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OPTIMIZATION MODELS AND SOLUTION METHODS FOR LOGISTICS NETWORK PLANNING

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OPTIMIZATION MODELS AND SOLUTION METHODS FOR LOGISTICS NETWORK PLANNING [1]

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Abstract

Logistics Network Planning (LNP) involves decisions such as facility location, demand allocation, inventory, and transportation management. These decisions differ in terms of periodicity and frequency over the planning horizon. However, the integration of these decisions has been receiving attention from academics and practitioners in the last years aiming to achieve an adequate service level and efficient performance, in terms of network logistics costs and competitive advantages. Nevertheless, there is still a lack of research in this area. Thus, in this work, we study integrated planning in logistics networks. Foremost, we carry out a systematic literature review to understand the main decisions in logistics planning, the integration approaches, and the solution methods.

Then, we present a generic mathematical model for the integration of network design, inventory, and transportation planning. We integrate features and characteristics of the real-world application, such as demand variability, location-based lead times, storage capacity constraints in distribution centers (DCs), piecewise linear transportation costs, and a multi-period and multi-product context. The model determines the DC locals to rent; the selection of the capacity level at the DCs; the assignment of retailers to DCs; the cycle, safety stock, and anticipation inventory levels at DCs; the selection of the cost range/segment for transportation. In addition, we investigate solution methods exploring specific characteristics of the problem. A Logic-based Benders decomposition (LBBD) that enhances the master problem with a non-standard decomposition and a piecewise linear lower bound function of safety stock is proposed.

Furthermore, we address the case of a pharmaceutical logistics network in Brazil to propose mathematical modeling for location and transportation planning with some characteristics such as safety measures in cargo transportation and tax issues. Particularly, we address the Tax of Circulation of Goods and Services (*Imposto de Circulação de Mercadorias e Serviços* - ICMS, in Portuguese), a relevant tax for supply chains in Brazil, but it is little explored in the literature. We also handle uncertainty in demand by proposing a robust counterpart of the mathematical model. We deal with instances based on real data, for which a general-purpose software provides poor-quality solutions. Therefore, we propose a Fix-and-Optimize heuristic to solve the models near optimality. We also present robustness analyses and practical insights about the problem.

The results show the potential of the models and solution methods to address integrated problems in LNP. Therefore, by studying relevant practical features and suggesting effective solution methods, this thesis contributes to the literature on supply chain optimization and the development of tools to support decision-making in practice.

Keywords: Logistics; location; inventory policy; safety stock; transportation; Logic-based Benders decomposition; Fix-and-Optimize heuristic; uncertainty; robust optimization.

Resumo

O Planejamento de Rede Logística (LNP em inglês) envolve decisões como localização de instalações, alocação de demanda, gerenciamento de estoque e transporte. