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Priscila Mara Cota

Integrating Vehicle Scheduling and Open Routing Decisions in a Cross-Docking Center with Multiple Docks

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Integrating Vehicle Scheduling and Open Routing Decisions in a Cross-Docking Center with Multiple Docks

PRISCILA MARA COTA

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Prof(a). Martin Gomez Ravetti - Orientador
UFMG

Prof(a). Mauricio Cardoso de Souza
UFMG

Prof(a). Eduardo Gontijo Carrano
UFMG

Prof(a). Thiago Henrique Nogueira
UFV

Prof(a). Angel Alejandro Juan
Universitat Politècnica de València

Prof(a). Thiago Augusto de Oliveira Silva
UFOP

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Resumo

A sociedade enfrenta uma série de desafios, como o crescimento da população urbana, a expansão do *e-commerce*, a pandemia (COVID-19) e muitos outros que levam a mudanças na cadeia de suprimentos das empresas. Mudanças como: necessidade de redução do tempo de entrega dos produtos, maior atenção ao bem-estar do consumidor, atenção ao impacto ambiental, e outros. Assim, a gestão eficiente de soluções logísticas como *cross-docking* e rotas inteligentes podem contribuir para melhorar o desempenho da cadeia de suprimentos. Esse estudo tem como objetivo a integração de dois problemas logísticos, o sequenciamento de caminhões em um centro de *cross-docking* e o roteamento para entrega de mercadorias nos clientes; a integração dessas estratégias pode reduzir significativamente os custos e ajudar a organizar os centros de distribuição e o atendimento aos clientes. Esta Tese analisa o problema de sequenciamento de caminhões em um centro de *cross-docking* com múltiplas docas integrado ao problema de roteamento de veículos aberto, denominado *Open Vehicle Routing Problem With Cross-Docking (OVRPCD)*. Essa abordagem visa minimizar as penalidades causadas por atrasos no atendimento aos clientes. Primeiramente, um modelo de programação linear inteira mista é proposto para resolver de forma ótima pequenas instâncias. A seguir, duas heurísticas são propostas para encontrar a solução dos dois problemas de forma integrada. Essas heurísticas são: a *Vehicle Routing Cross-Docking Heuristic* (VRCDH) e a *Cross-Docking Vehicle Routing Heuristic* (CDVRH), cada uma focando em um dos problemas que são integrados. Posteriormente propõe-se uma Heurística Lagrangeana de Priorização, chamada *Prioritization Lagrangian Heuristic* (PLH) baseada na utilização dos multiplicadores de Lagrange para melhorar as soluções encontradas via VRCDH e CDVRH. Essas três heurísticas são comparadas, considerando duas abordagens de busca *(i)* uma versão construtiva (HC) usando a heurística *swap*; e *(ii)* uma versão usando o *framework* metaheurístico baseado em uma busca de analise de vizinhanças, *Variable Neighborhood Search* (VNS). Os resultados alcançados utilizando a busca VNS superaram os resultados que utilizaram o método HC. E uma relação de superioridade foi identificada para as três heurísticas sendo que: a heurística PLH superou a VRCDH, enquanto esta última superou a CDVRH. Por fim, propõe-se um *framework* de tempo computacional polinomial, denominado *Robust Dynamic Prioritization Lagrangian Heuristic* (RDPLH), que estende a heuristica PLH, considerando incertezas nas datas de liberação dos caminhões e nos tempos de viagem, aproximando o problema em estudo a realidade de um centro de *cross-docking.* A simplicidade do *framework* e a qualidade dos resultados permitem afirmar que esta abordagem pode ser utilizada em centros reais de *cross-docking* (CDCs).

Palavras-chave: Sequenciamento de veículos, Roteamento de veículos, Heurísticas, *Cross-docking*, Incertezas.

Abstract

Society is facing a series of challenges, as the growth in urban population, the expansion of e-commerce, the pandemic moment (COVID-19), and many others leading to changes in companies' supply chain, like reducing product delivery time and attention to consumer welfare, the environmental impact, to mention a few. The efficient management of logistic solutions such as cross-docking can contribute to improving the supply chain performance. This Thesis focus on the integration of scheduling of trucks and routing decisions; the integration of these strategies can significantly reduce costs and help organize the distribution centers and the customers' services. This thesis analyzes the integrated problem in which trucks' scheduling in a cross-docking center with multiple docks is combined with the associated open vehicle routing problem, called Open Vehicle Routing Problem With Cross-Docking (OVRPCD). This approach aims to minimize penalties caused by delays in servicing customers. First, a mixed-integer linear programming model is proposed to solve small instances optimally. Next, two heuristics are proposed to contribute to the solution of the two problems in an integrated way. These heuristics are: the Vehicle Routing Cross-Docking Heuristic (VRCDH) and the Cross-Docking Vehicle Routing Heuristic (CDVRH), each focusing on one of the problems. Also proposing a Prioritization Lagrangian Heuristic (PLH) based on a model decomposition to improve the solutions found. These three heuristics are compared, considering two search approaches *(i)* a constructive version (HC) using the swap heuristic; and *(ii)* a version using the Variable Neighborhood Search (VNS) metaheuristic framework. The VNS-enhanced versions of the heuristics outperform the previous ones. Still, the same relation holds regarding the three heuristics, i.e.: the PLH heuristic outperforms the VRCDH one, while the latter outperforms the CDVRH one. Finally, a polynomial-time framework, called Robust Dynamic Prioritization Lagrangian Heuristic (RDPLH) is proposed, which extends PLH, considering trucks' release dates and travel times uncertainties, approximating our problem to a real cross-docking center. The framework's simplicity and the quality of the results allow us to assert that this approach can be used in real cross-docking centers (CDCs).

Keywords: Truck scheduling, Vehicle Routing, Heuristic, Cross-docking, Uncer-

tainties.

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Summary

Chapter 1

Introduction

The current market environment, characterized by increasingly fierce competition, globalization of the economy, and an accelerated technological revolution, leads companies to improve their logistics, distribution, and production systems. Furthermore, the increase in electronic commerce demands more efficient and effective logistical solutions. All of these increase the pressure on suppliers and distributors to deliver products to customers quickly and efficiently. To this end, Cross-Docking Centers (CDC) and smart distribution routes are attractive logistic strategies to increase the system's efficiency.

According to Gruler et al. (2018), a critical component in logistics decisions is to reduce the total inventory cost to raise the efficiency of the whole distribution process. Cross-docking (CD) is one alternative as it works reducing two functions of the conventional distribution centers: stocking and picking products, working with a limited or, if possible, null stock. Ladier and Alpan (2016), discussed industry practices and CDC problem characterization. The operation in a CDC consists of assigning inbound trucks from different suppliers to inbound docks; if the number of trucks is higher than the number of inbound doors, some of them have to wait in a queue until further assignment. Once in docks, the cargo of the trucks is unloaded, scanned, sorted, moved across the center, and loaded into outbound trucks for delivery. This outbound truck can visit one or more customers.

According to Boysen and Fliedner (2010), the use of the cross-docking center has several advantages for the distribution system: reduction of distribution costs, of the physical area, of out-of-stocks in retail stores, of the number of storage locations, of the complexity of deliveries, of stock levels, an increase of product availability, smooth the flow of goods, among others. Such advantages make cross-docking an important logistics strategy and have gained increasing attention in the global competitive landscape. Increasingly, clients require fast deliveries, requiring the logistics operator flexibility and agility in scheduling and distribution operations. Given this scenario, the adoption of strategies that reduce operational costs and enable such flexibility is fundamental for the logistics company to be competitive in the market, and the cross-docking system has proved adequate in this regard. However, efficient transshipment processes and careful operations planning become indispensable within a CDC. Inbound and outbound flows need to be synchronized to keep the terminal storage as low as possible and on-time deliveries. Many articles in the literature develop procedures that work the CDC with different goals and restrictions. In cases where an outbound truck must visit more than one customer, route construction becomes another critical component in logistical strategy.

The classical Vehicle Routing Problem (VRP) determines vehicle routes through a set of geographically dispersed clients, subject to constraints. The common objective of the VRP is to deliver a set of clients with known demands on minimum-cost vehicle routes originating and terminating at a depot. Some other purposes can be to minimize the total cost of transportation, minimize whole transportation time, minimize the total distance traveled, minimize waiting time, maximize benefit, maximize client service, minimize vehicle use. The problem is extensively studied and belongs, in most cases, to the NP-class. Dantzig and Ramser (1959) first studied this problem; they treated the application in the distribution of gasoline to fuel sales stations proposing a linear programming formulation.

Although many studies on cross-docking and vehicle routing have considered them separately, dealing simultaneously with both decisions has become even more critical due to the amount of uncertainty regularly dealing in a logistic center. Making last-minute changes in the scheduling of trucks, delivery routes, and the prioritization of clients is already in a daily routine of an actual CDC. The integration of VRP with CD strategy has been increasingly appreciated and investigated in recent studies as an effective strategy for distribution management and logistics. Gunawan et al. (2021b) in your recent article extends the benefit of cross-docking with reverse logistics, Kaboudani et al. (2020) considered both forward and reverse logistics in an integrated model, Shahabi-Shahmiri et al. (2021) solve the problem considering perishable products. The first study, which considered the Vehicle Routing Problem with Cross-Docking (VRPCD) in an integrated way, was proposed by Lee et al. (2006) considering the cross-docking from an operational viewpoint to find the optimal vehicle routing schedule. Table 2.1 maps some of the research conducted on a VRPCD presented in the literature.

According to Lee et al. (2006), the pickup and delivery processes must be considered to apply cross-docking effectively. The flow from the supplier to the cross-docking is called the pickup process. The core issue in the pickup process is simultaneous arrival at the cross-docking. Thus, this dissertation consider the vehicle routing and scheduling for the arrival. In the cross-dock, arrived products are sorted according to their destination. These products are then delivered to customers without delay or storage. The process from the cross-docking to the customers is called the delivery process. Thus, improving the supply chain's physical flow can be achieved by modeling all processes together, including pickup, cross-docking, and delivery. It is possible to find different CDC circumstances. Large quantities of inbound goods are transported from suppliers using large vehicles to a CDC, where small cars await transport commodities to customers. However, the opposite situation is also common, as in supermarket chains or large retailers, where the number of suppliers is significantly higher than the number of stores, and small vehicles are expected at the CDC to compose a mixed cargo in large trucks for the final delivery. These variations increase the number of studies in the literature that address the problems, increasing the range of treatments.

The problem studied consider an Open Vehicle Routing Problem With Cross-Docking (OVRPCD). The "Open" variant of the problem implies that vehicles do not return to the cross-docking center after visiting the customer acknowledging the scheduling of inbound and outbound trucks with the routing of the trucks to their final destination (delivery processes), as presented in Figure 1.1.

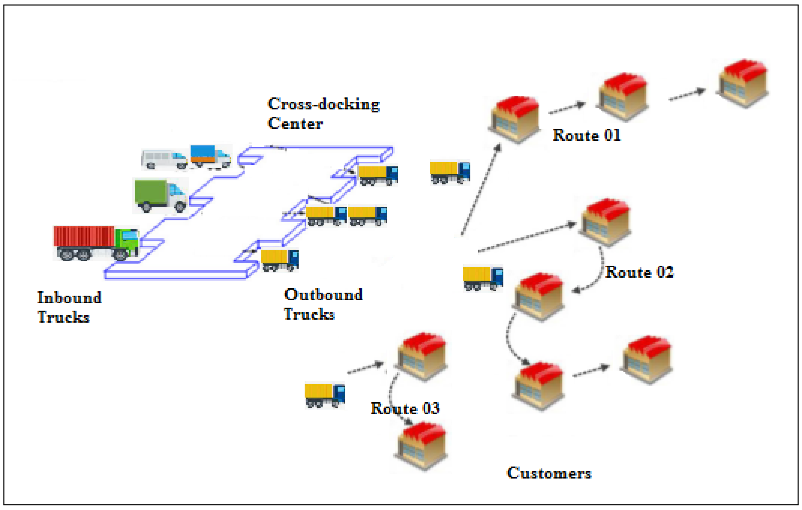

Figure 1.1: Open Vehicle Routing Problem with Cross-Docking (OVRPCD) studied

This thesis aims to model and solve the Open Vehicle Routing Problem with Cross-Docking, to minimize the weighted delay. Five specific goals are outlined:
i) Contextualization of the studied scenario to define the problem;
ii) Comprehension literature review analysis to expand the current literature;
iii) Development and implementation of mathematical model and heuristics to solve the integrated truck scheduling and routing problem;

iv) Development and implementation of a heuristic to treat the problem considering uncertainties - in the release dates of the trucks and in the travel times.; and to finalize
v) Analysis of the problem studied and suggestion of new research tendencies.

The following subsections present the thesis's contributions, justifications, and organization.

1.1 Contributions

To solve the integrated problem, this thesis works with different solution methods. It is important to emphasize that all the proposed methods solve the Open Vehicle Routing Problem with Cross-Docking. First, will be offered a mixed-integer linear programming model to solve small instances optimally, based on the models proposed by Chen and Song (2009), Yu et al. (2016) e El-Sherbeny (2010). To test the model, the time execution was limited to 1000 seconds, solving instances of up to 30 clients within this computational time, varying the number of docks and trucks. For the tests, three scenarios were analyzed, a scenario with a stressed vehicle routing problem, one with a stressed scheduling problem, and a balanced one (with considerable difficulties in both scheduling and routing). Subsequently, two constructive heuristics are proposed to solve the integrated problem. These constructive heuristics use the PFIH heuristic, presented by Solomon (1987), and the CDH heuristic, proposed by Cota et al. (2016). The proposed constructive heuristics solve small, medium, and large OVRPCD instances. After, a Lagrangian decomposition heuristic based on the model and in the constructive heuristics, are constructed dualizing the complex constraints of the model and penalizing their violations in the objective function.

Finally,a polynomial-time framework is proposed, using a dynamic re-scheduling and re-routing approach to solve the problem with multiple docks under uncertainty in inbound and outbound trucks' arrival times and travel times. For this test, the same previous scenarios were tested. However, the instances had to be changed to prove the proposed strategy's applicability. The results demonstrate that our methodology can support managers in their daily cross-docking operations, which may need to be changed throughout the day, integrating the real situations experienced by CDCs, the proposed algorithms, and the technologies available in the market to increase customer satisfaction. The estimated arrival time of trucks can be easily collected by a Global Positioning System (GPS) installed on the trucks. Thus, the proposed method must be fast and flexible to be integrated with current logistics technologies, bringing our approach closer to the operation of an actual cross-docking center.

The main contributions are summarized in the topics below:

i) investigate cross-dock treating total delay.
ii) integrate of truck scheduling with multiple docks (i.e., vehicle inbound/outbound), and open delivery orders considering multi-clients.
iii) provide a mathematical model to describe the integrated problem and to solve small instances optimally;
iv) provide two heuristics, VRCDH and CDVRH, to contribute to the solution of the two problems in an integrated way; they differ in how they tackle the solution (while VRCDH solves the vehicle routing problem to adjust the scheduling later, CDVRH does the opposite);
v) provide a Prioritization Lagrangian Heuristic (PLH) to improve the solutions found through the Lagrangian Multipliers treating the routing and the scheduling solutions simultaneously, achieving better results than the constructive heuristics used separately; These heuristics are proposed and compared considering two versions in the search for an answer, a constructive version (HC) based on the swap local search and a version based on the VNS metaheuristic framework;
vi) provide a framework considering uncertainties trucks' arrival dates and travel times, which can be used in real centers combined with current technologies. This framework is called Dynamic Prioritization Lagrangian Heuristic (DPLH).
vii) publication in Computers & Industrial Engineering that deal with the OVRPCD theme titled: Integrating vehicle scheduling and open routing decisions in a cross-docking center with multiple docks

1.2 Justification

This dissertation is justified by two factors, one academic and the other practical. From the practical point of view, it is justified due to the positive impact that the integrated approach of cross-docking centers and vehicle routing can bring to the supply chain. It can be used in genuine cases to satisfy the customer, who requests more frequent and faster deliveries. Academically, it is justified to present a mathematical model and heuristics to treat a problem with so many study gaps by publishing an article in Computers & Industrial Engineering that deals with the cross-docking theme.

1.3 Organization of the thesis

This thesis is organized into nine chapters structured as follows: Chapter 2 offers a literature review on related papers and describes the problem in more detail. Chapter 3 brings definitions, general formulation, and a model are proposed and discussed. Chapter 4 offers two constructive procedures (VRCDH and CDVDH) and a Prioritization Lagrangian Heuristic. The test instances and the computational experiments without uncertainties are discussed in Chapter 5. The next two Chapters 6 and 7 presents the strategy to deal with uncertainties. Discussions and conclusions are offered at Chapter 8 and 9. At the end of the text, two chapters of annexes present the adapted heuristics used from the literature and the extended summary of the thesis.

Chapter 2

Literature Review

The purpose of this chapter is to provide a review of the literature on Vehicle Routing Problem with Cross-Docking. Some papers that deal with VRPCD problems will be highlighted and recent surveys will be presented addressing uncertainties in cross-docking environments.

2.1 Vehicle Routing Problem with Cross-Docking (VRPCD)

An important point nowadays is the efficient control of the supply chain, so many companies are trying to develop efficient methods to increase client satisfaction and reduce costs. Cross-docking is considered a good method to reduce inventory and improve responsiveness to clients' diverse demands. The vehicle routing problem is used for faster attending clients facing the various impositions of the cities' logistics and economical ways to visit clients. As presented, it is easy to find papers treating cross-docking and many articles treating the vehicle routing problem. However, a combination of these two problems is not much explored in the literature.

The first study, which considered the VRPCD in an integrated way, was proposed by Lee et al. (2006). In VRPCD, a set of vehicles collects goods from suppliers, delivering them to their final destinations, after loading and unloading operations at the cross-docking center. The products are received and delivered, considering time windows constraints. The objective is to find routes that satisfy vehicles'capacities and minimize the total transportation cost. The authors proposed an integrated model and a heuristic algorithm based on a Tabu Search (TS) algorithm. In 30 randomly generated testes, they found solutions whose average percentage error was less than 4% if compared with the optimal solution in a reasonable amount of time.

The authors analyzed three sets of problems, 10, 30, and 50 nodes. A new TS algorithm was proposed by Liao et al. (2010) to minimize the sum of transportation and operational costs. The results showed improvements as significant as 10–36% for various sizes of problems compared to the results obtained by Lee et al. (2006). The logic of VRPCD is illustrated in Figure 2.1.

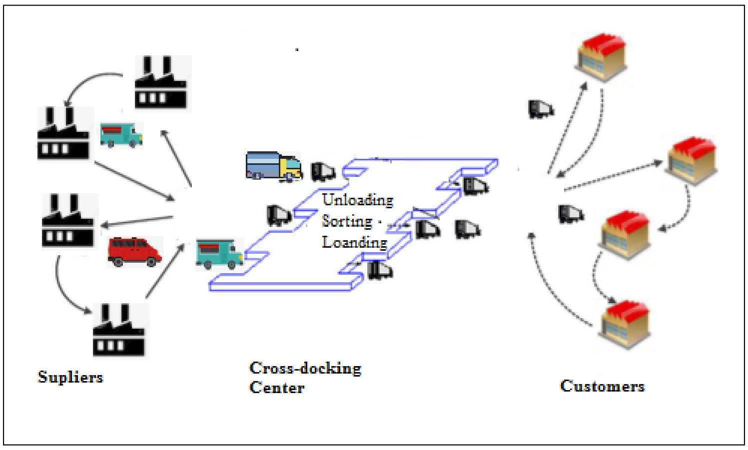

Figure 2.1: Vehicle Routing Problem with Cross-Docking (VRPCD)

Wen et al. (2009) studied a problem similar to the one studied by Lee et al. (2006). In the paper produced by Wen et al. (2009), there is no constraint on simultaneous arrival for all the vehicles. The consolidation decisions determine the dependency among the vehicles. Moreover, each pickup and delivery has predetermined time windows. A mixed-integer formulation is presented, followed by a TS heuristic. The algorithm solves 200 supplier-client pairs, showing promising results, less than 5% away from optimal solution values. Tarantilis (2013) solve the same problem considering the use of different inbound and outbound vehicles for pickup and delivery processes. An adaptive multi-restart procedure associated with a TS algorithm was applied and found better solutions than Wen et al. (2009).

According to Agustina et al. (2014), cross-docking is especially suitable for distributing fresh products with a short shelf life due to non-stocking the products. This research studied cross-docking operations to ensure food was delivered on time, with the minimum cost. The problem included inventory maintenance, transportation, and penalty for early or late delivery. Two mixed-integer linear program models were proposed. First, they present the model of vehicle routing and scheduling problem of CD to solve small-size issues in a reasonable time. After they offer a model treating vehicle routing and scheduling problems with client zones and hard time windows, the model can be solved in a matter of minutes for large-scale real-life problems, which have 20-30 doors and up to 200 supplier-client.

Santos et al. (2011a) and Santos et al. (2011b) considered a slightly different VRPCD, without time windows. They used an objective function cost when a good is moved from a vehicle to another at the CD. Santos et al. (2011a) the authors proposed the reformulation of a Branch-and-Price (BP) algorithm to solve the problem. Results indicated that the reformulation provides bounds much stronger than network flow bounds from previous studies. The BP algorithm dominated the Linear Programming based on the Branch-and-Bound (BB) method regarding the quality of the lower and upper bounds founded. Santos et al. (2011b), presented a novel Column Generation (CG) formulation and a BP algorithm for the problem that dominated the previous one in terms of the quality of lower and upper bounds and also can evaluate optimal solutions faster.

Dondo and Cerdá (2013) constructed a monolithic formulation for the VRPCD that determines pickup/delivery routes and schedules simultaneously with the terminal's truck scheduling. A sweep algorithm was incorporated into the model, being that near-optimal solution to significant problems (up to 50 clients). Dondo and Cerdá (2015) presented a new solution approaches for VRPCD to determine truck scheduling, vehicle routing dock assignment all at once, and the routing and scheduling of a heterogeneous fleet.

In papers presented previously, vehicles must stop at the CDC after the goods are collected from the suppliers, whether if the truck needs to be unloaded or not. Santos et al. (2013), extended their previous papers Santos et al. (2011a) and Santos et al. (2011b) considering a VRPCD where vehicles are allowed to avoid stopping at the CDC, in such cases reducing the transportation costs and freeing space and resources at the station. They introduced the Pickup and Delivery Problem with Cross-Docking (PDPCD), proposing an Integer Programming Formulation and a Branch-and-Price (BP) algorithm. Results indicated that the total costs could be significantly reduced.

Ahmadizar et al. (2015) considered the routing of inbound and outbound trucks and multiple products, the total volume assigned by a client can be more significant than the capacity of a vehicle, allowing more than one truck to visit. Birim (2016) also considered routing of pickup and delivery trucks. This study developed a VRPCD model. A heterogeneous fleet of vehicles without considering splitting orders for pickup and delivery processes is supposed to find the routes that minimize the total distribution costs. Theeb et al. (2019) produced a mixed-integer model and a heuristic to provide efficient distribution plans to route a set of inbound/outbound heterogeneous vehicles in the cross-docking systems with allowed split deliveries. The objective was to minimize the total commodity deviations and the overall distribution time or cost of vehicles. Hasani-Goodarzi et al. (2020) still consider orders with time windows at supplier and retailer locations, optimizing two conflicting objectives to minimize the total operational cost and the sum of the maximum earliness and tardiness.Gunawan et al. (2021a) minimize the operational and transportation costs without violating the vehicle capacity and time horizon constraints. A two-phase metaheuristic based on Column Generation (CG) is proposed by implementing an Adaptive Large Neighborhood Search (ALNS) algorithm. Gunawan et al. (2021b) extends the benefit of cross-docking with reverse logistics developing a mathematical model to minimize the costs and a metaheuristic based on ALNS. Kaboudani et al. (2020) considering both forward and reverse logistics in an integrated model after proposing a SA algorithm. Shahabi-Shahmiri et al. (2021) solve the problem considering perishable products, heterogeneous vehicles, and split delivery offering a multi-objective MIP model and a novel hybrid solution method, namely AUGMECON2-VIKOR that was used in a case study. Qiu et al. (2021) studied the two-echelon production routing problem with cross-docking satellites, not considering the scheduling trucks but the operation in the CDC. The objective function minimizes the total operational cost, including production, inventory, first and second echelon routing, and satellite handling costs. They proposed a Branch-and-Cut algorithm and a metaheuristic that can provide feasible initial solutions.

The Open Vehicle Routing Problem (OVRP) is an extension of VRP characterized by an "open" network wherein the flow starts at the depot. It finishes at one of the customers without returning to the depot. Since OVRPCD contains OVRP as a sub-problem and OVRP is an NP-hard problem, OVRPCD is also NP-hard. Yu et al. Yu et al. (2016) studied the OVRPCD to find the number of vehicles to be contracted (outsourcing the fleet of vehicles) and their corresponding routes under the lowest possible total cost. This study considers a single product, and a single cross-dock, wherein capacitated homogeneous vehicles start at different pickup points and times during pickup operations. The vehicles are scheduled to route in the network synchronously to simultaneously arrive at the cross-dock center. In the delivery operations, all customers must be served at most once, and deliveries should be finished within a predetermined duration. They propose a mixed-integer linear program model and a Simulated Annealing (SA) algorithm to solve the problem.

Baniamerian et al. (2018) analyze a Hybrid Metaheuristic combining a Genetic Algorithm (GA) and a modified VNS for the VRPCD. Grangier et al. (2017) propose a methodology based on large neighborhood search, periodically solving a set partitioning and matching problem with third-party solvers. Grangier et al. (2019) adapted the metaheuristic in Grangier et al. (2017) to solve the Vehicle Routing Problem With Cross-Docking with Time Window (VRPCDTW) considering the limitation of the number of dock doors that can be used simultaneously. Hasani-Goodarzi and Tavakkoli-Moghaddam (2012) viewed a vehicle fleet that was allowed to make split deliveries and pickups in different nodes of the network. They formulated a Mixed-Integer Programming Model (MIP) that minimizes transportation. A group of articles that considers stochasticity or uncertainties in the data to solve the VRPCD is discussed in the following subsection.

2.1.1 Problems under Uncertainties

In this subsection, some articles that address the problem of scheduling and routing research in cross-docking distribution centers considering stochasticity or uncertainties in the data will be discussed. The truck scheduling and routing problem play an essential role in most cross-docking systems, as it affects the efficiency of operations in terms of speed and reliability of deliveries. According to AL-Behadili (2018), in static problems, all data is known a priori (such as truck arrival times, due dates, truck processing times, machine availability, etc.), does not include stochastic's factors. In the literature, it is possible to find several papers assuming that all problem data has constant values and is known in advance, as presented previously. But now, let's bring some authors who deal with the problem under study but consider uncertainties in some problem variables.

Konur and Golias (2013) investigated a cross-docking operator's truck scheduling problem at inbound doors in case of unknown truck arrival times, considering variations in costs of serving the trucks. Their study assumes that the cross-docking operator only acknowledges the arrival time window of each truck. They analyze and compare three approaches: deterministic, pessimistic, and optimistic. A bi-objective problem is formulated. They proposed a genetic algorithm to find efficient schedules. The authors Mousavi et al. (2014), study a location of cross-docking centers and vehicle routing scheduling under uncertainty. This paper first develops a novel two-phase mathematical programming model. After the uncertainties are incorporated, a new hybrid solution approach is introduced, combining fuzzy heuristic programming. The uncertainties parameters include the distance of pickup and delivery nodes from CDCs, transportation costs, operation costs at CDCs, operation costs of vehicles, vehicles' volume capacity, time for trucks to move, and maximum work time of vehicles.

Mohtashami (2015) proposes a Dynamic Genetic algorithm for scheduling vehicles in cross-docking centers minimizing the total operation time. This article assumes temporary storage at the shipping dock, and inbound trucks are allowed to enter and leave the CDC to unload their products repeatedly. Two different kinds of chromosomes for inbound and outbound trucks are proposed. Some algorithms are also presented, and a dynamic approach is proposed for performing crossover and mutation operations in a genetic algorithm. The computational results reveal good performance, providing solutions with shorter operation times.

The authors Mousavi and Vahdani (2017) introduced a robust optimization model to deal with the inherent uncertainty of input data in the location and vehicle routing scheduling problems in cross-docking distribution networks. They proposed a two-phase deterministic Mixed-Integer Linear Programming (MILP) model for locating cross-dockings and scheduling vehicle routing. Then a new robust optimization model was proposed and compared with the deterministic MILP model's solutions. To finish, a meta-heuristic algorithm, namely a Self-Adaptive Imperialist Competitive Algorithm (SAICA), was presented for the multiple vehicle location-routing problems.

Rahbari et al. (2019) analyzed the vehicle routing and scheduling problems with cross-docking for perishable products under uncertainty. This paper presented a bi-objective model and demonstrated that considering merely one objective sacrifices the other and that the metric method makes a suitable trade-off. Two robust models were developed when the outbound vehicles' travel time and the products' freshness-life were uncertain. They prove that the delivered products' freshness increases by 74.14% on average without increasing the distribution cost, decreasing the waste.

Table 2.1 maps some of the research conducted on a VRPCD. In the last row of Table 2.1, characteristics of the problem studied are presented, highlighting similarities and differences to others.

Table 2.1: A summary of previous studies.

Author	Objective		Dock Door		Product		Vehicle		Scheduling		Routing		Open network	Time windows	Observations
	Multi	Single	Multi	Single	Multi	Single	Hetero.	Homo.	Outb.	Inb.	Deliv.	Pickup			
Dondo et al. (2011)	X			X		X	X		X	X	X	X		X	Minimize the total transportation cost
Hasani-Goodarzi Tavakkoli-Moghaddam(2012)		X		X	X		X				X	X			Minimize the transportation cost
Santos et al. (2013)		X		X		X		X			X	X			Reduce the transportation cost and the occupation of space and resources at the CDC
Dondo and Cerdá (2013)	X		X			X		X	X	X	X	X			Minimize the transportation cost and makespan
Tarantilis (2013)		X		X		X		X			X	X		X	Minimize the travelling distance
Dondo and Cerdá (2014)	X		X			X		X	X	X	X	X		X	Minimize the cumulative vehicle routing cost, cumulative distribution time, and makespan
Morais et al. (2014)		X		X		X		X			X	X		X	Minimize the travel cost
Ahmadizar et al. (2015)	X			X	X		X		X	X	X	X			Minimize transportation cost, the purchasing, and holding costs
Dondo and Cerdá (2015)	X		X			X	X		X	X	X	X		X	Minimize the vehicle routing cost, the distribution time, and the total makespan
Yu et al. (2016)		X		X		X		X			X	X	X	X	number of vehicles and their corresponding routes under the lowest possible total Transportation cost
Theeb et al. (2019)		X	X		X		X		X	X	X	X			Minimize the total prioritized commodity deviations
Grangier et al. (2019)		X	X			X		X	X	X	X	X		X	Minimize the volume transferred at the CDC
Hasani-Goodarzi et al. (2020)	X			X	X		X		X	X	X	X		X	Optimize cost efficiency and responsiveness
Qiu et al. (2021)		X		X	X		X				X				Minimize the total operational cost
Gunawan et al. (2021a)		X		X		X		X			X	X			Minimize the operational and transportation costs
Shahabi-Shahmiri et al. (2021)	X		X		X		X		X	X	X	X		X	Reduce distribution cost, accelerate distribution processing time and maximize the cross-docking network's capacity utilization
This research		X	X		X			X	X	X	X		X	X	Minimize penalties caused by delays in servicing customer

From the literature review presented, it is possible to verify that the terms truck scheduling at the cross-docking and the delivery vehicle routing are NP-hard problems and solvable only for small instances using exact methods. This thesis explore an Open vehicle Routing Problem with Cross-Docking (OVRPCD), considering the scheduling of inbound trucks and outbound trucks, and the routing of the outbound trucks, as presented in Figure 1.1. It is important to note that trucks do not return to the cross-docking center and the routing of the inbound trucks are not considering.

Although most of the articles in the literature deal with a single objective function, the aim is to minimize the cost of transportation or total distance traveled in most cases. At the same time, customer service received little attention in the related literature. Our research focuses on customer satisfaction by minimizing the total weighted delay. This objective function is justifiable considering customers' increasing volume and speed demands for fast delivery. Thus, an integrated solution for truck scheduling and routing problems is essential in most cross-docking systems dealing with last-mile deliveries. Unlike most studies in the literature, this thesis consider a CDC with multiple docks for receiving and dispatching, and they are appropriately specified for one or another function. Making the scheduling problem essential impacting the vehicle routing, fully integrating the two issues affecting the objective function studied. Few works analyze the "open" routing, and almost all the pickup and delivery activities are considered in vehicle routing.

Chapter 3

Mathematical Formulation for the Open Vehicle Routing Problem with Cross-Docking (OVRPCD)

This chapter will present definitions and general formulation for the Open Vehicle Routing Problem with Cross-Docking (OVRPCD), explaining the mathematical model restrictions. The model aims to minimize the total average weighted delay, considering the weight (importance) and the delay of each client.

According to Chen and Lee (2009), the problem of cross-docking scheduling is a NP-hard problem. Consequently, the VRPCD problem is also a NP-hard problem since it extends the cross-docking problem. So the mathematical model proposed can solve problems with small instances.

A practical example of an organization that could use the mathematical model proposed is a small construction material company. This company has a small cross-docking center (around two or four inbound/outbound docks) that receives materials and stores (about 10) throughout the city that need to receive them. In these situations, most of the time, suppliers are responsible for deliveries in the CDC. The company's responsibility is to receive the orders, unload the inbound trucks, load the outbound trucks, and make the deliveries in the building material stores.

3.1 Analyzed Problem - OVRPCD

In studied problem, the inbound trucks that arrive in the CDC, loaded with different goods from one or more suppliers, are assigned to one inbound door to unload the cargo. The inbound truck scheduling considers only the current day's vehicles, where each truck's arrival time is known in advance. In the second part of our study, this is an estimated information. The goods received by various suppliers are prepared to be transferred to the dispatch area and loaded in the outbound trucks on specific docks. Initially, all the outbound trucks are available at any moment to introduce uncertainties later. After assigning the outbound truck to a dock, their goods will be consolidated and fully loaded to go out to customers. These trucks will visit a group of customers, each with its demand, from different suppliers; no partial delivery is considered. The loading of an outbound truck can only be started after unloading all the inbound trucks on which it depends, considering the clients' demands. Each outbound truck can only leave the CDC after its charging has been completed. These trucks are identical, and there are a limited number of clients to visit. Each customer can be seen by only one truck; all customers must participate in a delivery route.

The problem considers the existence of more than one door (dock, processor) to unload and load. So the cross-docking problem is modeled as a hybrid two-stage flow shop scheduling problem with identical machines and cross-docking constraints as proposed by Chen and Song (2009). Once a truck begins to be processed, the operation should be terminated, with no interruptions allowed. The processing time to unload and load is known and is different for each truck. The movement time of goods between the inbound and outbound doors within the CDC is disregarded. Constant speed is assumed for all delivery trucks in the first moment, for later some uncertainties to be considered. The distances of clients to each other and clients to the deposit are given by the travel time. Each client has a close time window, an end time, to receive its goods. If a client is not visited before this time, it creates a penalty varying according to the client (represented by a weight associated with each client). The objective is to minimize penalties caused by customer service delays, so the proposed methods focus on increasing customer satisfaction.

3.2 Definitions and Formulation

In this section, a formal description of the OVRPCD problem is presented and the model is proposed.

- *Input parameters:*
  - nv_1: number of inbound trucks.
  - nv_2: number of outbound trucks.
  - n: number of customers.

- m_1: number of inbound doors.
- m_2: number of outbound doors.
- p_k: processing time of each truck, $k \in K$.
- w_c: customer's weight, $c \in N$.
- M: a very large integer number.
- l_c: maximum time at which customer c can be visited, $c \in N$.
- S_{ck}: a set of precedent subset inbound trucks, $k \in K1$, corresponding to each customer $c \in N$.
- d_{ac}: distances between two points, $(a, c) \in PL, a \neq c$.

• *Sets:*

- K: set of all trucks $K = \{1, 2, \ldots, nv_1 + nv_2\}$.
- $K1$: set of all inbound trucks $K1 = \{1, 2, \ldots, nv_1\}$.
- $K2$: set of all outbound trucks $K2 = \{nv_1 + 1, nv_1 + 2, \ldots, nv_2\}$.
- Maq: set of all doors $Maq = \{1, 2, \ldots, m_1 + m_2\}$.
- N: set of all customers $N = \{1, 2, \ldots, n\}$.
- PL: set of all places in the supply chain, customers and deposit (CDC), $PL = \{0, 1, \ldots, n\}$.

• *Decision variables:*

- v_c: time at which customer c is visited, $c \in N$.
- T_c: delay of each customer, $c \in N$.
- C_k: completion time for each truck $k \in K$.
- $y_{jk} = 1$ if truck $j \in K$ precedes truck $k \in K, j \neq k$; otherwise $y_{jk} = 0$.
- $z_{km} = 1$ if truck $k \in K$ is processed by door $m \in Maq$; otherwise $z_{km} = 0$.
- $u_{jk} = 1$ if truck $j \in K$ and truck $k \in K, j \neq k$ are processed in different doors; otherwise $u_{jk} = 0$.
- $x_{ca} = 1$ if customer $c \in N$ is serviced before customer $a \in N, c \neq a$; otherwise $x_{ca} = 0$.
- $r_{ck} = 1$ if customer $c \in N$ is serviced by truck $k \in K$; otherwise $r_{ck} = 0$.

- $q_{ca} = 1$ if customers $(c, a) \in N, c \neq a$ are not serviced by the same truck; otherwise $q_{ca} = 0$.

Next, the mathematical model can be expressed as follows:

$$\min \sum_{c \in N} w_c T_c \tag{3.1}$$

subject to:

$$C_j \geq C_k + p_j - M(1 - y_{kj}), \quad \forall (k, j) \in K1 \text{ or } \forall (k, j) \in K2, k \neq j, \tag{3.2}$$

$$y_{jk} + y_{kj} + u_{kj} = 1, \quad \forall (k, j) \in K1 \text{ or } \forall (k, j) \in K2, k \neq j, \tag{3.3}$$

$$z_{km} + z_{jm} + u_{kj} \leq 2, \quad \forall m \in Maq, \forall (k, j) \in K1 \text{ or } \forall (k, j) \in K2, k \neq j, \tag{3.4}$$

$$\sum_{m \in Maq} z_{km} = 1, \quad \forall k \in K, \tag{3.5}$$

$$C_k \geq C_j + p_k - M(1 - r_{ck}), \quad \forall k \in K2, j \in K1, c \in N, S_{cj} \neq 0, \tag{3.6}$$

$$x_{ac} + x_{ca} + q_{ca} = 1, \quad \forall (a, c) \in N, a \neq c, \tag{3.7}$$

$$r_{ak} + r_{ck} + q_{ac} \leq 2, \quad \forall (a, c) \in N, a \neq c, k \in K2, \tag{3.8}$$

$$v_c \geq v_a + d_{ac} - M(1 - x_{ac}), \quad \forall (a, c) \in N, a \neq c, \tag{3.9}$$

$$v_c \geq C_k + d_{0c} - M(1 - r_{ck}), \quad \forall k \in K2, c \in N, \tag{3.10}$$

$$T_c \geq v_c - l_c, \quad \forall c \in N, \tag{3.11}$$

$$\sum_{c \in N} r_{ck} \leq Q, \quad \forall k \in K2, \tag{3.12}$$

$$\sum_{k \in K2} r_{ck} = 1, \quad \forall c \in N, \tag{3.13}$$

$$C_K \geq 0, \quad \forall k \in K, \tag{3.14}$$

$$y_{jk} \in \{0, 1\}, \quad \forall (j, k) \in K, j \neq k, \tag{3.15}$$

$$u_{jk} \in \{0, 1\}, \quad \forall (j, k) \in K, j \neq k, \tag{3.16}$$

$$z_{km} \in \{0, 1\}, \quad \forall k \in K, m \in Maq, \tag{3.17}$$

$$r_{ck} \in \{0, 1\}, \quad \forall c \in N, k \in K2, \tag{3.18}$$

$$q_{ca} \in \{0, 1\}, \quad \forall (c, a) \in N, c \neq a. \tag{3.19}$$

The objective function (3.1) aims at minimizing the number of weighted delays, considering the weight (importance) and the delay of each customer. The set of constraints (3.2) ensures that each truck has a completion time greater than the completion time of the predecessor task plus its own processing time. Constraint sets (3.3) and (3.4) work together, they ensure that if trucks are not processed at the same dock, they have no precedence relation. Constraint set (3.5) ensures that each truck is processed at exactly one dock. Constraints (3.6) ensure that the outbound trucks' completion time should be higher than its processing time plus the maximum completion time of its precedents. This set is the cross-docking constraint of the model. Constraint set (3.7) ensures that if two customers are serviced by the same truck, one must be serviced before the other. Constraints (3.8) ensure that if two customers are serviced by the same truck, they have to be part of the same route. The conservation of the routing flow is guaranteed by constraint sets (3.9) and (3.10). Constraint set (3.9) guarantees the viability concerning times, being the time associated with the visit of a customer greater than the time associated with the previous customer's visit plus the travel time between them. Constraints (3.10) work the same way, but they deal with the first customer in any route. They ensure that the first customer will only be serviced after the truck is loaded and travels from the warehouse to the customer. Constraint set (3.11) computes the delay for each customer, which is given by the difference between the starting time of the service and the upper extreme of its processing time window. Constraints (3.12) restrict the number of customers serviced by each outbound truck, which must be less than or equal to its maximum capacity. Constraint set (3.13) ensures that every customer is visited by just one outbound truck. Finally, constraint sets (3.14) – (3.19) specify the domains of the model variables.

Given the constraints above, it is possible to verify that the model constraints may be divided into three groups. The first group solves the classical parallel machines problem, which involves constraints (3.2) – (3.5). The second group, constraints (3.7) – (3.9) deals with the classic VRP. Finally, constraints (3.6) and (3.10) are the ones integrating both problems by arranging inbound trucks with the routes of the outbound trucks, while considering the customers in each route. Thus, disregarding constraints (3.6) and (3.10), two individual problems (cross-docking and vehicle routing) are obtained, this fact will be explored in section 4.2.3.

Chapter 4

Heuristics without Uncertainty for the Open Vehicle Routing Problem with Cross-Docking

This chapter details the heuristics implemented to solve the OVRPCD problem for small, medium, and large scale to solve the integrated problem without uncertainty. Given the complexity of the problem and the difficulty of solving medium and large instances by the mathematical model heuristic methods are explored. The starting point for the heuristics is the lower bound adapted from Lawler (1964), three heuristics will be proposed. First, two constructive heuristics VRCDH (Vehicle Routing Cross-Docking Heuristic) and CDVRH (Cross-Docking Vehicle Routing Heuristic), and after, with a model-based decomposition, a Prioritization Lagrangian Heuristic (PLH) is introduced. These heuristics use two heuristics adapted from the literature: CDH proposed by Cota et al. (2016) and PIFH proposed by Solomon (1987), and are compared, considering two search approaches *(i)* a constructive version (HC) using the swap heuristic; and *(ii)* a version using the Variable Neighborhood Search (VNS) metaheuristic framework. In the following subsections, each one is described in detail. All the heuristic codes and instance tests are available at `https://github.com/PriscilaCota/OVRPCD---Files`.

Before presenting the proposed heuristics, it is important to perform and describe some changes in the lower bound and in the literature heuristics used in all proposals. So, the chapter will be divided into two sections. The first presents the adaptations proposal in the literature algorithms and the following section presents the heuristics proposed for solving the OVRPCD.

4.1 Adapted Literature Heuristics

Three heuristics from the literature were adapted to be used later in the proposal algorithms: The lower bound adapted from Lawler (1964); The CDH proposed by Cota et al. (2016) and PIFH proposed by Solomon (1987). This adaptation is discussed in the following subsections.

4.1.1 Lower Bound Adapted from Lawler (1964)

To improve the quality of the results obtained, a lower bound based on the minimum time of each process was utilized, the lower bound was adapted from Lawler (1964), and it is explained next:

Step 1: For each customer $c \in N$, the service release date (rc_c) was computed using the following equation:

$$rc_c = max(\sum_{k \in K1, S_{ck}>0} \frac{p_k}{min(m_1, nv_1)}, max_{\{k \in K1, S_{ck}>0\}}(p_k)) + min_{\{k \in K2\}}(p_k) + \frac{d_{0,c}}{vel},$$

this date represents the minimum time that any client can be visited, where vel is the average speed of the truck.

Step 2: After computing each customer's service release date, calculate the worst possible customer service date as follows:

$$UBe = max_{\{c \in N\}}(rc_c) + \frac{\sum_{c \in N} max_{\{a \in N\}}(d_{ca}/vel)}{min(nv_2, n)}.$$

Step 3: For each customer, $c \in N$, compute the shortest possible travel time for the next customer, pc_c, as follows:

$$pc_c = \frac{min_{\{a \in N, a \neq c\}}(d_{ca})}{vel}.$$

Step 4: For each customer $c \in N$, compute the visit cost (ϵ_{ct}) in the time network t, where $t \in (rc_c, ..., UBe)$; remember that l_c is the maximum time of the customer c; this cost will be used to sort customers according to the following criterion:

$$\epsilon_{ct} = w_c \frac{max(0, t - l_c)}{pc_c}.$$

Step 5: For each available truck, $k \in K2$, choose the next customer $c \in N$ that has the smallest ϵ_{ct}, where t is the availability date of the truck. Then, update the route from the truck with pc_c. If there are no customers $c \in N$ to allocate the route at time t, add the one with the smallest rc_c, considering ϵ_{c,rc_c}, and then update the route.

Step 6: The sum of all ϵ_{ct} associated with allocated customers is our lower bound.

4.1.2 Push Forward Insertion Heuristic (PIFH) Adapted from Solomon (1987)

Adapted code used in the proposal heuristics.

1. For each customer c is calculated the service release date (rc_c) by the following equation:

$$rc_c = max(\sum_{k \in K1, S_{ck} \neq \emptyset} \frac{p_k}{min(m_1, nv_1)}, max_{\{k \in K1, S_{ck} \neq \emptyset\}}(p_k)) + min_{\{k \in K2\}}(p_k) + \frac{d_{0,c}}{vel}$$

this date is the minimum moment that any customer can be visited, vel is the average speed of the truck.

2. Calculate the insertion cost ($cost_c$) of each customer c. This cost is calculated based on the equation that follows.

$$cost_c = (-\alpha d_{0,c} + \beta * max((l_c - rc_c), 0) + \gamma po_c d_{0,c}) w_c$$

In this equation, the values of the parameters α, β and γ were defined by Solomon (1987) empirically, being fixed at $\alpha = 0,7$; $\beta = 0,1$ and $\gamma = 0,2$. Once po_i is the polar angle of the customer i in relation to the deposit.

3. Create an ordered list in which the customers will be chosen to be inserted into the solution route. Sort the customers c in ascending order of $cost_c$.

4. Following the list insert the customers into the solution. Its insertion cost is verified in all possible positions of the routes belonging to the current solution. The number of routes must be less than or equal to the number of outbound trucks. Each customer will be entered in the solution respecting the service release date (rc_c) calculated.

4.1.3 Cross Docking Heuristic (CDH) Adapted from Cota et al. (2016)

Adapted code used in the proposal heuristics.

Step 1: Calculated the fictitious processing time $p'_k \in k \in K1$: consider $c \in N$, $S_{ck} > 0$ and $p^{(out)}_{min}$ is a variable that contains the minimum processing time of outbound trucks if $(l_c - p_k - p^{(out)}_{min} - d_{0,c}) > 0)$:
$p'_k = \frac{p_k+(l_c-p_k-p^{(out)}_{min}-d_{0,c})}{w_c}$,

otherwise

$$p'_k = p_k + (l_c - p_k - p^{(out)}_{min} - d_{0,c})w_c$$

The fictitious processing time:

$$p'_k = \frac{p'_k}{\sum_{c\in N} S_{ck}}$$

.

Step 2: Sort the jobs in increasing order of the average weight processing time, p'_k.The resulting order is given by L.

Step 3: The inbound trucks are scheduling at the inbound docks following the list L.

4.2 Proposal Heuristics without Uncertainty for the OVRPCD

In this section, three proposed heuristics without uncertainty will be presented and discussed in detail. All heuristics solve the OVRPCD problem in its entirety. The proposed heuristics will make use of the heuristics adapted from the literature discussed in the section 4.1.

4.2.1 Vehicle Routing Cross-Docking Heuristic (VRCDH)

The VRCDH focuses first on the vehicle routing and then on the CDC schedule. The heuristic initializes the variables, including α, β, and γ, which are defined empirically in Solomon (1987). The minimum service release date for each customer is computed by the processing time of the customer's inbound trucks, the minimum processing time of the outbound trucks, and also the necessary traveling time leaving the deposit (customer can not be serviced before this time), vel is the average speed of the truck ($rc_c = max(\sum_{k \in K1, S_{ck} \neq \emptyset} \frac{p_k}{min(m_1, nv_1)}, max_{\{k \in K1, S_{ck} \neq \emptyset\}}(p_k)) + min_{\{k \in K2\}}(p_k) + \frac{d_{0,c}}{vel}$). Later, the lower bound (LB) is computed in adapted form as proposed by Lawler (1964) - section 4.1.1.

Finally, the adapted PIFH heuristic proposed by Solomon (1987) - section 4.1.2 is performed. This heuristic first calculates an insertion cost for each customer: $cost_c = (-\alpha d_{0,c} + \beta * max((l_c - rc_c), 0) + \gamma po_c d_{0,c})w_c$, where po_c is the polar angle of the client c in relation to the deposit, creating an insertion list for building routes. The insertion cost is computed considering all possible positions of the current solutions' routes. The number of routes must be less than or equal to the number of outbound trucks. Each customer composes the solution respecting the service release date (rc_c). Once the routes have been built, the date when the customer is visited is calculated (v_c). It is not yet the final value as the scheduling has not yet been performed. Next, the criticality route $k \in K2$, $\triangle_k$ (given by the sum of the critically of each client that belongs to the route) is computed. This value represents the sum of weighted route delays. The critical level of each customer is obtained, $\triangle_c$ the lower this value, the greater the impact of this customer's delay on the total delay. So, a route list, SCD, is build in ascending order of the criticality route. In each position of SCD, there is an outbound truck and a set of clients served by the truck.

The next step is the scheduling of the trucks. The inbound trucks, $k \in K1$, are scheduled following the list SCD. For each route k in SCD, the inbound trucks are chosen to enter in the solution via the Longest Processing Time (LPT). Subsequently, the outbound trucks are scheduled following the ready times of the inbound trucks (considering the maximum completion time of all precedent inbound trucks). If there is more the one outbound truck choose one using the LPT. Then, update the instant in which the customer is visited (v_c), the new delays for each customer, and the total weighted delay. To finalize, check the possibility of improvement for each route by exchanging delayed customers for earlier customers, verifying if the exchange caused a reduction in the objective function. If there is an improvement, the procedure is carried out, and the route analysis restarts. The process analyzes all positions in each route and computes the value of the total weighted delay.

4.2.2 Cross-Docking Vehicle Routing Heuristic (CDVRH)

The CDVRH primarily solves the scheduling to later assign vehicles to routes. The heuristic, initializes the variables and computes the Lower Bound (LB) as pro-

Algorithm 1 VRCDH - Vehicle Routing Cross-Docking Heuristic

Set all initial variables as null;
Set $vel = 1$; $\alpha = 0.7$, $\beta = 0.1$, and $\gamma = 0.2$;
while $(c \leq N)$ **do**

$$rc_c = max(\sum_{k \in K1, S_{ck} \neq \emptyset} \frac{p_k}{min(m_1, nv_1)}, max_{\{k \in K1, S_{ck} \neq \emptyset\}}(p_k)) + min_{\{k \in K2\}}(p_k) + \frac{d_{0,c}}{vel};$$

end while
Compute the Lower Bound (LB) as proposed by Lawler (1964) - section 4.1.1;
Build the delivery route via PIFH Solomon (1987) - section 4.1.2;
Update v_c;
if $v_c \leq l_c$ **then**
    $\triangle_c = (l_c - v_c)/w_c$;
else
    $\triangle_c = (l_c - v_c)w_c$;
end if
Compute the critical Delta of each route: $\triangle_k = \sum_{c \in N'_k} \triangle_c$;
SCD = Ascending order $\triangle_k$;
Scheduling the inbound trucks following a list SCD, via LPT;
Scheduling the outbound trucks following ready times of the inbound trucks. If there is more the one use LPT;
Update v_c; T_c; FO_{min};
Check each customer in each route option;
end algorithm

posed by Lawler (1964) - section 4.1.1. The CDVRH heuristic schedule the inbound trucks using fictitious processing times based on CDH, proposed by Cota et al. (2016) - section 4.1.3 , first define the fictitious processing times for each inbound truck, p'_k, considering the weighted average remaining processing time. To calculate p'_k, consider $k \in K1$, $c \in N$, $S_{ck} > 0$ and $p^{(out)}_{min}$ is a variable that contains the minimum processing time of outbound trucks, if $(l_c - p_k - p^{(out)}_{min} - d_{0,c}) > 0)$ calculate $p'_k = p_k + (l_c - p_k - p^{(out)}_{min} - d_{0,c})/w_c$, otherwise $p'_k = p_k + (l_c - p_k - p^{(out)}_{min} - d_{0,c})w_c$ to finalize the fictitious processing time $p'_k = (p'_k)/(\sum_{c \in N} S_{ck})$. Subsequently, the inbound trucks are scheduling at the inbound docks following an increasing order of the average weight fictitious processing time, p'_k, if there is more than one available truck at a given time, use LPT and ends here the contributions of CDH - section 4.1.3.

The next step computes the service release date, for each customer $rc_c = max_{\{k \in K1, S_{ck}>0\}}(C_k + p_k) + min_{\{k \in K2\}}(p_k) + (d_{0,c}/vel)$, where C_k is the completion time of each inbound truck. Then, perform the PIFH - section 4.1.2 to build the delivery route. Customers will compose a route attending the $cost_c$ and the new service release date (rc_c). For each outbound truck, their ready time rt_k is computed considering the maximum completion time of all precedent inbound trucks. Afterward, build a list for the outbound trucks, SCD, in ascending order of availability times rt_k. Scheduled the outbound trucks following the SCD list, using the LPT if there is more than one available truck at a given time. The algorithm computes the time each customer is visited (v_c), respecting the outbound trucks scheduled. It also computes the new delays for each route and the value of the total weighted delay. As a final improvement, check the possibility of exchanging delayed customers for earlier customers for each course. If there is an improvement in the objective function, the procedure is carried out, computing the weighted delay of each client and the value of the total weighted delay.

4.2.3 Prioritization Lagrangian Heuristic (PLH)

The first two heuristic procedures (VRCDH and CDVRH) focus first on one of the problems, then, in a second stage, they adjust the solution for the integrated version. To cope with the integrated problem from the beginning, a Prioritization Lagrangian Heuristic (PLH) is propose. The independent solutions provided by VRCDH and CDVRH can be used in PLH. A problem is constructed in PLH, dualizing the complex constraints and penalizing their violations in the objective function. PLH is a Lagrangian feasibility heuristic that always guarantees a feasible solution. From the Lagrangian relaxation, a lower bound is built. For the construction of the upper bound, use the constructive heuristic procedure of feasibility through the

Algorithm 2 CDVRH - Cross-Docking Vehicle Routing Heuristic

Set all initial variables as null;
Set $vel = 1$; $\alpha = 0.7$, $\beta = 0.1$, and $\gamma = 0.2$;
Compute the Lower Bound (LB) as proposed by Lawler (1964) - section 4.1.1;
$p^{(out)}_{min} = min_{k\in K2} p_k$;
for $(k = 1$ to $K1)$ **do**
  for $(c = 1$ to N: S[c,k]) **do**
    if $((l_c - p_k - p^{(out)}_{min} - d_{0,c}) > 0)$ **then**
      $p'_k = p_k + (l_c - p_k - p^{(out)}_{min} - d_{0,c})/w_c$;
    else
      $p'_k = p_k + (l_c - p_k - p^{(out)}_{min} - d_{0,c}) * w_c$;
    end if
  end for
  $p'_k = (p'_k)/(\sum_{c\in N} S_{ck})$;
end for
$L = p'_k$ in ascending order;
Scheduling the inbound trucks, following list L. If there is more the one use LPT;
while $(c \leq N)$ **do**
  $rc_c = max_{\{k\in K1, S_{ck}\neq\emptyset\}} C_k + p_k) + min_{\{k\in K2\}}(p_k) + \frac{d_{0,c}}{vel}$;
end while
Build the delivery route via PIFH Solomon (1987) - section 4.1.2;
while $(k \leq K2)$ **do**
  $rt_k = max_{\{k1\in K1, S_{ck1}\neq\emptyset\}}(C_{k1})$;
end while
$SCD = rt_k$ in ascending order;
Scheduling the outbound trucks following SCD. If there is more the one use LPT;
Update v_c; T_c; FO_{min};
Check each customer in each route option;
end algorithm

Lagrange multipliers described in Algorithm 3, dualizing the constraint set (3.10), which uncouples both problems. The multipliers guide the search for feasible solutions. For each constraint of the group (3.10), a multiplier μ is associated. These weights are assigned to the violation of that constraint in the objective function. Thus, the set of Lagrangian multipliers is denoted by μ_{kc}, where $k \in K2$ refers to the outbound trucks $c \in N$, the customers. Hence, for each pair (k, c),it has:

$$v_c \geq C_k + d_{0c} - M(1 - r_{ck}) \longleftarrow \mu_{kc} \tag{4.1}$$

$$\mu_{kc} = v_c - C_k - d_{0c} + M(1 - r_{ck}) \tag{4.2}$$

The Lagrangian sub-problem is necessary to solve the dual Lagrangian, thus providing the set of weights μ_{kc} that maximize the lower bound for the integrated problem. First, the heuristic initializes the variables, computes the minimum service release date for each customer (rc_c), and keeps the minimum value of Objective Function (FO_{min}) obtained by the Algorithm 1 or Algorithm 2. For the first iteration, the date that each client is visited, v_c^0, is calculated as the service release date (rc_c). This date is the minimum moment to visit a client, allowing to compute the completion time of the outbound trucks $k \in K2$ in the first iteration, C_k^0. Afterward, the loop starts stopping after two subsequent solutions without improving in FO_{min}.

Next, the algorithm defines the step length (st_c^{it}) of the multipliers for each client. In *it* interaction, the multipliers are updated. The μ_{kc}^{it} represents the maximum slack time of each customer on the route ($v_c - C_k - d_{0,c}$), considering each customer as the first one visited in the route. Thus, the customer's real slack time in the route will be equal to or less than μ_{kc}^{it}. Therefore, the customer with the shortest maximum slack time has greater chances of being delayed. The slack time-weighted of each customer in the route, θ_{kc}^{it}, is calculated, and the customers are sorted in ascending order of θ_{kc}^{it}. Lower θ_{kc}^{it} values have greater chances of impacting the weighted delay, which guarantees a greater chance of exchanges in the route, verifying lesser possibilities of delay. This slack time-weighted of each customer in the route defines the impact of choosing the client in the outbound truck. Later, define the total slack time of each customer η_c performing the sum of each slack time-weighted of each customer in each route for all customers. Thus, clients with lower η_c have greater chances of being exchanged in the routes, as they provide a greater impact on the total weighted delay. So, the list L, for the inclusion of customers in the routes is built in ascending order of η_c.

The Routing and scheduling are produced following the Algorithm 1. C_k and v_c are updated, and the new solution is computed. If FO^{it} is less than $FOmin^{it}$ the algorithm continues and $FOmin^{it+1}$ is updated. If there is no improvement of the objective function in two consecutive interactions, the heuristic ends. Algorithm 3 describes this heuristic.

Algorithm 3 PLH - Prioritization Lagrangian Heuristic

Set Lagrangian multipliers and initial variables as null; $\mu_{kc} = 0$; $it = 0$; $vel = 1$;

$FO_{min} = \min(FO_{VRCDH-HC}, FO_{CDVRH-HC})$;
Compute the Lower Bound (LB) as proposed by Lawler (1964) - section 4.1.1;
while $(c \leq N)$ **do**

$$rc_c = max(\sum_{k \in K1, S_{ck} \neq \emptyset} \frac{p_k}{min(m_1, nv_1)}, max_{\{k \in K1, S_{ck} \neq \emptyset\}}(p_k)) + min_{\{k \in K2\}}(p_k) + \frac{d_{0,c}}{vel};$$

  $v_c \longleftarrow rc_c$;
end while
for $(k = 1$ to $K2)$ **do**
  $C_k^0 = p_k + min_{k1 \in K1, S_{ck1} \neq \emptyset}(p_{k1})$;
end for
while $(it \leq 2)$ **do**
  Define the step length: $st = 1 + (FO_{min} - LB)/FO_{min}$;
  Updated the multipliers: $\mu_{kc} = \mu_{kc} + st(v_c - C_k - d_{0,c})$ for $k \in K2$ and $c \in N$;

  Calculate the slack time customer in the route: $\theta_{kc} = \mu_{kc}/w_c$ for $k \in K2$ and $c \in N$;
  Calculate the total slack time of each customer $\eta_c = \sum_{k \in K2} \theta_{kc}$ for $c \in N$;
  Sort the customers in ascending order of η_c in a list L;
  Perform steps 7 through 17 - Algorithm 1 VRCDH;
  Update C_k and v_c;
  Calculate $FO = \sum_{c \in N} T_c$;
  if $(FO \leq FO_{min})$ **then**
    $FO_{min} = FO$;
    $it = 0$;
  else
    $it = it + 1$;
  end if
end while
end algorithm

4.3 Search methods used in the proposed heuristics

Our article uses two strategies to explore the space of solutions of the proposed heuristics. First, exploring the space with a constructive algorithm by using a swap structure returning the best solution in the neighborhood, without considering restart or perturbations in the neighborhoods (algorithms $VRCDH_{HC}$, $CDVRH_{HC}$ and PLH_{HC}). Later, carrying out new tests integrating our proposed heuristics with a VNS framework, Hansen and Mladenovic (2001), using two neighborhoods (l): one based on the swap structure ($l = 1$, nxn) and the other based on insertion structure ($l = 2$, nxn). In all proposed algorithms, the search structure does not have a restart. In VNS versions starts the analysis by the swap neighborhood ($l = 1$), the best solution found is saved, then the insertion neighborhood ($l = 2$) is analyzed, begins with the best solution obtained by $l = 1$. This leads to algorithms $VRCDH_{VNS}$, $CDVRH_{VNS}$, and PLH_{VNS}.

Figure 4.1 illustrates how the VNS framework is incorporated. Following the suggestion found in Nogueira et al. (2020), it starts with the current neighborhood set to one ($l = 1$) and with the candidate solution (list) provided by the initial procedure considered ($VRCDH_{HC}$, $CDVRH_{HC}$, PLH_{HC}). Then, VNS iterations run until no improvements are made on the last VNS_{max} iterations (nxn). At the beginning of each VNS iteration, a perturbation procedure is performed on the current solution by executing an l-insertion move (single customer movement), where l indicates the current neighborhood (number of movements to be performed). Its perturbation procedure chooses all customers at random, taking into account their η_c associated in PLH_{HC}. Customers with a lower η_c have priority chances to be selected and moved first. The solution is refined using the local search procedure. For $VRCDH_{HC}$ and $CDVRH_{HC}$, the perturbation procedure happens randomly because they do not have the η_c. The local search is based on the union of a swap and an insertion algorithm. It efficiently analyzes all pairwise customer swaps (between customers) and all single customers movements (change of positions), accepting a better solution immediately (first-improvement local search).

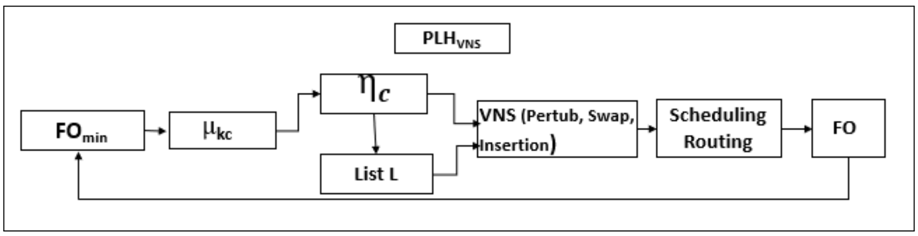

Figure 4.1: PLH_{VNS} Scheme

Figure 4.1 shows the VNS scheme incorporated in Algorithm 3, it is aggregate in list L, presented in line 16. In Algorithm 1 the VNS was executed on the SCD list (line 15). And in Algorithm 2 in list L (line 15). The VNS performance depends on the initial solution, which is sequentially improved.

Chapter 5

Computer Experiments - Heuristics without Uncertainty

The computational experiments were performed on a computer with Intel Core i7-4700HQ, 2.40GHz, 12GB RAM, in the Windows 10 64-bit, version 1607. The programming language used was AMPL and CPLEX optimization software 12.6.3.0. All instances and results are available at https://github.com/PriscilaCota/OVRPCD---Files.

5.1 Instance Generation

The instances were generated through the pseudo-random number generator Mersenne Twister for a day of operation between 7:00 a.m. and 7:00 p.m. . To simplify the magnitudes and avoid results with unrealistic precision, each unit of time, in an instance, corresponds to 5 real minutes (operation between 0 until 144). The properties of the instances generated and applied in the study methods follow below.

1. The processing time of each truck, for unloading or loading, follows a uniform distribution between 5 and 50 minutes.

   $p_k \sim Unif[1, 10]$.

2. The maximum number of inbound trucks in demand by any client follows a uniform distribution between 1 and half of the total number of inbound trucks.

   Maximum of elements in $S_c \sim Unif[1, n_1/2]$

3. To obtain the travel time between clients and CDC coordinates x and y were generated for each node to calculate the Euclidean distance between them, al-

ways rounded to return an integer number. The speed of the trucks is assumed to be constant so that distances can be given by time.

$x_i, y_i \sim Unif[15, 45]$

4. The weight of a client can assume three forms: low (1), medium (2), or high (3), following a uniform distribution between 1 and 3.

   $w_c \sim Unif[1, 3]$

5. The maximum number of customers that a truck can serve is represented by a normal distribution among the number of customers divided by the number of delivery trucks (always rounded up) plus two units.

   $Q \sim Unif[x, x + 2]$, being that, $x = [nc/n_2]$.

6. The final time of each client's time window is given by: $l_c \sim Unif[20, 100]$.

5.1.1 Instance Scenarios

Instances were generated for three different scenarios. These scenarios were chosen to test the model in different situations:

- Balanced: Scheduling and vehicle routing have the same weight in the solution. The problem must solve both parts in a non-trivial way. The two parts of the model have the same importance.

- Scenario with a stressed vehicle routing problem: there are more outbound trucks than inbound trucks; the number of customers is higher than in the other scenarios; the number of trucks is equal to the number of docks. So there is simple scheduling to be solved, and the difficulty of solving the problem lies in the trucks' routing. In this scenario, can be represented for a carrier that deliveries to many clients. A few trucks arrive at the CDC with orders from various clients. The difficulty of the solution lies in making the deliveries and not in the order of scheduling the trucks.

- Scenario with a stressed scheduling problem: the number of trucks is substantially higher than the number of docks; the number of outbound trucks is equal to the number of customers, so the difficulty of the solution is in solving the scheduling sub-problem. The number of clients is the same as the number of outbound trucks. So the vehicle routing has a simple solution, making scheduling the most critical resolution step. An example of a possible situation to observe this scenario is the CDC of a supermarket chain. This center receives numerous trucks from several suppliers and then loads the products on some delivery trucks, which will deliver the goods to the network stores, which are a lot smaller than the number of suppliers.

For each scenario, four subdivisions were analyzed, varying small, medium, and large-scale instances. A total of 176 cases were tested, divided into three scenarios, each scenario with four subdivisions with 11 instances each. Table 5.1 shows the values considered for the number of inbound and outbound docks, the number of inbound and outbound trucks, and the number of customers from different scenarios and their subdivisions.

Table 5.1: Variation of test instances.

		Trucks		Docks		
Scenario	Subdivision	Inbound	Outbound	Inbound	Outbound	clients
Balanced	1.1	10	4	4	2	10
	1.2	30	10	8	4	30
	1.3	50	10	8	4	50
	1.4	80	10	8	4	70
with a stressed vehicle routing problem	2.1	2	4	2	4	10
	2.2	4	8	4	8	20
	2.3	4	8	4	8	50
	2.4	4	10	4	10	100
with a stressed scheduling problem	3.1	10	2	4	1	2
	3.2	20	4	5	2	4
	3.3	50	8	8	3	8
	3.4	100	20	8	5	20

5.2 Results

To better present the test results, Table 5.2 reports for each subdivision five results: best case, worst case, average gaps, percentage of times providing the best solution (winning), and average computational time for the eleven instances of each group. In the first two columns, are computed the lower bound gap calculated from Equation (5.1). The UB_{known} is the best result achieved by the proposed methods, and LB is the lower bound produced according to Lawler (1964) in the first column and the lower bound produced by the mathematical model in the second.:

$$GapLB = \frac{(UB_{known} - LB) * 100}{UB_{known}}. \tag{5.1}$$

The following four columns present another comparative test, including the model and procedures VRCDH, CDVRH, and PLH. These three heuristics are divided into two versions (columns): HC and VNS. In total, seven columns are comparing the $GapUB$. Gaps were computed, as shown in Equation (5.2). Where UB_{known} refers to the best result achieved by the proposed methods, while $UB_{calculated}$ is the upper bound of the associated method.

$$GapUB = \frac{(UB_{calculated} - UB_{known}) * 100}{UB_{calculated}}. \quad (5.2)$$

Regarding the lower bound results ($GapLB$), it is possible to verify the superiority of the lower bound proposed by Lawler (1964) over the lower bound obtained by the model. As mentioned by Nogueira et al. (2019) models based on Completion Time and Precedence formulation (CTP) and based on Assignment and Positional Date (APD) formulations present poor lower bounds when they treat machine scheduling problems. Therefore it is justifiable to use the one proposed by Lawler (1964) in the proposed constructive heuristics.

Analyzing the methods proposed, $GapUB$ takes the value zero whenever it outperforms the others. The line winning in Table 5.2 represents the percentage of wins of each method in the tested group, the sum of the line can exceed the 100% due to the possibility of more than one method presenting the best value for a single test instance. In groups 1.1, 2.1, 2.2, 3.1, and 3.2, the mathematical model performs better than the proposed heuristic procedures for small groups, finding the optimal and superior solutions in almost all instances, with a single exception in the group 3.2. In subdivision 1.2, the model's performance is much inferior to the previous subdivision, not be solved optimally in 1000 seconds of execution. Considering the cases solved by the mathematical model and a 95% of confidence level, the PLH_{HC} constructive heuristic is the one that presents better average Gap results (average in $(11.3\%, 12.0\%)$), followed by $VRCDH_{HC}$ (average in $(13.9\%, 14.8\%)$), and $CDVRH_{HC}$ (average in $(21.9\%, 23\%)$). The percentages of instances resolved optimally are 21.8%, 16.4%, and 10.9%, respectively. Comparing the model and the heuristics that use the VNS framework, a reduction in the average calculated gaps is verified. Again the PLH_{VNS} heuristic presents the best result (average in $(8.2\%, 8.6\%)$), followed by $VRCDH_{VNS}$ (average in $(9.5\%, 10.0\%)$), and $CDVRH_{VNS}$ (average in $(21.9\%, 23\%)$). In this case, the percentages of optimal solutions are 21.8%, 21.8%, and 10.9%, respectively. Figure 5.1 contains results for all these test instances groups analyzed, proving the VNS versions of the heuristics outperform the HC ones. Still, the same relation holds regarding the three heuristics: the PLH heuristic outperforms the VRCDH one, while the latter outperforms the CDVRH one.

Figure 5.2 compares methods using the constructive approach in sub-figure a) and using the VNS framework in b). Each sub-figure displays the average GapUB for all scenarios presenting best, worst, and average values. In both graphs of Figure 5.2, is noticeable a smaller dispersion and smaller average gaps in the balanced scenario, also note that PLH offers the best results, followed by the $VRCDH$, which

Table 5.2: Comparative results of the proposed methods without uncertainty to solve the OVRPCD problem in three different test scenarios.

		GapLB (%)		*GapUB* (%)						
		Lower Bound		Model	VRCDH		CDVRH		PLH	
		Lawler (1964)	Model	Proposed	HC	VNS	HC	VNS	HC	VNS
1.1	Best case	48.0	100.0	**0.0**	11.2	4.5	11.2	11.2	10.3	4.5
	Worst case	16.0	100.0	**0.0**	32.1	26.0	40.3	35.1	27.6	26.0
	Average	32.8	100.0	**0.0**	19.4	14.4	27.2	23.7	16.9	14.4
	Winning	100.0	0.0	**100.0**	0.0	0.0	0.0	0.0	0.0	0.0
	Average Computational time (sec)				0.2	2.4	0.2	4.5	0.5	3.4
1.2	Best case	40.8	100.0	1.6	3.2	**0.0**	8.1	4.5	2.1	**0.0**
	Worst case	536	100.0	20.8	11.3	6.6	15.6	13.2	11.3	**1.3**
	Average	48.9	100.0	9.9	7.1	2.6	12.1	8.7	5.0	**0.1**
	Winning	100.0	0.0	0.0	0.0	9.1	0.0	0.0	0.0	**90.9**
	Average Computational time (sec)				13.2	200.0	14.0	200.0	44.0	200.0
1.3	Best case	55.1	100.0	52.0	**0.0**	**0.0**	3.9	3.9	**0.0**	**0.0**
	Worst case	64.5	100.0	100.0	4.8	5.2	10.4	11.4	**2.7**	3.1
	Average	60.5	100.0	95.2	2.3	1.7	6.4	7.6	0.9	**0.4**
	Winning	100.0	0.0	0.0	18.2	27.3	0.0	0.0	45.5	**73.0**
	Average Computational time (sec)				99.8	200.0	94.7	200.0	197.4	200.0
1.4	Best case	58.4	100.0	93.0	**0.0**	**0.0**	**0.0**	0.4	**0.0**	**0.0**
	Worst case	69.6	100.0	95.3	0.9	1.6	4.5	8.4	**0.0**	**0.0**
	Average	64.2	100.0	94.0	0.2	0.4	1.5	2.4	**0.0**	**0.0**
	Winning	100.0	0.0	0.0	63.6	45.5	18.2	0.0	**100.0**	**100.0**
	Average Computational time (sec)				200.0	200.0	200.0	200.0	200.0	200.0
2.1	Best case	0.7	100.0	**0.0**	0.6	**0.0**	3.6	3.6	0.6	0.6
	Worst case	54.9	100.0	**0.0**	48.5	37.2	59.9	59.9	48.5	37.2
	Average	12.6	100.0	**0,0**	11.8	7.0	21.0	21.0	10.2	6.9
	Winning	100.0	0.0	**100.0**	0.0	9.1	0.0	0.0	0.0	0.0
	Average Computational time (sec)				0.3	6.8	0.0	0.1	0.6	4.6
2.2	Best case	15.0	100.0	**0.0**	11.9	6.0	17.0	17.0	8.5	3.4
	Worst case	44,9	100.0	**0.0**	58.9	36.3	58.4	58.4	40.2	28.1
	Average	23.6	100.0	**0.0**	24.6	14.8	34.3	34.3	18.1	10.1
	Winning	100.0	0.0	**100.0**	0.0	0.0	0.0	0.0	0.0	0.0
	Average Computational time (sec)				2.6	119.9	0.1	0.7	8.3	95.4
2.3	Best case	30.0	100.0	23.6	1.5	1.5	11.2	11.2	**0.0**	**0.0**
	Worst case	44.5	100.0	100.0	12.9	11.0	27.4	27.4	8.2	**3.4**
	Average	36.9	100.0	92.3	7.7	6.9	18.5	18.5	2.7	**0.5**
	Winning	100.0	0.0	0.0	0.0	0.0	0.0	0.0	27.3	**72.7**
	Average Computational time (sec)				95.0	200.0	0.6	3.7	192.6	200.0
2.4	Best case	28.5	100.0	97.9	**0.0**	**0.0**	1.8	1.8	**0.0**	**0.0**
	Worst case	45.3	100.0	98.9	7.7	7.7	25.1	25.1	**0.0**	2.0
	Average	35.6	100.0	98.5	1.8	2.8	10.0	10.0	**0.0**	0.4
	Winning	100.0	0.0	0.0	36.4	18.2	0.0	0.0	**100.0**	63.6
	Average Computational time (sec)				200.0	200.0	3.0	17.7	200.0	200.0
3.1	Best case	0.0	0.0	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Worst case	19.8	100.0	**0.0**	24.4	24.4	22.0	22.0	19.3	19.3
	Average	6.7	90.9	**0.0**	2.7	2.7	8.2	6.6	1.9	2.8
	Winning	100.0	9.0	**100.0**	72.7	72.7	45.5	45.5	81.8	81.8
	Average Computational time (sec)				0.0	0.0	0.0	0.4	0.0	0.0
3.2	Best case	0.0	0.0	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Worst case	57.6	100.0	**1.7**	40.0	27.0	34.9	34.9	40.0	34.9
	Average	27.0	90.9	**0.2**	14.1	10.1	21.4	16.7	12.5	10.9
	Winning	100.0	0.0	**90.9**	9.1	27.3	9.1	9.1	27.3	27.3
	Average Computational time (sec)				0.0	0.1	0.0	8.6	0.0	0.1
3.3	Best case	33.5	100.0	**0.0**	1.1	**0.0**	6.3	**0.0**	**0.0**	**0.0**
	Worst case	84.9	100.0	19.9	14.8	11.4	31.3	20.3	**11.2**	**11.2**
	Average	51.9	100.0	9.5	6.5	3.9	18.8	10.2	4.5	**3.4**
	Winning	100.0	0.0	9.1	0.0	**45.5**	0.0	18.2	9.1	27.3
	Average Computational time (sec)				0.2	1.9	0.4	200.0	0.4	3.0
3.4	Best case	50.6	100.0	51.8	1.3	**0.0**	8.6	6.9	1.3	**0.0**
	Worst case	71.3	100.0	91.2	6.7	**2.0**	14.0	13.7	6.7	3.6
	Average	61.5	100.0	82.6	3.8	**0.3**	11.1	10.2	3.5	1.3
	Winning	100.0	0.0	0.0	0.0	**72.73**	0.0	0.0	0.0	27.27
	Average Computational time (sec)				4.2	108.3	19.1	200.0	8.4	164.4

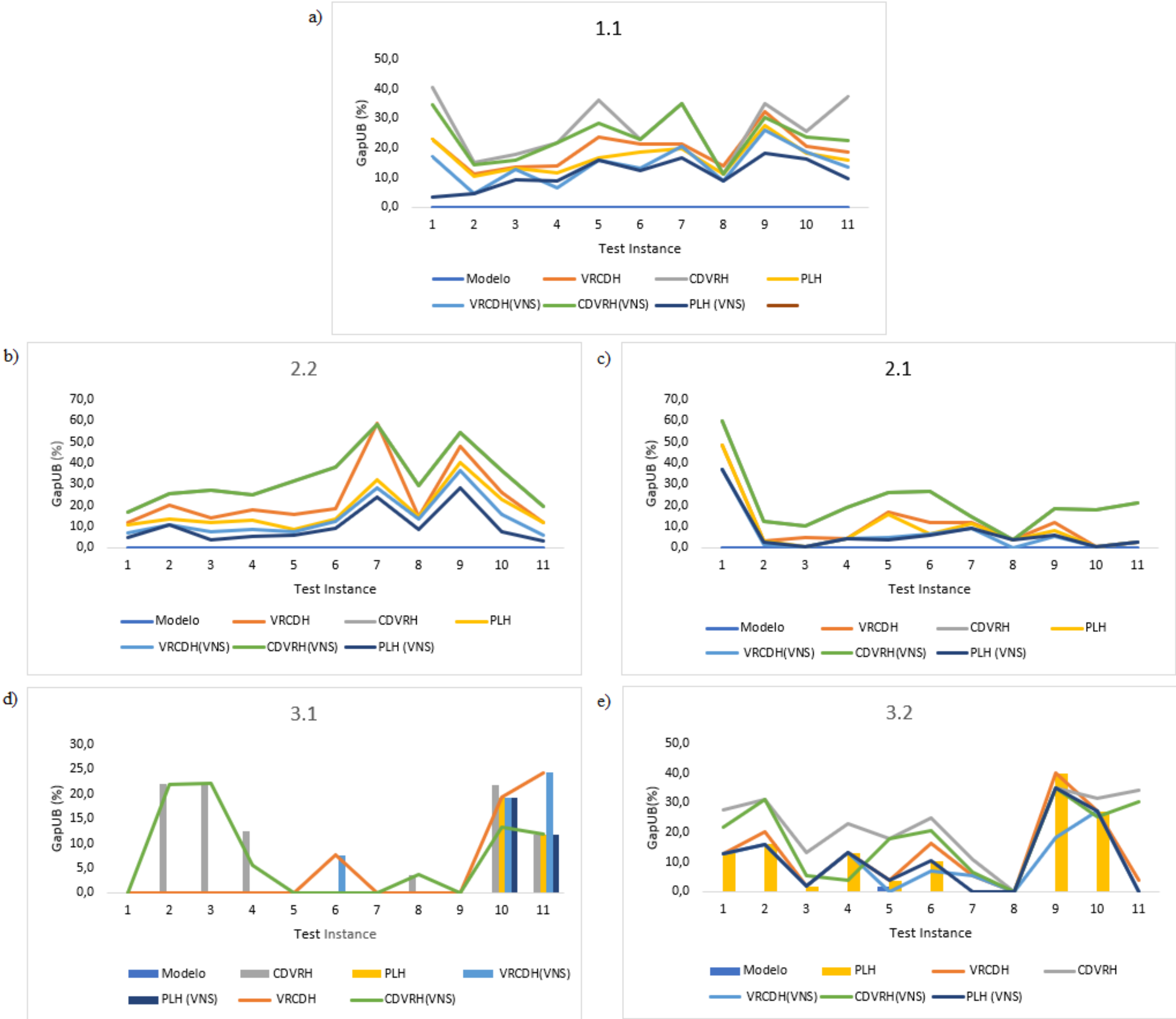

Figure 5.1: Results of GapUB. Comparing the model and the proposed heuristics for small groups (the mathematical model outperforms the proposed procedures) in all analyzed scenarios. a) Subdivision 1.1, Balanced Scenario. b) Subdivision 2.1, Scenario with a stressed vehicle routing problem. c) Subdivision 2.2, Scenario with a stressed vehicle routing problem d) Subdivision 3.1, Scenario with a stressed scheduling problem. e) Subdivision 3.2, Scenario with a stressed scheduling problem.

outperforms $CDVRH$. Figure 5.3 analyzes in more detail comparison between the methods and between versions. The 95% confidence level of the average gaps for PLH_{HC} is $(6.0\%, 6.3\%)$, while it is $(8.2\%, 8.6\%)$ for $VRCDH_{HC}$ and $(15.6\%, 16.1\%)$ for $CDVRH_{HC}$, which indicates that PLH_{HC} variant leads to better average results (lower GapUB) for the constructive methodology. Making a comparison of how many times each method found the best result within this constructive group, was observed 99.2%, 43.2%, and 10.6%, indicating a possible superiority of PLH_{HC}.

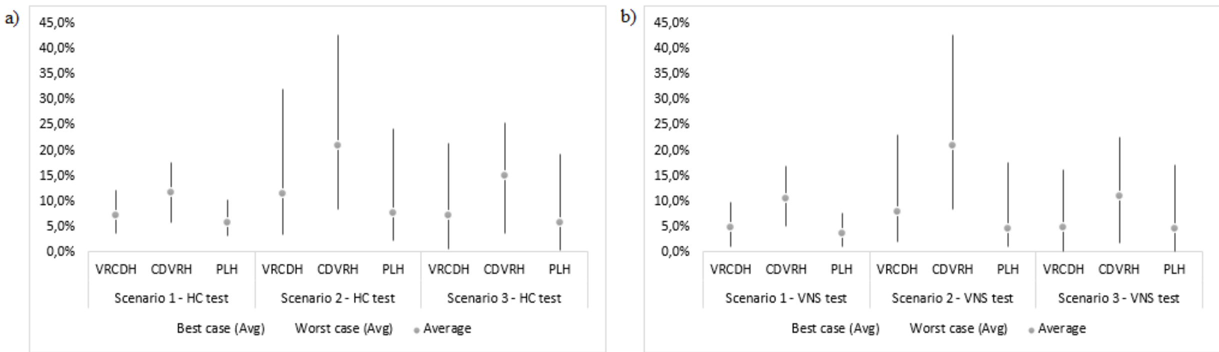

Figure 5.2: Results of GapUB for best case, worst case, and the average for each scenario analyzed. a) Versions of the proposed constructive methodology. b) Versions of the proposed VNS methodology.

Analyzing the proposed VNS heuristics group Figure 5.2-b) the results are not very different from the constructive heuristics. The 95% confidence level of the average Gap for PLH_{VNS} is [3.9%, 4.1%], [5.6%, 5.7%] for $VRCDH_{VNS}$ and [14.0%, 14.4%] for $CDVRH_{VNS}$, which indicates that PLH_{VNS} variant leads to better average results (lower GapUB) for the VNS methodology. Making a comparison of how many times each method found the best result within this VNS group, was observed 78.0%, 40.9%, and 9.1%, respectively, proving again a possible superiority of PLH_{VNS} compared with the other proposed methods.

The VNS heuristics group can identify a reduction of best results mainly in the PLH (from $99.2\% to 78.0\%$). It happens because in the constructive group PLH_{HC} always finds a value equal to or better than the solution obtained by $VRCDH_{HC}$ or $CDVRH_{HC}$ – since the former uses the latter constructive heuristics as the basis for finding an initial solution. The PLH_{VNS} heuristic no longer has the guarantee that it will always be better than or equal to the two others in the group $VRCDH_{VNS}$ and $CDVRH_{VNS}$). Analyzing how many times each method finds the best result, was obtained the following values: 20.5% for $VRCDH_{HC}$, 6.8% for $CDVRH_{HC}$, 38.6% for PLH_{HC}, 40.9% for $VRCDH_{VNS}$, 9.1% for $CDVRH_{VNS}$, and 70.5% for PLH_{VNS}, proving that the VNS methodology makes the heuristics stronger, thus finding better results. Still, the superiority between the proposed methods remains evident, PLH being superior to $VRCDH$, which finds better results than $CDVRH$, as displayed in Figure 5.3.

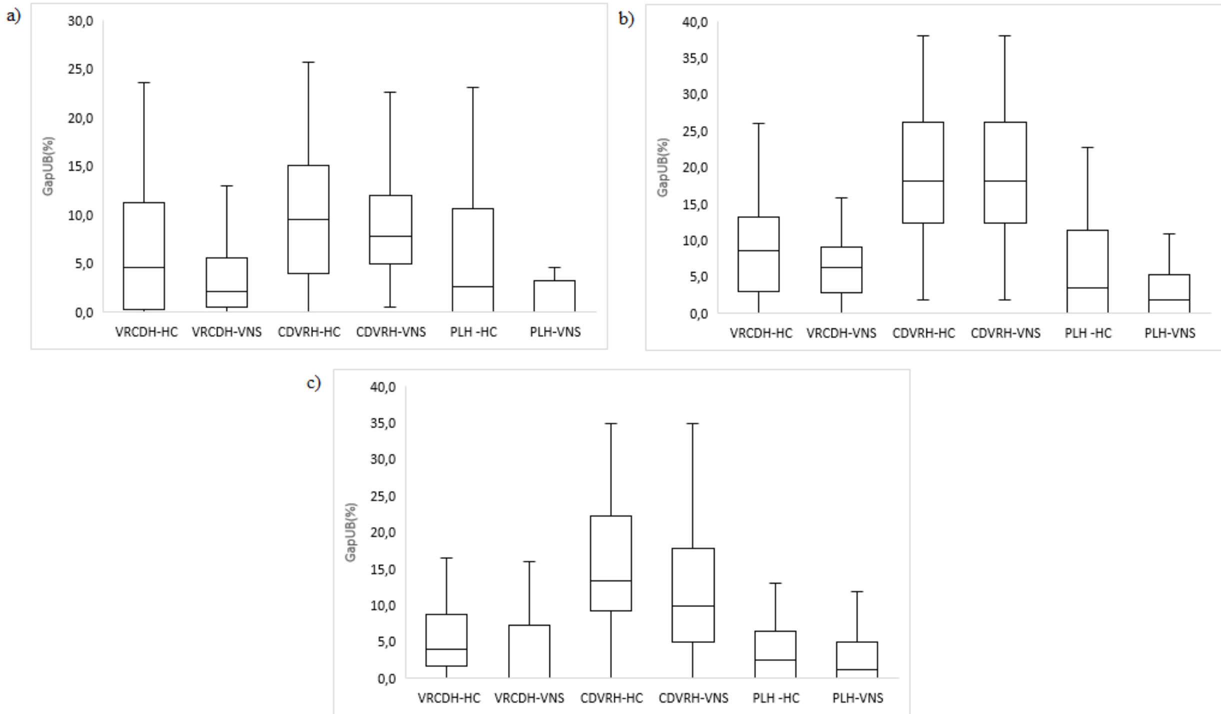

Figure 5.3: Boxplot graphs constructed using the GapUB for all proposed methods in all test scenarios. a) Results for the Balanced Scenario. b) Results for the Scenario with a stressed vehicle routing problem. c) Results for the Scenario with a stressed scheduling problem.

Boxplot is a graphical way of representing the change in the data of a variable through quartiles. In a boxplot, five statistics are presented: the minimum, the first quartile, the median, the third quartile, and the maximum. The rectangle length offers the amplitude interquartile (difference between the third and the first quartile). Figure 5.3 presents three graphs, one for each scenario. Each graph contains six boxplots, analyzing the proposed methods (HC and VNS versions). Each boxplot was built considering the entire sample group scenario. Thus, to construct each boxplot, 44 test instances were considered, in all the three graphs, the methods have different dispersion and average levels of GapUB. These levels are increased comparing the heuristics PLH, VRCH, and CDVRH, respectively. There is also a growing relationship comparing HC and VNS versions, making evident the improvement of the solutions with the insertion of the VNS framework. Analyzing the median to understand the symmetry of the data, it is verifiable that in situations that did not identify symmetry, it is verifiable positively asymmetric (median is close to the first quartile). It is positive for the heuristics proposed since our objective is a smaller GapsUB. In two cases, the median was zero value (balanced scenario- PLH_{VNS} and scenario with a stressed scheduling problem - $VRCDH_{VNS}$).

To analyze the existence of a significant difference between the average GapUB solutions obtained by the proposed methods, it was performed the Analyse of Variance (ANOVA). This test confirmed a significant difference between the methods for a significance level of 0.05 (p-value = $6.6\text{x}10^{-31}$). To analyze each method in pairs, it was performed Tukey's pairwise test for a significance level of 0.05, whose result is shown in Figure 5.4.

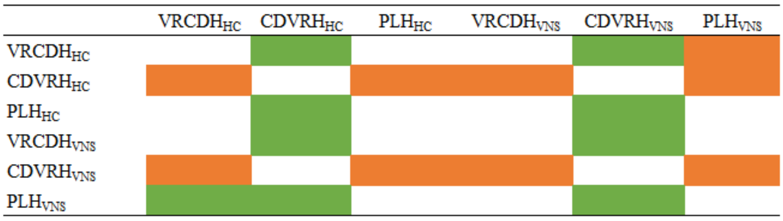

Figure 5.4: Tukey's test results for a significance level of 0.05. The rectangles green and orange indicate a significant difference between the related methods. The green rectangle means superiority, and the orange inferiority of the method is presented in the line about the method shown in the column.

In Figure 5.4, the rectangles green and orange indicate a significant difference between the related methods. The green rectangle means superiority, and the orange inferiority of the method is presented in the line about the method shown in the column. From the figure, the $VRCDH_{HC}$ heuristic offers a significantly higher difference than the $CDVRH_{HC}$ and $CDVRH_{VNS}$ heuristics. And a lower relationship to the PLH_{VNS} heuristic. However, with the other proposed heuristics, it is impossible to verify significant differences considering a significance level of 0.05. The CDVRH heuristic was the heuristic that presented the worst results, not being confirmed a negative difference only between the two versions of this method (HC and VNS). The heuristic that showed the best results was as expected the PHL_{VNS}, with significant positive differences when compared to the heuristics $CDVRH_{HC}$, $CDVRH_{VNS}$ and $VRCDH_{HC}$, the test did not perceive any difference about $VRCDH_{VNS}$ and PLH_{HC}.

The tests performed in this section indicates that the VNS methodology can bring gains. Still, Tukey's pairwise test indicates there isn't a significant difference considering the level of 0.05 between the versions HC and VNS for all three methods. Still, the superiority order is kept: PLH outperforms VRCDH, which in turn outperforms CDVRH.

Chapter 6

Heuristic under Uncertainties for the Open Vehicle Routing Problem with Cross-Docking

As previously discussed, a CDC's main objective is to reduce inventory within the center and arrive at the customer faster, strongly linked to vehicle routing, which is the reason for integrating these two problems in this dissertation. However, all methods previously proposed considered all trucks available at the center at the right time and the travel time to visit each customer as input parameters with fixed values, unchanged throughout the models, which in the CDC's practice is different.

Globalization, an increase in urban population, the rapid growth of e-commerce, and the COVID-19 pandemic, have led to changes in service habits and in the consumer's purchase profile, increasing the complexity of logistics strategies. These strategies are linked with uncertainties and disruptions that require constant revision and new tactics to guarantee the delivery of products in time.

According to the National Transport Confederation CNT (2018), in its yearbook publish in 2018, road transport is responsible for handling more than 60% of goods. However, this modal faces severe problems with the low quality of infrastructure in Brazil, with only 12.4% of the road network being paved, and most of the paved roads are single-lane (92.7%). This problem can cause uncertainty in handling times and the consequent delay in the CDC's trucks' arrival. According to CNT CNT (2018), these factors are an overload of the network and increase the risk of accidents. In 2017 alone, on federal highways, 5716 accidents with victims and 6243 deaths on federal highways were recorded. More than half of the occurrences were on roads with a simple two-way track to give you an idea. These episodes corresponded to 71.4% of the deaths registered in the year, making travel times challenging to predict accurately. These are some situations that can impact the delay in the arrival of trucks at the CDC or at the customer. But there are several others that can be perceived considering the daily activity, such as traffic jams, changes of address, defective vehicles, changes of direction of the road, parking difficulties, delays in the service of the truck by the customer, among others.

This context justifies a new heuristic proposal considering uncertainties in the arrival times of inbound and outbound trucks at the CDC and uncertainty in the travel time to go to each customer. The idea is that the cross-docking operator only knows the estimated time arrival of each truck in each real-time analysis. This time can be collected by a Global Positioning System (GPS) installed in the trucks. Throughout this chapter, the heuristic is discussed and presented, and later the results are treated.

6.1 Problem description

This chapter focuses on the inclusion of uncertainties in the OVRPCD. These uncertainties will be included in the trucks' arrival time at the CDC, both inbound and outbound trucks, and also incorporate in travel time, changing the customer's arrival time and, consequently, the total weighted delay's value, our objective function. These uncertainties aim to approximate our approach to the actual operation of a cross-docking center.

The operator has no total control over the trucks in the cross-docking and knows each truck's estimated arrival time. So they need to define the schedule for unloading trucks that arrive and, consequently, the outbound trucks' loading schedule. From there, delivery routes are built, and each customer's arrival time is also an estimated time. So the Dynamic Prioritization Lagrangian Heuristic (DPLH) performs the PLH heuristic at certain times throughout the day to check whether or not there is any change in the scheduling or routing of vehicles. Depending on the trucks' estimated arrival time or travel times, the scheduling or the delivery route can be reorganized to reduce the total delay. To better understand the dynamics of the problem, below there is some critical information:

- The cross-docking center operates receiving trucks from 7 am to 6 pm. There is a checkpoint every hour (the first execution can take place the day before or simply before starting the working day, 7 am. A horizon of 11 periods, every working hour (from 8 am until 6 pm), is analyzed.
- Each inbound and outbound truck will have an estimated time of arrival.

- Arrival times are updated every hour, and an assessment is done to verify if adjustments in the scheduling or routing are needed.
- Trucks already scheduled/routed before the current time cannot be changed.
- A truck that has already left the CDC may receive changes in the order of non-serviced customers. However, the list of customers in the route can not be changed.

