicle *k* summing across all routes gives the total operational cost.

Constraints (2) state that each customer is visited for one vehicle. Equation (3) ensures the vehicle of the same type arriving at a customer will also leave the customer (different kind of vehicle can go in the same arc). (4) Represents the movement of goods, considering that all customer demands must be satisfied. Equations (5) and (6) ensure that the total quantity when leaving the depot is equal to the customer demands on the routes and that nothing is returned to the depot. Constraint (7) make sure that goods can travel from *i* to *j* only when there is a vehicle traveling from I to j, and that total load on arc (i, j) cannot exceed the capacity of the vehicle assigned to that edge. Constraint (8) calculates the total number of vehicles per type K (it is not completely necessary). Constraint (9) says that each vehicle that leaves the depot node i0, it must eventually return to the depot node. Constraint (10) eliminates sub cycles per vehicle. Constraint (11) ensures deliveries are made only when the vehicle is allowed to enter the destination node. Under certain conditions, depending on the infrastructure of cities, Equation 12 says that the amount of product transported in vehicle k along path i-j, cannot exceed the maximum load allowed in the destination node j. In case the situation involves time windows equations 13 to 16 should be used and not the equation 10. Equation (13) determines the instant when vehicle k arrives at node k, Equation (14) determines the moment when vehicle k leaves node k. Equation (15) set the early time to enter node c for each truck that goes there. Equation (16) allows to set a delay time to leave node c for each vehicle that was there, and equations (17) and (18) are the binary and favorable conditions for the variables.

Most of the approach solutions in the literature are heuristic or metaheuristic algorithms; good heuristics can provide the right answers in a reasonable time. For small instances, the integer programming formulation works well. For bigger instances, this model takes a long time to find optimal solutions. As we mentioned exact, heuristic and hierarchical algorithms continue been proposed to bring fast and reliable solutions for real-world applications.

To reduce the routing planning time for bigger instances a 3-parts approach heuristic is proposed:

Part 1: Mixed Integer Programming model to identify the number of vehicles to use.

Index

- i, j $nodes/customers$
- K $vehicle\ type\ k$

Parameters

- *wc_k capacity vehicle type k (weight)*
- *vc_k capacity vehicle type k (volume)*
- *w_i demand node i (weight)*
- *v_i demand node i (volume)*
- *$d_{i,j}$ distance between nodes (customers).*
- *$maxTw_k$ Upper limit for time window for vehicle k*
- *tc_i Total customer i service time*
- *c_k Fixed cost of vehicle k*

Variables

- *Z Objective function*
- *Y_k 1 if vehicle k is used*
- *$X_{i,k}$ 1 if the customer i is assigned to vehicle k*

Equations

$$\text{Min } z = \sum_k Y_k * c_k \tag{19}$$

Subject to:

$$\sum_i w_i * X_{i,k} \leq WC_K \quad \forall k \tag{20}$$

$$\sum_i v_i * X_{i,k} \leq VC_K \quad \forall k \tag{21}$$

$$\sum_i X_{i,k} = 1 \quad \forall i \tag{22}$$

$$X_{i,k} \leq Y_k \qquad \forall i,k \tag{23}$$

$$\sum_i \; X_{i,k} * tc_i \leq \; maxTw_k \qquad \forall k \tag{24}$$

$$X_{i,j,k} \in \{0,1\} \tag{25}$$

$$Y_{i,j,k} \in R^+ \tag{26}$$

Part 2: In the second part is necessary to allocate customers to vehicles. Clustering analysis aims to set clusters or groups. In logistics operations methods like K-means, K-medoids and DBSCAN have been used to do clustering (Cömert, et al. 2017). This part consists of two main parts. Once we have the locations of the clients in the geographical area and the number of vehicles to be used, it is necessary to assign the clients to the vehicles. For this purpose, we first identify the location of "centroid" clients, that is, clients that will serve as a starting point in the different zones. This can be done with a clusterization method, k-means for example which help to identify the centroids which are apart from each other depending of distances. Then following phase, it to use a classic assignation model where customers have to be assigned to the founded centroids to meet the weight and volume restrictions. Figure 26a represents the first step, blue points are the "centroid". Figure 26b shows the assignment.

Figure 26: Customer Allocation to vehicles.

In the third part is necessary to set up the sequence of the visiting for each of the customers and validated with the actual grid of the city (e.g. with google maps). For this we propose to use the formulation for the travel salesman problem for each of the vehicles.

$$Min \sum_{i,j \in A} X_{i,j} * d_{i,j} \tag{27}$$

$subject\ to$:

$$\sum_j X_{i,j} = 1 \; \forall i \tag{28}$$

$$\sum_i X_{i,j} = 1 \; \forall j \tag{29}$$

$$U_{i,k} - U_{j,k} + |N| * X_{i,j,k} \leq |N| - 1 \tag{30}$$

Figure 27 shows a summary of the general steps to find the routes:

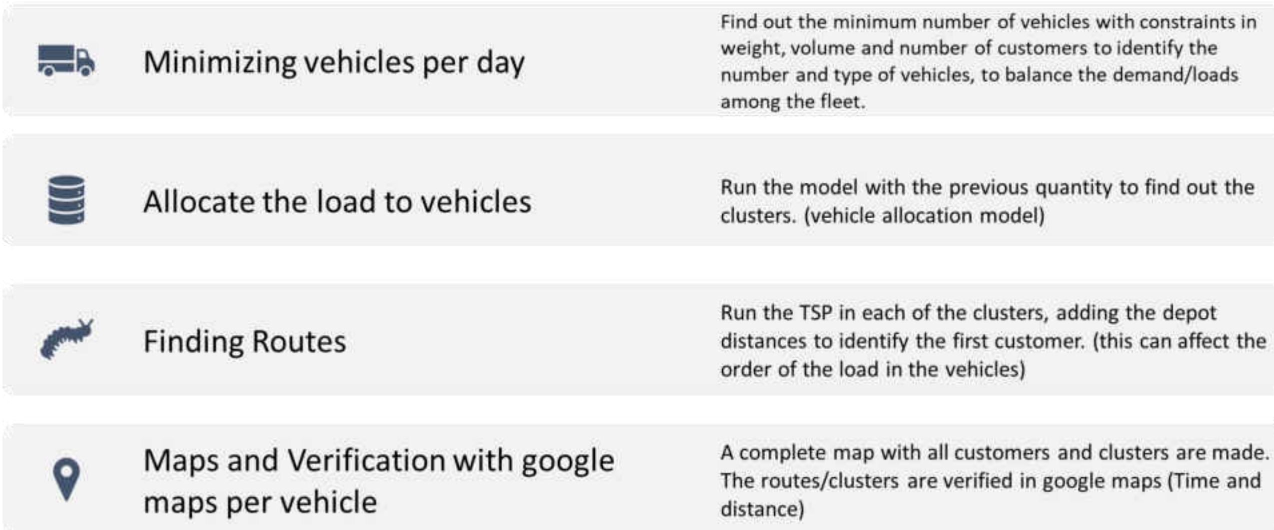


Figure 27: Phases to find out the routes per vehicle.

3.2.5.4 Step 4: Simulation and Experiments

Once is clear each of the routes for each of the vehicles, the methodology proposes the use of simulation models to run experiments (parameter variation) and analyze the outputs to make better decisions about the real-world operation. Furthermore, due to the complexity of last-mile operations, this methodology also has into account the advantages of learning procedures. We are proposing the use of Discrete Event Simulation due to model (discrete) sequence of events in time agent-based simulation, to recreate behavior and interrelationships between stakeholders (agents) and system dynamics to recreate causality between entities in the system and to evaluate policy analysis and design. to extract decisions (policies) from the simulated system, combining the simulation modeling environment with reinforcement learning.

The simulation environment allows representing the different steps involved in the last-mile delivery operation. Figure 28 illustrates the decision process for the vehicles. Once the vehicle is loaded with goods, it follows the following actions:

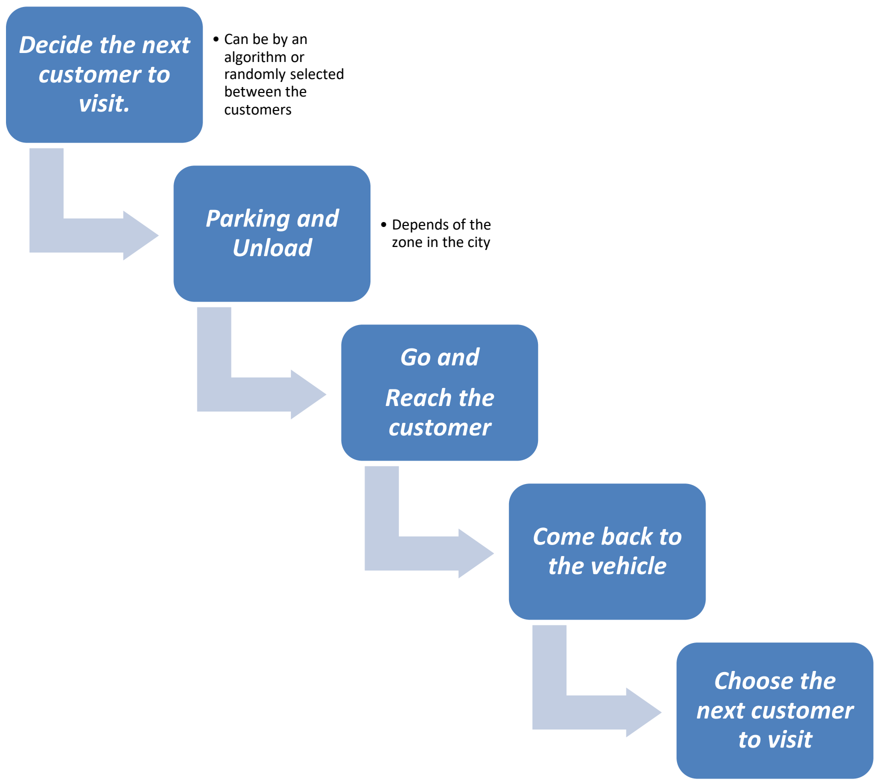


Figure 28: Last-mile delivery steps.

3.2.5.5 Step 5: Learning

Once the optimization models have been used to configure the resources (vehicles) and the routes have been defined and recreated in a simulation model, to check the assumptions in time, the last-mile operation becomes an execution problem. That is, the execution of the delivery translates into predicting and executing the best routes in the environment to provide an excellent service level.

Define the best sequence of visiting customers is a crucial factor for service time. This is the classical problem called Milk Route or Traveling Salesman Problem (TSP) which involves the visiting of a set of customers, starting and finishing at the same place (generally a hub or depot), visiting each customer one time at a minimum cost. The most useful algorithms in mathematical programming to solve the TSP are based on decomposition methods (e.g., Branch and Cut, Column Generation), which indicates using solvers and high computational time for larger instances. As we saw, changes in the environment or customer behavior like new orders and cancellations are frequent in distribution logistics. Consequently, the first routes from the optimization models can change and should be modified in a short time. Have algorithms that can handle these behaviors in a short time is a great advantage to improve the operation.

Recent advances in the use of machine learning in logistics and supply chain problems (Rabelo et al. 2018), has demonstrated how neural networks and reinforcement learning approaches are good choices to handle the problem of the VRP (Bello, et al., 2016; Nazari, et al., 2018)

Our methodology proposes the use of a playground where the agents can learn in the simulation environment. As was shown in the previous section, conditions affect the time of the delivery. Different situations can be simulated in this playground to do trial and error and to learn from the mistakes and achievements. The research contributes by considering learning procedures to create an effective prediction and prescription tools to achieve last-mile delivery goals.

We are proposing the use of Reinforcement Learning with neural networks to capture the behavior of routes and the environment. Once these algorithms are trained, the velocity of the solution is very convenient for transportation managers, in contrast with classical optimization models or heuristics, that does not have into account the changes of conditions of the environment or customers mind, by learning from the experience. Figure 29 recreates a neural network, where the input data are the environmental conditions, and the output is the sequence of the customers to visit. To train the networks is used the recognized policy gradient approaches.

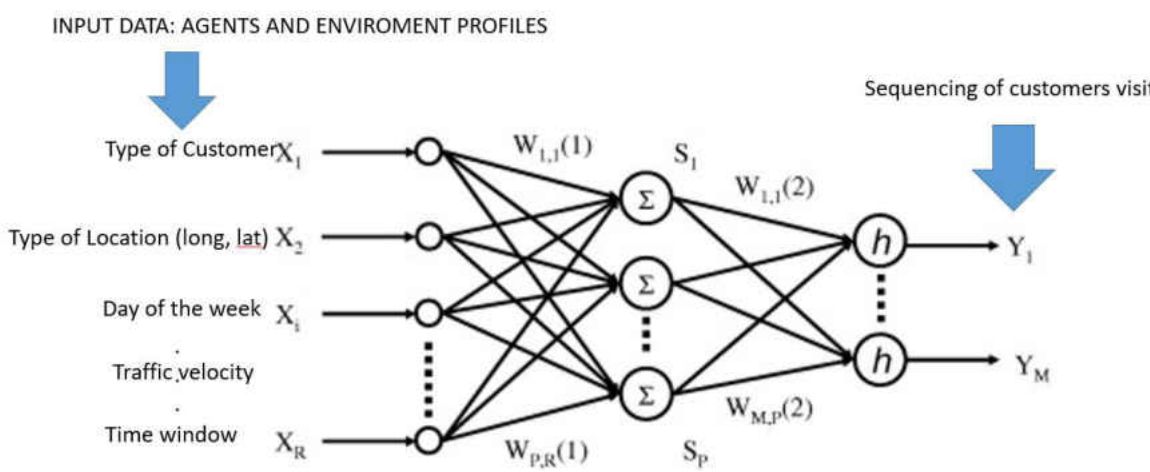


Figure 29: Neural network representation.

First, we define a neural network that can learn from optimal or best solutions in the environment. Usually, geometric metrics have been very successful in predicting the order of visiting, when, for example, a new customer arrives or cancel (Abdel, 2010). The output is the sequence that the driver must follow.

Secondly, we are proposing to use the principles of Reinforcement Learning (RL), which is an area of machine learning which use software agents to take actions in an environment to achieve a goal. The impact of the action in the environment is called a reward. The rewards are used to measure the performance of the agents (Sutton et al. 2018). Figure 30 depicts the interaction between the environment (real or simulated) with the agents, creating states, and rewards from the actions in a feedback loop.

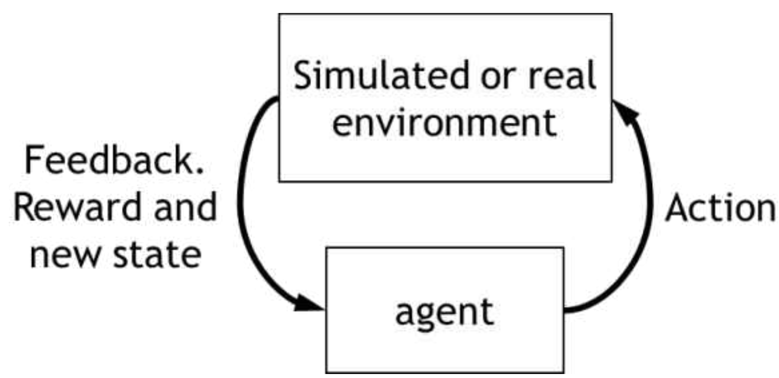


Figure 30: Interaction Agent-Environment.

The last-mile process involves agents (vehicles, customers) interacting with an environment (city, ocean, air); the interaction provides numerical reward signals (route time). The general goal is then, learn how to take actions (which customer to visit next) to maximize the reward (time service).

The simulations can generate scenarios, creating situations not realized or experienced in the last-mile operations to be trained on. Once the decision maker has had into account different “emergent behaviors” the same simulation environment can be used to test the outputs of the learning algorithms (e.g., neural networks) and explore their capability to be used more confidently for the transportation managers. The objective of the training experiments is to train an artificial neural network to be able to control the decisions to find a route. It will do this by learning policy (or its strategy for which action to choose) that best decide the path in geographical space.

Once the initial routes are defined, either by any of the methods (exact, heuristic, and clustering) or by the trained neural network, it will be used to explore new routes and try to find best trajectories under a dynamic environment in terms of rewards. Then samples of such paths are collected to re-train initial policies and used them in the simulation environment. With this pre-processing sequence, the “agent: driver” set possible decisions, resulting in an efficient operation, identifying the rewards and feeding future choices. The general process is represented in Figure 31.

Figure 31: Route improvement.

Thanks to the simulation environment, it is possible to learn better routing policies from thousands of simulation experiments in many different conditions that reproduce behaviors analyzed in the real world. These measurements guide management decisions for the platform and support the decision making for various stakeholders by considering their experience and interactions to get mutual benefits.

We are proposing a learning process based on indicators (rewards). The system can "learn" from the best practices and follow a continuous learning process. Based on the experience of past deliveries and logistics operations, the system captures rewards and acquires those which improve the system.

The simulation and the learning procedures support the dynamic, stochastic decision making by considering how distribution strategies are performing versus pre-defined goals. Feedback loops help to adjust plans to react to deviations based on available resources and feeding data from self-learning processes.

The methodology assumes to have traffic and customer patterns as data entry, using the location data collected from the GPS tracking technology and sensor in the streets. However, given that the schedule of a customer and the traffic can change, for unpredicted reasons is possible the existence of differences between the planned delivery routes and the execution. Thus, a set of distinct patterns for the estimation process and determination of scenarios can be used as an *initial solution.* They are predicting the last-mile routing and their corresponding KPIs, given real-time information from sensors and customer service. The data is given to select supplementary scenarios that support decision making under diverse circumstances to improve various KPIs.

3.2.5.5.1 Formalization of the Reinforcement Learning approach

We can formalize the RL problem for last-mile operations under the view of a Markov Decision Processes (MDP). The MDP is the mathematical formulation of the RL problem and satisfies the Markov property, which is that the current state completely characterizes the state of the environment.

With the MDP is possible to represent the decision-making at different epochs or states, which the operation evolves stochastically (Powell, 2007).

The Markov Decision Processes (MDP) is represented by tuples of elements which are: possible states, actions, and rewards, in consequence, a state, action pair create a function mapping from state action to obtain a reward. Also, the MDP is a transition probability distribution over the next states that are given to transition for the state, action pair. And finally, it has a gamma, a discount factor between 0 and 1, which is to set how much we value rewards soon versus later (Puterman, 1994). A continuation is a description of the last-mile delivery problem.

A set of state spaces {s1 ⋯ SN}: which contain the information to make routing decisions and each epoch k. It includes Vehicle location, Customer Location, time window. The next state is predicted given the current state and the decision (Action) to go to the subsequent request.

A set of actions {a1 ⋯ aM}: action should be selected and each decision epoch k. This determines the next customer to serve or not. When the vehicle is in the route is possible to change the order in which it serves the customers. It depends on real-time information.

A set of rewards {r1 ⋯ rN} (one for each state). The reward is calculated as a contribution and comes from the calculation of the performance indicators. In RL is expected to learn the best actions to obtain the best rewards to improve the total system. In the case of last-mile, the rewards can be calculated from distances or time of the routes (logistics performance indicators).

A transition probability function ***P*** is a Markovian transition model where P(x_j | x_i, k) represents the probability of going from state x_i to state x_j with action a_t

$$P_{ij}^{k} = \mathrm{Prob}\left(\mathrm{Next} = j \middle| From = i \text{ and using action } k\right)$$

Therefore, the way the Markov Decision Process works is that at time step t=0, environment samples initial state $S_0 \sim P(s_0)$. Then, for t=0 until is done, the algorithm iterates in this loop (Figure 32):

- Agent selects action a_t
- Environment samples reward $r_t \sim R(. \mid s_t, a_t)$
- Environment samples next state $s_{t+1} \sim P (. \mid s_t, a_t)$
- Agent receives reward r_t and next state s_{t+1}

The agent keeps looping until the episode is over.

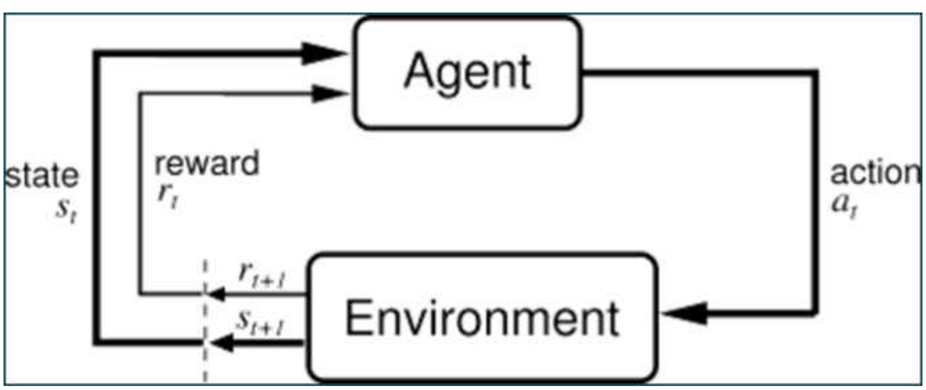


Figure 32: State-Action Loop.

Based on these characteristics, it is possible to define policy π. This is a function from the states to the actions that specifies what action to take in each state (this can be either deterministic or stochastic). The objective now is to find an optimal policy π*, that maximizes (minimizes) the cumulative discounted reward.

Policy: a policy π is a sequence of decisions. Π represents the set of all possible policies. The agent (vehicle) receives the “value” captured by the objective function to continue to the next customer (e.g. Lookahead, value function approximation policies).

Objective: the objective is to choose the best policies. It is defined as an action-value function. For the objective function is necessary a discount factor gamma

$0 < \gamma < 1.$

We want to find an optimal policy that maximizes the sum of rewards. To do this, we maximize the expected sum of rewards.

$$\sum_{t=0} \gamma^t R_{a_t}(s_t, s_{t+1})$$

The application of Markov Decision Processes in logistics problems can be characterized by the curse of dimensionality, due to the number of possible state-spaces. There are many algorithms and methods which approximate the results that have been applied to handle the dimensionality issues, for example, Q-Learning and Policy Gradients.

Q-Learning

When the “agent vehicle” chooses an action, gains feedback (good or bad) for that action and uses that feedback to update its record. In its history, the agent saves a Q-factor for every state-action pair. The feedback consists of the immediate value gained or reward plus the cost of the next state.

The cost or value for each state depends on the future rewards (feedback). The total amount is represented by $Q_t(s_t, a_t)$ of the actions taken in state t, is the sum of the immediate reward and the approximation of the value of the next state:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha[r_{t+1} + \lambda max\ Q_t(s_{t+1}, a_{t+1}]$$

The learning rate is represented by α, and λ is the discount factor (Watkins, 1992). These two parameters are used in the simulations (Figure 33). The better ones can be found with the help of neural networks or another kind of regression analysis. (Bertsekas et al., 1995).

Below are the main assumptions for this system:

- There is a central agent planner (vehicle) that has control of the path of the stochastic process.
- The vehicles “agents” need to know: the state where it is in at any time, the possible actions to follow, the rewards (Indicators) associated with the actions and the consequential next state.

- It is expecting that solving an RL algorithm helps to find the policy (set of actions) that reaches as much reward as possible over the long run.

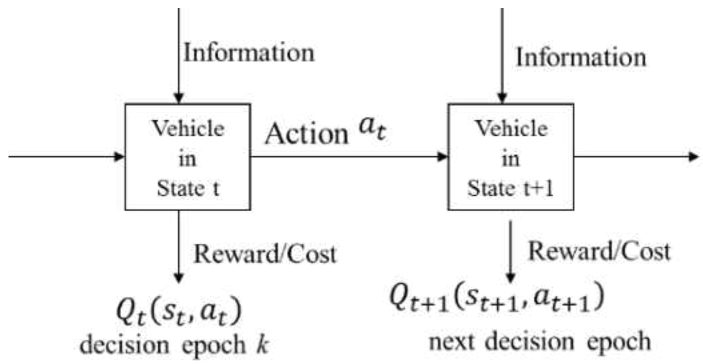


Figure 33: Action by agent vehicle.

The "agent" driver uses the reinforcement learning to update its knowledge, becomes smarter in the process, and then selects a better action.

Rewards: The rewards R (S, x) of a decision x given state S are recording each time the vehicle do a delivery.

After the simulation, distances/time between consumers are recorded, and the "best" minimum distances have good rewards.

After many simulations, the agent detects what the best decisions are. An agent-based model (ABM) can simulate the actions and interactions of agents to evaluate their effects on the system, the interaction between the model, the environment and the decision maker is represented in Figure 34.

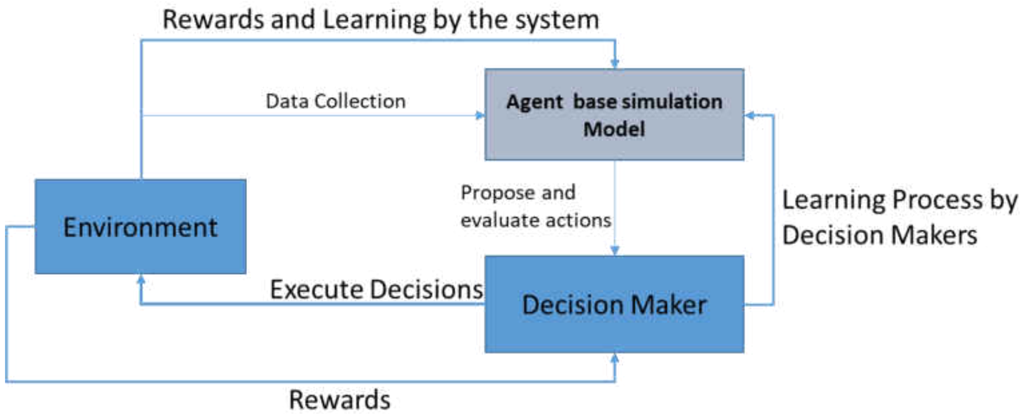


Figure 34: Rewards learning by the system.

To obtain possible routes, an action-value function is determined. This function depends on policy **π**. The learning process is based on repeated random sampling (Surto et al., 1998). The function assigns a Q-value in the edges, which depends on the rewards received by the environmental signals. The action-value function of delivery vehicles based on the expected value $\boldsymbol{Q_{t+1}(s_t, a_t)}$ represents the expected action-value of the vehicle (agent) when taking an action $\boldsymbol{a_t}$ under the state $\boldsymbol{s_t}$ and $\boldsymbol{\alpha}$ as the learning rate is (Figure 35):

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha[r_{t+1} + \min[\, Q_t(s_{t+1}, a_{t+1})] - Q_{t+1}(s_t, a_t)]$$

Initialize *Q*
Repeat (for each episode):
    Initialize *s*
    Repeat (for each step of the episode):
        Choose an action ***a*** from state ***s*** using policy defined by the planner (e.g., greedy)
        Take action ***a***, define the rewards ***r***, and go to next state
        Update value ***Q***
        Update the state ***s***
    Until state (node) *s* is the end

Figure 35: Pseudo Algorithm Q Learning.

Q-Learning and Neural Networks

For our methodology, we propose to use the use of Neural Networks and the Reinforcement Learning (RL) concept (Q-Learning) to solve the MDP (throughout policy function approximations). One of the main characteristics of the RL method is the use of rewards, the system learns what to do throughout time, and is capable of mapping situations into actions (i.e., customer demand behaviors, better routes depending environmental conditions) as to maximize the total reward signal (Figure 36). In this approach, a model is training to find near-optimal solutions to route vehicles by observing the reward signals and following feasibility rules (Nazari et al., 2018).

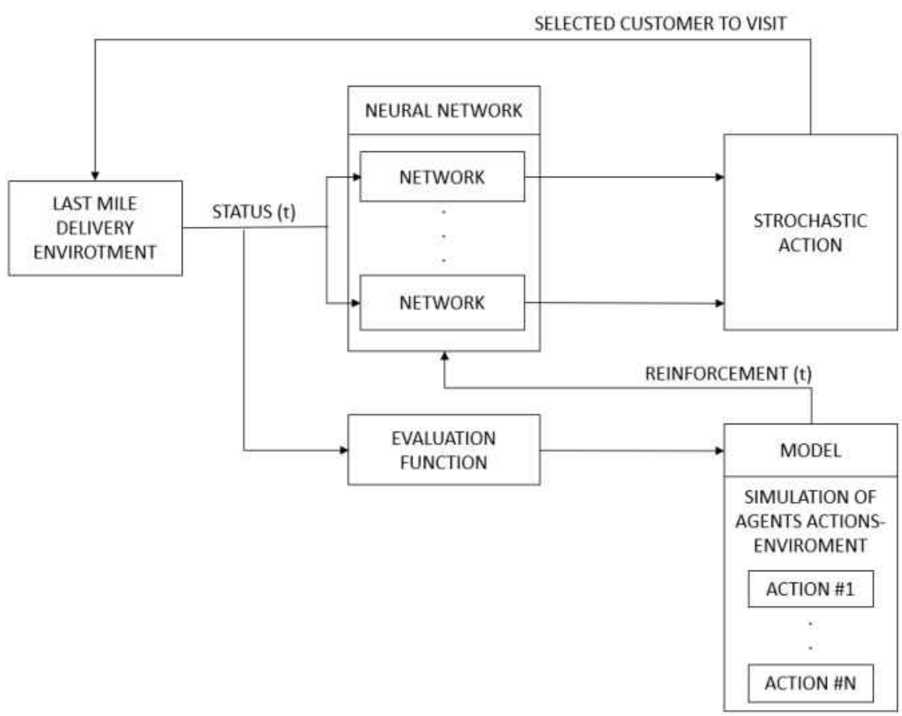


Figure 36: Simulation and Learning process.

It is not reasonable to store every Q-factor separately. Then, it makes sense to store Q-factors for a given action within one neural network. When a Q-factor is needed, it is extracted from its NN. When a Q-value is to be updated, the new Q-value is used to update the neural network itself (Gosavi et al., 2002). The following Figure is the general scheme of how the simulation environment, the evaluation function, and the neural network interact.

For any given action, Q (s, a) is a function of s, the state. In the case of reinforcement learning, every time the agent receives feedback, it is obtained a new piece of data that must be used to update some neural network. The Q value can be learning by parameterizing the Q function with a neural network (Figure 37).

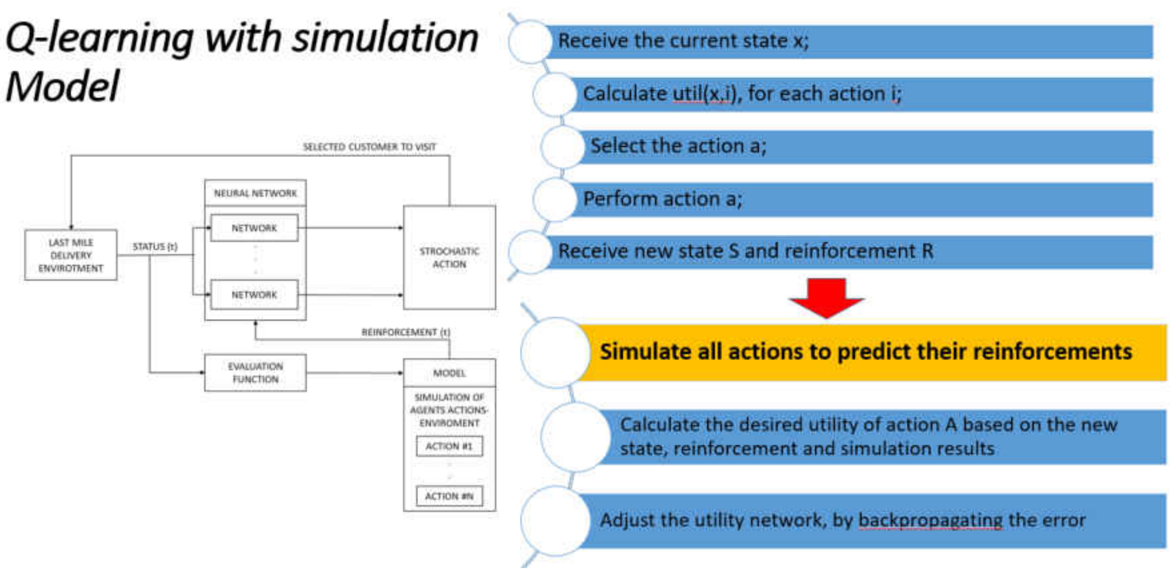


Figure 37: Q-learning and simulation model.

Lately, authors are proposing the use of the neural network with the actor-critic mechanism (Nazari et al. 2018; Kool et al. 2018). The appealing of this machine learning technique is in contrast of heuristics for VRP, where the complete distance matrix must recalculate this technique does not require an explicit distance matrix, and a feed-forward pass of the network update the paths based on the new instance. Once we have a solution, this one can be applied to our environment under dynamic conditions.

The use Actor-Critic Methods, where: “Critic” estimates the value function, this is the “evaluation function,” and the “Actor” updates the policy distribution in the direction suggested by the Critic. (Sutton et al., 1999). The actor-critic can be described as the subtraction of Q value term with the V value. Instinctively, this means how much better it is to take a specific action compared to the average, general action at the given state. It is calling the advantage value: $A(s_t, a_t) = Q_w(s_t, a_t) - V_v(s_t)$

Using the relationship between the Q and the V from the Bellman optimality equation: $Q(s_t, a_t) = \mathbb{E}[r_{t+1} + \gamma V(s_{t+1})]$

So, it can be rewritten as: $A(s_t, a_t) = r_{t+1} + \gamma V_v(s_{t+1}) - V_v(s_t)$

Then, one neural network for the V function (parameterized by v above). Finally, it can rewrite the update equation as the Actor Critic.:

$$\begin{aligned}\nabla_\theta J(\theta) &\sim \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t)(r_{t+1} + \gamma V_v(s_{t+1}) - V_v(s_t)) \\ &= \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t)\end{aligned}$$

This solution adjusts the policies as a result of observations and reinforcing the right actions relative to the wrong actions. The rewards represent the desired goals, which are calculated with our performance indicators. By maximizing these indicators, the algorithm will improve the system towards the goals. These indicators are continuously calculated due to the learning interaction of the different “agents” and the environment (the last-mile operations). The learning process is shown in Figure 38.

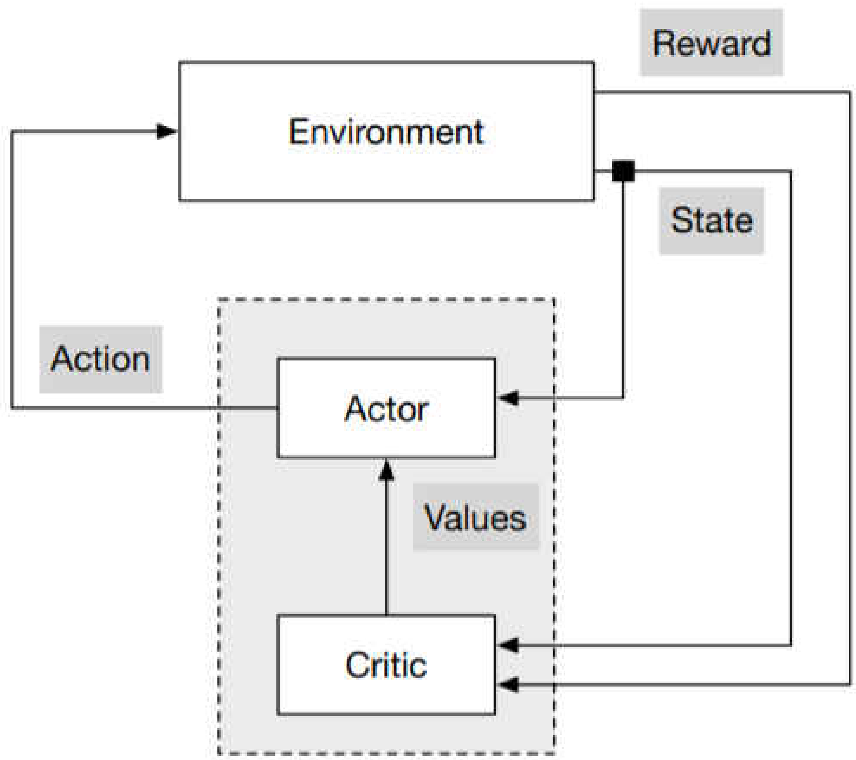


Figure 38: Actor-critic architecture.

The uncertainty came from the incorporation of customer demand uncertainty and the flow of information from customers and drivers. The main objective is to find the best actions for each state (policies) that accomplishes as much reward as possible.

The way of the model works is at every time step produces the probability distribution over the customers to decide where to go next. Figure 39 is a snapshot of the training process, the picture on the left shows the sequence (this is a small example for ten nodes) and the image on the right the correspondent probabilities, if the node is located in a lighter area, it means it prefers over other nodes.

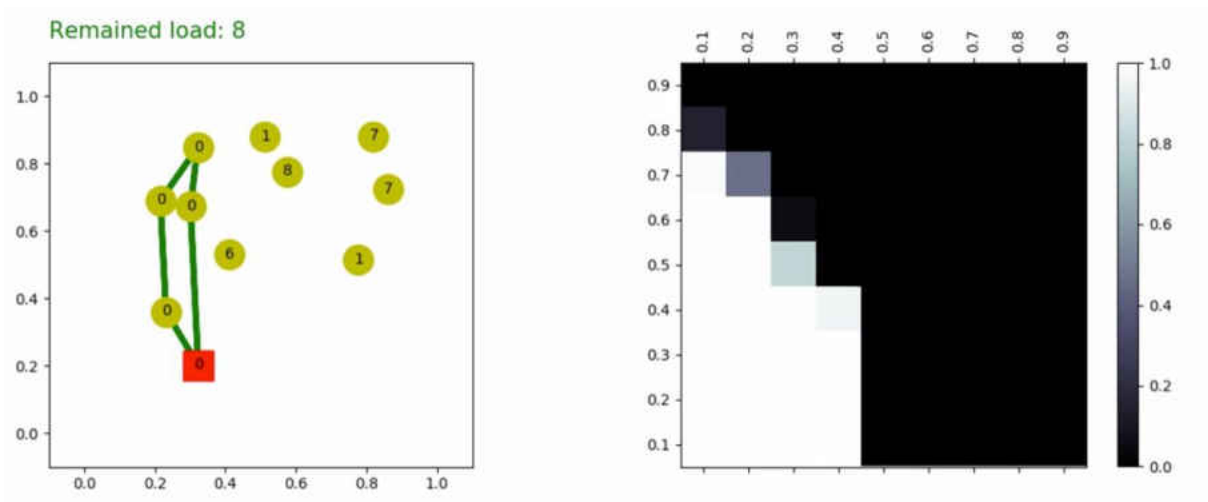


Figure 39: Probability matrix (based on Nazari et al.2018)

Figure 40 illustrates how the learning process is conducted based on the rewards received for the performance indicators. In this situation, the anomaly can be a delay between two clients. This delay can be due to closed roads, infrastructure, etc. which is reflected in the distance or the time to go from one customer to another.

In consequence, the best route visits the customer in the following order: [C4, C6, C10, and C7]. Once the route is executed (day 1 in the graph) and evaluated, the system highlights a delay between customers C6 and C10 throughout performance indicators (rewards). Once the system recognizes this delay is a “pattern” is expected to propose a new route, having into accounts that delay. The new planned route is then

[C4,C6,C10,C7] which is not the best one based on the geographical conditions but taking into account other features of the environment (such as a possible traffic jam or road closures between C6 AND C7) allows a more flexibility to accomplish all orders on time.

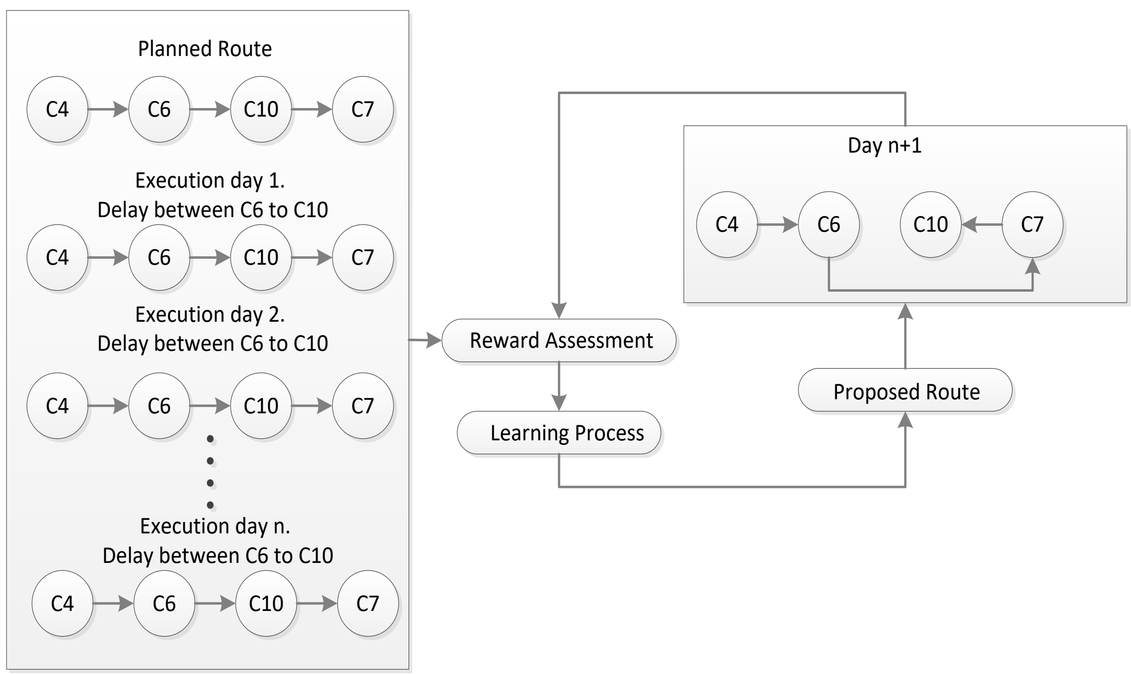


Figure 40: Learning process for delays in routes.

The model represents a stochastic policy, and by applying a policy gradient algorithm, the trained model solves an arrangement of successive actions.

3.3 Methodology Development and Validation

Besides the literature review and the gap research identification, a set of interviews were conducted with logistics experts in the industry, academia, and government to understand the potential of the proposed methodology. Based on the insight's discovery from the interviews and the research trends in supply chain management and specifically in last-mile operational conditions, we identify and build the case studies. Finally, in this chapter, we present the expected conclusions, future research, and the case study validation checklist.

3.3.1 Experts insights

A set of interviews were performed with experts from industry and academia from 2014 to 2019. This acquired knowledge about industry and research necessities helped to narrow down the case studies and the validation checklist. Table 6 depicts the job position of the person, the sector, the type of primary business model (B2B, B2C), their main last-mile challenge, necessity, and primary fleet type (Homogeneous or Heterogeneous) to do the operation.

Table 6: Expert interviews, 2014-2019.

Expert*	Industry	Main Type of Service	Last Mile Challenge	Necessity	Fleet Type (Last Mile)
Manager at Crowley Maritime	Maritime	B2C	Fleet Optimization	Minimize costs	Heterogenous
Director at Amazon	Retail	B2C	Daily Delivery Efficiency	Prediction and Service Time	Homogeneous
Manager at Walmart	Retail	B2C	Daily Delivery Efficiency	Prediction and Service Time	Homogeneous
Manager at Homecenter	Retail	B2C	Daily Delivery and Fleet Optimization	Service Time	Homogeneous
Manager at Fallabella	Retail	B2C	Daily Delivery and Fleet Optimization	Minimize costs	Homogeneous
Manager at SABMiller	Beverage	B2B	Daily Delivery and Fleet Optimization	Minimize costs	Homogeneous
Manager at LOGYCA	Consultancy	Consultancy	Resources Optimization and Customer Service	Support tools	NA
Senior Researcher MIT-CTL	Academia	Outreach	Advance methodologies	Methodologies	NA
Senior Researcher ISU	Academia	Research	Daily Operation-Humanitarian Logistics	Service Time	NA
Researcher Javeriana University	Academia	Research	Agroindustry deliveries First and Last Mile	Service Time	NA
Manager Consultancy Industry	Consultancy	Consultancy	Efficient algorithms	Minimize costs	NA
Software Engineers	Consultancy	Consultancy	Efficient algorithms	Support tools	NA
VP. Chamber of Infrastructure	Government	Laws, Policies	City Infrastructure	Support tools	NA

*Job position in Summer 2014-2019

As a conclusion of this interviews plus own experience, and research trends, two case studies are proposed to apply the methodology.

3.3.2 Last-mile Operational Conditions

Conditions about weight and volume of products can be determinant in some industries, in the case of retail sectors due to the variety of goods these two conditions must be into account to assign products to the vehicles. Product is standardized, and the priority is then determining the maximum quantity that can be transported in vehicles of different capacity.

Figure 41: Standard package for products (beverage industry).

Figure 42: Water package, all of the same size

On the other hand, other kinds of industries transport a more uniform size of packaging for products, like beverage or supermarkets industries (Figure 41 and 42).

Finally, the type of vehicles varies as well depending on the industry. Generally, for retail industries is common to have a heterogeneous fleet and dynamic demand (different customers every day). On the other hand, the Food & Beverage industry is common to have a homogeneous fleet and the same customers frequently, like deliveries from manufacturers to mom and pop stores and supermarkets (Figure 43).

In all cases, the main objective is to minimize costs and use the resources most efficiently. A variety of objectives functions can be set up for industries, like reduce costs, reduce delays, maximize utilities, and minimize CO2 emissions and so on.

Figure 43: Delivery conditions.

In summary, the most common cases in last-mile delivery are in the next table:

Table 7: Cases classification.

Fleet	Delivery	Type of Industry	Objective function	Case
Heterogeneus	Split	Maritime	Minimize Fleet	A
Heterogeneus	Single	Retail	Minimize Fleet	B1
Homogeneus	Single	Retail, Beverage, Supermarkets, Restaurants	Minimize Fleet	B2

Depending on the combination of the conditions, and the type of customers (dynamic or fixed) table 8 point put some of the possible main learnings' outcomes, from the methodology.

Table 8: Learning from simulations.

Main Learnings	
Dynamic Cus. (B2C)	**Fixed Cus. (B2B)**
Zone Velocity	Customer Service Time
Capacity Utilization	Driver Behaviour
Zone Parking Time	

After the literature review and the knowledge acquired about the last-mile delivery business research gaps are summarized in table 9.

Table 9: Literature Review Gaps Versus Research Methodology.

Real-World Implementation for Coordination of different decision levels			
Integration of the Execution Level	**Process Production Systems**	**Service Industry (Transportation & Logistics)**	**Proposed Research Methodology**
Solution Approach			
Mathematical Programming (MP)	x	x	x
Artificial Intelligence (AI)	x	x	x
Simulation - Optimization	x	x	x
Hybrid (MP and AI)	x		x
Feedback learning processes	x		x
Decision Levels			
Strategic-Execution			x
Tactical-Execution	x		x
Operational-Execution	**x**		x
Operational-Strategic	x		x
Strategic-Tactical	x	x	x
Operational-Tactical	x	x	x
Behaviour Analysis			
Customer behaviour		x	x
Worker Behaviour			x
Enviromental Conditions		x	x

3.3.3 Case Studies

Two case studies represent the main challenges faced by last-mile operations. The Table 10 depicts the “why” and “how” that should be followed for any situation or case study in general terms.

Table 10: Last-Mile Methodology Steps justification

WHY	HOW
Step 1: Historical and data collection	
Collection of the necessary information to set up mathematical, simulation, and machine learning models. Definition of key performance indicators.	Descriptive Statistics. Interviews. Time and motion studies. Expert Opinion. Literature Review
Data for the next step: Velocities in the different zones of the city, Service, and parking times. Industry Necessity. Research directions.	
Step 2: Data Analysis	
Identify the correct insights/parameters for the decision-making tools: Optimization, Simulation, and, Machine Learning methods.	With forecasting, clustering, data mining, techniques. Among with probability distributions.
Data for the next step: definition of clusters, demand tendencies, forecasting, customer, and driver behavior profiles. Among with parking and service time probability distributions.	
Step 3: Modeling Formulation	
Identify the best combination of resources to meet the management objectives like the reduction of cost and high services levels.	Linear Programming. Mixed Integer Linear Programming. Nonlinear Programming. Heuristics and Metaheuristics.
Data for the next step: Quantity of Cars, Routing Sequences, Optimal Amount of Resources.	
Step 4: Simulation and Experiments	
Run experiments (parameter variation) and analyze the outputs to make better decisions about the real-world operation.	Discrete Event Simulation. Systems Dynamics. Agent-Based Simulation.
Data for next step: Calibrated velocities in different zones of the city, number of customer per vehicle per zone, distances and time between zones and customers, calibrated parking and services time per type of customer.	
Step 5: Learning	
Learn the best routes in the environment to provide an excellent execution and service level.	Reinforcement Learning.
Output: Best routes definition for last-mile delivery	

These cases are presented in chapter 4, along with their analysis and results. For some industries the last-mile operations allow multiple vehicles to supply the demand of a single customer, for this reason, a split delivery case is analyzed for the maritime sector where is split delivery is a common practice, the second is a comprehensive case for home deliveries in a city, situations based in the industry necessities are analyzed.

3.3.3.1 Case A: Maritime Logistics

This case examines a Maritime Corporation's delivery of fuel to Western Alaska. More specifically, it is concerned with the specialized fleet of vessels that reaches the remote parts of Western Alaska as they become accessible during the summer months. In the process of fuel delivery, MR tankers hold fuel, where pocket tankers and lighter vessels collect a supply that they then deliver.

3.3.3.2 Case B: Urban Logistics

The proposed methodology is applied to create a digital twin for last-mile operations in a megacity, to support the delivery of goods and to generate tools which can help the near real-time decisions for dispatchers and transportations managers and allows the detection of potential issues and adjust last-mile operations depending on the circumstances. These decisions are taken under conditions and behavior patterns from drivers, customers, locations, and traffic. The digital twin aims to bring, the possibility to predict future scenarios and plan strategies for the most likely situations to the dispatchers of vehicles in a logistics company. Scenarios with heterogeneous (Case b1) and homogenous fleet are discussed (Case b2)

3.3.4 Validation, Conclusions and Further Research

From the case studies, we expect to bring state of the art analytic methodologies to detect and understand the different behaviors of last-mile delivery stakeholders and their dynamic interactions. Also, bring a method that can serve as a prediction and analytic tool to gain insights into current and future operations between the stakeholders and physical elements in the distribution process. With the learning procedures, we expect to bring a way of adjusting routes responding to possible anomalies, changes in customer schedules, or traffic flow. We aim to bring optimization modeling, combined with simulation and visualization technology for effective goods delivery. Our approach contributes to the scientific and practitioners' community by considering learning processes to create effective, proactive distribution systems to achieve short and long-term goals (Sutton et al. 1998). Making decisions about which route to select to arrive at a destination in the shortest time under dynamically traffic environment is a daily challenge for delivery drivers. The goal is to decide which customer to go next, under traffic conditions and environment status. The methodology is designed to set up efficient routes along with information about road traffic, the zone of the city, waiting time of the customer, among other indicators. (Kim et al., 2005).

The case study for urban logistics is aiming to bring an efficient solution to set up routes to deliver orders in the city. This methodology is aiming to help transportation managers to support peak and valley delivery orders. In general, bring the way to define the correct combination of the type of vehicles that would be used and their quantity, together with the number of orders that each vehicle would carry to have an efficient operation. Finally, and the essential part, to bring a simulation learning methodology to improve the processes.

Also, we expect to set the up the conditions to further research to have better traffic predictions and services time through the analysis of the patterns from data collected from GPS tracking technology, sensors, and experiences from past delivery locations.

Based on the literature review, interviews with industry experts and last logistics tendencies in last-mile delivery, we create the following checklist table to help us to validate the methodology:

Table 11: Validation Criteria.

Routing Models
Georeferencing of directions with coordinates
Find the best combination of vehicles of different capacity
Allocation of demand in vehicles according to its configuration capacity in weight and volume
Planning according to the result of the variables (weight and volume)
Validation of models
Accuracy between routing times in the simulation model and times in google maps
Learning from environment
Accuracy in velocities in the different zones of the last mile geography zone

CHAPTER 4: CASE STUDIES ANALYSIS AND RESULTS

This chapter applies the last-mile delivery methodology described in chapter three to two case studies, based on real product delivery situations. The first case is in maritime logistics, which discusses the decision process to find the type of vessels and routes to deliver petroleum derivate from ships to villages. This case study is characterized to allowing split deliveries, where a customer can be attended for more than one vehicle. The objective is to minimize the total fleet satisfying clients' demands. In this case, the methodology is focusing on the use of optimization and simulation techniques to handle the problem. The second case is in city logistics, analyzes the network of stakeholders during the city or urban distribution process. This case shows the potential benefits, especially in understudied metropolitan areas. Potential applications of this system will leverage growing technological trends (e.g., deep reinforcement learning for logistics and supply chain management, internet of things).

4.1 Case Study A: Maritime Logistics

This case examines a Maritime Corporation's delivery system of fuel in Western Alaska. More specifically, it is concerned with the definition of a specialized fleet of vessels that reaches the remote parts of Western Alaska as they become accessible during the summer months. In the process of fuel delivery, the hub "mother tankers (MR)" hold fuel, where pocket tankers and lighter vessels (smaller ships of different capacities) collect a supply that they then deliver.

The last-mile delivery in the distribution of petroleum and their derivate in maritime logistics appears when actors in the maritime supply chain have the responsibility of the transportation of these goods to the ports from a central tanker (mother tanker), localized some miles from the ports. This transportation is made, most of the times, with heterogeneous vessels that make deliveries to the customers. These vessels deliver the product due to the mother tanker cannot go directly to each of them because of the draft and the size of the ship. As depicted in Figure 44 In consequence, improvements in fleet utilization can translate into cost reductions (Agra et al., 2013).

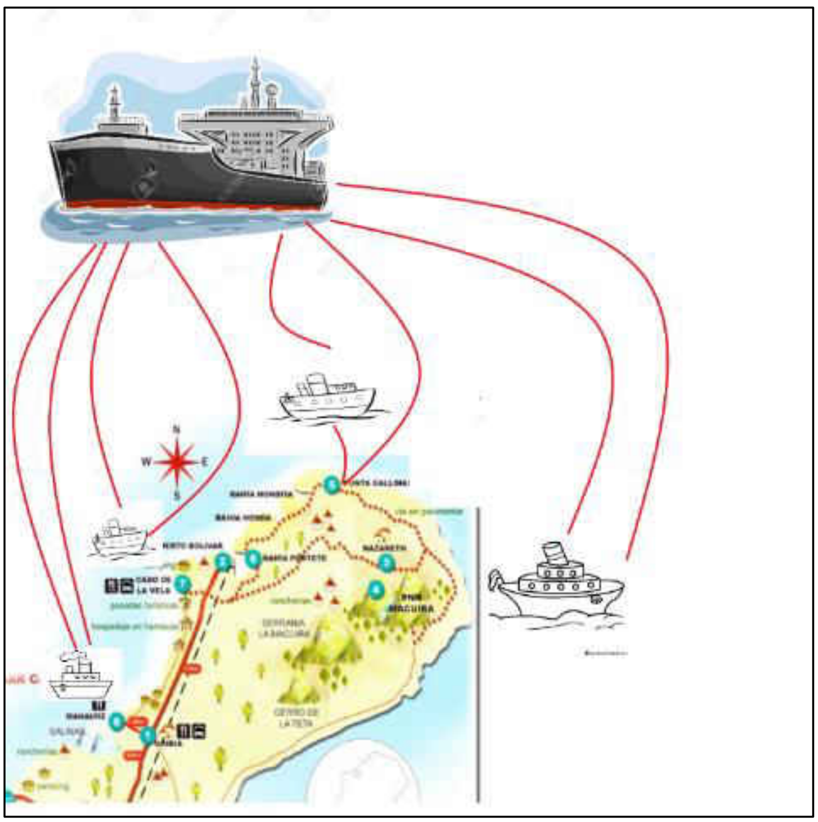


Figure 44: Last-mile operation in Maritime Logistics.

As the current fleet ages out, the organization was seeking to replace old vessels with new. For this reason, it is essential to determine the optimal mix of ships that would serve the company's Alaskan customers at the lowest cost.

The purpose of this case was to create an analytical decision tool that would determine the optimal configuration of vessels to meet seasonal demand at the lowest cost. This process would include a mathematical optimization model (solved in GAMS) and a simulation to validate the model (in SIMIO). Steps one to five of the methodology are used: data collection, data analysis, modeling, simulation, and learning.

The case considers six main classes of vessels (each with different carrying capacity and costs) and four geographical regions in which to make deliveries (each serving a few villages with many customers in each). In the Measure phase, all data was provided by the maritime corporation. From this data, four key input variables were selected for the model: vessel capacity, vessel cost, village demand, and village location. Key output variables include an assignment of vessels to routes in an optimal configuration, the total number, and types of ships needed to make these deliveries, and the (minimized) total cost to acquire this specific fleet. Table 12 depict the justification for each of the steps. The completed design comprises two components: (1) a mathematical optimization model in the form of a mixed integer linear program and (2) a simulation model including villages as servers, and vessels as entities that travel and interact with the servers. In the verification phase, the completed mathematical model and simulation were confirmed to provide a reasonable recommendation of vessels and routes for seasonal deliveries (Goodhope Bay), at a lower cost than in prior seasons.

Table 12: Steps justification and description Case A

CASE A: MARITIME LOGISTICS	
WHY	**HOW**
Step 1: Historical and data collection	
Data about villages: demands, location, and draft. Data about Vessel capacities in volume and weight. Fixed and Variable costs.	Descriptive Statistics. Interviews. Time and motion studies. Expert Opinion. Literature Review. Geographical Information Systems.
Data for the next step: Vessel velocities in the different zones of the ocean. Capacity in volume and weight of vessels. Draft characteristics for each of the villages. Service and unloading times. Fixed and variable costs. Industry Necessity. Research directions.	
Step 2: Data Analysis	
Identify the correct insights/parameters for the decision-making tools: Optimization, Simulation and, Machine Learning methods.	Forecasting techniques, clustering, data mining, probability distributions.
Data for the next step: Group of villages to attend, demand tendencies, forecasting, velocity probability distributions per ocean zone.	
Step 3: Modeling Formulation	
Identify the best combination of resources to meet the management objectives like the reduction of cost and high services levels.	Mixed Integer Linear Programming.
Data for the next step: Quantity of vessels, Routing Sequences, Optimal Amount of Resources.	
Step 4: Simulation and Experiments	
Run experiments (parameter variation in vessel velocities) and analyze the outputs to make better decisions about the real-world operation. For this case the vessels are simulated as entities, rather than agents.	Discrete Event Simulation. For this step was used the Software SIMIO thanks to its capabilities in the simulation of maritime and port solutions and determine the sensitivity parameter analysis. Also, their 3D animation, and other tools promote communication and understanding across broad managers, technicians (decision-makers). (https://www.simio.com/applications/port-simulation-software/)
Data for next step: Calibrated velocities in different ocean/villages zones, number of villages per vessel, distances and time between zones villages, calibrated velocities and unloading time per type of village (draft restrictions).	
Step 5: Learning	
Learn the best routes in the environment to provide an excellent execution and service level.	Reinforcement Learning.
Output: Best routes definition for last-mile split delivery for villages	

This case was significant because it serves as an excellent approximation to the solutions of last-mile deliveries. We expect this model can help to streamline the last-mile operations decision-making: allowing for a better decision in reduced time

4.1.1 Step 1: Historical and Data Collection

Several details complicate this process of fuel delivery. The timeframe available for delivery - the "season" - is determined by the time that access to ports is not blocked by ice in the surrounding sea. In general, the season for delivery operations is May-October. In the earlier months, the southernmost part of the Western Alaska coast is served. As the season progresses and ice melts further north, villages further up along the coast become accessible for service. Another subtlety of the process is that demand occasionally exceeds capacity for certain villages. In this case, the fleet would make a delivery that partially satisfies their demand on its way up the coast, and later re-supply them on their way down the coast, when they are ready to accept more fuel.

The different classes of vessels and their roles in fuel delivery are shown in Figure 45.

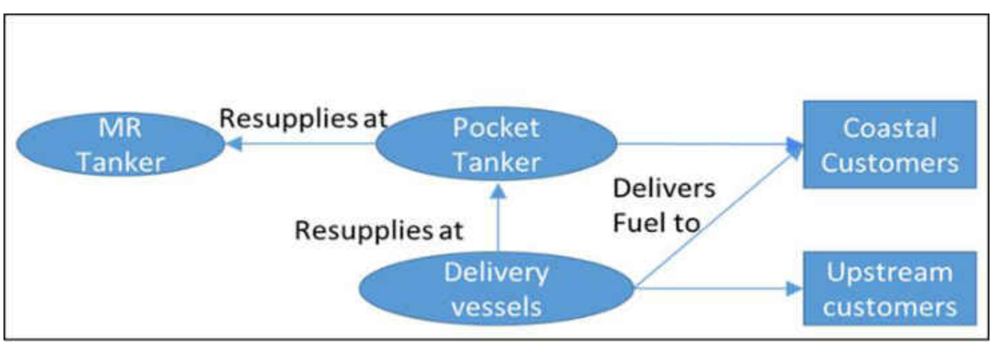


Figure 45: High-level process map.

MR Tankers have the largest capacity and primarily store fuel from which smaller vessels restock. These smaller vessels, including pocket tankers (which can themselves be used for fuel storage, as "floating warehouses"), and coastal lighter ships, make the deliveries.

Several parameters associated with each type of vessels will be considered, including but not limited to type, capacity, draft depth, optimal speed, fixed costs, and operating costs. Parameters associated with each village are including, but not limited to, geographical location/zone, demand, and maximum draft depth.

For illustrative purposes, this instance assumes seven customers/villages (Good Hope). The example below shows a snapshot of the data into the GAMS IDE (Figure 46).

	i00	i01	i02	i03	i04	i05	i06	i07	i08
i00	0	32	147	191	265	366	445	691	0
i01	32	0	130	170	247	336	414	660	32
i02	147	130	0	36	116	201	278	524	147
i03	191	170	36	0	77	165	244	490	191
i04	265	247	116	77	0	84	160	406	265
i05	366	336	201	165	84	0	79	352	366
i06	445	414	278	244	160	79	0	246	445
i07	691	660	524	490	406	352	246	0	691
i08	0	32	147	191	265	366	445	691	0

Figure 46: Distance Matrix.

To develop this basic model, assumptions were made regarding factors of secondary importance; these assumptions are explained below:

- Rather than considering an entire market of individual vessels available for the company to purchase, six specific types of ships/vessels were used:
    - o Coastal lighter vessel DBL 165
    - o Coastal lighter vessel 180-1
    - o Coastal lighter vessel DBL 289
    - o Coastal lighter vessel Kays Pt
    - o Pocket tanker Nordisle
    - o MR tanker

4.1.2 Step 2: Data Analysis

- The geographical scope of this project includes these regions in Western Alaska (and the villages therein):
- Goodhope Bay (Figure 47).

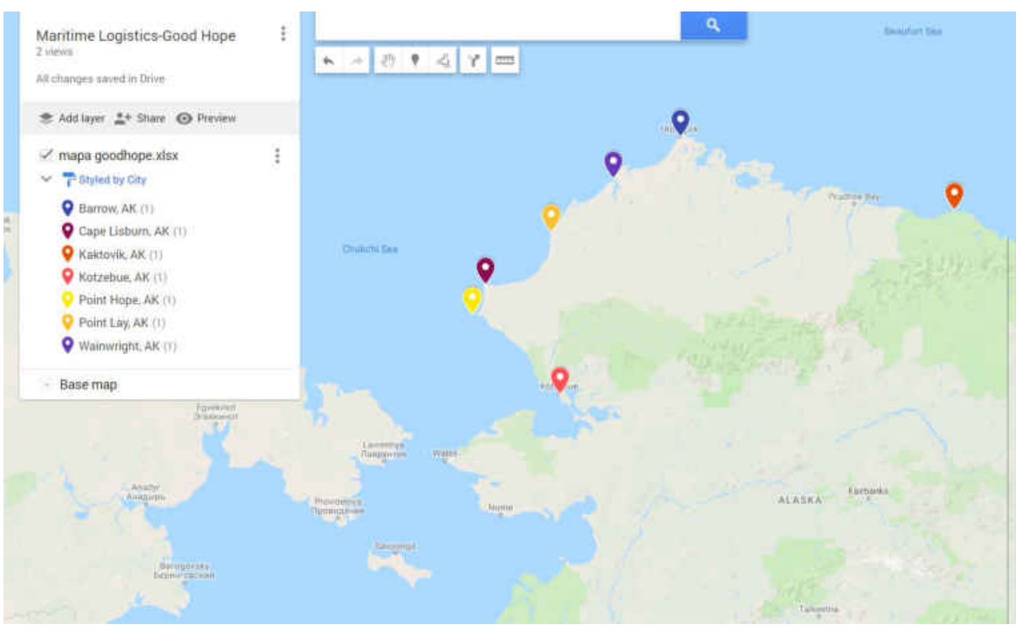


Figure 47: Villages location in Alaska.

For this case study, only the total volume of fuel offered will be considered disregarding the difference among them as the company delivers more than one type of fuel.

- Delivery points upriver are excluded. In these cases, the model will stop making deliveries to tank farms at the mouth of the river (and exclude the vessels that solely operate along a river, from the tank farm to the villages and back).

- Similarly, the occasional instance where a vessel must be deployed to make the final leg of delivery will not be considered. In general, this model will stop once the delivery is made by a lighter vessel (or pocket tanker).

The organization provided both current and historical data (spanning the last five years). This step consisted mostly of studying the extensive data to determine what was useful for creating the model, what was extraneous, and what information was yet needed. The objective for the measure phase was to understand data requirements to start the mathematical modeling.

A summary of the data is given below in Table 13.

Table 13 Refined data summary.

Title	Information	Use
Planning Schedule	• Schedule of deliveries in 2017 by day, vessel, and village	• Validation of model output
Village Restrictions	• Deliveries to customers by name, zone, village, phase, month and week of delivery, volume, source, and time to pump • Total demand by village, types of vessels allowed at each village, maximum load, whether tide restricted • For five relevant classes of vessels: name, type, capacity, draft depth, optimal speed, cost	• Input to model • Parameter for simulation
Data 3-26	• Log of deliveries to all customers, including vessel, zone, village, volume, price, delivery month and week, etc. • Log of the ship to ship transfers	• Validation of model output
Alaska Lighter Locations and Distance Chart by Zone	• Distances between supply point and villages for each of four regions	• Input to model • Parameter for simulation

From this data, key performance input variables (KPIV) and key performance output variables (KPOV) were derived:

- KPIV
    - Vessel fuel-holding capacities

- Vessel costs
- Village locations
- Village demands

• KPOV

- Vessel type used to make each delivery in season
- Types of vessels in the fleet
- Number of vessels (of each type)
- Total fleet cost

4.1.3 Step 3: Modeling Formulation

This model allows a decision maker to define a heterogeneous fleet size and vessel routing to serve a set of customers. Symmetric costs for distances are assumed and the costs are dependent on the vessel type.

The model will take in the KPIVs, already provided in the data from the case study, and express the KPOVs. All the data examined in this project describes either vessels or villages. Two KPIVs report vessel information: maximum capacities to hold fuel for delivery, and fixed/operating costs. Two report village information: geographical locations, and demand levels. All four KPIVs will be used by the model to express a the KPOV of all the deliveries made in the season, and by which vessels, in matrix form. Once the model assigns a vessel to each delivery, the KPOVs total number of vessels by type will be expressed. Then, the KPOV total cost will be calculated. In general, the model will seek to provide the minimum number of vessels needed to compose a fleet that will make all deliveries.

The data did not require any extensive further transformation. Once it was determined what factors the model should consider, finding the data and entering it into the mixed integer linear model in a usable format was simple.

The full set of data is not presented here. However, some essential information of deliveries is.

Most deliveries are concentrated in July. The average operation in the planning period is between 6 and 15 by zone. A mother tanker can attend ten villages. Figure 48 depicts the number in villages for a "summer" season, having its peak in July.

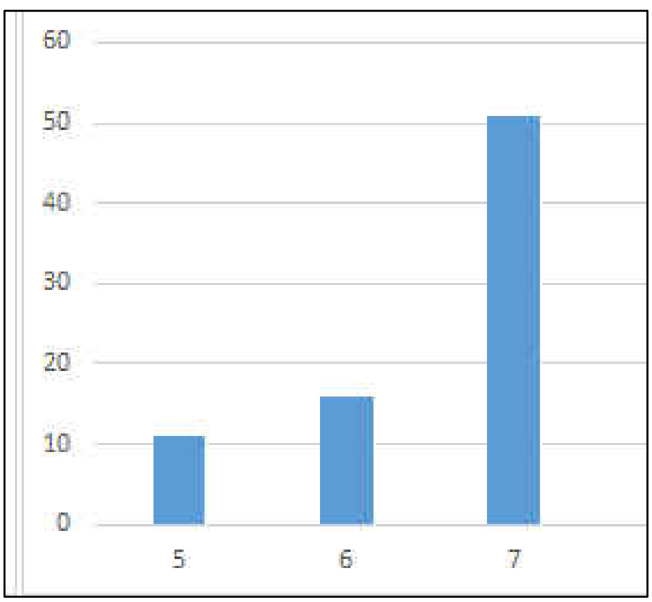


Figure 48: Number of villages served per month.

Primary Assumptions

- A limited number of different vessel types
- MR tankers do not move; the model looks at a new “scene” once the MR is stationary again (treating the MR as a warehouse)
- “Charter costs” provided and the bunkering costs will be input as operating expenses for comparison
- Any vessel can travel anywhere—constraints to put restrictions on certain villages are currently drafted but not yet implemented in the model
- Consider only the total volume of fuel being delivered (no distinction between different types)
- Timeframe begins when vessels arrive in the “Alaskan Theater.” In general, the model will stop once delivery is made by lighter ship or pocket tanker: exclude delivery point’s upriver (stop at deliveries to tank farms at the mouth of the river) and exclude truck deliveries.

Follow the notation and description of the equations in Chapter 3, section 3.2.4.3 for the modeling formulation; the following are the equations used for this case. Equation 32 allows more than one vessel per node.

$$Z = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} ((C_k * (S_k)^{-1} * X_{i,j,k} * d_{i,j}) + \sum_{k \in K} V_k * FCOST_k) \qquad (31)$$

$$\sum_{k \in K} \sum_{j \in N} X_{i,j,k} \geq 1 \qquad \forall i \in N \qquad (32)$$

$$\sum_{i \in N} X_{i,j,k} = \sum_{i \in N} X_{j,i,k} \qquad \forall j \in N, k \in K \qquad (33)$$

$$\sum_{i \in N} \sum_{k \in K} Y_{i,j,k} - \sum_{i \in N} \sum_{k \in K} Y_{j,i,k} = D_j \qquad \forall j \in N \qquad (34)$$

$$\sum_{j \in N} \sum_{k \in K} Y_{i0,j,k} = \sum_{i \in N} D_i \quad (35)$$

$$\sum_{k \in K} \sum_{i \in N} Y_{i,i0,k} = 0 \qquad \forall i \in \boldsymbol{N} \quad (36)$$

$$Y_{i,j,k} \le X_{i,j,k} * CAP_k \qquad \forall i \in N, j \in N, k \in K \quad (37)$$

$$\sum_{j \in N} X_{i0,j,k} = VK_K \qquad \forall k \in K \quad (38)$$

$$\sum_{j \in N} X_{i0,j,k} = \sum_{i \in N} X_{i,i0,k} \qquad \forall k \in K \quad (39)$$

$$U_{i,k} - U_{j,k} + |N| * X_{i,j,k} \le |N| - 1 \quad (40)$$

$$x_{i,j,k} \le y_{i,j,k} * Tv_{i,j,k} \quad (41)$$

$$y_{i,j,k} \le MaxLoad_j \qquad \forall i \in N, j \in N, k \in K \quad (42)$$

$$X_{i,j,k} \in \{0,1\} \quad (43)$$

$$Y_{i,j,k} \in R^+ \quad (44)$$

The model output includes an assignment of paths for each vessel to take, in order, including to and from the MR tanker to refuel. It also consists of the total amount of vessels of each type and the total cost of chartering this fleet to make these deliveries. Figures 49 and 50 shows the statistics of the model and the vessel assignation respectively.

MODEL STATISTICS			
BLOCKS OF EQUATIONS	12	SINGLE EQUATIONS	4,566
BLOCKS OF VARIABLES	7	SINGLE VARIABLES	3,452
NON ZERO ELEMENTS	16,328	DISCRETE VARIABLES	1,425

Figure 49: Model Statistics.

---- 322 VARIABLE x.L 1 if the vehicle k travels the arc (i-j) and 0 if the vehicle k does not travel the arc (i-j)

	K21	K22	K23	K24
i00.i01			1.000	
i00.i02	1.000			
i00.i05		1.000		
i00.i06				1.000
i01.i08	1.000		1.000	
i02.i01	1.000			
i02.i08		1.000		1.000
i03.i02		1.000		1.000
i04.i03		1.000		1.000
i05.i04				1.000
i05.i07		1.000		
i06.i04		1.000		
i06.i05				1.000
i07.i06		1.000		

Figure 50: Binary variable Value.

The routes are:

- Vehicle 21: i0-12-i1-i8
- Vehicle 22: i0-i5-i7-i6-i4-i3-i2-i8
- Vehicle 23: i0-i1-i8
- Vehicle 24: i0-i6-i5-i4-i3-i2-i8

Fuel transported by arc (i-J), i8 is not in the table because it represents the mother tanker. Figures 51 and 52 represents the solution.

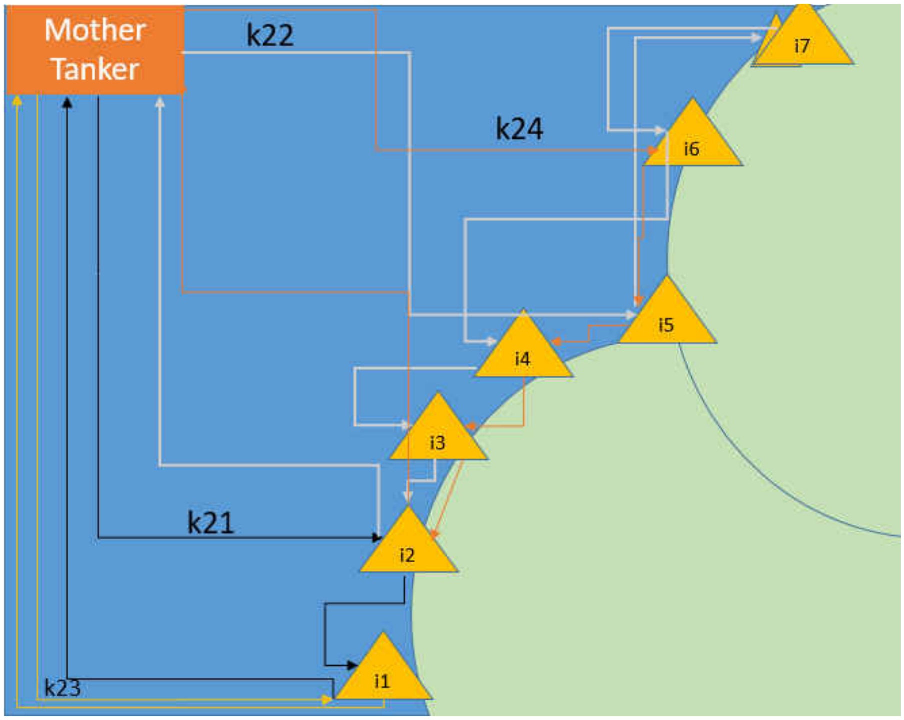


Figure 51: Routes solution schema.

```
----     323 VARIABLE y.L  amount of product transported by the arch (i-j) in the
                           vehicle type k

                K21          K22          K23          K24

i00.i01                             2650540.000
i00.i02 3001885.000
i00.i05              3185299.000
i00.i06                                          2831353.000
i02.i01 2100000.000
i04.i03               250000.000                   63777.000
i05.i04                                           819277.000
i05.i07              1391022.000
i07.i06               450000.000
```

Figure 52: Amount of product in the arc i-j.

4.1.4 Step 4: Simulation and Experiments

A simulation was created in the software SIMIO (www.simio.com) for the primary purpose of verifying the mathematical model. The simulation contains servers and entities. Servers are fixed locations, such as villages, set at specific coordinates. Entities are individuals that visit servers— in this case; they are vessels. A server represents every village that receives fuel deliveries. Each server is accessible by a fixed path, but the travel time will vary depending on the speed of the vessel. Each server has a different capacity. Each server has different processing times depending on characteristics of the entity, such as how fast a vessel can unload fuel and time needed to reposition the vessel with a tug. Each entity's features include top speed (loaded and ballast) and capacity. The reliability of the servers reflects whether a village is accessible or inaccessible at a particular time due to tides or weather. Simulation logic models the conditions under which certain vessels can visit specific nodes. This logic determines where a vessel goes and in what order the nodes are visited, based on the characteristics of both the vessels and the villages.

Figure 53 shows a map of simulated paths, which includes the village's northwest of Goodhope Bay. It's important to note that these paths are not to scale: their lengths and trajectories are exaggerated to be easily visible. The "background" simulation logic calculates travel time based on the real-life distance of each path from given data.

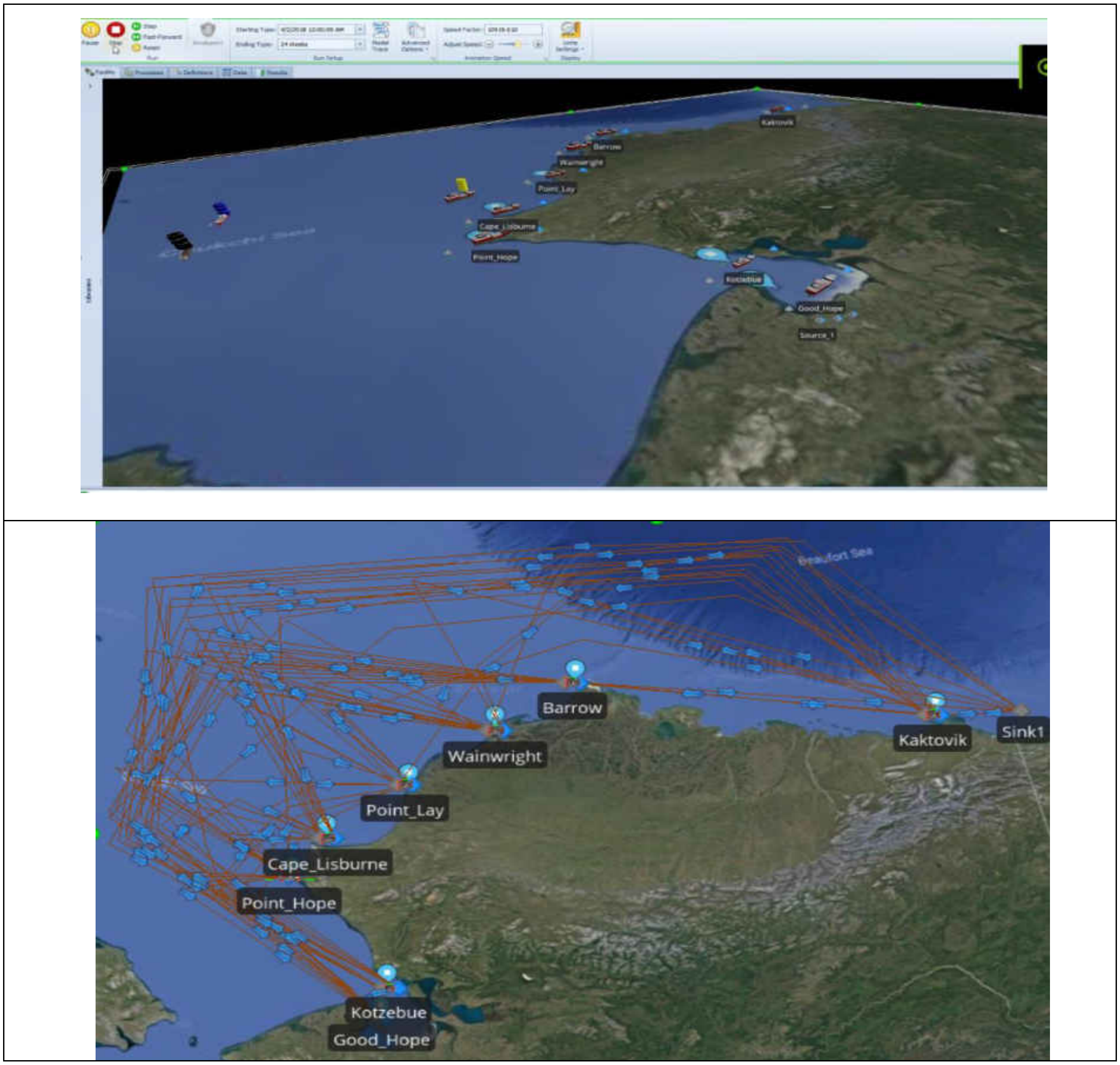


Figure 53: Simulation map of villages and routes in Goodhope Bay.

The verification phase confirmed the accuracy of both the mathematical model and the simulation model of the company’s fleet. Because of the lack of reliability in much of the granular data, it was necessary to find a higher-level aggregate measure of validity in the models for verification. The method of verification determined was to compare the aggregate cost requirements of the models against an estimate of the total aggregate cost from an actual season of fuel distribution.

The final scope of the model included one portion of the entire delivery network—Goodhope Bay—which simplified the task and encouraged localized accuracy. To compare the models against the real-life scenario, information such as actual fuel demand, actual distances between villages, vessel capabilities, and vessel costs were input into the model. The notion was that given the same information, the model should produce a comparable result to the total historical cost of operations. However, an important note is that the mathematical model provides the optimal values; for example, it supposes that vessels are always traveling at optimal speed. Though this is not realistic, it was determined appropriate due to the aim of the mathematical model to provide optimal results. Furthermore, such conclusions based on ideal travel times may be adjusted for sensitivity (e.g., multiplied by a factor of less than 100% efficiency) to more closely represent actual times and results.

The models produced are easy to apply to each region of the fuel distribution network. By merely substituting the locations of each delivery point and using the historical data for that specific region, a new verification can be performed for each portion of the greater Alaskan delivery network.

Given that some assumptions were made to create these models, a degree of variation is to be expected between the produced results and historical results. This preliminary model assumes efficient operations by using optimal speed (as explained above) and leaving out some sources of error and uncertainty like inclement weather and equipment reliability, which are the possible disruptions in the operation. The result is a reasonable fleet configuration with a lower projected cost than the actual operational cost. Overall, the developed mathematical model was shown to be a successful tool for fulfilling the given task.

The speed and capacity of these vessels, as well as the demand at and location of each village, are essential input variables to the model. Key output variables include an assignment of vessel used to make each delivery, the total type and number of vessels composing the heterogeneous fleet, and total cost to acquire the new fleet. The simulation verifies the mathematical model. The result was a reasonable fleet configuration with a lower projected cost than the actual operational cost.

4.1.4.1 Lessons Learned

Thanks to this case study: we realized that a methodology to attack the last-mile problem was necessary when larger instances are needed. Patterns of behavior are found in urban logistics in the last-mile operation. That is the justification for applying algorithms that learn the operations. The use of optimization and simulation models can be complemented with machine learning techniques. We consider the routing situation called split delivery vehicle routing problem (SVRP) where a village can be supplied by more than one vessel when its demand exceeds the vessel capacity.

4.1.5 Step 5: Learning Procedures

The methodology is proposing a playground where the agents learn in a simulation environment. In the case of maritime logistics, environmental conditions affect the time of the delivery (bad weather). Different circumstances were simulated to do trial and error tests and to learn from the assumptions and results. This part of the methodology is proposing to use the deep reinforcement learning explained in chapter three.

For our purpose, geographical information and demand are used as an input to the network. Once the algorithm is trained for the problem, the information is normalized to follow the network structure. Given these inputs like localization longitude and latitude, these are normalized and are given by values between [0,1]. The algorithm used for training the vehicles to find the shortest delivery path follows a deep reinforcement learning trained policy. This approach does not need to calculate the distance matrix each time that need to find the routes. It is calculated based on the rewards signals and the feasibility constraints in capacity in vehicles. Also, it is not required to retrain for every new situation. Figure 54 depicts the steps of how actor-critic works.

batch actor-critic algorithm:

1. sample $\{\mathbf{s}_i, \mathbf{a}_i\}$ from $\pi_\theta(\mathbf{a}|\mathbf{s})$
2. fit $\hat{V}^\pi_\phi(\mathbf{s})$ to sampled reward sums
3. evaluate $\hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i) = r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \hat{V}^\pi_\phi(\mathbf{s}'_i) - \hat{V}^\pi_\phi(\mathbf{s}_i)$
4. $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$
5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Figure 54: Batch actor critic algorithm.

The training method for this experiment makes use of two networks. The first one is the actor-network used to predict the probability distribution over the next action at any given step, which reduces the problem of choosing a customer from a very specific area. The second network, the critic, provides an estimated reward for any problem instance which helps to take the best decision from the distribution pool of the actor-network (Figure 55).

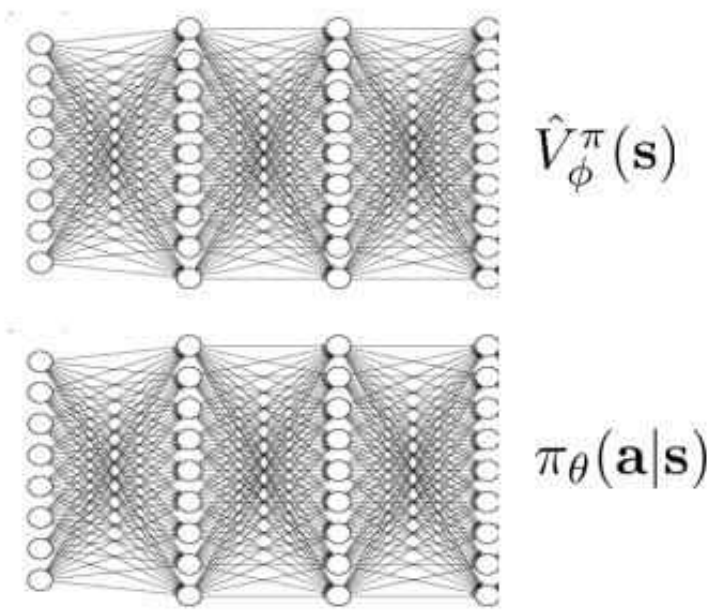


Figure 55: Actor and critic neuro network.

On the contrary of the classical vehicle routing problem (in urban environments) where it is expected the demand can be served by one vehicle, due to complexities in traffic and resources, it is common in maritime logistics to allow the split delivery.

In consequence, the constraint over just is allowed one vehicle per customer is relaxed in the “masking scheme” in the code. The relaxed masking allows split deliveries, so that the solution can assign the demands of a given village into more than one route. It is important to highlight that it is not necessary to re-train the algorithm.

To calculate the position of each customer in the square built, the map latitude/longitude is subtracted from the minimum of all latitudes/longitudes and divided by the difference between the maximum and the minimum of all, which will always give us a value between 0 and 1. Then the points can be rendered on a graph as is depicted in Figure 56.

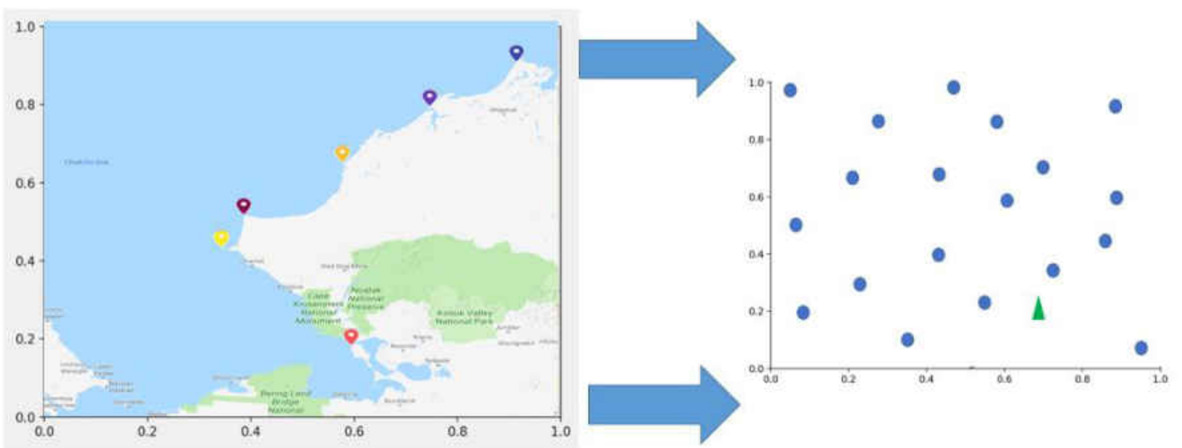


Figure 56: Playground for split delivery.

For this model, The SVRP has two dynamic elements: the capacity of the vehicle and the demand of the customer. The following assumptions are used for this example: ships can visit any village, and one village can be visited for more than one vessel.

The output of the test run provides a tour of the nodes to visit and a visualization of the trip. The training method for this experiment makes use of two networks, one the actor-network to predict the probability distribution over the next action at any given step which reduces the problem of choosing a customer from a very specific area. The second network, the critic provides an estimated reward for any problem instance which helps to take the best decision from the distribution pool of the actor-network. Once the algorithm is trained it can solve the problem in an instant. In contrast with solutions that only use the mathematical model. For example, to find a solution for ten nodes with only optimization procedures, can take around 285 seconds and it is necessary to have a solver. Figure 57 depict the solution for ten nodes in an algebraic modeling software.

```
Root node processing (before b&c):
  Real time             =    2.70 sec. (3524.69 ticks)
Sequential b&c:
  Real time             =  285.50 sec. (485669.15 ticks)
                          ------------
Total (root+branch&cut) =  288.20 sec. (489593.83 ticks)
MIP status(102): integer optimal, tolerance
Cplex Time: 288.20sec (det. 489593.83 ticks)
Fixing integer variables, and solving final LP...
Tried aggregator 1 time.
LP Presolve eliminated 6447 rows and 6127 columns.
Reduced LP has 2250 rows, 250 columns, and 4500 nonzeros.
Presolve time = 0.00 sec. (3.55 ticks)

Iteration log . . .
Iteration:     1   Dual objective     =         49184.767857
Fixed MIP status(1): optimal
Cplex Time: 0.00sec (det. 7.78 ticks)

Solution satisfies tolerances.

MIP Solution:        49184.767857    (3586572 iterations, 54693 nodes)
Final Solve:         49184.767857    (7 iterations)
```

```
----     333 VARIABLE x.L  1 if the vehicle k travels the arc (i-j) and 0 if the
                           vehicle k does not travel the arc (i-j)
```

	K11	K21	K22	K23	K24	K25
100.101	1.000					1.000
100.102			1.000			
100.105				1.000		
100.106					1.000	
100.110		1.000				
101.111	1.000					1.000
102.103		1.000				
102.107			1.000			
103.111		1.000				
104.111				1.000		
105.104				1.000		
106.111					1.000	
107.109			1.000			
108.102		1.000				
109.108		1.000				
109.111			1.000			
110.109		1.000				

Figure 57: Solution for 10 nodes in split delivery

Using the learning procedure, we can find the following tours for each of the vehicles.

N10	N09	N07	N00	N06	N00	N01	N00	N01	N05	N08	N00	N02	N04	N03	N07

Figure 58: Tours Split Delivery

4.2 Case Study B: Digital Twin for Last-Mile Operations in a Megacity

The proposed methodology is applied to support the decision making of goods delivery in a city, and to support the near real-time decisions for dispatchers and transportation managers. These decisions are taken under conditions and behavioral patterns from drivers, customers, locations, and traffic congestion. The digital twin aims to predict future scenarios and plan strategies for the most likely situations to the dispatchers of vehicles in business which (e.g., retail, logistics companies, restaurants). This will help to determine and support the accurate calculation of performance indicators.

The methodology is applied for the last-mile operations in one of the most difficult congested cities in the world: Bogota, Colombia. With a total area of 613 square miles, Bogota is the third-highest capital in South America with around 12 million inhabitants. It is characterized for the diversity in population density, regular road infrastructure, and diversity in population economic conditions. Data and terms of the problem are based in a real retail organization which operates in the city. This case discusses the main issues and provides guidelines and implications for the last-mile delivery problem. Optimization models are programmed in algebraic modeling systems software (e.g., Gurobi, GAMS) to identify the fleet and type of vehicles. Also, it assesses the dynamic and learning process of the solution using agent-based simulation. Table 14 depict the justification for each of the steps.

Table 14: Steps justification Case B

<table>
<tr><th colspan="2">CASE B: URBAN LOGISTICS</th></tr>
<tr><th>WHY</th><th>HOW</th></tr>
<tr><td colspan="2">Step 1: Historical and data collection</td></tr>
<tr><td>Data about customers’ demands, location, and type (nanostore, townhouse, or building). Data about Vehicles capacities in volume and weight. Fixed and Variable costs.</td><td>Descriptive Statistics. Interviews. Time and motion studies. Expert Opinion. Literature Review</td></tr>
<tr><td colspan="2">Data for the next step: Vehicles velocities in the different zones of the city. Capacity in volume and weight of Vehicles. Draft characteristics for each of the customers. Service and unloading times. Fixed and variable costs. Industry Necessity. Research directions.</td></tr>
<tr><td colspan="2">Step 2: Data Analysis</td></tr>
<tr><td>Identify the correct insights/parameters for the decision-making tools: Optimization, Simulation, and, Machine Learning methods.</td><td>Forecasting techniques, clustering, data mining, probability distributions</td></tr>
<tr><td colspan="2">Data for the next step: clusters, tendencies, forecasting, customer behavior (profiles), driver behavior, parking and service time in city zones (districts) and probability distributions for speed, parking and service time.</td></tr>
<tr><td colspan="2">Step 3: Modeling Formulation</td></tr>
<tr><td>Identify the best combination of resources to meet the objectives on the reduction of cost and high services levels.</td><td>Linear Programming. Mixed Integer Linear Programming. Heuristics.</td></tr>
<tr><td colspan="2">Data for the next step: Quantity of Cars, Routing Sequences, Optimal Amount of Resources.</td></tr>
<tr><td colspan="2">Step 4: Simulation and Experiments</td></tr>
<tr><td>Run experiments (parameter variation in Vehicles velocities, service times and diferent zones in the city) and analyze the outputs to make better decisions about the real-world operation.</td><td>Agent Base Simulation. Software Anylogic. The capabilities to linking maps and simulation was very useful for this case. The model build a transportation model with GIS maps. With Agent based the model focuses on the individual active components of a the system and their interrelations (vehicles, customers and city). https://www.anylogic.com/use-of-simulation/agent-based-modeling/</td></tr>
<tr><td colspan="2">Data for next step: Calibrated velocities in different city/customers zones, number of customers per Vehicles, distances and time between zones customers, calibrated speeds, parking and service time per type of customer. Time of arrival and departure per customer. Schedule per vehicle.</td></tr>
<tr><td colspan="2">Step 5: Learning</td></tr>
<tr><td>Learn the best routes in the city to provide an excellent execution and service level.</td><td>Reinforcement Learning.</td></tr>
<tr><td colspan="2">Output: best routing sequence to do the delivery task to customers</td></tr>
</table>

4.2.1 Step 1: Historical and data collection

To have a sense about a retail operation for home delivery in Bogota, Table 15 depicts the average numbers of daily customers. Around three weeks were analyzed for each demand type (peak and valley).

Table 15: Average customer order per day in a Megacity.

Average per day:	
DEMAND	**CUSTOMERS**
PEAK	327
VALLEY	200

On the other hand, Table 16 shows the typical configuration of vehicles.

Table 16: Type of vehicles for home delivery (1 retail store).

Criteria	Quantity (#)	Cubic capacity m3	Type Vehicle	Load Capacity (Kg)	total volume	total weight
Type of vehicles	3	4	Carry	700	12	2100
	3	20	Turbo	3500	60	10500
	14	14	Turbo	2000	196	28000

The possible clients can place an order one or more days prior the delivery day. Moreover, the order can be associated with a time window or not.

4.2.2 Step 2: Data Analysis

Megacities as Bogota are characterized by traffic congestions, slow speeds limits, longer trip times, pollution, and increased vehicular queueing. Along with their growth in urban areas of housing, retail stores, and regular roads, with little concern for urban planning make more challenging the task of urban logistics. Figure 59 shows the differences in the density population between different zones in the city.

Figure 59: Bogota City. Conditions of Urban Logistics in a Megacity.

Bogota is divided into 20 districts (Figure 60). Each of these districts has its own rules and government budget for infrastructure, laws that influence road construction, parking conditions, among others. One thing in common is they can have different road infrastructure characteristics, as shown in Figure 61, which affects the speed of vehicles (Akbar et al. 2017).

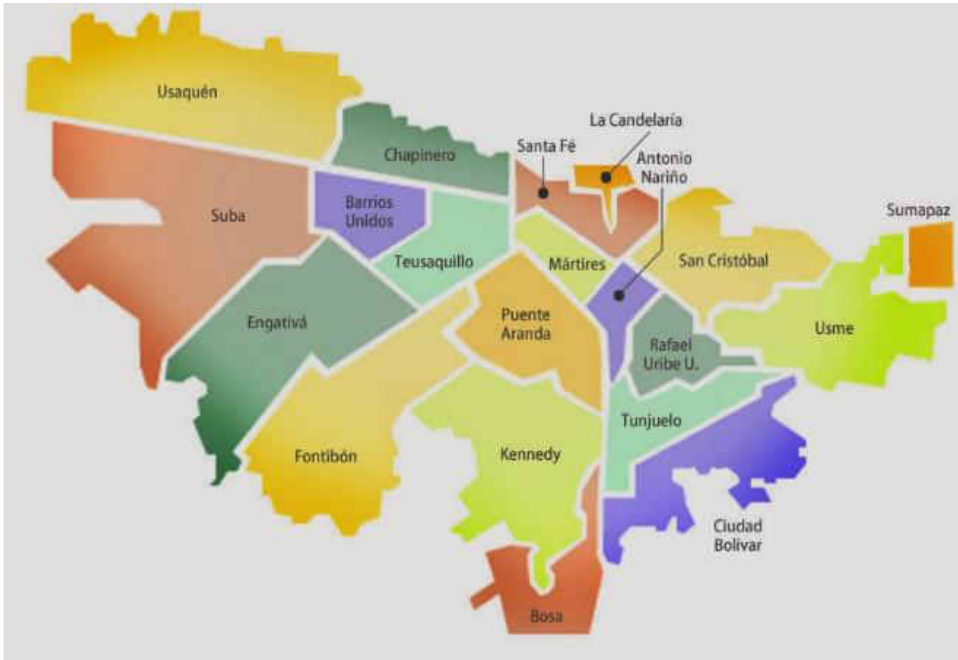


Figure 60: Districts in Bogota.

Table 17 shows this classification, subdivided the surface size, population, and density. Traveling times were retrieving using Google Maps, considering real traffic conditions. Each of the districts has a different density of habitants per square kilometer.

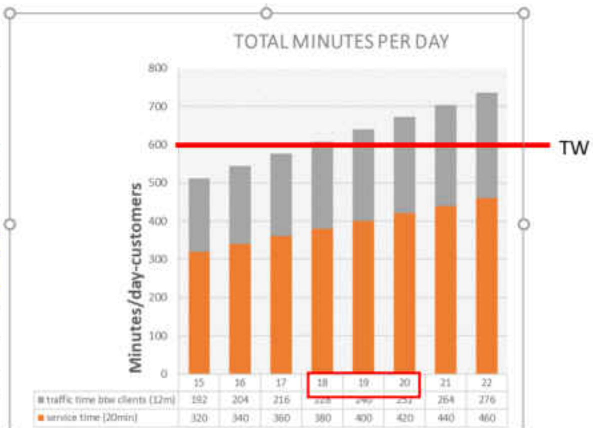
Table 17: Locality average velocity.

Locality name	Surface km²	Population	Density hab/km²	Average Velocity (km/h)
Kennedy	39	1,088,443	28,205	20
Bosa	24	673,077	28,126	23
Rafael Uribe Uribe	14	374,246	27,060	24
Engativá	36	887,080	24,723	18
Antonio Nariño	5	109,176	22,372	25
Barrios Unidos	12	243,465	20,459	22
Tunjuelito	10	199,430	20,124	20
Los Mártires	7	99,119	15,225	24
Puente Aranda	17	258,287	14,921	25
Suba	101	1,218,513	12,117	27
Fontibón	33	394,648	11,858	18
La Candelaria	2	24,088	11,693	21
Teusaquillo	14	153,025	10,784	21
San Cristóbal	49	404,697	8,243	29
Usaquén	65	501,999	7,686	21
Ciudad Bolívar	130	707,569	5,442	26
Chapinero	38	139,701	3,661	22
Santa Fe	45	110,048	2,436	29
Usme	215	457,302	2,126	26
Sumapaz	781	6,531	9	29

Figure 61: Diversity in city infrastructure.

To identify the maximum number of customers that each of the vehicles can visit in a day, an assumption for the optimization model was set up: the traffic time between customers is around 10 to 15 minutes and the service time is about 20 minutes (which include parking and the delivery of the product). With these conditions with a time window of 600 minutes, a maximum of 20 customers is set up to be visited during the day. Figure 62 depicts the analysis.

Clients	service time (20min)	traffic time btw clients (12m)	TOTAL (min)
15	300	150	450
16	320	192	512
17	340	204	544
18	**360**	**216**	**576**
19	**380**	**228**	**608**
20	**400**	**240**	**640**
21	420	252	672
22	440	264	704
23	460	276	736



TW: Time window per vehicle to do deliveries in the city.

Figure 62: Finding the maximum quantity of customers per vehicle.