It is essential to highlight that the exact method is not justified for the problem in question. It happens because an optimal result of a certain verification period does not guarantee an optimal for the subsequent verification time. It is interesting to build a fast and efficient methodology with low computational time and high-quality solutions to solve the dynamic problem, which justifies the DPLH proposal.

6.2 Dynamic Prioritization Lagrangian Heuristic (DPLH)

The proposed Dynamic Prioritization Lagrangian Heuristic (DPLH) considers the current time for predicting the arrival time of the trucks and the travel times. The objective is to approach an actual cross-docking center that does not have vehicles available at all times, considering uncertainties in travel time for delivery, which can impact customs delays. The DPLH aims to verify the scheduling and routing of every hour of work to find possible improvements in the face of a change.

The DPLH heuristic first executes the PLH_{VNS}, generating the first solution to the problem considering each truck's probable release date and the customers' travel times, generating a scheduling and routing plan. Notice that PLH_{VNS} use the constructive heuristics in its base ($VRCDH_{HC}$ and $CDVRH_{HC}$). Once all routes have been constructed, each estimated delivery date becomes the due date of each customer (d_c), and the total delay is calculated. As time advances, the RT (Real-Time) variable receives the value 8 (8:00 a.m.), the moment of the first verification of changes in release dates or travel times. This verification will take place up to 6 p.m. ($RT <= 18$). As time passes by, new data is collected. This data can then be used to update the release dates of trucks with an arrival date (rk) higher than the actual date. The data also allows us to update travel times. Consequently, the DPLH recomputes the new service time for each customer and updates the total weighted delay. Hence, a sensitivity analysis is conducted to analyze the impact of new dates on the weighted total delay, defining a tolerance level (Tolerance = 10% in our case). On the one hand, if the impact on the value of the weighted total delay is higher than the tolerance, the PLH is executed for the available trucks, i.e., respecting the trucks already scheduled and the customers already visited to update each customer's due date. If the CDC close time is reached (i.e., $RT > 18$), the algorithm ends. If the impact delay is less than the tolerance,it is not necessary to perform the PLH again; just update the customer's due date.

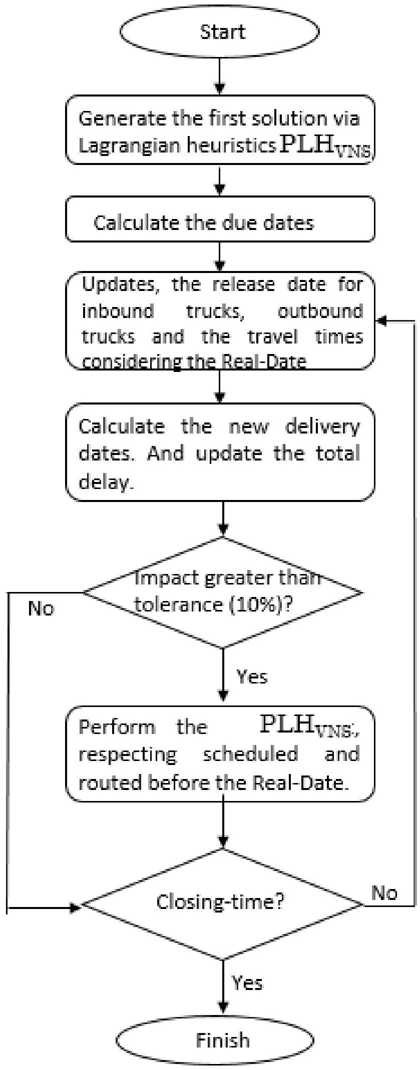

Figure 6.1: DPLH scheme.

Algorithm 4 DPLH - Dynamic Prioritization Lagrangian Heuristic

Generate an initial scheduling, routing, and total delay (FO) using PLH_{VNS} - section 4.2.3
$T_c \longleftarrow max\{0, v_c - l_c\}$;
$FO \longleftarrow \sum_{c \in N} w_c T_c$;
Define Customer's Due Dates; $d_c \longleftarrow v_c$;
set $RT = 8$;
SOL = FO;
while $(RT \leq 18)$ **do**
    Update trucks' release dates (r_k);
    Recalculate FO;
    if $(FO \geq (SOL + Tol))$ **then**
        Execute PLH_{VNS} for $r_k \geq RT$;
        Update SOL;
        $SOL \longleftarrow \sum_{c \in N} w_c T_c$;
    end if
    $RT \longleftarrow RT + 1$;
end while
end algorithm

Chapter 7

Computer Experiments - Heuristics under Uncertainties

The computational experiments were performed on a computer with Intel Core i7-4700HQ, 2.40GHz, 12GB RAM, in the Windows 10 64-bit, version 1607. The programming language used was AMPL and CPLEX optimization software 12.6.3.0. All instances and results are available at https://github.com/PriscilaCota/OVRPCD---Files.

7.1 Instance Generation

The instances built for testing the DPLH followed the premise established in section 5.1.1. However, some adjustments were necessary:

1. For each inbound truck, the problem set the initial release (r_{in}) date and eleven estimated arrival dates. One estimated arrival date for each hour of activity (8 a.m, 9 a.m, 10 a.m, ... 6 p.m), considering a horizon of 11 times. The estimated arrival dates followed a normal distribution between 0 and 108 centered on 60 (hours 7 a.m and 2 p.m centered in 11 a.m). To avoid a vast discrepancy between the times of the same truck once the first date was set, the others respect a specific uniform variation, divided into three groups: small, medium, and large variation, exposed in Table 7.1.

2. For each outbound truck, the problem set the initial release date (r_{out}) and eleven estimated arrival dates. One estimated arrival date for each hour of activity (8 a.m, 9 a.m, 10 a.m, ... 6 p.m), considering a horizon of 11 times. The estimated arrival dates followed a normal distribution between 24 and 132 centered on 96 (9 a.m and 5 p.m centered in 2 p.m). To avoid a vast discrepancy

between the times of the same truck once the first date was set, the others respect a specific uniform variation, divided into three groups: small, medium, and large variation, exposed in Table 7.1.

3. define a travel factor for each analysis within the planning horizon. Thus eleven values were determined. These values represent the possibility of the trucks to delay depending on the vehicle traffic. The variation follows a uniform distribution divided into two groups, a group of rush times (7 a.m, 8 a.m, 12 p.m, and 4 p.m) and the standard times. They were still divided into three groups: small, medium, and large, exposed in Table 7.1.

4. Change in the time window of customers following a uniform distribution between 4 p.m and 8 p.m. $l_c \sim Unif[108, 156]$.

Table 7.1: Group Variations.

	Estimated arrival dates		Travel factor	
Group variation	Inbound trucks	Outbound trucks	Rush time	Standard time
Small	Unif[0.95,1.10]r_{in}	Unif[0.95,1.10]r_{out}	Unif[0.95,1.15]	Unif[0.90,1.05]
Medium	Unif[0.90,1.25]r_{in}	Unif[0.90,1.25]r_{out}	Unif[0.90,1.25]	Unif[0.85,1.15]
Large	Unif[0.90,1.40]r_{in}	Unif[0.90,1.40]r_{out}	Unif[0.90,1.40]	Unif[0.90,1.40]

Thus, a new test instance scenario was built, called a mixed scenario, considering the small, medium, and large variations in release dates and travel times. This latest test scenario's characteristics are shown in Table 7.2.

Table 7.2: Variation of the instances for the mixed scenario.

		Trucks		Docks		
Scenario	Subdivision	Inbound	Outbound	Inbound	Outbound	Clients
Mixed	4.1	10	4	4	2	10
	4.2	30	10	8	4	30
	4.3	4	8	4	8	50
	4.4	50	8	8	3	8

Table 7.2 shows that the mixed scenario use test subgroups from the other three scenarios studied previously, Balanced (subgroups 4.1 and 4.2), with a stressed VRP (subgroup 4.3), and with stressed scheduling (subgroup 4.4). It is important to note that the instances' construction was changed, following the points described, to test this new scenario.

7.2 Results

To better present the test results, Table 7.3 reports for each subdivision five results: best case, worst case, average gaps, percentage of times providing the best solution (winning), and average computational time for the eleven instances of each group. The three columns present the comparative test based on the $GapUB$ 5.2 for the three versions analyzed. The first column shows the GapUB for Probable Best Option (PBO). To find the PBO solution, it is considered the arrival time of each truck, and the PLH procedure is used to define scheduling and routing plans. The second column shows the results provided by the $DPLH$ procedure. And the last column has the solution value without adjustment (NA), calculated considering each hour of activity updating each truck's arrival time, which also changes the time each customer is visited. The computational processing times are displayed in seconds.

As displayed in Table 7.3, the PBO column results are, most of the time, the best achieved. Hence, the "winning" line is always greater than that produced by the other resolutions. Considering the average results found by the NA and $DPLH$ resolutions, $DPLH$ finds results closer to those found by the PBO, which means rescheduling or re-routing improves the value of the objective function. The worst values detected by the three forms of explanation are perceived by the NA resolution, proving the importance of using DPLH. Notably, the PBO methodology is an idealized solution. It was created to carry out a comparison, impossible to be achieved in the practice of the CDCs, as in the first execution of the method, the arrival time of each truck throughout the day is already known through the general reading of the test instance, which would be impossible in practice daily. Figure 7.1 compares the mean values of best case, worst case, average gaps for each group variation in the three proposed versions. It is noticeable that the DPLH heuristic achieves more exciting results than the NA version in all group variations.

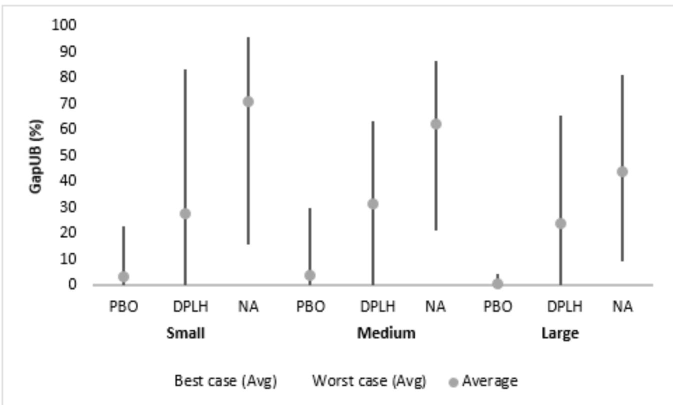

Figure 7.1: Results under uncertainty a) Results of GapUB for best case, worst case, and the average for each group variation. b) Boxplot graphs constructed using the GapUB for all proposed methods in all group variation.

In the average (GapUB) line, it is possible to count how far each resolution form is distant from the other in the Group Variation. Considering all the solved instances, the 95% confidence level of the average GapUB for PBO is $(2.7\%, 3.0\%)$, (27.2%, 30.8%) for $DPLH$ and (59.2%, 62.2%) for NA, which indicates that $DPLH$. The results prove the importance of rescheduling and/or re-routing to gain customer satisfaction (less weighted total delay).

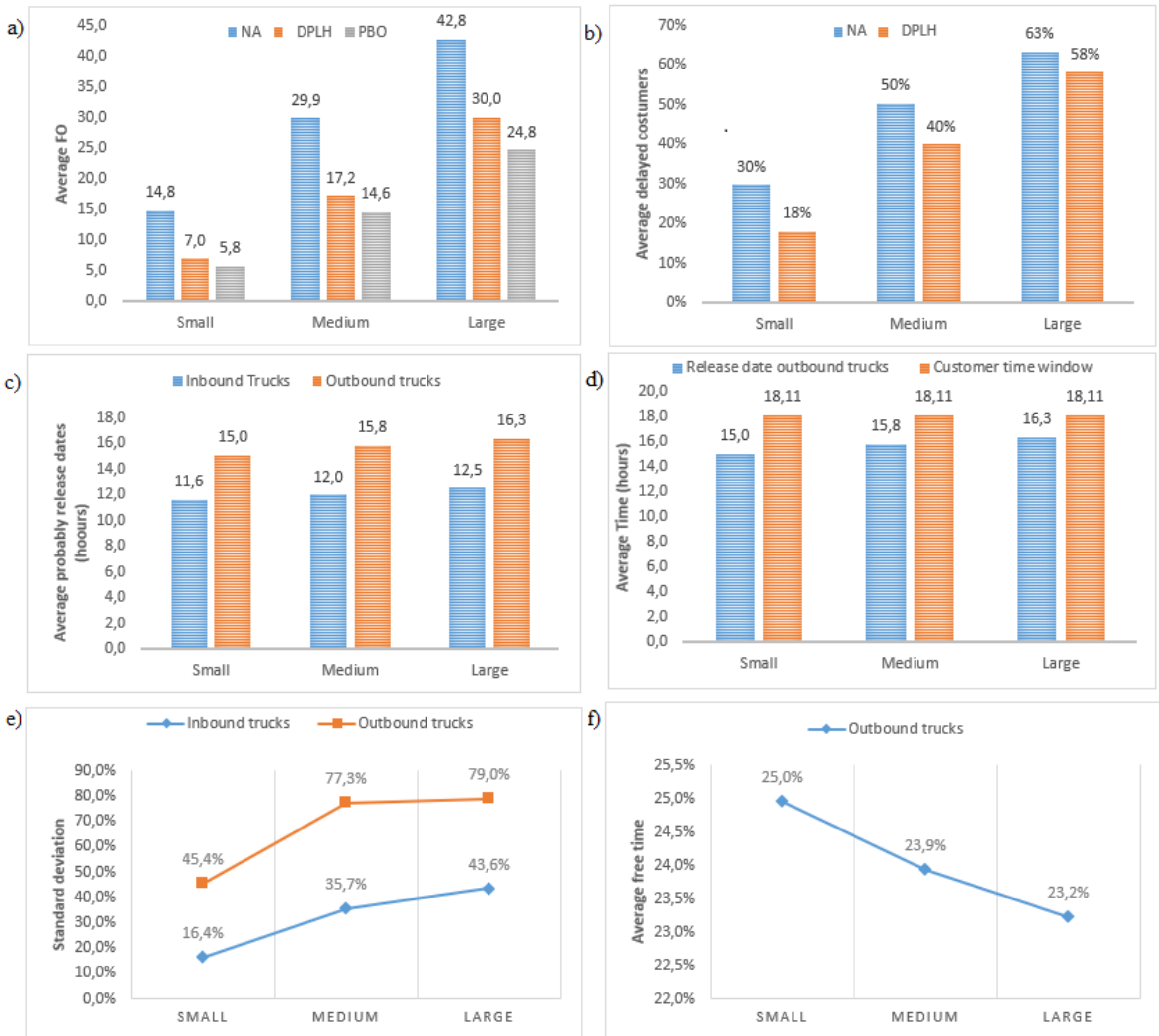

Figure 7.2: DPLH graphics. Graphic-a) presents the average value of the objective function for each method in each group variation. Graphic-b) identify the average percentage of delayed customers. Graphic-c) shows the average probable release date for inbound and outbound trucks. Graphic-d) Exhibit the average time (hour) for the probable release dates (outbound trucks) and for the final time window (customers). Graphic-e) represent the standard deviation average in the probable release date of inbound and outbound trucks. And Graphic-f) expose the average free time of the outbound trucks in each group variation

Figure 7.2(a) shows, as expected, that, increasing the variation in release times and travel times, there is an increase in the value of the objective function. The more uncertainty, the more difficult it is to fulfill the delivery on time, consequently increasing the percentage of delayed customers as presented in (b), which displays the average rate of delayed customers in each group variation for each method. The $DPLH$ method outperforms the NA solution, thus confirming that the pro-

Table 7.3: Results DPLH under uncertainty.

Group	Variation		Probable Best Option(%)	DPLH(%)	No adjustment(%)
Small	1.1	Best case	0.0	0.0	0.0
		Worst case	11.5	94.9	100.0
		Average	1.3	14.4	70.7
		Winning	81.8	72.7	9.1
		Average computational time(sec)		1.6	1.1
	1.2	Best case	0.0	0.0	62.8
		Worst case	65.6	100.0	100.0
		Average	10.7	48.8	85.5
		Winning	63.6	36.4	0.0
		Average computational time(sec)		156.2	98.7
	2.3	Best case	0.0	0.0	0.0
		Worst case	11.8	38.6	83.8
		Average	2.4	11.2	45.9
		Winning	63.6	36.4	18.2
		Average computational time(sec)		200.0	200.0
	3.3	Best case	0.0	0.0	0.0
		Worst case	2.5	100.0	100.0
		Average	0.2	36.3	81.3
		Winning	90.9	54.5	9.1
		Average computational time(sec)		4.6	8.9
	Average (GapUB)		3.6	27.7	70.8
Medium	1.1	Best case	0.0	0.0	0.0
		Worst case	51.6	72.6	89.3
		Average	5.9	41.1	60.6
		Winning	81.8	9.1	9.1
		Average computational time(sec)		3.1	1.7
	1.2	Best case	0.0	0.0	25.1
		Worst case	21.1	62.2	90.9
		Average	5.9	16.9	62.0
		Winning	63.6	36.4	0.0
		Average computational time(sec)		175.3	77.7
	2.3	Best case	0.0	0.0	13.8
		Worst case	7.5	19.0	65.4
		Average	0.7	8.2	40.0
		Winning	90.9	18.2	0.0
		Average computational time(sec)		200.0	200.0
	3.3	Best case	0.0	0.0	46.7
		Worst case	40.0	100.0	100.0
		Average	3.6	59.5	87.1
		Winning	90.9	9.1	0.0
		Average computational time(sec)		1.5	8.5
	Average (GapUB)		4.0	31.5	62.4
Large	1.1	Best case	0.0	0.0	2.4
		Worst case	8.1	82.5	92.9
		Average	0.7	37.8	55.5
		Winning	90.9	9.1	0.0
		Average computational time(sec)		2.7	1.2
	1.2	Best case	0.0	0.0	13.5
		Worst case	0.5	54.0	73.6
		Average	0.0	15.9	39.6
		Winning	90.9	9.1	0.0
		Average computational time(sec)		168.5	102.7
	2.3	Best case	0.0	0.0	21.4
		Worst case	0.0	26.1	57.5
		Average	0.0	13.2	39.8
		Winning	90.9	9.1	0.0
		Average computational time(sec)		31.7	200.0
	3.3	Best case	0.0	0.0	0.0
		Worst case	8.8	100.0	100.0
		Average	2.4	44.7	60.0
		Winning	72.7	9.1	18.2
		Average computational time(sec)		1.7	8.6
	Average (GapUB)		0.8	27.9	48.7

posed framework reduces the number of delayed customers considering the variations throughout the CDC in a daily operation. The percentage of delay reduction is about 12% for the small group, 10% for the medium, and 5% for the large one. Despite the smaller percentage difference in the large group, it is justified by the greater difficulty in achieving on-time deliveries. However, in the case of (a), it is possible to see an improvement in the objective function achieved by $RPDLH$ compared to the NA method. Also, notice that the $DPLH$ procedure presents results closer to PBO and superior to those found by the NA procedure –which guarantees that re-scheduling and/or re-routing brings real advantages to cross-docking centers. Figure 7.2(c) shows that the inbound trucks have a lower average than the outbound ones. Still, it is also verifiable that the inbound trucks are not available when the CDC opens, increasing the perceived delay (increase in the objective function). Figures 7.2(d)-(f) deal with delays. As shown in (d), the average probable release dates for the outbound trucks is lower than the customer's average time window. Thus, trucks can leave the CDC on time. Figure 7.2(f) exhibits the average percentage of free time. Finally, (e) shows the standard deviation of the release dates for the inbound and outbound trucks in each variation group.