4.2.3 Step 3: Modeling Formulation

Besides the districts in the city, clustering is used to assign vehicles to customers. In the case of Bogota city, there are some suburbs around the city. Where customers also ask for goods delivery. Figure 63 shows the first approach to do clusters, that customers that are outside the country are analyzed apart.

C1: Bogota
C2: North Cluster: Chia, Zipaquira, Cajica, Sopo, Cota, Tocancipa, Nemocon, Cogua, Gachancipa, Tabio, El Rosal, Subachoque, Tenjo.
C3: South Cluster: Sibate, Soacha.
C4: West Cluster: Facatativa, Funza, Madrid, Mosquera.

UPLOAD DATE	27-Nov	
CLUSTER	Sum of WEIGHT	Orders
C1	16,379	365
C2	1,460	28
C4	1,378	35
C3	174	11
Grand Total	19,390	439

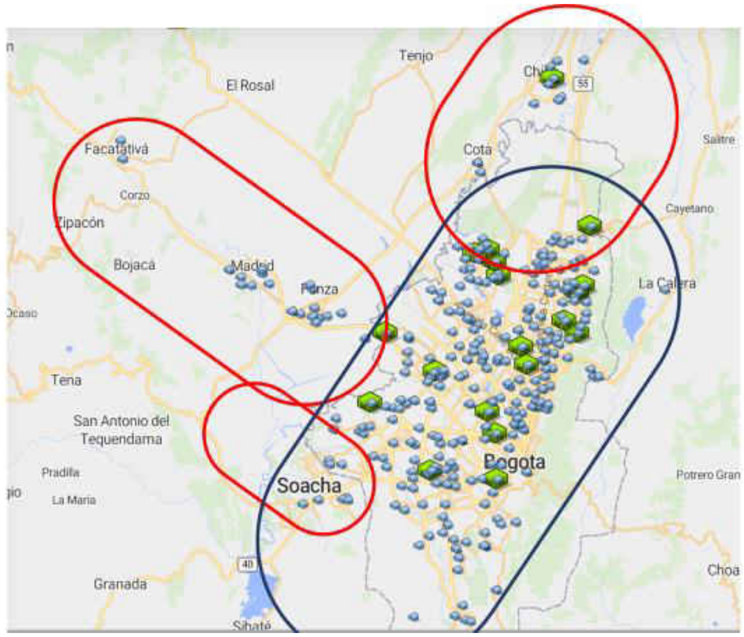


Figure 63: Bogota and suburbs demand clusters

After this division is defined, it is necessary to plan the number of resources to serve the demand in the city. An optimization model is applied to define the number of vehicles of different characteristics and the routes to fulfill the demand of the customers.

Phase 1: Mixed Integer Programming model to identify the number of vehicles to use (equations 19-26).

Figures 64 and 65 depict the result of the model. Identifying the number of vehicles.

```
---- VAR y  if vehicle k is used

          LOWER      LEVEL      UPPER

K01         .          .        1.000
K02         .          .        1.000
K03         .          .        1.000
K04         .        1.000      1.000
K05         .        1.000      1.000
K06         .        1.000      1.000
K07         .        1.000      1.000
K08         .        1.000      1.000
K09         .        1.000      1.000
K10         .        1.000      1.000
K11         .        1.000      1.000
K12         .        1.000      1.000
K13         .        1.000      1.000
K14         .        1.000      1.000
K15         .        1.000      1.000
K16         .        1.000      1.000
K17         .        1.000      1.000
K18         .        1.000      1.000
K19         .        1.000      1.000
K20         .        1.000      1.000
```

Figure 64: Vehicles to be used.

```
G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m
Model Statistics    SOLVE marcerut Using MIP From line 537


MODEL STATISTICS

BLOCKS OF EQUATIONS           6     SINGLE EQUATIONS        7,117
BLOCKS OF VARIABLES           3     SINGLE VARIABLES        6,741
NON ZERO ELEMENTS        40,261     DISCRETE VARIABLES      6,740


GENERATION TIME      =        0.234 SECONDS     13 MB  24.1.3 r41464 WEX-WEI


EXECUTION TIME       =        0.390 SECONDS     13 MB  24.1.3 r41464 WEX-WEI
```

Figure 65: Model statistics.

Phase 2: Allocate customers to vehicles.

Once we know the type and quantity of vehicles, an assignation model serves to do the allocation of customers to each vehicle. For this is step os follow the algorithm K-means, which outputs the cluster centers for the number of vehicles. The clustering uses the Euclidean distance. Figure 66 shows the location of the customer in a cartesian plane. The color represents the assignation of the cluster. Figure 67a shows the initial nodes, which are known as the "centroids" described in Tabl8 15, to do the assignation. Figure 67b shows the correspondent customer to each of the clusters for each of the "centroids".

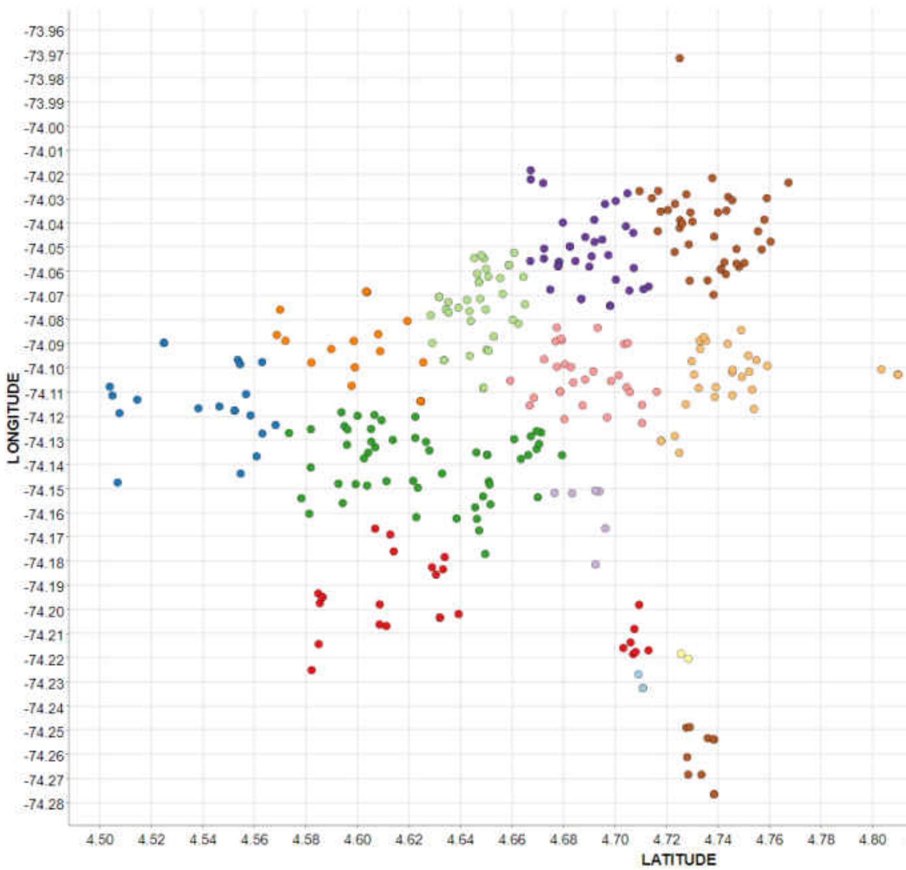


Figure 66: Longitude and latitude customers in Bogota.

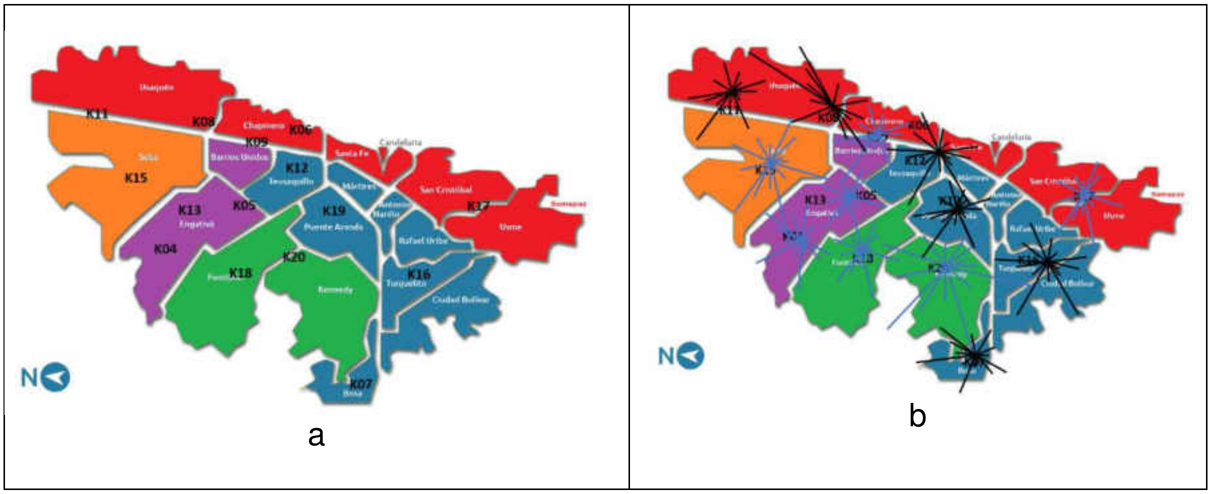


Figure 67: Customer allocation in vehicles.

Table 18: Centroid allocation.

Clusters - 0:2 - k-Means

File Hilite Navigation View

Table "default" - Rows: 17 | Spec - Columns: 2 | Prop

Row ID	D LATITUDE	D LONGIT...
cluster_0	4.656	-74.144
cluster_1	4.609	-74.194
cluster_2	4.689	-74.159
cluster_3	4.71	-74.231
cluster_4	4.727	-74.219
cluster_5	4.603	-74.136
cluster_6	4.708	-74.213
cluster_7	4.734	-74.261
cluster_8	4.907	-74.037
cluster_9	4.818	-74.352
cluster_10	4.737	-74.041
cluster_11	4.689	-74.052
cluster_12	4.541	-74.114
cluster_13	4.604	-74.092
cluster_14	4.647	-74.075
cluster_15	4.748	-74.105
cluster_16	4.688	-74.104

Once the vehicles are assigned to their customers, we use google maps to locate the customers in their longitude and latitude in the map (Figure 68).

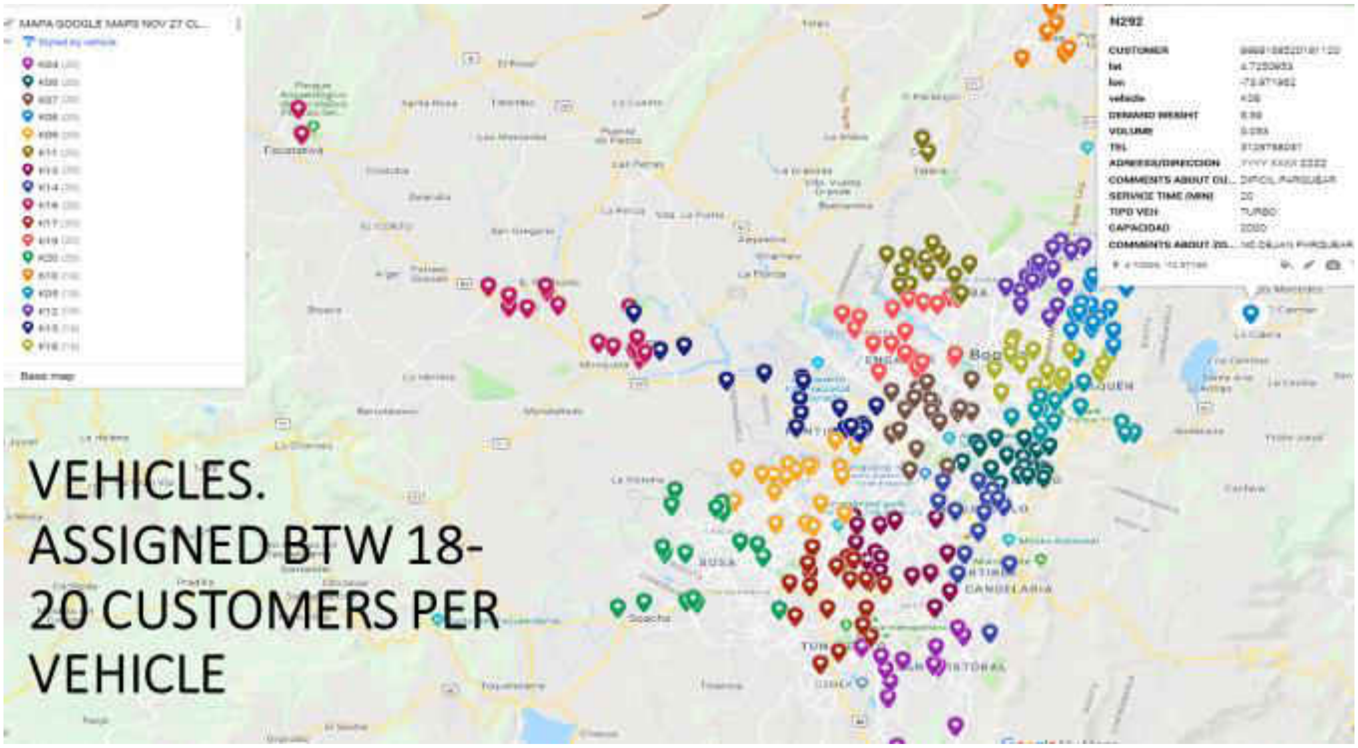


Figure 68: Vehicle allocation.

Figure 69 identifies the capacity utilization in volume, weight, and time. Verifying the constraints for each of those.

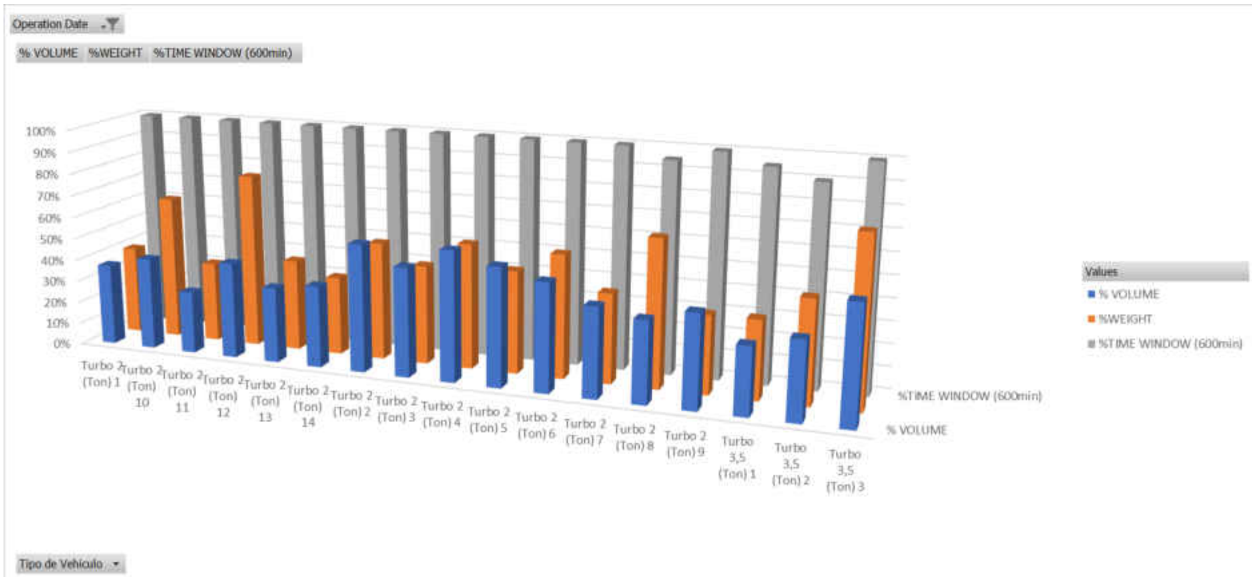


Figure 69: Capacity utilization.

Even the volume and weight have the unutilized capacity; the time window is full in almost all cases. Lastly is a tendency for industries to have smaller vehicles, due to the traffic conditions and their utilization. Table 19 shows the capacity utilization.

Table 19: Locality average velocity.

VEHICLE TYPE	% VOLUME	%WEIGHT	%TIME WINDOW (600min)
Turbo 2 (Ton) 1	37%	40%	100%
Turbo 2 (Ton) 10	42%	65%	100%
Turbo 2 (Ton) 11	28%	36%	100%
Turbo 2 (Ton) 12	43%	79%	100%
Turbo 2 (Ton) 13	34%	41%	100%
Turbo 2 (Ton) 14	37%	35%	100%
Turbo 2 (Ton) 2	58%	53%	100%
Turbo 2 (Ton) 3	49%	45%	100%
Turbo 2 (Ton) 4	59%	56%	100%
Turbo 2 (Ton) 5	53%	46%	100%
Turbo 2 (Ton) 6	49%	55%	100%
Turbo 2 (Ton) 7	40%	40%	100%
Turbo 2 (Ton) 8	37%	66%	95%
Turbo 2 (Ton) 9	42%	35%	100%
Turbo 3,5 (Ton) 1	30%	35%	95%
Turbo 3,5 (Ton) 2	35%	46%	90%
Turbo 3,5 (Ton) 3	53%	76%	100%

Use the formulation for the travel salesman problem for each of the vehicles and the notation in chapter 3.

$$Min \sum_{i,j \in A} X_{i,j} * d_{i,j} \tag{45}$$

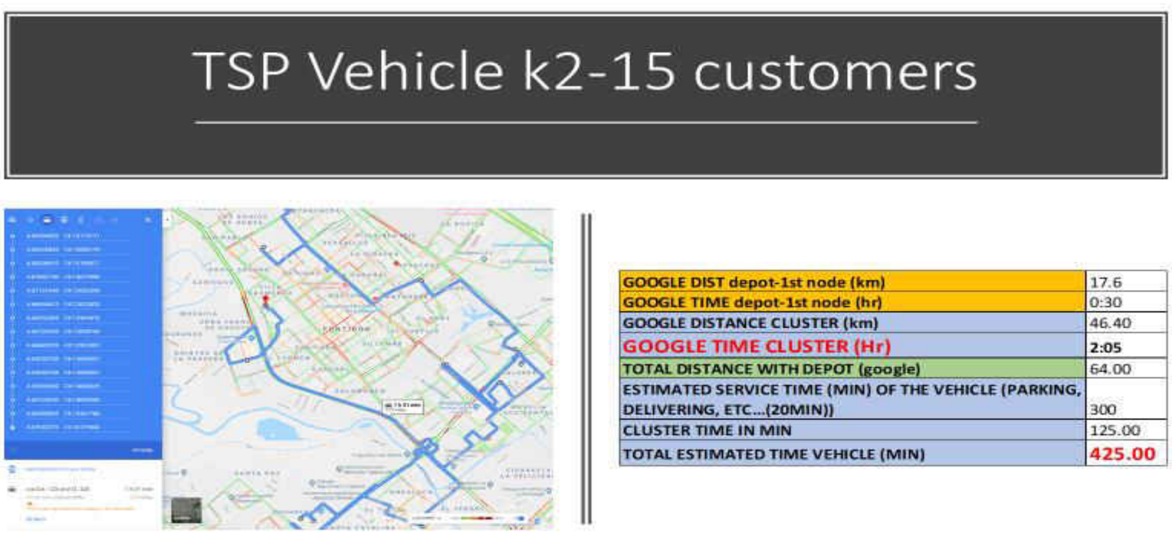
$subject\ to$:

$$\sum_j X_{i,j} = 1 \ \forall i \tag{46}$$

$$\sum_i X_{i,j} = 1 \ \forall j \tag{47}$$

$$U_{i,k} - U_{j,k} + |N| * X_{i,j,k} \leq |N| - 1 \tag{48}$$

A verification process is made to verify the model assumptions. The route meets the constraints in service and travel time (Figure 70)



GOOGLE DIST depot-1st node (km)	17.6
GOOGLE TIME depot-1st node (hr)	0:30
GOOGLE DISTANCE CLUSTER (km)	46.40
GOOGLE TIME CLUSTER (Hr)	2:05
TOTAL DISTANCE WITH DEPOT (google)	64.00
ESTIMATED SERVICE TIME (MIN) OF THE VEHICLE (PARKING, DELIVERING, ETC...(20MIN))	300
CLUSTER TIME IN MIN	125.00
TOTAL ESTIMATED TIME VEHICLE (MIN)	425.00

Figure 70: Google maps verification.

Table 20 has the routes in google maps, which were used to verify velocities, time, and routing directions.

Table 20: District average velocity

Vehicle	The route in Google Maps. Link	Average Velocity (km/h)	Main Locality
K04	https://bit.ly/2VnGe2e	19.29	Engativa
K05	https://bit.ly/2VELunf	19.84	Engativa / Teusaquillo
K06	https://bit.ly/2W4KGHk	23.83	Usaquen
K07	https://bit.ly/2LGE5iB	17.17	Bosa
K08	https://bit.ly/2VXGc5v	17.88	Chapinero / Usaquen
K09	https://bit.ly/2W3eC6N	15.21	Chapinero / Barrios unidos
K10	https://bit.ly/2Ynewob	21.10	Madrid / El Corzo / Facatativa
K11	https://bit.ly/2Q4rpQX	18.20	Suba / Usaquen
K12	https://bit.ly/30kC6Uv	19.89	Teusaquillo
K13	https://bit.ly/2VxGKQ1	16.31	Suba / Engativa
K14	https://bit.ly/2Q0Hl6U	26.79	Chia / Canelon / La Naveta
K15	https://bit.ly/2JqUSH1	17.45	Suba
K16	https://bit.ly/2YqltDS	17.17	Tunjuelito /Ciudad Bolivar
K17	https://bit.ly/2YtnNep	20.18	Usme / San Cristobal
K18	https://bit.ly/2Hh8wHC	18.29	Fontibon
K19	https://bit.ly/2PYINrB	19.81	Puente Artanda / Antonio Narino
K20	https://bit.ly/2vYcfDz	19.29	Kenedy / Fontibon

4.2.4 Step 4: Simulation and Experiments

Simulation assumptions and parameters to recreate the routes execution and the scheduling for each of the vehicles are:

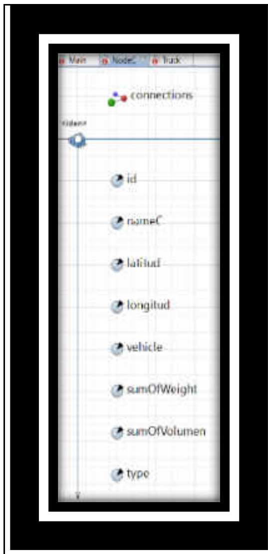
- Total service time: It is dependent on the parking time plus the delivery time. Varies depending on the type of customer (nanostore, townhouse or building).
- Time window per day to do deliveries: 600min
- Vehicle Velocity: It varies depending on the locality of the city (e.g., 30km/h for the

valley in the locality Engativa)

The vehicles already have an “optimal” route, which was set up with the help of better knowledge of the customers, drivers, and the city grid. However, due to the variance in velocity and service times, it is necessary to simulate the solution. Localities were defined with “urban metrics” (Merchan et al., 2015) which have into account metrics such as density, land use, complexity, road network,and the clusters procedure.

An agent-based model of last-mile delivery was built where each stakeholder is an agent, to help understand how the last-mile delivery task is executed under environmental city conditions. Since uncertainties in driver behavior, traffic, parking time include stochasticity, agent-based modeling is a useful tool for modeling last-mile simulations.

First, we create a population of customers with their parameters. For this simulation, we are considering three types of customers: Town Houses, Buildings, and Nanostores (i.e., mom and pop stores).



Name	Latitud	Longitud	Vehicle	Sum of Weight	Sum of Volumen	type
N01	4.709352	-74.198120	K18	92.4	0.314	town_house
N02	4.703184	-74.215988	K20	6.5	0.162	nanostore
N03	4.710766	-74.232552	K10	76.2	0.285	town_house
N04	4.710766	-74.232552	K10	42.5	1.191	town_house
N05	4.728393	-74.220398	K10	54.03	0.221	town_house
N06	4.696234	-74.166496	K18	732	0.48	Building
N07	4.725585	-74.218353	K10	70.6	0.361	town_house
N08	4.738458	-74.253876	K10	106.195	0.343	Building
N09	4.713043	-74.066406	K04	32.2	0.088	town_house
N10	4.824690	-74.352470	K10	46.5	0.195	Building
N11	4.704219	-74.041473	K06	1312.67	0.708	town_house

Figure 71: Customer data.

Figure 71 depicts the data for customers. Location in latitude and longitude, vehicle assigned, demand in weight and volume and their type. Table 21 is an example of the service time, depending on the kind of customer.

Table 21: Time customers' parameters.

Cust. type	service time mean (minutes)	service time std dev	parking time mean (minutes)	parking time std dev
Building	10	3	5	3
town_house	8	3	3	1
nanostore	11	3	4	1
default	10	3	4	2

The agent driver is representing through a vehicle and is modeled through a state chart in Anylogic (www.anylogic.com). Figure 72 shows the state chart.

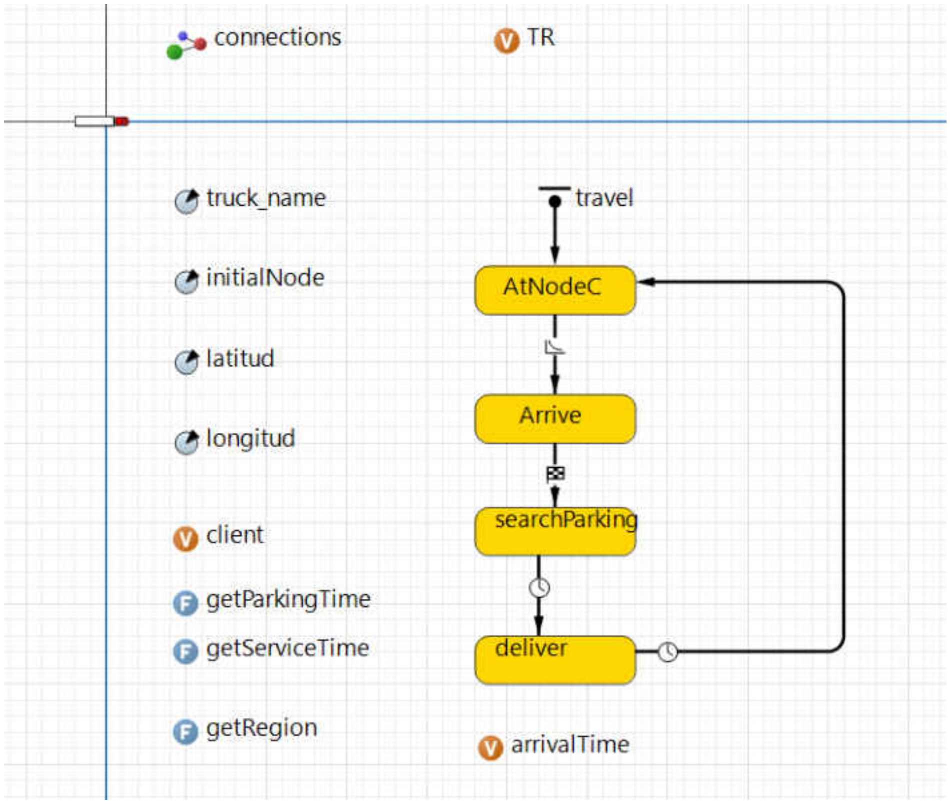


Figure 72: Vehicle state chart.

A GIS (Geographic Information System) is utilized. To represent the change in velocity in the city due to the peak and valley hours, we set up schedules in the simulation model. For example, for peak hours (6:00h to 10:00h and 15:00h to 18:00h) the average velocity is between 14km/h to 18km/h, and 10:00h to 15:00h the average is 22km/h. Table 22 depicts the velocity for each of localities in Bogota city.

On a map, we place the customers, the routes from the optimization models, and regions (localities). Figure 73 shows two shaded areas (Engativa and Fontibon) each one with their respective characteristics (traffic velocity, parking time).

Table 22: Velocity in each locality.

id	Name	normal speed	peak speed
1	Usaquén	20.00	14.00
2	Chapinero	17.00	11.90
3	Santa Fe	19.89	13.92
4	San Cristóbal	25.00	17.50
5	Usme	25.00	17.50
6	Tunjuelito	25.00	17.50
7	Bosa	23.00	16.10
8	Kennedy	25.00	17.50
9	Fontibón	20.00	14.00
10	Engativá	25.00	17.50
11	Suba	25.00	17.50
12	Barrios Unidos	20.00	14.00
13	Teusaquillo	25.00	17.50
14	Los Mártires	19.81	13.87
15	Antonio Nariño	20.00	14.00
16	Puente Aranda	25.00	17.50
17	La Candelaria	19.89	13.92
18	Rafael Uribe Uribe	17.17	12.02
19	Ciudad Bolívar	17.17	12.02
20	Sumapaz	19.81	13.87

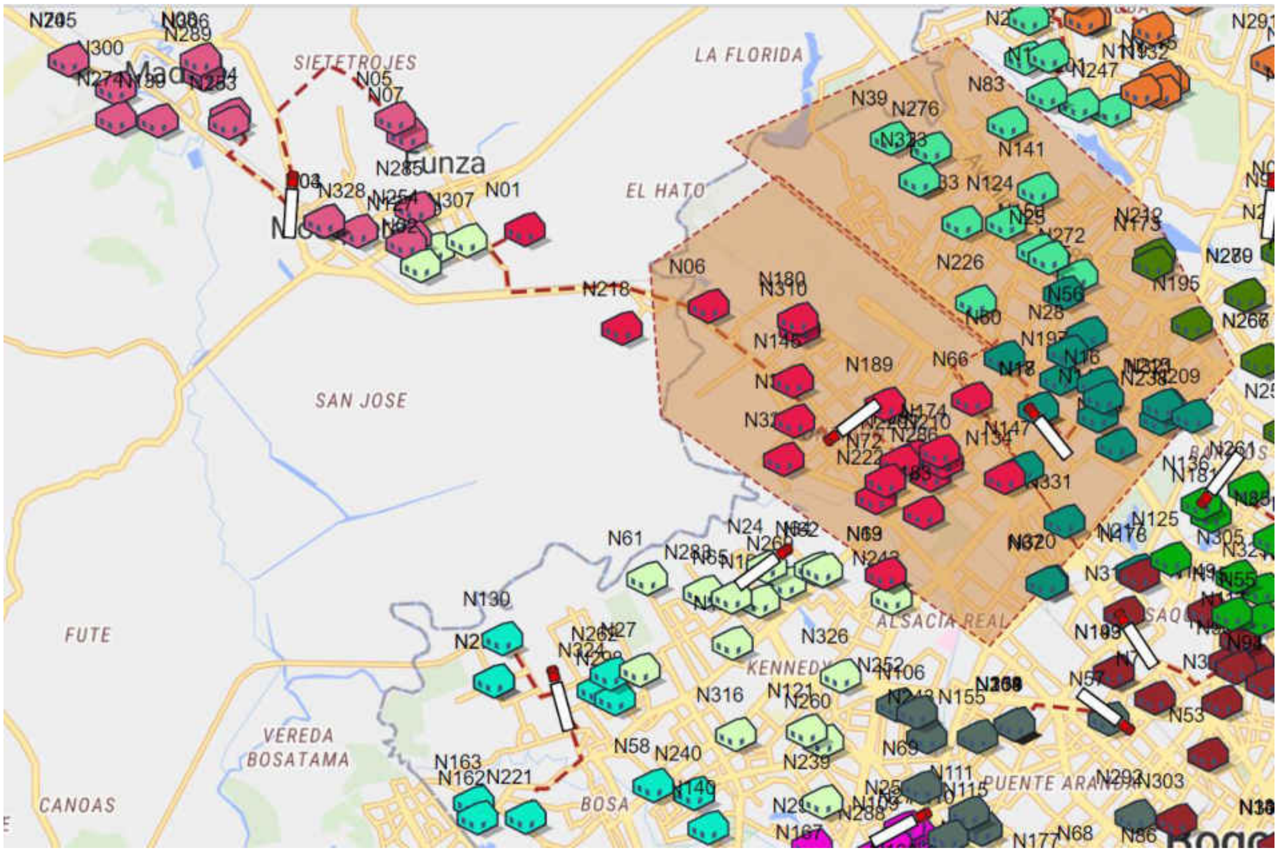


Figure 73: Regions (Localities) in the city.

Once all the steps are solved is possible to simulate the solution. Figure 74 depicts the animation of the delivery process for a day. Each of the colors means a different vehicle; the lines in red are the paths that are followed by each of the cars. With these paths, it is possible to know what the directions are for each of the vehicles to do the deliveries.

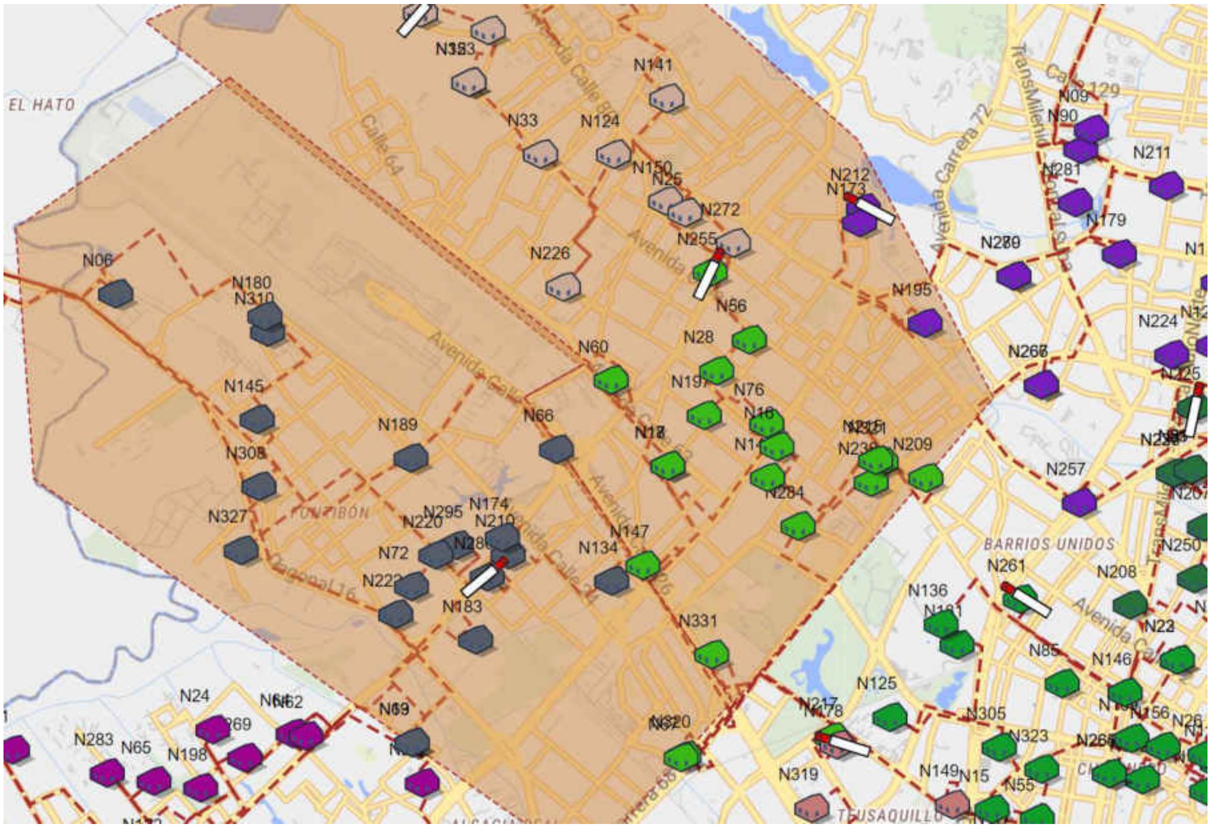


Figure 74: Home delivery simulation.

Figure 75 is a screenshot of the main class in the simulator software, where are all the agents, parameters, functions, and variables.

Figure 75: Main class simulation.

Figure 76 depicts the average velocity of vehicles in the city.

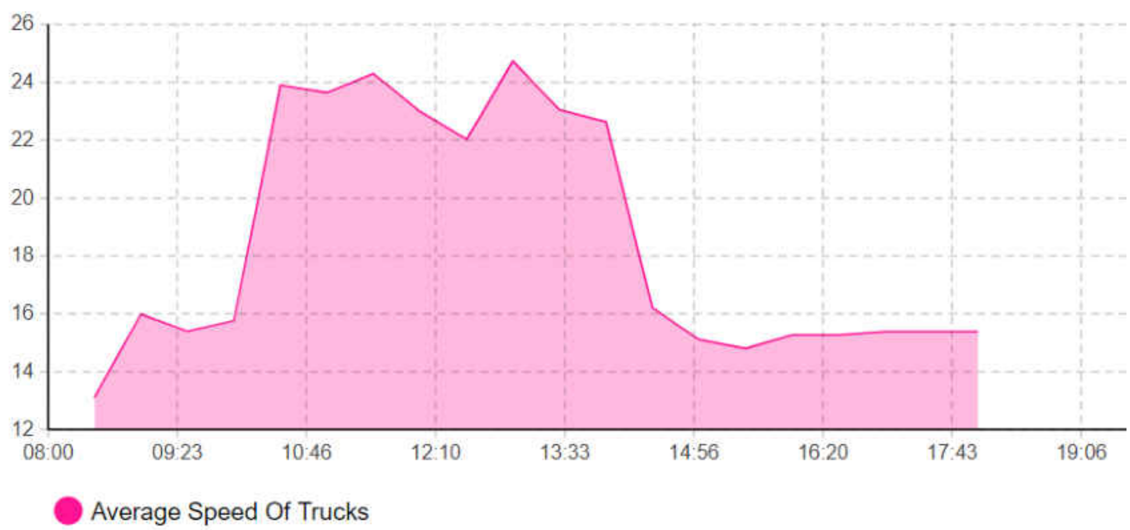


Figure 76: Average speed of all vehicles in the city.

The simulation helps to have clarity of the schedule for each of the vehicles under the simulated conditions (e.g., traffic, service times). For all customers, the schedule is shown in Appendix 1. Table 23 depicts the time for vehicles in the district of Usaquen, showing the arrival and departure time and the service time (parking + delivery).

Table 23: Sample vehicle indicators.

Vehicle Name	Zone Name	Customer ID	Arrival Time	Departure Time	Service Time
K06	Usaquén	186	8:53:59	9:10:33	0:16
K06	Usaquén	161	9:15:04	9:29:11	0:14
K06	Usaquén	84	9:34:59	9:50:41	0:15
K06	Usaquén	88	9:54:16	10:14:22	0:20
K06	Usaquén	131	10:17:23	10:39:00	0:21
K06	Usaquén	29	10:43:30	10:57:30	0:14
K06	Usaquén	81	10:59:56	11:13:48	0:13
K06	Usaquén	237	11:15:57	11:26:44	0:10
K06	Usaquén	202	11:28:05	11:42:08	0:14
K06	Usaquén	42	11:45:31	12:04:01	0:18
K06	Usaquén	11	12:10:00	12:19:34	0:09
K06	Usaquén	282	12:26:54	12:45:15	0:18
K06	Usaquén	223	12:49:31	13:02:11	0:12
K06	Usaquén	229	13:04:02	13:19:25	0:15
K06	Usaquén	256	13:23:31	13:38:27	0:14
K06	Usaquén	334	13:40:49	13:54:59	0:14
K06	Usaquén	107	17:01:44	17:18:29	0:16
K06	Usaquén	271	17:33:29	17:48:05	0:14

Now we can check the total simulated time for each of the vehicles to verify if the assumption about the maximum number of customers per vehicle is accurate and to find out if some adjustments are necessary. The daily time window is from 8:00 to 18:00h.

Table 24: Vehicle indicators.

Vehicle	Number of Customers	Average of Service Time (min)	Start Time (hr)	End Time (hr)	Total operation hous	Total operation min	% Utilization Time window
K04	19	13.5	8:20	15:31	7:11	431.1	72%
K05	20	15.5	8:14	15:00	6:45	405.8	68%
K06	20	12.3	8:13	17:48	9:34	574.2	96%
K07	20	12.9	8:17	15:50	7:33	453.0	76%
K08	20	15.0	8:07	15:35	7:28	448.4	75%
K09	20	13.2	8:16	15:32	7:15	436.0	73%
K10	20	13.1	8:28	16:35	8:06	486.2	81%
K11	20	14.8	8:04	14:49	6:45	405.3	68%
K12	20	15.0	8:10	15:49	7:38	459.0	76%
K13	20	14.7	8:17	15:42	7:24	444.2	74%
K14	19	13.9	8:18	16:19	8:01	481.2	80%
K15	18	12.9	8:44	15:42	6:58	418.0	70%
K16	20	14.7	8:08	15:41	7:33	453.1	76%
K17	20	13.3	8:03	16:08	8:05	485.1	81%
K18	20	13.8	8:42	15:55	7:13	433.1	72%
K19	20	13.0	8:07	15:43	7:35	455.9	76%
K20	20	14.4	8:07	16:43	8:36	516.0	86%

One of the significant advantages of the simulation process is to verify the assumptions in the optimization model. For example, after the analysis of these results, it is interesting to notice the time utilization percentages. Some transportation managers are minded leaving some time gap in case of incidentals events (accidents, unions) in the execution. It is expected to improve the parameter utilization with the experience in the operation execution. To the extent that the actual operation is compared with the results of the optimization and simulation models, the parameters can be calibrated.

4.2.5 Step 5: Learning

The methodology is proposing a playground where the agents learn in a simulation environment. As it was shown in the previous section, environmental conditions affect the time of the delivery. Different circumstances were simulated to do trial and error tests and to learn from the assumptions and results. Once the decision maker has had into account different “emergent behaviors” the same simulation environment can be used to test the outputs of the learning algorithms and explore their capability to be used by transportation managers. This part of the methodology is proposing three machine learning techniques: reinforcement learning, neural networks, and deep reinforcement learning.

The reinforcement learning approach is to recreate as an illustrative example with the shortest path route; for this, we will use a grid with nine nodes (that can represent neighborhoods in the city, or a specific type or nodes) and 18 edges representing the possible paths between nodes. The grid structure allows the vehicle (agent) to adjust the path to the road conditions (e.g., traffic density, velocity, and flow) and learn through the use of rewards what the best path is. The goal of the vehicle is to go from an origin node to a destination node.

Then we train an artificial neural network to be able to control the decisions to find routes in the city. As it was explained, once the assignation of resources is made, the problem becomes finding more efficient customer visiting sequences. It does this by learning a policy (i.e., actions) that decides the best route between one point to another or the sequence of visiting “nodes” in a geographical space based on the current status of the environment. Deep reinforcement learning and its respective architecture can learn from simulations to support exploration and optimization.

4.2.5.1 Reinforcement Learning

Nodes and edges are superimposed in the grid (Figure 77). It is assumed that each node represents an aggregate demand for a zone in the city (Neighborhood) instead of a singular customer. In Bogota is calculated around 40,000 Nano stores. Most of the time, these Nano stores are very close to each other in the localities. With these characteristics make sense to create groups of demand and customers. The proposed algorithm uses reinforcement learning to find the next node to be visited, as discussed in chapter 3. This methodology helps to exploit the temporal structure of the problem in terms of current and future states, actions, and rewards. Therefore, on the way to find the route between two nodes for each state, the algorithm chooses the minimum future weight in the edges as a substitute of maximum future reward. Furthermore, with this methodology, it is possible to find multiple paths.

During the execution process, travel time plays a vital role in delivery tasks, besides customer service and parking time. Therefore, it is essential to include information about the current situation (from traffic and weather information systems) to determine travel times during the operation. In consequence, the sequence can be updated with this information, identifying the best path between nodes or between an origin node (i.e., depot) and a destination node.

Table 25 depicts the traffic indicators to find the travel time for each edge. The records represent hourly counts collected on one day for street segments. The traffic flow follows a normal distribution. These indicators are used to find out the travel time in the arcs of the network, described in the last row of the table.

Table 25: Indicators for last-mile deliveries.

Indicator		**Units**	**a1 -a2**	**a1 -a3**	**a1 -a4**	**a2 -a8**	**a3 -a4**	**a3 -a6**	**a4 -a5**	**a4 -a9**	**a5 -a3**	**a5 -a6**	**a5 -a7**	**a5 -a9**	**a6 -a2**	**a6 -a8**	**a7 -a6**	**a7 -a8**	**a7 -a9**	**a9 -a8**
Route Longitude	***L***	km	14	10	5	8	8	5	3	15	4	3	6	11	7	12	8	7	6	4
#lanes	***Ln***	NA	2	2	3	2	2	1	1	3	2	1	2	3	3	1	1	1	2	2
Free Speed	***Uf***	(km/h)	45	60	60	45	45	60	60	45	45	60	60	45	45	60	60	45	45	45
Traffic Flow	***q***	vh/h	623	655	612	573	544	628	532	543	612	522	556	631	571	535	536	691	535	571
Traffic jam	***K***	Veh/Km/lane	28	22	20	25	24	21	18	24	27	17	19	28	25	18	18	31	24	25
Traffic density	***Kj***	Veh/Km/lane	55	44	41	51	48	42	35	48	54	35	37	56	51	36	36	61	48	51
Speed	***U***	(Km/h)	34	45	45	34	34	45	45	34	34	45	45	34	34	45	45	34	34	34
Total travel Time		min	25	13	6	15	14	7	5	26	6	4	7	19	12	15	11	12	10	7

Traffic speed, flow, and density are defined for a given period to mimic possible changes in traffic during the day to find the traffic time per edge. These times can change dynamically depending on the environment during the traffic simulation. We will find the route(s) to go from one node to another. Figure 78 shows the same grid under different conditions. The calculations showed in Table 25, allows to derive the total travel time for each segment and the shortest route from node 1 to node 9 (Figure 78a). Figure 78b and 78c are other scenarios where calculations on some segments changed, representing how possible anomalies can do variations between zones and their consequences in the travel times.

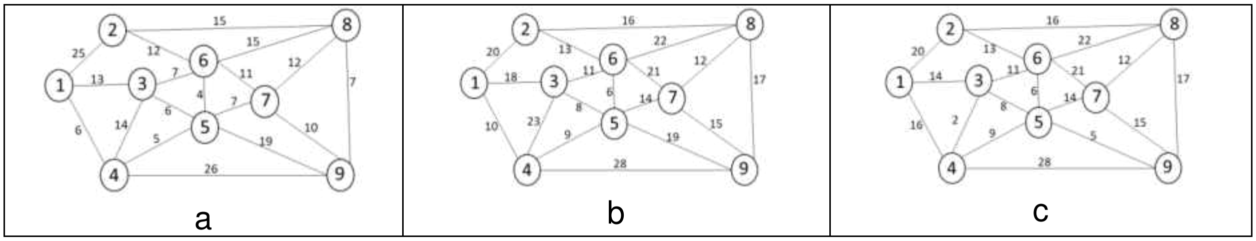


Figure 77: Grid representation with total travel time per edge different time slots.

Conditions on routes can change (dynamic environment. With the information from the environment, the agent will try to avoid congested roads to find a lower time in the route. Figure 78 depicts changes values on routes 1-3, 1-4, 3-4, 3-5, and 5-9.

Table 26 depicts the parameters used during the simulation and the RL algorithm, along with the number of possible routes and the ETA for each scenario. Figure 78 shows the grid with the routes.

Table 26: Scenarios ETA.

Simulations/Days:	1000		
Learning Rate:	0.7		
Epsilon	0.1		
Grid Scenario	a	b	c
Routes	1	2	1
CPU Time	0.015	0.015	0.015
ETA (min)	28	38	27

The algorithm adjusts the policies as a result of observations, reinforcing the good “actions,” which means shortest times, relative to the bad actions (longer time). The rewards represent the desired goals, which are calculated with performance indicators. By maximizing these indicators, the algorithm will improve the system towards the goals.

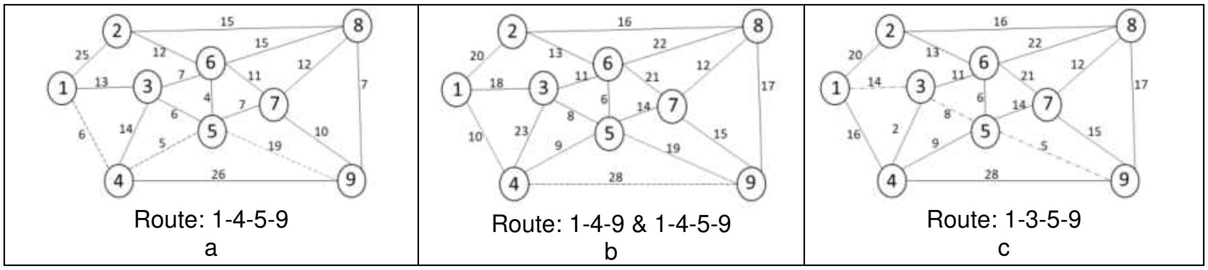


Figure 78: Scenario Routes.

These indicators are continuously calculated due to the learning interaction of the different “agents” (Consumers, Drivers) and the environment (last-mile operations). The uncertainty came from the incorporation of customer demand uncertainty and the real-time flow of information from customers and drivers.

4.2.5.2 Neural Networks

Neural networks are used to define routes of visiting for customers (Traveling Salesman Problem). The objective of this is to establish a tool that outcomes a good and quick solution when transportation companies face routing problems. Neural networks are used to learn from optimal solutions of the TSP.

Given the coordinates of the customers, we defined a grid where customers are located. Slopes, angles, and hypotenuses created from their positions (Figure 79) are used to set up their locations.

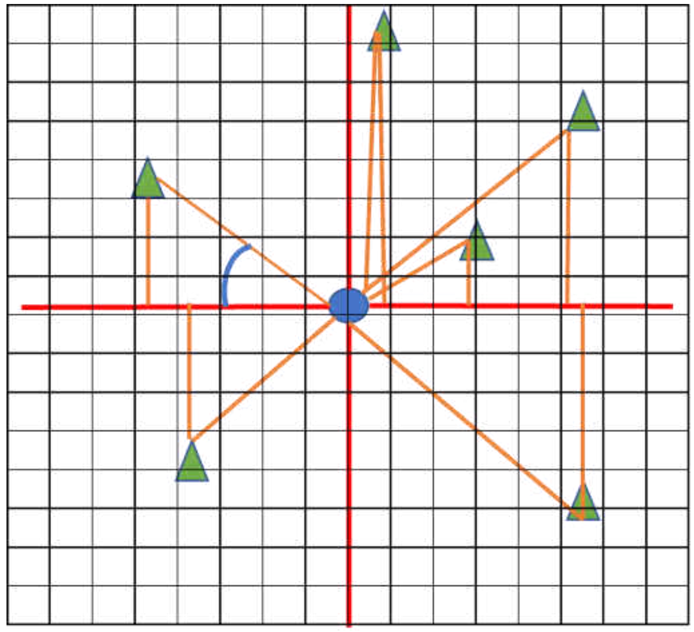


Figure 79: Nodes in a grid with Cartesian coordinates.