To prove if there is a significant difference between the three solutions analyzed, which are measured based on the average GapUB solutions, considering all the instances tested. First, its performed the Analyse of Variance (ANOVA). This test confirmed a significant difference between the methods for a significance level of 0.05 (p-value = $1.0\text{x}10^{-52}$). Two other tests were performed to analyze each method in pairs, Test-t and Tukey's pairwise test.

7.2.1 Test T - under uncertainties

Using the Test-t, was compared first the NA and DPLH heuristic and later DPLH with the PBO solutions, considering μ_{NA}, μ_{DPLH} and μ_{PBO} the average of the Gaps produced by NA, DPLH, and PBO, respectively. The hypotheses of the first comparison were stated as shown in 7.1.

$$\begin{cases} H_0 : \mu_{NA} = \mu_{DPLH} \\ H_1 : \mu_{NA} \neq \mu_{DPLH} \end{cases} \tag{7.1}$$

The differences were compared using a two-sided T-test for a significance level (α) of 0.05. The p-value obtained by the test is $1.1\text{x}10^{-20}$, which supports the rejection of the null hypothesis, indicates that the DPLH variant leads to better average results (lower Gaps). Therefore, it is reasonable to assume that the DPLH heuristic presents results superior to NA, which guarantees the quality and usability of the proposed dynamic heuristics.

In the second comparison, the DPLH heuristic and PBO were compared as shown in 7.2.

$$\begin{cases} H_0 : \mu_{DPLH} = \mu_{PBO} \\ H_1 : \mu_{DPLH} \neq \mu_{PBO} \end{cases} \tag{7.2}$$

The p-value obtained by the Test is 5.6x10^{-14}, which supported the rejection of the null hypothesis. It was already expected that the solution obtained by PBO would be superior to the solution obtained by DPLH since PBO is an impossible solution to be achieved in practice. Still, the confidence level shows us that PBO does not always find the best solution, proving that DPLH is an exciting option for cross-docking centers.

7.2.2 Tukey's Pairwise Test - under uncertainties

To analyze each method in pairs, Tukey's pairwise test was performed for a significance level of 0.05, whose result is shown in Figure 7.3, the rectangles green and orange indicate a significant difference between the related methods. The green rectangle means superiority, and the orange inferiority of the method is presented in the line about the method shown in the column.

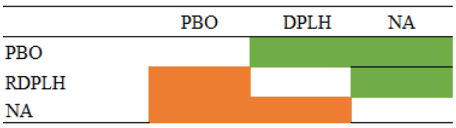

Figure 7.3: Tukey's test results for a significance level of 0.05 considering the methods under uncertainties. The rectangles green and orange indicate a significant difference between the related methods. The green rectangle means superiority, and the orange inferiority of the method is presented in the line about the method shown in the column.

From Figure 7.3, it is possible to see that the PBO heuristic offers a significantly higher difference than the DPLH and NA heuristics. However, DPLH presents a significant difference considering a significance level of 0.05 compared with NA, proving the importance of applying the proposed DPLH heuristic in improving results under uncertainty.

These issues of scheduling, routing, delivery logistics, and customer service are always important issues for increasing organizations' competitiveness. Studies that deal with better routes, time uncertainties, faster deliveries, time savings, and deliveries on time are crucial factors for organizations. Nowadays, the world lives in a critical and pandemic moment, so these activities have become even more essential. Therefore, the next chapter makes a critical qualitative analysis of this studied problem, raising hypotheses, presenting advantages, and even unexplored gaps.

Chapter 8

A qualitative analysis of cross-docking centers

This dissertation has been concerned with proposing and discussing scheduling trucks in a cross-docking center and routing the vehicles for delivery to customers to minimize the total service delay. Customers are a priority for any organization. Without customers, companies lose their objective, leaving them without generating sales and, consequently, not generating revenues that guarantee their existence. It is essential to understand that even nonprofit organizations need the customer. So the general objective of all organizations is to satisfy customers and reduce costs. But, is it a simple objective in organizations? The answer is no. Because of this, some questions are necessary at this time. These questions are: What is the customer's profile currently? Does this customer only care about costs and on-time delivery? What does the customer buy with a particular organization? What is the behavior of cities about delivery logistics? What changed in the logistics chains? Are there changes in the market inserted? Can the proposed methods be applied? What are the advantages of using them? How do uncertainties affect organizations?

There are some others questions considering the study's context. This chapter will answer some of these questions to analyze critically, in the view of the production engineer, the cross-docking centers, the consumer profile, and the logistical changes occurring in the market.

8.1 Supply Chain

In the face of globalization, the market is becoming increasingly competitive, and the customer is more rigorous about their purchase decisions. Today, the customer is more aware and wants a large product variety with quality and quick delivery. Customer satisfaction is a significant issue for companies. Therefore, companies focus more on the collaborative supply chain nowadays. Collaboration in the supply chain contributes to overall performance by minimizing the uncertainty in demand and supply (Singh et al. (2018)). Thus, understanding the supply chain is fundamental for this paper's critical analysis of the cross-docking center treated.

According to Rahmandoust and Soltani (2019) supply chain include purchase and supply, logistics and transportation, marketing, organizational behavior, network, strategic management, information systems management, and operation management. It has consisted of five levels: suppliers, producers, distributors, retailers, and the final customers, which are all interrelated for the last customer to be served appropriately. It is noticeable that several techniques can make this supply chain more efficient, and some of these techniques are linked to cross-docking centers and routing of deliveries. According to Slack et al. (2008), the supply chain can be classified into three stages: suppliers, production operation, and consumers, as shown in Figure 8.1. In the OVRPCD treated, the cross-docking center is in the middle of the supply chain, the production operation. Not all CDCs work in the same way, so different parts of the supply chain may be part of cross-docking centers. This CDC can be independent or handle collection from suppliers or delivery to customers or even collection and delivery.

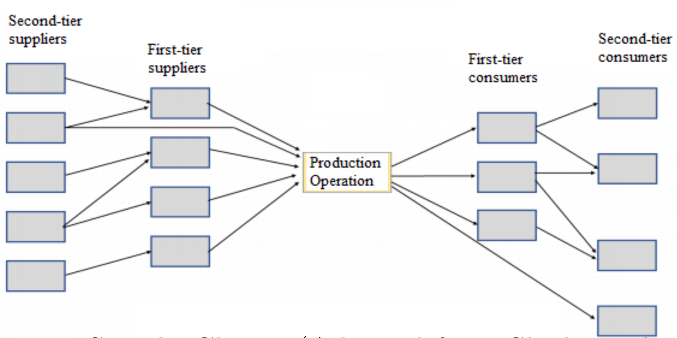

Figure 8.1: Supply Chain. (Adapted from Slack et al. (2008)).

In all methods proposed in this thesis, the cross-docking center is responsible for delivering to the first-tier customers. The OVRPCD is accountable for scheduling the inbound and outbound trucks and is also responsible for routing the delivery vehicles. The considered network is in Figure 8.2. The VRCDH, CDVRH, and PLH methods, assumes that the trucks coming from suppliers and the trucks that left the CDC to go to customers are available at the necessary time. However, this is not a reality for all CDCs, since one of the difficulties of cross-docking centers is to make this integration of suppliers, CDC, and customers happen.

The DPLH method deals with CDC and deliveries to customers but considers some uncertainties to have greater control of the center not controlling trucks coming

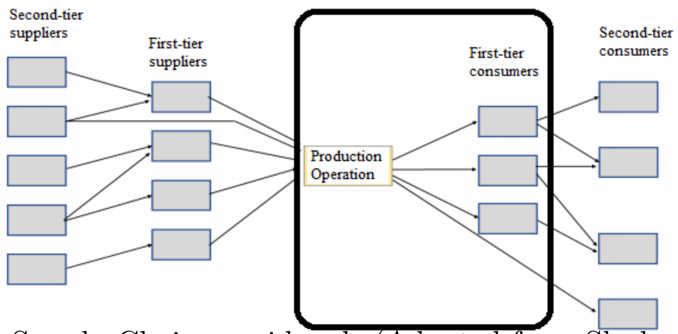

Figure 8.2: Supply Chain considered. (Adapted from Slack et al. (2008)).

from suppliers, so it is impossible to believe that it is always available when necessary. But, an integrated system to the supplier is possible, through a GPS, to estimate the trucks' arrival times from the suppliers to the center, which is done in the DPLH. Every hour of the CDC's activity, the possibility of delay or the advance of the trucks arriving at the CDC from the suppliers is verified.

For outbound trucks, this dissertation also considered a possible release date and possible variations on that date. These variations are analyzed every hour of activity at the center, exactly as inbound trucks. Since the CDC is responsible for deliveries, it would be acceptable to consider the outbound vehicles available at any necessary time. However, this article aims to make the problem more realistic, so we believe possible variations in release dates to make the problem more adaptable to different situations. If these trucks are always available, a simple adaptation in test instances must be made, setting all possible release date values equal to zero. This variability was considered because although the company is responsible for the CDC and deliveries, these outbound trucks may not be available all the time. In some cases, for example, because of the maintenance of the vehicles. If the CDC is responsible for the trucks, they went through activities such as refueling, cleaning, breaks, and support, altering the trucks' availability. According to Campos (2006), in line with the maintenance process, Maintenance Planning and Control (PCM) emerged, with the need to increase the machines' physical availability reliably. For Kardec and Nascif (2010), maintenance is an activity that is continuously evolving to meet the demands of the competitive market, that needs the equipment's reliability to supply the productions that have grown over the years. The maintenance practiced decades ago must be improved since reliable results cannot be sustained without a proper maintenance strategy or just practicing corrective maintenance. Kardec and Nascif (2010) divides maintenance into four different types: corrective, planned corrective, preventive, and predictive, both of which interfere in the truck's availability. Still thinking that these trucks belong to the distribution center, they can carry out other activities and deliveries not related to the CDC, making it necessary to inform the truck's release date.

Another practice that justifies a method that considers the variation in the outgoing trucks' release dates is outsourcing the fleet or the employees responsible for delivery. According to Bourlakis and Melewar (2011), many companies began to consider outsourcing their logistical processes. Because managing all operations has become a challenge given the full range of logistics functions, the inherent complexity of dealing with large quantities of products, the substantial capital investment required for these operations. The authors point out that logistical outsourcing reduces investments in facilities, information technology, and human resources. Outsourcing can reduce operating costs and losses due to depreciation and maintenance and decrease responsibilities of the delivery process. However, in some cases, it can increase the instability of deliveries when they are carried out in a shared way with other companies. It can make loading and dispatching the truck a factor with time uncertainties, where GPS technology can only help the CDC predict when these trucks will arrive at the center.

As the delivery to the customer is part of the responsibility of the cross-docking center's activities, to bring more realism, travel factors are considered because they can impact the moment of delivery. Every hour, the travel time to a customer may increase or decrease depending on this factor. There is a higher possibility of vehicle traffic at rush times, often delaying delivery. However, there is a higher possibility that the speed will continue as expected or have fewer variations at standard times. The traveling factors are in Table 7.1 for each time.

According to Savelsbergh and Woensel (2016), the increase in online sales from the Internet and e-commerce has given a significant boost to sales by retail companies and has given rise to new and different business models. The growth in online sales leads to a rise in deliveries to customers, which justifies new practices and logistical studies to make deliveries that meet customers' needs (section 8.2). Thus the proposed methods are justifiable.

8.2 Customer's needs

Many different indicators can measure the performance of cross-docking centers and vehicle routing problems. Here possibles performance measures are analyzed, which might also be elements of the objective function for optimizing the OVRPCD problem studied.

In all methods proposed in this dissertation, the objective function treated is always the same. The objective is to minimize the sum of the total weighted delay. There is a final time window for each customer, so each customer has a specification of the maximum time to receive their purchase. If the customer's deadline is met, there is no delay (the customer's delay is zero and has no impact on the objective function). However, suppose the service forecast is after the customer's final time window. There is a difference between the delivery time and the customer's time window (delay more significant than zero and impact the objective function). The objective function also has a weighted delay accounting since each client has a weight or a degree of importance. This thesis recognize three different significance to customers. Customers with less importance have weight one, the customer with medium priority has weight two, and most prestigious customers with weight three. Thus, customers with value three have a more significant impact on the objective function, which leads our proposed methods to attempt customer service first for the weighted total delay to be as short as possible. The three different types of weight for customers are in Table 8.1.

Table 8.1: Customers weight.

Weight w_c	Importance
1	Low
2	Medium
3	High

Many cross-docking papers have the objective of minimizing the makespan. According to Ladier and Alpan (2016), makespan or schedule length is an important goal, consisting of finishing the operations as early as possible. The total schedule length or makespan, according to the authors, is the difference in the time at which the last process is completed and the time at which the first operation has started. This metric is concerned with the shortest time to complete all jobs, thus thinking about all general jobs. As previously mentioned, not adapting to our problem because it has time windows for service and has different importance, not thinking about the situation in a general way, minimizing the total time of completion of jobs. Many articles are concerned about reducing travel costs in the vehicle routing problem, which in OVRPCD is also not a focus. The focus of this problem is the customer. The objective is the reliability perceived by the customer since they define an ideal time for receipt. The problem tries to adjust to having less customer dissatisfaction due to the delay. Timeliness of delivery is one of the critical parameters to judge the production department's effectiveness, in our case, to evaluate the CDC's effectiveness. Table 2.1 shows that most of the papers that solve the VRPCD have the objective of reducing costs. However, in the practice of organizations, not only does cost matter to the client.

Skinner (1978) defined manufacturing's objectives as cost, quality, delivery time, and flexibility and indicated that there were trade-offs between them. Later, Slack (1983) defended five dimensions, being quality, cost, flexibility, delivery time, and service, on the manufacturing objective. The proposed methods' objective function deals with two dimensions of the manufacturing objectives, delivery time and service, working with the scheduling integrated to the routing, worrying about the delivery time, and customer satisfaction with the service provided to serve the customer in the stipulated time. In an increasingly competitive and globalized world, doing the client well is essential for future purchases.

The objective function analyzed considers that all customers will be served, some before the final window and some with a time delay. However, this dissertation have not examined whether all of them can be attended to within a whole working day. A plausible option is to establish a final service period for each truck, and after that period, the trucks return to the CDC for deliveries to be made in the following days. It causes a stock of material within the cross-docking center to be managed.

Thinking in a real CDC, the mixed scenario analyzed is more suitable. However, it is necessary to reflect on real centers that often do not have so many trucks to be processed at docks or haven't so many customers to be served on the same day. If you consider a large center with about 50 trucks to be unloaded, you also need to think about several inbound docks to process, so these trucks can be unloaded in time to be loaded and carry out deliveries. Talking about 100 or 50 customers, it is necessary to have many trucks considering that the travel time between customers is significant. Some instances were thought of in extreme scenarios to test the proposed heuristics.

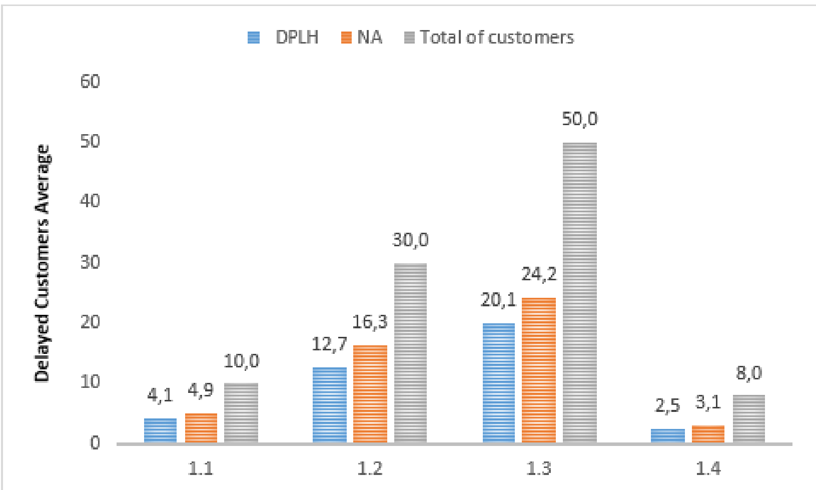

Figure 8.3: Average delayed customer for each subgroup in a mixed scenario.

Figure 8.3 shows the average number of delayed customers and the total number of customers in each subgroup. It is possible to verify the DPLH solution's superiority over the NA solution. In the DPLH solution, there are fewer customers in arrears, and more than half of the customers are served. But it is important to remember that the outbound trucks have probable release dates. If these trucks were available at the CDC, this average number of delays would be reduced. But as our objective is to treat the question of uncertainties times, this insertion became interesting to analyze the problem.

One exciting option for our objective function is to consider multi-periods. Observing the results is possible to verify that, for many instances, there is no possibility of visiting all customers in one day of operation. These items can be considered in the next day's process, reorganizing the customers that must be seen, performing new scheduling, and a new routing considering the items not delivered. It is essential to understand that these outbound trucks would be inbound in the next day for new scheduling and routing because each customer's items should be reorganized considering the new delivery routes. Or a further option would be to consider this an outbound truck that already has some customers to visit. These trucks need a new routing built. The objective function can be more realistic with a different fine for each no visited customer. These fines could work together with the weight of each customer, to continue trying to minimize our objective function to minimize the delay, considering the cost of non-service in a financial fine.

This option requires the management of items within the CDC inventory, which was not considered in this dissertation. It is essential to highlight that cross-docking and routing studies, as already mentioned, involve many areas of research, and there are papers focused on several different areas. The more variables are assigned, the more complicated this problem becomes. This final chapter had as objective to present positive points and present possible points of improvement, considering the realities of the cross-docking centers, providing some options for continuing this study in the analysis of real centers. Cross-docking distribution centers are considered by most companies a strategic issue, which makes it difficult to visit, visualize the operation, and apply new proposals. Cross-docking by companies is treated as a logistics strategy, a competitive differential, and due to this fact, little information is found in practice. Companies that use cross-docking sometimes tend to have only part of the CDC that works with zero or almost zero inventory. These justify the use of the heuristics proposed, mainly the heuristic DPLH, applied in centers that most of the time have a balanced number of trucks, docks, and customers.

So, for the proper functioning of cross-docking, the company needs to be efficient in synchronizing the flow of goods, internal information, and external information. Everyone involved in the process needs to be provided with all information about the operations. This means: knowing when it will be received, in what quantity, and with what destination are essential for good planning the processes, which again justifies using DPLH heuristics to treat suppliers, CDC, and customers in an integrated and dynamic way.

Chapter 9

Conclusions and perspectives

This thesis discussed an integrated scheduling-and-routing optimization problem in cross-docking distribution centers developing efficient ways to solve the integrated scheduling and open routing optimization problem in cross-docking distribution centers, aiming at minimizing penalties caused by delays in servicing customers. Given the intrinsic difficulty of this problem, approximation methods can offer suitable solutions for practical size problems. The proposed methods have feasible computational times with simple programming mechanics, ensuring flexibility in different situations. They can easily integrate current technologies to monitor the localization or other similar systems of delivery vehicles.