Different measures can be extracted from the grid, like coordinates (x,y), quadrant, slopes, angle hypotenuse, among others. The neural network was programmed in Python 3.7. A neural network of five neurons (inputs), one hidden layers with five neurons and one neuron for the output layer was designed. The output neuron is a vector that represents the sequence of visit for customers. An example of 20 vehicles is used to illustrate how neural networks work. Then test with 50, 70, and 100 nodes are discussed. To obtain the optimal solutions, we are using GAMS-CPLEX and equations 27-30 from chapter 3. Figure 80 are cardinal coordinates for 20 nodes.

```
x=[30, 46, 45, 10, 8, 50, 16, 10, 46, 10, 39, 13, 1, 47, 27, 30, 33, 22, 43, 23]
y=[20, 24, 7, 9, 31, 30, 36, 49, 45, 9, 38, 23, 17, 47, 25, 41, 40, 13, 47, 29]
```

Figure 80: Coordinates of 20 nodes.

A grid is created to identify a central point, and from there, calculate the geometric inputs. It is necessary to calculate the distance matrix (Euclidian, Manhattan, Geographical). We are using Euclidian distances. Figure 81 is the snapshot of the input values. Each customer has five features.

```
input
[[0.03446505146500207, 0.95, 0.8329081415441687, 0.4285277034855043, 0.731292567040338],
[0.03898956518868466, 0.55, 0.5256140684467968, 0.4852444235449945, 0.058895499499136646],
[0.12210659256663896, 0.8, 0.7778036871864629, 0.5650863537788684, 0.5556190310379042],
[0.12308256333926366, 1.0, 0.9192005255670906, 0.6453259822308219, 0.8384019154816437],
[0.12678818253937607, 1.0, 0.9494465145241476, 0.6727263202057518, 0.8990007829095054],
[0.14261164373863863, 1.0, 0.9099419140144213, 0.6787652772285188, 0.8231748373798408],
[0.17416785496852, 0.8, 0.7407182582152667, 0.6208313334414897, 0.49831382688756815],
[0.20317111453406034, 0.6, 0.7256908563120464, 0.6516189246911963, 0.49254801826406525],
[0.3165624693738283, 0.55, 0.528710496225116, 0.5659883277827278, 0.14068361385863254],
[0.3374356648599556, 0.2, 0.714355667428935, 0.9035286422385511, 0.820692398562676 7],
[0.35568622925507243, 0.35, 0.5627344554345302, 0.7073231651711667, 0.4171883424044294],
[0.44187638404188573, 0.15, 0.4573193540999116, 0.7456600953247, 0.5199547953292483],
[0.5197917120802827, 0.3, 0.37738563075878157, 0.6223085283918932, 0.345490079778659],
[0.5482056239896147, 0.1, 0.24325212770525995, 0.740855976587418, 0.7183433297242443],
[0.6276088637381544, 0.05, 0.1921750205483284, 0.5856545280968558, 0.6162129703367684],
[0.6276088637381544, 0.05, 0.1921750205483284, 0.5856545280968558, 0.6162129703367684],
[0.7093864611426898, 0.5, 0.3650179648599167, 0.44096497845293275, 0.33953290766683597],
[0.883368854178287, 0.5, 0.515026202624604 7, 0.4040197934145309, 0.1921750205483284],
[0.8855946523174733, 0.85, 0.6505220542555358, 0.1228778230440368, 0.7592186621412048],
[0.9962113124122141, 0.9, 0.7411313365584898, 0.34755096772751615, 0.6001088114623685]]
```

Figure 81: Inputs of the neural network.

Once, the inputs are set, the neural network is ready to make the prediction. Figure 82 are the values of the weights for each of the layers.

```
Values w1
[[0.28803932 0.2740337  0.45721387 0.48434419 0.42207487]
 [0.36859369 0.301598   0.80473312 0.82724669 0.95927542]
 [0.12932425 0.85988855 0.60310581 0.15971601 0.48909108]
 [0.67371835 0.60787217 0.01439159 0.74524397 0.15527053]
 [0.47151776 0.8790307  0.67696473 0.2077457  0.06806722]]
Values W2
[[0.85105938 0.90087974 0.48735208 0.59905126 0.62224859]
 [0.828811   0.01452107 0.54579461 0.66510122 0.52621233]
 [0.92328481 0.18212709 0.03719529 0.13160936 0.89292472]
 [0.91231711 0.62743209 0.81789169 0.68001702 0.66522892]
 [0.83732339 0.98099052 0.93197866 0.07854932 0.23922153]]
Values W3
[[0.95190363]
 [0.51264901]
 [0.60936463]
 [0.16998906]
 [0.37122076]]
```

Figure 82: Weights of the Neural Network.

The network is trained with optimal solutions that were generated by previous step three.. Figures 83 shows the optimal solution in Figure 83a and the Neural Network solution in Figure 83b for this example.

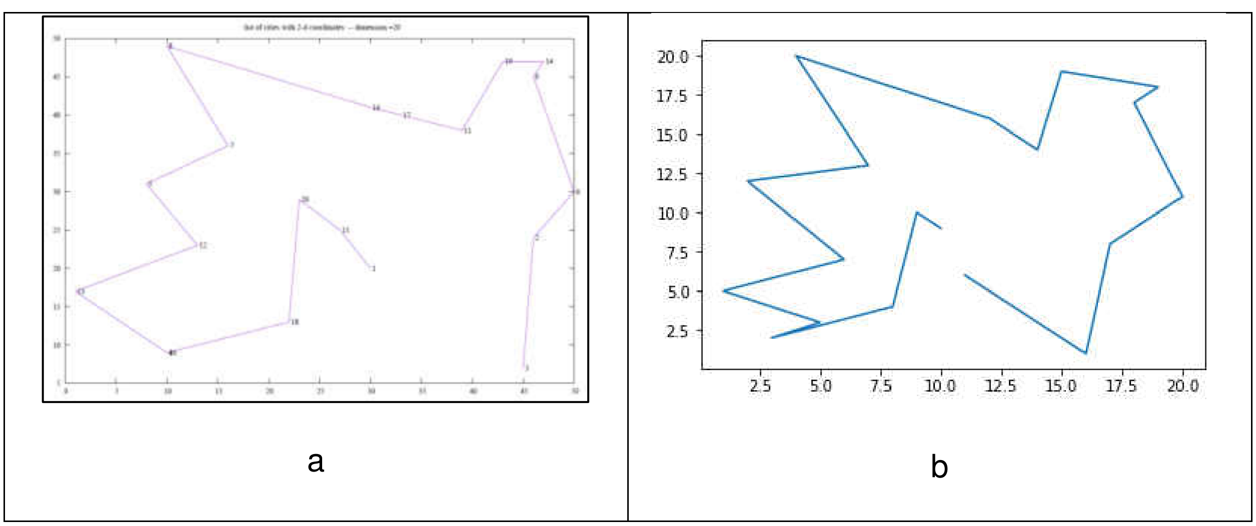


Figure 83: Optimal and trained Neural Network tour

Now, this process is repeated with many instances and their optimal tour, to train the neural network. Once the neural network is prepared, the next step is to put any other instance to find the order.

4.2.5.3 Deep Reinforcement Learning

Delivery Nano stores are a common task in many cities. The transportation of goods is made from CPGs, soft-drinks, or breweries companies and is an everyday logistics task. Customer demands are related to events or market seasons in the year and are regularly considered to be delivered with a frequency to the same places.

The purpose of this example is to demonstrate how these companies, restaurants, or supermarkets can make use of learning procedures to improve their planning delivery fleet and satisfy customer demands. In a city as Bogota, a car can deliver to around 50 to100 mom and pop stores, due to the proximity between them, but a company can deliver to around 1500-2000 mom and pop stores

We use deep reinforcement learning to handle problems where it is necessary to have quick and near-optimal solutions for the vehicle routing problem based on the environmental conditions. These algorithms are very convenient, where it is needed to handle many customers. As it was discussed in chapter 3, the algorithm learns from the environment. For our purpose, geographical information is used as an input to the network and demand distribution as dynamic information. Once the algorithm is trained for the problem, the information is normalized to follow the network structure. Given these inputs like localization x and y (cardinal coordinates) are given by values between [0,1]. The normalization algorithm starts by creating a square grid by calculating the maximum and minimum values for latitude and longitude. The difference between these two values gives the domain and range. The algorithm used for training the vehicles to find the shortest delivery path follows a deep reinforcement learning trained policy. This approach does not need to calculate the distance matrix each time that need to set the routes. It is calculated based on the rewards signals and the feasibility constraints in capacity in vehicles. Also, it is not required to retrain for every new situation.

The points can be rendered on a graph as is depicted in Figure 84.

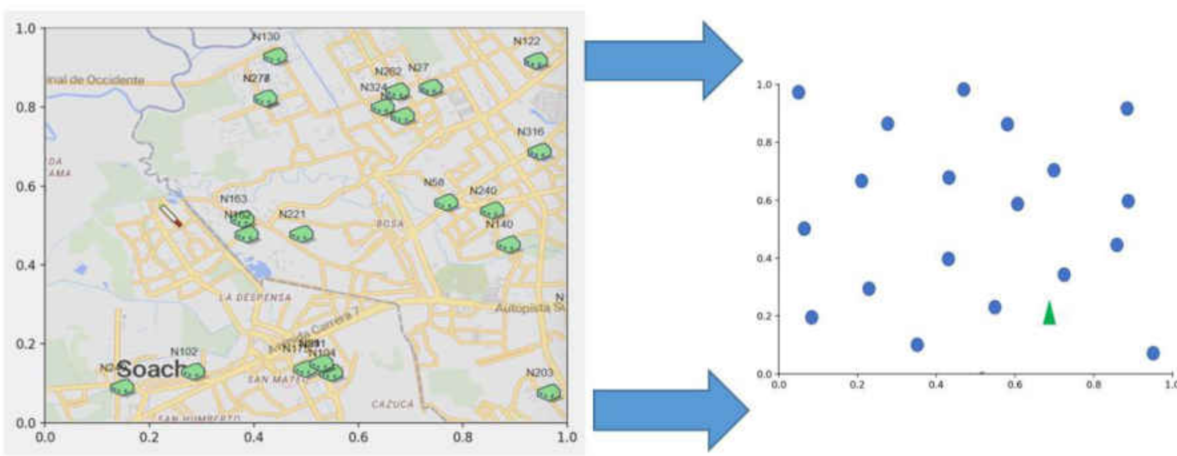


Figure 84: Playground for VRP.

For this model, The VRP has two dynamic elements: the capacity of the vehicle and the demand of the customer. The following assumptions are used for this example: the driver can visit any customer, to fully satisfy requirement (it can be modified for split deliveries).

The output of the test run provides a tour of the nodes to visit and a visualization of the trip. We took different snapshots at different parts of the training to provide better visualization of the learning process. The training method for this experiment makes use of two neural networks, one is the actor-network to predict the probability distribution over the next action at any given step which reduces the problem of choosing a customer from a very specific area. The second network, the critic, provides an estimated reward for any problem instance which helps to take the best decision from the distribution pool of the actor network. Figure 85 depicts the average rewards for each 100 runs over 10 generations.

Figure 85: Rewards in the training phase for 20 nodes.

The first case represents a demand for 20 customers, and a vehicle with capacity of 700 ton. Figure 86 depicts de demand.

Figure 86: Demand 20 customers.

Figures 87 and 89 illustrates 10 generations of training for a sample of 20 and 50 nodes respectively. Figures 88 and 90 display the best solution for each instance.

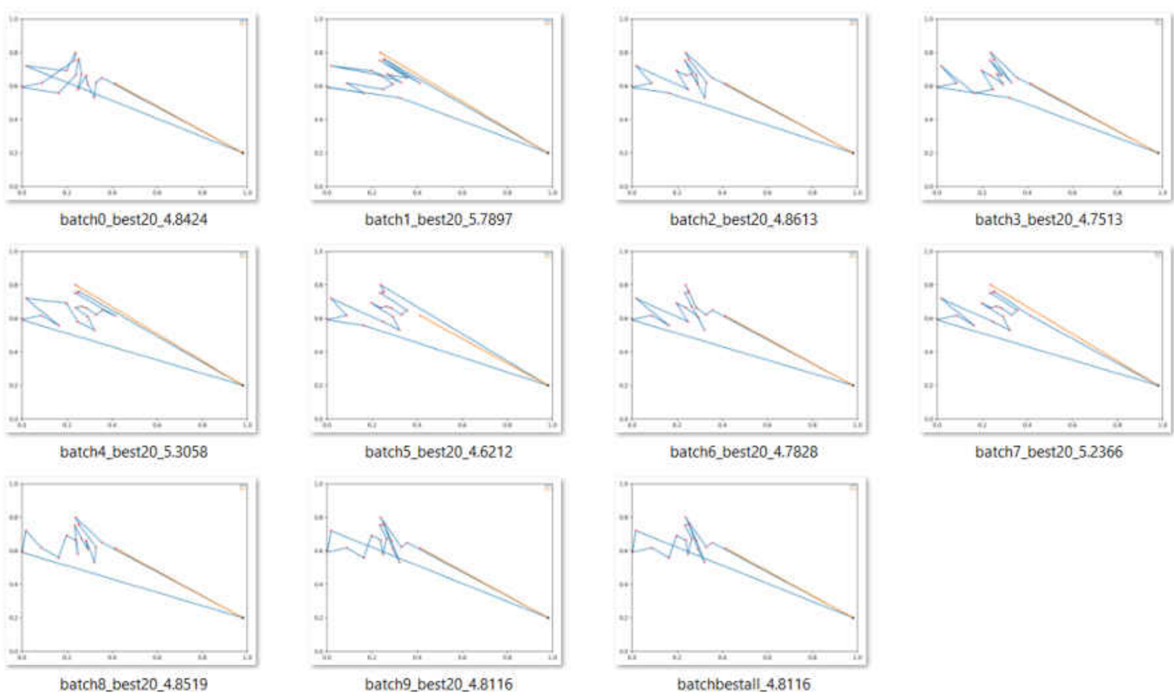


Figure 87: Batch Generations 20 nodes.

The best solution is depicted in Figure 85. Two vehicles are needed for this demand.

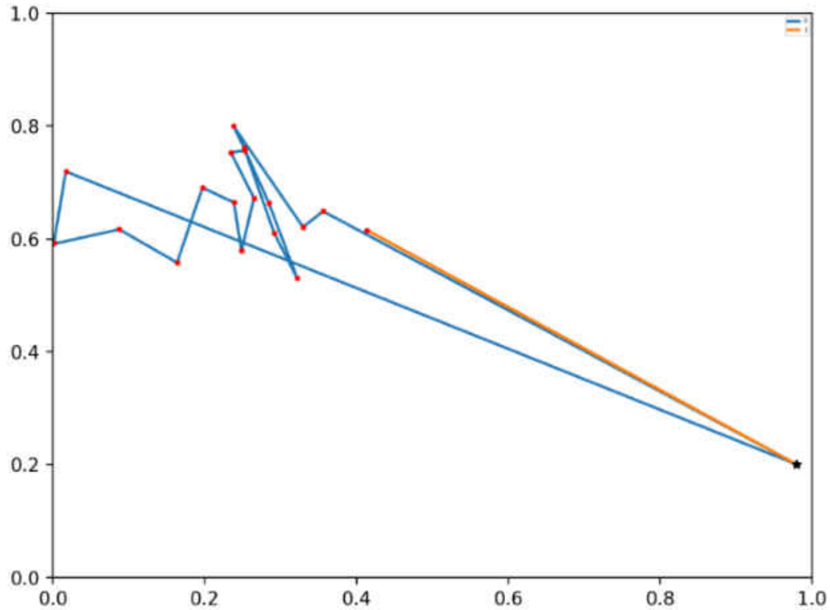


Figure 88: The Best solution.

The sequence for this example is (N00 is the depot):

N217	N320	N67	N331	N147	N284	N142	N17	N18	N16	N238	N215	N197	N60	N76	N321	N209	N28	N56	N00	N255	N00

A greedy policy was used to produce the routes. These solutions are not optimal. However, Figure 89 illustrates how well the policy model has understood the structure and is improving generation to generation. Of course, each of the solutions satisfies demands and propose the use of fewer vehicles. Then following is an instance with 50 customers.

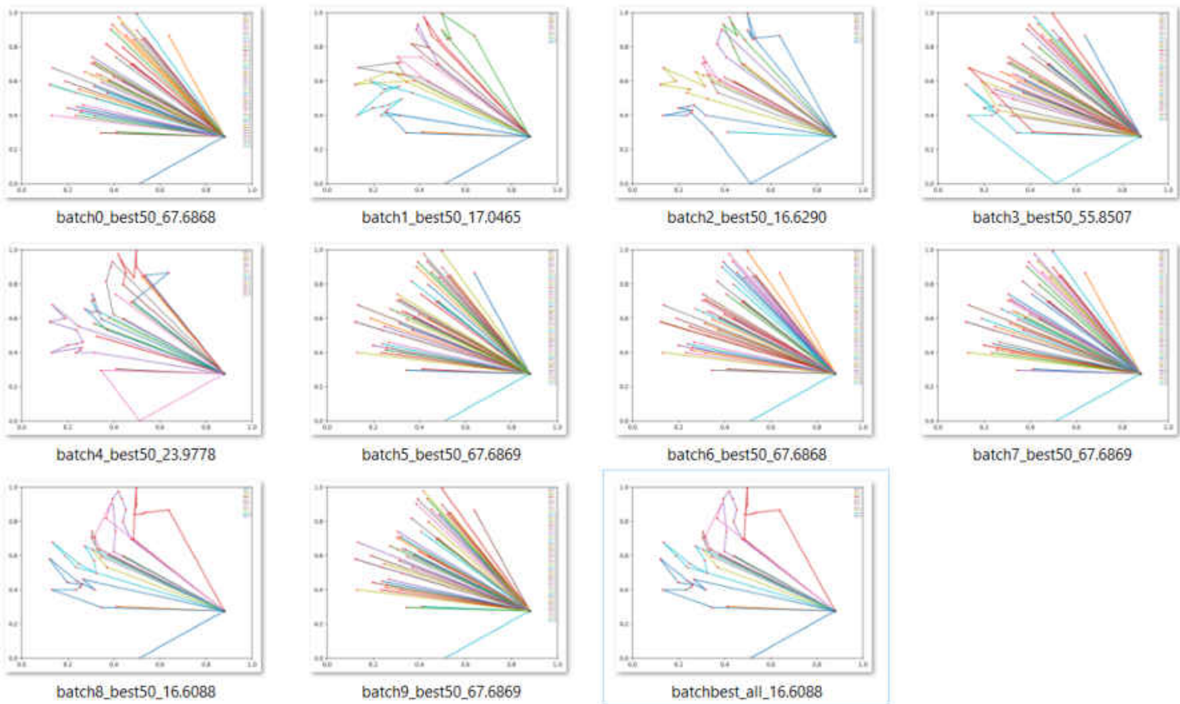


Figure 89: Batch Generations 50 nodes.

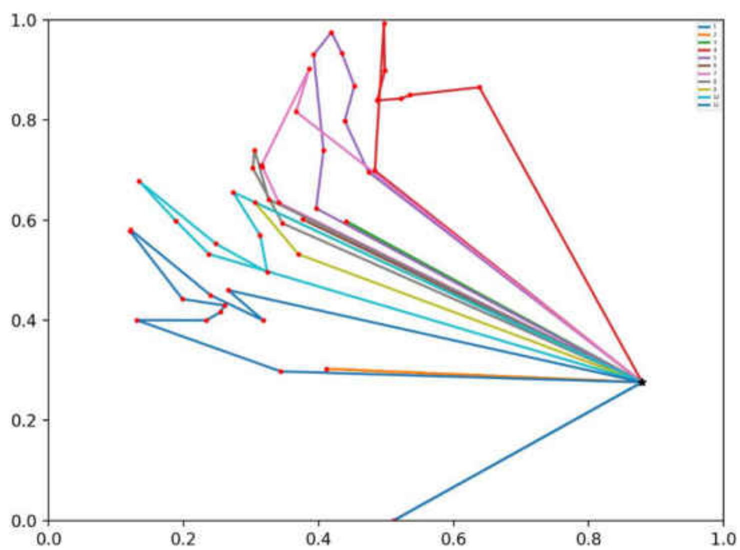


Figure 90: The best solution.

The experiments were conducted on a PC Intel® Core™ i7-7700K CPU @ 4.20GHz CPU 4 cores eight threads with a GeForce GTX 1060 6GB/PCIe/SSE2 graphics card and 16 GB RAM. Operating System Ubuntu 18.04.2 LTS.

4.3 Analysis

Improving operational efficiency is an opportunity for companies facing both commercial B2B and B2C delivery to compete against large logistics multinationals and to improve the customer levels service. The area of last-mile delivery planning has gained popularity because of customers expecting to receive fast and reliable service. Typical problems in vehicle routing are random customer requests and demands. Possible solutions for these issues are accounting for these random occurrences when operational planning or incorporate changes to the plans while vehicles are in their route. Changing while operating can yield a significant amount of information, but it may not reach optimum efficiency. The use of simulations can help successfully anticipate random problems that happen in vehicle routing to tackle them early on. Offline simulations can assist in optimizing the vehicle routing operations.

Building a generic system that integrates metrics, various decision levels, multiple stakeholders, and supplementary techniques is a huge challenge (Anand et al. 2012; Macharis et al. 2014). Furthermore, current proposals have focused on developed, mature environments that possess different characteristics of growth, developing contexts. Despite complex interactions and dynamic behaviors among various stakeholders are present in both cases, the evolution of the latter is more dependent on a set of features related to urbanization, socioeconomic changes, accessibility and retailing footprint (Mejia et al. 2017) and not just technologically driven as the former. These characteristics hinder or boost the performance of planning and execution of urban distribution strategies. (Prahalad 2005). There are just a handful of studies in developing countries that characterize urban logistics operations, but they do not address dynamic decision making. Also, there are no discussions regarding a methodology composed of various complementary methodologies to analyze, tailor urban distribution for these countries to keep profitable operations and improve performance (Schmidt, 2015; Joerss et al. 2016). Most of the studies in urban logistics discuss mathematical models related to the vehicle routing problem (VRP), location problems, inventory models, etc. Ritzinger et al. (2016) present an in-depth review of dynamic and stochastic VRPs without analyzing the difference between emerging economies.

Predictive and prescriptive hybrid techniques must be used to support the delivery process and adjust plans according to changes in critical factors to set potential scenarios and address dynamic behavior and unstable conditions from logistics operations in urban environments. Data analytics might be a first step to understand critic issues, build proper measurement systems, predict the evolution and lead stakeholders to reinvent their strategies, policies embracing technology and a data-driven culture (Hey et al., 2009; Brynjolfsson et al., 2011). This methodology, together with techniques that improve logistics operations through optimization, agent-based modeling, among other methods can leverage a framework for urban freight transport in megacities (Kim et al. 2017; Velasquez et al. 2017).

The methodology makes use of stakeholder behavior patterns. Allowing a better decision-making process and modify routes ahead of time to increase the possibility of meeting the demand within the customer time window. Also, these patterns are combined with the knowledge of traffic conditions. Furthermore, it was possible to propose suboptimal policies for the Dynamic Vehicle Routing Problem DVRP, which is faced by many industries around the world.

CHAPTER 5: CONCLUSIONS AND FUTURE RESEARCH

This research proposes a methodology that supports decision making for the execution of daily last-mile operations. This approach takes into consideration critical factors in the distribution environment, such as sociodemographic diversity, fragmentation, higher congestion factors, and dense areas. The methodology allows to plan any delivery task efficiently with optimization, simulation and machine learning models, supporting delivery processes and proactive, dynamic decision-making during the execution stage.

This research proposed a new perspective to solve the last-mile delivery problems. Explicitly, it shows that optimization, simulation, and Deep Reinforcement Learning methods can be used to build last-mile distribution policies. The data generated by consumers, drivers, and traffic is an opportunity to incorporate that knowledge in the models. Simulations allowed the exploration of the execution in the delivery environment to improve decisions. These improved policies are then used to train the learning models further.

5.1 Summary of Research and Conclusions

A new methodology was developed to serve as a prediction and analytic tool to gain insights into current and future operations between the stakeholders and physical elements in the distribution process. Five main steps compose it. First, we proposed the management of data in having into account how to collect it and use it to improve decisions. Second, is proposed to analyze this data with statistical tools. Third, a modeling phase where optimization models help to find the best solutions under assumptions and constraints of the environment. Four, is proposed the use of simulation techniques to recreate the results of the previous step and add more complexities to the models and calibrate the parameters used in the optimization models. We proposed optimization modeling, combined with simulation and visualization technology for effective goods delivery. Finally, in the fifth step is proposed to have learning procedures, where is created algorithms that can have into account the results of the optimization and simulation models and can learn the best practices and take decisions in a short time. With the learning procedures, was demonstrated a way of adjusting routes responding to possible anomalies in traffic flow.

Our approach contributes to the scientific and practitioners' community by considering learning processes to create effective, proactive last-mile distribution systems to achieve short and long-term goals. The designed methodology set up efficient routes along with information about road traffic, the zone of the city, waiting time of the customer, among other indicators.

The methodology was applied in wo case studies. State of the art analytic techniques to detect and understand the different behaviors of last-mile delivery stakeholders and their dynamic interactions were used.

The first case is in last-mile delivery in maritime logistics, where the main concern is the definition of a specialized fleet of vessels that reaches the remote parts of Western

Alaska as they become accessible during the summer months. This process included a mathematical optimization model that have into account split deliveries and heterogeneous fleet and a simulation model to recreate the proposed routes under different scenarios. Steps one to five of the methodology are used: data collection, data analysis, modeling, simulation, and learning.

The second case study is in urban logistics, it serves to demonstrate an efficient solution to set up routes to deliver orders in a megacity. The methodology can help transportation managers to support peak and valley delivery orders. In general, the case discusses ways to define the correct combination of the type of vehicles that would be used and their quantity, together with the number of orders that each vehicle would carry to have an efficient operation. Finally, and the essential part, to bring a simulation learning methodology to improve the processes.

The research set up the conditions for further research to have better traffic predictions and services time through the analysis of the patterns from data collected from Geographical Positions Systems (GPS), tracking technology, sensors, and experiences from past delivery locations. The methodology also has into account diverse, hybrid, and complementary techniques (e.g., optimization, machine learning, geographic information systems, statistical, dynamic, and stochastic methods) to understand logistics operations. Based on the literature review, interviews with industry experts and last logistics tendencies in last-mile delivery, we meet the requirements of the checklist in chapter three.

5.2 Research Contributions

Potential applications of this system will leverage growing technological trends (e.g., deep reinforcement learning in logistics and supply chain management, virtual simulation, internet of things). One feature is the utilization of self-learning procedures to iteratively test and adjust the gaps between the expected and real performance in last-mile operations. The methodology to understand the behavior of a network of stakeholders during the complex last-mile distribution process, showing the potential benefits of this methodology, especially in maritime logistics and metropolitan areas.

The last-mile delivery research community has been working on better practices to solve issues in operation using different kinds of techniques, from mathematical programming to heuristics. However, there was a lack of a unified framework to build a methodology, and a software architecting, where different approaches can be used in a synchronized form, which allows to researches and other interested people to see the connection between the methodologies and techniques. With this research, it was possible to bring advanced technologies in routing practices and algorithms to decrease operating cost and leverage the use of offline and online information, thanks to connected sensors (in vehicles or phones) to support decisions.

The methodology iteratively tests and adjust gaps between expected (assumptions in the models) and real performance of distribution operations (key performance indicators). This methodology takes advantage of learning procedures that self-adjust to meet the goals of the stakeholders in mutually beneficial situations.

5.3 Directions for Future Research

There are some identified directions for future research, such as:

1. Parallel Distributed Processing to accelerate the speed of solutions: The decomposition of the problem, taking into consideration the response time and the clusters to be used, represents an important area of research. There are many parallel distributed schemes, and the research work has to include the respective selection. To improve the real-life elements and the size of instances and velocity of the solution, it is proposed to use distributed and parallel computing implementations.
2. Learning of delivery/parking process and the velocity of vehicles as a function of the weather and events: Deep learning can contribute to providing the times of the delivery process based on the conditions of the client's area with more detail. This research also is an approach to use more complex hybrid modeling and specifically deep reinforcement learning techniques in dynamic vehicle routing problem. It is proposed to explore other features of the environment and to include more information besides the demand, location, and service time. This aspect will improve the architecture of learning algorithms.

3. Bin packing problem: The delivery process can be complemented with the efficiency in the loading and unloading of products. Define an integrated solution packing-distribution seems to be an interesting research topic. Define how to allocate the merchandise base on the routing, characteristics of the products (beyond weight and volume), and to potentially consider the size of the fleet.
4. Tracking using IoT and the re-scheduling issue: Mobile computing, IoT, and GIS can provide information on the current positions of the vehicles. Therefore, re-scheduling can be optimized. A big problem is when you have hundreds of thousands of clients that have to be monitored and synchronized with customer needs.
5. Study of drivers' behavior and how to model it: Drivers tend to follow their intuition, and sometimes they do not like to be commanded by a computerized system. It is essential to understand the human-machine interface and provide mechanisms for the interactions of decisions and insights from the drivers.
6. Feedback from clients and drivers: One crucial point not considered in this research is the feedback from the drivers and the clients of the system. Social media and text mining can be used to improve the system.
7. Balance Scorecard and Strategy Maps: From management practice, this research proposes the use of these key performance indicators to support other managerial tools like the Balance Score Card and Strategy Maps. Figure 91 depicts how a strategy map can be built from the outputs of this methodology and for each of its

perspectives, thanks to the reinforcement learning approach, the organization can detect the best policies in each decision.

Figure 91: Strategy map based on reinforcement learning rewards.

APPENDIX A: SCHEDULE FOR EACH CUSTOMER CASE B

Vehicle Name	Zone Name	Customer ID	Arrival Time	Departure Time	Service Time
K04	Suba	100	8:20:40	8:34:19	0:13
K04	Suba	9	8:47:39	8:57:51	0:10
K04	Suba	90	9:06:46	9:25:19	0:18
K04	Suba	281	9:36:55	9:52:35	0:15
K04	Suba	179	10:01:18	10:25:34	0:24
K04	Suba	211	10:34:34	10:53:23	0:18
K04	Usaquén	234	11:02:02	11:13:52	0:11
K04	Usaquén	236	11:18:58	11:36:29	0:17
K04	Usaquén	159	11:40:26	11:53:12	0:12
K04	Usaquén	129	11:56:23	12:09:51	0:13
K04	Suba	224	12:13:59	12:30:17	0:16
K04	out	257	12:38:26	12:49:25	0:11
K04	Suba	267	12:58:35	13:10:36	0:12
K04	Suba	266	13:12:59	13:33:32	0:20
K04	Suba	279	13:41:25	13:55:34	0:14
K04	Suba	280	13:55:49	14:15:26	0:19
K04	Engativá	195	14:34:39	14:45:34	0:10
K04	Engativá	173	14:52:57	15:12:07	0:19
K04	Engativá	212	15:13:09	15:31:46	0:18
K05	Engativá	60	8:14:17	8:33:28	0:19
K05	Engativá	18	8:41:25	8:55:26	0:14
K05	Engativá	17	8:55:37	9:17:06	0:21
K05	Engativá	147	9:22:27	9:34:12	0:11
K05	Engativá	331	9:51:58	10:06:14	0:14
K05	Fontibón	67	10:11:30	10:26:21	0:14
K05	out	320	10:26:35	10:41:32	0:14
K05	Teusaquillo	217	10:50:38	11:11:16	0:20
K05	Engativá	284	11:22:48	11:32:18	0:09
K05	Barrios Unidos	209	11:39:10	11:52:01	0:12
K05	Engativá	321	11:59:05	12:10:02	0:10
K05	Engativá	238	12:11:02	12:24:34	0:13
K05	Engativá	215	12:26:46	12:48:23	0:21
K05	Engativá	142	12:53:12	13:12:46	0:19

K05	Engativá	16	13:14:45	13:27:20	0:12
K05	Engativá	76	13:29:52	13:45:22	0:15
K05	Engativá	197	13:48:08	13:59:33	0:11
K05	Engativá	28	14:01:15	14:14:47	0:13
K05	Engativá	56	14:20:10	14:37:43	0:17
K05	Engativá	255	14:43:15	15:00:05	0:16
K06	Suba	165	8:13:53	8:35:09	0:21
K06	Usaquén	186	8:53:59	9:10:33	0:16
K06	Usaquén	161	9:15:04	9:29:11	0:14
K06	Usaquén	84	9:34:59	9:50:41	0:15
K06	Usaquén	88	9:54:16	10:14:22	0:20
K06	Usaquén	131	10:17:23	10:39:00	0:21
K06	Usaquén	29	10:43:30	10:57:30	0:14
K06	Usaquén	81	10:59:56	11:13:48	0:13
K06	Usaquén	237	11:15:57	11:26:44	0:10
K06	Usaquén	202	11:28:05	11:42:08	0:14
K06	Usaquén	42	11:45:31	12:04:01	0:18
K06	Usaquén	11	12:10:00	12:19:34	0:09
K06	Usaquén	282	12:26:54	12:45:15	0:18
K06	Usaquén	223	12:49:31	13:02:11	0:12
K06	Usaquén	229	13:04:02	13:19:25	0:15
K06	Usaquén	256	13:23:31	13:38:27	0:14
K06	Usaquén	334	13:40:49	13:54:59	0:14
K06	out	296	14:46:53	15:07:27	0:20
K06	Usaquén	107	17:01:44	17:18:29	0:16
K06	Usaquén	271	17:33:29	17:48:05	0:14
K07	out	130	8:17:19	8:29:16	0:11
K07	out	277	8:34:39	8:46:30	0:11
K07	out	278	8:49:40	9:05:40	0:16
K07	out	162	9:35:07	9:49:11	0:14
K07	out	163	9:52:43	10:06:16	0:13
K07	out	221	10:13:29	10:30:03	0:16
K07	out	249	10:49:29	10:57:09	0:07
K07	out	102	11:00:09	11:13:17	0:13
K07	out	175	11:19:59	11:46:36	0:26
K07	out	104	11:51:17	12:00:12	0:08
K07	out	59	12:03:48	12:20:32	0:16
K07	out	231	12:20:35	12:32:31	0:11

K07	out	51	12:35:45	12:50:33	0:14
K07	Ciudad Bolívar	203	13:08:01	13:26:36	0:18
K07	Kennedy	140	13:43:51	14:03:16	0:19
K07	Kennedy	240	14:06:55	14:28:30	0:21
K07	Kennedy	58	14:33:24	14:48:53	0:15
K07	out	298	15:00:11	15:12:23	0:12
K07	out	262	15:17:16	15:34:12	0:16
K07	out	324	15:38:21	15:50:20	0:11
K08	Usaquén	214	8:07:34	8:25:25	0:17
K08	Usaquén	160	8:28:45	8:42:57	0:14
K08	Usaquén	40	8:50:25	9:05:32	0:15
K08	Usaquén	41	9:12:22	9:29:37	0:17
K08	Usaquén	133	9:55:24	10:16:55	0:21
K08	out	12	10:19:12	10:34:36	0:15
K08	out	335	10:37:25	10:55:52	0:18
K08	Usaquén	270	11:17:44	11:32:49	0:15
K08	out	250	11:39:51	11:54:31	0:14
K08	out	75	12:00:47	12:23:35	0:22
K08	out	208	12:28:27	12:45:55	0:17
K08	out	235	12:55:41	13:18:58	0:23
K08	out	207	13:24:05	13:38:29	0:14
K08	out	89	13:45:09	13:55:31	0:10
K08	out	227	13:57:16	14:14:00	0:16
K08	out	230	14:14:27	14:30:19	0:15
K08	out	21	14:35:38	14:43:01	0:07
K08	out	37	14:48:51	15:01:03	0:12
K08	out	36	15:01:32	15:13:51	0:12
K08	out	225	15:22:05	15:35:58	0:13
K09	Barrios Unidos	136	8:16:54	8:31:19	0:14
K09	Barrios Unidos	181	8:34:03	8:54:19	0:20
K09	Teusaquillo	125	9:06:46	9:27:50	0:21
K09	Barrios Unidos	305	9:32:47	9:44:41	0:11
K09	Teusaquillo	15	9:50:12	10:05:08	0:14
K09	Barrios Unidos	55	10:06:46	10:23:20	0:16
K09	Barrios Unidos	323	10:28:16	10:51:57	0:23
K09	Barrios Unidos	264	10:57:25	11:20:12	0:22
K09	Barrios Unidos	265	11:22:03	11:41:04	0:19
K09	out	302	11:43:24	11:55:43	0:12

K09	out	158	12:02:04	12:22:43	0:20
K09	out	118	12:28:30	12:47:37	0:19
K09	out	26	12:50:56	13:07:25	0:16
K09	out	156	13:10:07	13:22:47	0:12
K09	out	146	13:29:25	13:46:46	0:17
K09	out	22	13:51:50	14:09:24	0:17
K09	out	23	14:10:31	14:25:23	0:14
K09	Barrios Unidos	169	14:30:30	14:46:37	0:16
K09	out	85	14:54:32	15:08:09	0:13
K09	out	261	15:16:39	15:32:52	0:16
K10	out	5	8:28:46	8:44:50	0:16
K10	out	7	8:48:18	9:01:39	0:13
K10	out	285	9:10:51	9:31:32	0:20
K10	out	254	9:43:47	9:59:09	0:15
K10	out	127	10:08:14	10:28:16	0:20
K10	out	328	10:35:07	10:55:49	0:20
K10	out	3	11:01:17	11:17:15	0:15
K10	out	4	11:19:43	11:25:29	0:05
K10	out	139	11:38:15	11:51:35	0:13
K10	out	304	12:00:05	12:16:01	0:15
K10	out	253	12:17:42	12:38:09	0:20
K10	out	289	12:42:18	13:10:53	0:28
K10	out	306	13:13:30	13:25:33	0:12
K10	out	8	13:27:27	13:46:06	0:18
K10	out	300	13:51:54	14:02:33	0:10
K10	out	274	14:06:23	14:19:34	0:13
K10	out	74	14:27:18	14:42:23	0:15
K10	out	205	14:43:59	15:02:45	0:18
K10	out	77	15:49:16	16:02:17	0:13
K10	out	10	16:19:10	16:35:00	0:15
K11	Suba	268	8:04:06	8:16:32	0:12
K11	Suba	97	8:18:13	8:39:08	0:20
K11	Suba	330	8:41:49	8:54:12	0:12
K11	Suba	182	9:03:28	9:17:04	0:13
K11	Suba	20	9:21:05	9:48:11	0:27
K11	Usaquén	191	10:05:52	10:18:27	0:12
K11	Usaquén	138	10:23:40	10:37:53	0:14
K11	Usaquén	95	10:40:51	10:56:21	0:15

K11	Usaquén	101	11:03:28	11:20:18	0:16
K11	Usaquén	244	11:29:19	11:41:22	0:12
K11	Usaquén	185	11:43:27	11:55:58	0:12
K11	Usaquén	38	11:58:46	12:15:50	0:17
K11	Usaquén	322	12:19:02	12:35:43	0:16
K11	Usaquén	246	12:39:25	12:51:34	0:12
K11	Suba	206	12:56:50	13:10:38	0:13
K11	Suba	152	13:16:56	13:33:56	0:17
K11	Suba	54	13:39:04	14:03:35	0:24
K11	Suba	92	14:07:37	14:17:48	0:10
K11	Suba	314	14:18:42	14:30:11	0:11
K11	Suba	98	14:36:15	14:49:21	0:13
K12	Teusaquillo	319	8:10:27	8:29:40	0:19
K12	Puente Aranda	199	8:36:54	8:56:47	0:19
K12	Puente Aranda	143	8:57:33	9:17:31	0:19
K12	Teusaquillo	71	9:22:13	9:39:31	0:17
K12	Los Mártires	86	9:57:23	10:13:38	0:16
K12	Los Mártires	303	10:19:06	10:27:44	0:08
K12	Santa Fe	14	10:38:40	10:57:47	0:19
K12	Santa Fe	31	10:59:11	11:15:01	0:15
K12	Santa Fe	30	11:16:16	11:36:32	0:20
K12	Santa Fe	13	11:37:35	11:53:37	0:16
K12	Los Mártires	53	12:05:11	12:23:11	0:18
K12	Teusaquillo	313	12:28:32	12:58:38	0:30
K12	Teusaquillo	96	13:03:35	13:16:46	0:13
K12	Teusaquillo	204	13:18:17	13:37:06	0:18
K12	Barrios Unidos	93	13:39:43	13:53:33	0:13
K12	Barrios Unidos	94	13:53:37	14:13:14	0:19
K12	Barrios Unidos	332	14:20:22	14:37:25	0:17
K12	Teusaquillo	117	14:42:24	14:55:52	0:13
K12	Teusaquillo	149	15:02:33	15:24:57	0:22
K12	Teusaquillo	178	15:32:28	15:49:26	0:16
K13	Suba	154	8:17:48	8:37:14	0:19
K13	Suba	245	8:42:31	9:04:11	0:21
K13	Suba	34	9:08:15	9:22:00	0:13
K13	Suba	287	9:28:45	9:44:28	0:15
K13	Suba	112	9:51:50	10:07:37	0:15
K13	Suba	247	10:15:45	10:31:39	0:15

K13	Suba	201	10:36:59	10:50:30	0:13
K13	Suba	176	10:54:25	11:05:11	0:10
K13	Engativá	83	11:31:58	11:47:46	0:15
K13	Engativá	141	11:54:03	12:06:43	0:12
K13	Engativá	25	12:10:56	12:17:53	0:06
K13	Engativá	272	12:20:36	12:42:29	0:21
K13	Engativá	150	12:47:10	13:01:42	0:14
K13	Engativá	124	13:05:23	13:29:34	0:24
K13	Engativá	226	13:35:05	13:42:35	0:07
K13	Engativá	33	13:48:41	14:09:03	0:20
K13	Engativá	153	14:14:20	14:32:34	0:18
K13	Engativá	32	14:34:51	14:50:17	0:15
K13	Engativá	276	14:58:36	15:21:42	0:23
K13	Engativá	39	15:26:13	15:42:00	0:15
K14	out	45	8:18:43	8:32:29	0:13
K14	out	47	8:43:33	8:52:40	0:09
K14	out	91	8:54:30	9:04:42	0:10
K14	out	43	9:13:40	9:25:58	0:12
K14	out	99	9:30:56	9:45:25	0:14
K14	out	49	9:48:41	10:07:28	0:18
K14	out	317	10:07:46	10:24:06	0:16
K14	out	336	10:27:15	10:43:49	0:16
K14	out	193	10:50:56	11:06:17	0:15
K14	out	48	11:16:42	11:36:34	0:19
K14	out	46	11:52:00	12:07:09	0:15
K14	out	192	12:11:07	12:29:40	0:18
K14	out	135	12:31:15	12:56:06	0:24
K14	out	44	12:57:33	13:09:43	0:12
K14	out	137	13:12:01	13:23:46	0:11
K14	out	50	13:44:57	13:54:24	0:09
K14	out	148	14:07:25	14:13:06	0:05
K14	out	120	14:22:19	14:42:32	0:20
K14	out	190	16:07:22	16:19:55	0:12
K15	out	126	8:44:02	8:59:27	0:15
K15	out	290	8:59:41	9:18:21	0:18
K15	out	325	9:19:25	9:43:15	0:23
K15	Suba	299	9:48:51	10:02:45	0:13
K15	Suba	318	10:26:16	10:41:23	0:15

K15	Suba	170	10:44:56	10:59:02	0:14
K15	Suba	35	11:05:11	11:35:32	0:30
K15	Suba	263	11:44:40	12:00:32	0:15
K15	Suba	309	12:05:45	12:23:11	0:17
K15	Suba	291	12:34:41	12:42:21	0:07
K15	Suba	315	12:51:52	13:05:17	0:13
K15	Suba	312	13:07:48	13:25:51	0:18
K15	Suba	132	13:28:07	13:51:40	0:23
K15	Suba	119	13:53:43	14:10:49	0:17
K15	Suba	196	14:21:46	14:36:06	0:14
K15	Suba	188	14:41:08	14:54:44	0:13
K15	Suba	78	14:59:17	15:14:37	0:15
K15	Suba	144	15:20:21	15:42:03	0:21
K16	Kennedy	258	8:08:12	8:16:56	0:08
K16	Puente Aranda	273	8:19:48	8:35:36	0:15
K16	Kennedy	109	8:42:06	8:53:06	0:11
K16	Kennedy	288	8:57:23	9:12:33	0:15
K16	out	108	9:18:03	9:40:32	0:22
K16	out	251	9:44:52	9:59:30	0:14
K16	Antonio Nariño	114	10:03:37	10:20:33	0:16
K16	Antonio Nariño	216	10:24:55	10:41:04	0:16
K16	Rafael Uribe Uribe	157	10:46:53	11:03:55	0:17
K16	Tunjuelito	293	11:10:06	11:24:45	0:14
K16	Rafael Uribe Uribe	228	11:28:18	11:47:23	0:19
K16	Tunjuelito	194	11:52:27	12:08:11	0:15
K16	Bosa	311	12:11:44	12:24:51	0:13
K16	Ciudad Bolívar	113	12:35:04	12:49:52	0:14
K16	Ciudad Bolívar	187	13:03:34	13:22:47	0:19
K16	Tunjuelito	105	13:30:13	13:50:09	0:19
K16	Tunjuelito	294	13:59:08	14:12:42	0:13
K16	Ciudad Bolívar	128	14:33:40	14:46:32	0:12
K16	Kennedy	167	15:07:22	15:18:40	0:11
K16	Kennedy	297	15:21:49	15:41:20	0:19
K17	San Cristóbal	233	8:03:48	8:18:35	0:14
K17	San Cristóbal	70	8:24:01	8:38:54	0:14
K17	San Cristóbal	79	8:51:30	9:04:51	0:13
K17	San Cristóbal	80	9:05:36	9:24:01	0:18

K17	Usme	73	9:43:08	9:56:31	0:13
K17	Usme	116	9:58:09	10:09:48	0:11
K17	Ciudad Bolívar	232	10:42:56	11:00:15	0:17
K17	Usme	219	11:32:58	11:43:22	0:10
K17	Usme	103	11:50:38	12:04:36	0:13
K17	Usme	82	12:16:47	12:22:47	0:06
K17	Rafael Uribe Uribe	151	12:27:12	12:42:31	0:15
K17	Rafael Uribe Uribe	87	12:48:09	12:59:09	0:11
K17	Rafael Uribe Uribe	166	12:59:16	13:14:34	0:15
K17	Rafael Uribe Uribe	248	13:19:31	13:47:36	0:28
K17	Rafael Uribe Uribe	52	13:53:30	14:07:54	0:14
K17	San Cristóbal	171	14:27:38	14:49:04	0:21
K17	San Cristóbal	172	14:49:21	14:57:51	0:08
K17	San Cristóbal	275	15:11:29	15:25:44	0:14
K17	San Cristóbal	241	15:29:56	15:47:10	0:17
K17	San Cristóbal	333	15:51:22	16:08:55	0:17
K18	out	1	8:42:08	8:56:26	0:14
K18	out	218	9:17:23	9:32:02	0:14
K18	Fontibón	6	9:42:57	9:58:13	0:15
K18	Fontibón	180	10:09:53	10:26:32	0:16
K18	Fontibón	310	10:27:22	10:41:27	0:14
K18	Fontibón	145	10:46:58	10:55:57	0:08
K18	Fontibón	308	10:59:37	11:11:00	0:11
K18	Fontibón	327	11:13:25	11:29:58	0:16
K18	Fontibón	189	11:37:44	11:45:52	0:08
K18	Engativá	66	11:53:00	12:09:48	0:16
K18	Fontibón	134	12:15:28	12:29:38	0:14
K18	Fontibón	210	12:35:54	12:50:49	0:14
K18	Fontibón	174	12:53:13	13:12:16	0:19
K18	Fontibón	295	13:17:30	13:32:49	0:15
K18	Fontibón	220	13:35:24	13:48:20	0:12
K18	Fontibón	72	13:50:17	14:07:37	0:17
K18	Fontibón	222	14:09:47	14:26:22	0:16
K18	Kennedy	19	14:34:55	14:55:43	0:20
K18	Fontibón	183	15:05:15	15:23:40	0:18

K18	Fontibón	286	15:32:04	15:55:12	0:23
K19	Puente Aranda	57	8:07:30	8:25:15	0:17
K19	Los Mártires	292	8:37:22	8:54:00	0:16
K19	Puente Aranda	301	9:06:48	9:19:06	0:12
K19	Puente Aranda	164	9:21:39	9:39:18	0:17
K19	Puente Aranda	213	9:41:10	9:58:58	0:17
K19	Puente Aranda	168	9:59:21	10:18:51	0:19
K19	Puente Aranda	259	10:20:29	10:33:40	0:13
K19	Los Mártires	68	10:45:01	11:11:16	0:26
K19	Antonio Nariño	200	11:17:12	11:40:06	0:22
K19	Antonio Nariño	123	11:44:03	12:05:48	0:21
K19	Antonio Nariño	177	12:11:50	12:27:01	0:15
K19	Puente Aranda	184	12:33:03	12:46:25	0:13
K19	Puente Aranda	115	12:50:42	13:06:40	0:15
K19	Puente Aranda	111	13:08:30	13:20:41	0:12
K19	Puente Aranda	110	13:23:42	13:44:37	0:20
K19	Kennedy	69	13:48:52	13:59:31	0:10
K19	Puente Aranda	155	14:13:32	14:30:43	0:17
K19	Kennedy	243	14:38:26	14:58:34	0:20
K19	Kennedy	106	15:01:12	15:19:48	0:18
K19	Kennedy	252	15:23:35	15:43:21	0:19
K20	Kennedy	24	8:07:10	8:27:20	0:20
K20	Kennedy	269	8:33:36	8:55:30	0:21
K20	Kennedy	64	9:04:01	9:19:32	0:15
K20	Kennedy	62	9:20:33	9:35:57	0:15
K20	Kennedy	63	9:45:20	10:04:52	0:19
K20	Kennedy	242	10:08:36	10:21:23	0:12
K20	Kennedy	326	10:27:50	10:39:44	0:11
K20	Kennedy	121	10:45:31	10:58:55	0:13
K20	Kennedy	260	11:00:53	11:15:42	0:14
K20	Kennedy	239	11:23:24	11:36:02	0:12
K20	Kennedy	316	11:43:46	12:01:14	0:17
K20	Kennedy	27	12:10:10	12:22:46	0:12
K20	Kennedy	122	12:31:39	12:49:18	0:17
K20	Kennedy	198	12:56:24	13:10:04	0:13
K20	Kennedy	65	13:17:26	13:31:05	0:13
K20	Kennedy	283	13:34:02	13:56:12	0:22
K20	Kennedy	61	14:05:02	14:20:44	0:15

K20	out	2	15:38:40	15:50:17	0:11
K20	out	329	15:56:01	16:13:03	0:17
K20	out	307	16:21:28	16:43:11	0:21

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