For small instances, the mixed-integer linear programming model proved to be a reasonable option, finding the optimal solution in a feasible time (established 1000 seconds). The model solved the minor subdivision of each test scenario (around ten customers) within the established time. For medium and larger instances, the Prioritization Lagrangian Heuristic (PLH) outperformed the other procedures ($VRCDH$ and $CDVRH$), providing results close to the optimum when possible to compare. The insertion of VNS in the proposed heuristics improved the results achieved. However, the results continued proving the superiority of the heuristic PLH_{VNS} over $VRCDH_{VNS}$, and the superiority of the latter over $CDVRH_{VNS}$. The insertion of the VNS in the $VRCDH$ heuristic could not find results superior to those achieved by PLH_{HC} which outperformed $CDVRH_{VNS}$. Considering the instances solved by the mathematical model and using a 95% confidence level, the PLH_{HC} presents an average gap in $(11.3\%, 12.0\%)$, while PLH_{VNS} shows an average gap in $(8.2\%, 8.6\%)$, proving the excellent result of the proposed heuristic. Using reasonably low computing times, the PLH shows the capability to operate well in all tested scenarios. Despite presenting worse results, the heuristics $VRCDH$ and $CDVRH$ contribute to the PLH method (initial solution).

A Dynamic algorithm ($DPLH$) is proposed to deal with uncertain situations regarding arrival and travel times in a more realistic setting. By considering an estimated arrival time, the method changes the trucks' scheduling or routing to minimize customer delays. The benefits of this technique will undoubtedly change with the level of uncertainty and the number of daily deliveries. $DPLH$ and NA are compared through the gap values (without routing or schedule adjustments). The percentage of delay reduction caused by $DPLH$ is about 12% for the small group, 10% for the medium, and 5% for the large one, achieving a considerable average reduction in the total weighted delay. All in all, this practical and straightforward framework could be incorporated into a CDC operation, ensuring a reduction in the percentage of late customers and the weighted total delay.

Chapter 8 of this thesis concludes with a discussion aligned with production engineering, identifying positive points and gaps that can still be explored. One of the future study suggestions is the insertion of an objective function considering multiperiod. It is interesting to think of two or three days for deliveries to treat the deliveries that cannot be made in one day of activity. The number of periods considered should not be too large as the CDCs' objective is to work with zero inventory or the closest to that. Ultimately, it is possible to verify that the objectives initially proposed to construct this doctoral thesis are achieved from the results obtained throughout this work. The general purpose was to simultaneously solve the problem of scheduling trucks in a cross-docking distribution center and routing the trucks that leave the center, minimizing the delay on customers, called OVRPCD.

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Appendix A

Resumo Estendido

A.1 Appendix: Contextualização

O atual ambiente de mercado, caracterizado por uma concorrência cada vez mais acirrada, globalização da economia e uma acelerada revolução tecnológica, tem levado as empresas a melhorarem seus sistemas logísticos, de distribuição e de produção. Além disso, o aumento populacional e do comércio eletrônico vem exigindo soluções logísticas mais eficientes e eficazes. Aumentando a pressão sobre os fornecedores e distribuidores para entregar produtos aos clientes com rapidez e eficiência. Para este fim, centros de *cross-docking* e rotas de distribuição inteligentes são estratégias logísticas atraentes para aumentar a satisfação do consumidor e a competitividade das organizações.

Cross-docking (CD) é uma abordagem que elimina ou reduz duas funções dos centros tradicionais de distribuição que são a estocagem e coleta dos produtos, para isso, um Centro de *Cross-docking* (CDC) funciona com um estoque limitado ou, se possível, nulo. Esse centro opera recebendo caminhões com cargas de diversos pontos de fornecimento, cada um dos veículos é recebido em uma doca de entrada. Dentro do centro, as cargas são descarregadas, separadas, classificadas, combinadas e recarregadas em caminhões de saída, de acordo com os pedidos específicos dos clientes. Os caminhões então deixam o CDC com cargas combinadas, composta por produtos de diversos fornecedores, dedicadas a uma rota de clientes ou para um destino específico. Essa estratégia logística está sendo utilizada atualmente por empresas pertencentes a diferentes setores industriais e esta representada na Figura A.1. Simchi-Levi et al. (2003) nos mostra que empresas como Amazon, Coca-cola, Dell, Wal-Mart se tornaram referências em soluções inovadoras de gestão da cadeia de suprimentos.

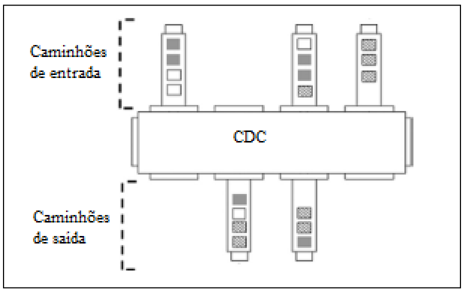

Figure A.1: Centros de *Cross-docking*- Cota et al. (2016)

A estratégia de *Cross-docking* nos últimos anos tem tido aplicações interessantes. Existem diferentes abordagens a respeito dos CDCs com enfoques nas diversas etapas do processo logístico. Boysen and Fliedner (2010) e Belle et al. (2012) apresentam uma revisão dos trabalhos presentes na literatura que possuem o tema *cross-docking* como foco principal. Já Ladier and Alpan (2016) apresentam uma pesquisa discutindo práticas da indústria e caracterização de problemas nos CDCs.

De acordo com Boysen and Fliedner (2010), o uso do CDCs apresenta várias vantagens para o sistema de distribuição como: redução de custos de distribuição, da área física, de falta de estoque nas lojas de varejo, do número de locais de armazenamento, da complexidade das entregas, dos níveis de estoque, um aumento da disponibilidade do produto, entre outros. No entanto, processos de transbordo eficientes e planejamento cuidadoso das operações tornam-se indispensáveis dentro de um CDC, onde os fluxos de entrada e saída precisam ser sincronizados para manter o armazenamento do centro o mais baixo possível e para aumentar a confiabilidade das entregas. Nos casos em que um caminhão de saída deve visitar mais de um cliente, essa confiabilidade pode ser aumentada ainda mais considerando a construção adequada da rota de visitação de clientes.

O Problema de Roteamento de Veículos (VRP) consiste em determinar uma ou mais rotas de visitação para um conjunto de clientes dispersos geograficamente, sujeitos a restrições, sendo que os clientes possuem demandas conhecidas e o caminhão deve partir do depósito e retornar ao mesmo ponto. Os estudos que tratam o VRP consideram diferentes funções objetivo, como: minimizar o custo total de transporte, minimizar tempo de transporte, minimizar a distância total percorrida, minimizar o tempo de espera, maximizar o serviço oferecido ao cliente, minimizar o uso de veículos. O problema é muito estudado em otimização combinatória por pertencer à classe de problemas NP-Difícil. Dantzig and Ramser (1959) foram os primeiros autores a estudarem esses problema, eles trataram o problema de distribuição de gasolina para postos de revenda de combustível, propondo uma formulação de programação linear.

Embora muitos estudos tenham considerado *cross-docking* e roteamento de veículos separadamente, lidar simultaneamente com os dois problemas tornou-se ainda mais crítico devido à quantidade de incerteza que ocorre regularmente em um centro logístico. Fazer mudanças de última hora na programação de caminhões, nas rotas de entrega e a priorização dos clientes fazem parte da rotina diária de um CDC. A integração das duas estratégias tem sido cada vez mais apreciada e investigada como uma estratégia eficaz para a gestão da cadeia de suprimentos. Lee et al. (2006) apresentou o Problema de Roteamento de Veículos com Cross-Docking (VRPCD). De acordo com o autor é preciso integrar as atividades do CDC ao roteamento dos caminhões de entrada e de saída. O fluxo do fornecedor para o CDC é chamado processo de coleta. No *cross-docking*, os produtos recebidos são classificados de acordo com seu destino. Esses produtos são então entregues aos clientes sem demora ou armazenamento. O processo desde o *cross-docking* até os clientes é denominado processo de entrega. Assim, a melhoria do fluxo da cadeia de abastecimento pode ser alcançado pela modelagem de todos os processos juntos, incluindo coleta, *cross-docking* e entrega. A Figura A.2 exemplifica o VRPCD. Existem estudos com diferentes situações, restrições e funções objetivos considerando o VRPCD.

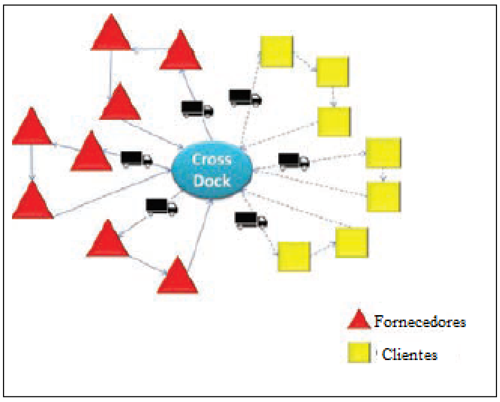

Figure A.2: Problema de Roteamento de Veículos com Cross-Docking (VRPCD) - Birim (2016)

A.2 Appendix: Definição do problema

Consideramos um problema de *cross-docking* com um roteamento de veículos abertos (OVRPCD), a característica aberta do problema implica que os veículos não retornam ao CDC depois de completar a rota de entrega. As atividades consideradas nessa dissertação são o sequenciamento dos caminhões de entrada e de saída e o roteamento dos caminhões de saída (caminhões que fazem a entrega final aos clientes) assim sendo, cada caminhão tem uma rota de entrega e visita mais de um cliente, como apresentado na Figuras 1.1 e A.3.

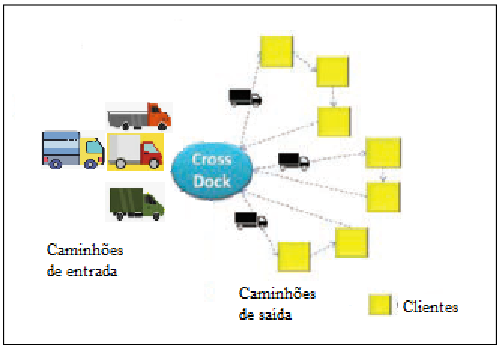

Figure A.3: Problema de Roteamento de Veículos com Cross-Docking Aberto estudado

No problema estudado, os caminhões de entrada que chegam no CDC, carregados com mercadorias diferentes de um ou mais fornecedores são atribuídas a uma doca de entrada, onde a carga é descarregada. O sequenciamento dos caminhões de entrada considera apenas o dia atual, onde o momento de chegada de cada caminhão é conhecido com antecedência. Na segunda parte de nosso estudo, esta é uma informação incerta. As mercadorias recebidas através dos vários caminhões de entrada são preparados para serem transferidos para a área de despacho e carregados nos caminhões de saída em docas específicas para o carregamento dos veículos de saída. Inicialmente, consideramos todos os caminhões de saída disponíveis a qualquer momento, e na segunda parte do trabalho incertezas são atribuídas a disponibilidade desse caminhões. Depois de atribuir o caminhão de saída para uma doca, suas mercadorias serão consolidadas e totalmente carregadas para realizar a entrega aos clientes. Esses caminhões vão visitar um grupo de clientes, cada um com sua demanda, de diferentes fornecedores; nenhuma entrega parcial é considerada. O carregamento de um caminhão de saída só pode ser iniciado após descarregar todos os caminhões de entrada do qual este depende, considerando as demandas dos clientes. Cada caminhão de saída apenas pode deixar o CDC após a conclusão do carregamento. Esses caminhões são idênticos, e há um número limitado de clientes para visitar. Cada cliente pode ser visitado por apenas um caminhão e todos os clientes devem participar de uma rota de entrega.

O problema considera a existência de múltiplas docas (portas, processador) para descarregar e carregar os caminhões, sendo denominado assim um *cross-docking* híbrido de dois estágios, ou seja, com várias máquinas em cada estágio, paralelas e idênticas, como proposto por Chen and Song (2009). Assim que um caminhão começa a ser processado, a operação deve ser encerrada sem interrupções. O tempo de processamento para descarregar e carregar é conhecido e diferente para cada caminhão. O tempo de movimento de mercadorias entre as portas de entrada e saída dentro do CDC são desconsideradas. A velocidade constante é assumida para todos os caminhões de entrega, no primeiro momento. Depois algumas incertezas nesse tempo de viagem são consideradas. As distâncias entre os vários pontos são dadas pelo tempo de viagem. Cada cliente tem uma janela de tempo de atendimento final, um horário máximo em que eles podem receber suas mercadorias. Se um cliente não for visitado antes desse horário, gera-se uma penalidade que varia de acordo com o cliente (representado por um peso associado a cada cliente). O objetivo é minimizar o somatório ponderado das penalidades causadas por atrasos no atendimento aos clientes. Dessa maneira os métodos propostos enfocam no sequenciamento de caminhões e na construção das rotas de entrega de forma a minimizar o atraso médio total, enfatizando a satisfação no atendimento ao tempo dos clientes.

Com o objetivo de desenvolver novas perspectivas de pesquisa em relação às operações e reduzir o gap entre a pesquisa acadêmica e as necessidades industriais, como destacado por Ladier and Alpan (2016), dividimos os nossos testes em duas etapas, na primeira consideramos os dados de entrada todos exatos, mas já na segunda etapa incertezas são incorporadas aos problemas tratados, considerando incertezas no tempo de chegada dos caminhões de entrada e saída e nos tempos de viagem, como discutido anteriormente.

A.3 Appendix: Contribuições

Para resolver o problema integrado, trabalhamos com diferentes métodos de solução, é importante ressaltar que todos os métodos propostos resolvem o Problema de Roteamento de Veículos com *Cross-Docking* Aberto. Primeiro, propomos um modelo de programação linear inteira mista para resolver pequenas instâncias de forma ótima, com base nos modelos propostos por Chen and Song (2009), Yu et al. (2016) e El-Sherbeny (2010). Para testar o modelo limitamos o tempo de execução em 1000 segundos, dentro desse tempo computacional, conseguimos resolver instancias de até 30 clientes variando o número de docas e de caminhões. Para os testes três cenários foram analisados, um cenário com maior dificuldade no roteamento dos veículos, um com maior dificuldade no sequenciamento, e um balanceado (com dificuldades consideráveis tanto no sequenciamento quanto no roteamento). Posteriormente, duas heurísticas construtivas são propostas para resolver o problema integrado. As heurísticas construtivas utilizam a heurística PFIH proposta por Solomon (1987) e a heurística CDH proposta por Cota et al. (2016), as heurísticas propostas são utilizadas para resolver pequenas, médias e grandes instâncias do OVRPCD. Os mesmos grupos de teste do modelo foram utilizados. Após as heurísticas construtivas trabalhamos em uma heurística de decomposição lagrangeana baseada no modelo e nas heurísticas construtivas dualizando as restrições complexas do modelo e penalizando suas violações na função objetivo.

Finalmente, propomos um *framework* de tempo polinomial que utiliza uma abordagem dinâmica de re-sequenciamento e re-roteamento eficiente para resolver o problema de sequenciamento e roteamento de caminhões com múltiplas docas sob incertezas no tempo de chegada dos caminhões de entrada e saída, e incerteza nos tempos de viagens. Para esse teste os mesmos cenários anteriores foram trabalhados entretanto as instancias precisaram ser alteradas a fim de comprovar a aplicabilidade da estratégia proposta. Os resultados demonstram que nossa metodologia pode apoiar os gerentes em suas operações diárias de *cross-docking* que podem ser necessárias de serem alteradas ao longo do dia, integrando as situações reais vivenciadas pelos CDCs, os algoritmos propostos e as tecnologias disponíveis no mercado para aumentar a satisfação dos clientes. O tempo estimado de chegada dos caminhões pode ser facilmente coletado por um *Global Sistema de Posicionamento* (GPS) instalado nos caminhões. Assim, é necessário que o método proposto seja rápido e flexível para ser integrado às tecnologias logísticas atuais, aproximando nossa abordagem da operação de um centro de *cross-docking* real.

A.4 Appendix:Organização do Texto

Esta dissertação está organizada em oito capítulos estruturados da seguinte forma: Capítulo 2 oferece uma revisão da literatura sobre artigos relacionados e descreve o problema com mais detalhes. O Capítulo 3 apresenta definições, formulação geral e um modelo proposto. O Capítulo 4 propõe dois procedimentos construtivos (VRCDH e CDVDH) e uma heurística Lagrangiana de Priorização Integrada. As instâncias de teste e os experimentos computacionais sem incertezas são discutidos no Capítulo 5. O Capítulo 6 apresenta a estratégia para lidar com as incertezas estudadas. As discussões e conclusões são oferecidas no Capítulo 8 e 9.

Appendix B

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Integrating vehicle scheduling and open routing decisions in a cross-docking center with multiple docks

Priscila M. Cota [a], Thiago H. Nogueira [b], Angel A. Juan [c], Martín G. Ravetti [d,*]

[a] Department of Production Engineering, Universidade Federal de Minas Gerais, Brazil
[b] Department of Production Engineering, Universidade Federal de Viçosa, Brazil
[c] Department of Statistics and Operations Research, Universitat Politècnica de València, Spain
[d] Department of Computer Science, Universidade Federal de Minas Gerais, Brazil

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ABSTRACT

Society is facing a series of challenges, as the growth in urban population, the expansion of e-commerce, the pandemic moment (COVID-19), and many others leading to changes in companies' supply chain, like reducing product delivery time and attention to consumer welfare, the environmental impact, to mention a few. The efficient management of logistic solutions such as cross-docking can contribute to improving the supply chain performance. Here we focus on the integration of scheduling of trucks and routing decisions; the integration of these strategies can significantly reduce costs and help organize the distribution centers and the customers' services. This article analyses the integrated problem in which trucks' scheduling in a cross-docking center with multiple docks is combined with the associated open vehicle routing problem, called Open Vehicle Routing Problem With Cross-Docking (OVRPCD). This approach aims to minimize penalties caused by delays in servicing customers. First, a mixed-integer linear programming model is proposed to solve small instances optimally. Next, two heuristics are proposed to contribute to the solution of the two problems in an integrated way. These heuristics are: the Vehicle Routing Cross-Docking Heuristic (VRCDH) and the Cross-Docking Vehicle Routing Heuristic (CDVRH), each focusing on one of the problems. We also propose a Prioritization Lagrangian Heuristic (PLH) based on a model decomposition to improve the solutions found. These three heuristics are compared, considering two search approaches (i) a constructive version (HC) using the swap heuristic; and (ii) a version using the Variable Neighborhood Search (VNS) metaheuristic framework. The VNS-enhanced versions of the heuristics outperform the previous ones. Still, the same relation holds regarding the three heuristics, i.e.: the PLH heuristic outperforms the VRCDH one, while the latter outperforms the CDVRH one. Finally, we propose a polynomial-time framework, called Robust Dynamic Prioritization Lagrangian Heuristic (RDPLH), which extends PLH, considering trucks' release dates and travel times uncertainties, approximating our problem to a real cross-docking center. The framework's simplicity and the quality of the results allow us to assert that this approach can be used in real cross-docking centers (CDCs).

1. Introduction

The current market environment, characterized by increasingly fierce competition, globalization of the economy, and an accelerated technological revolution, leads companies to improve their logistics, distribution, and production systems. Furthermore, the increase in electronic commerce demands more efficient and effective logistical solutions, increasing the pressure on suppliers and distributors to deliver products to customers quickly and efficiently. To this end, cross-docking centers and innovative distribution routes are attractive logistic strategies to increase efficiency.

According to Gruler, Panadero, de Armas, Moreno, and Juan (2018), a critical component in logistics decisions is to reduce the total inventory cost to raise the efficiency of the whole distribution process. Cross-docking (CD) is one alternative as it works reducing two functions of the conventional distribution centers: stocking and picking products, working with a limited or, if possible, null stock. Ladier and Alpan (2016), discussed industry practices and CDC problem characterization.

* Corresponding author.
E-mail addresses: priscila.maracota@gmail.com (P.M. Cota), thnogueira.ufv@gmail.com (T.H. Nogueira), ajuanp@upv.es (A.A. Juan), martin@dcc.ufmg.br (M.G. Ravetti).

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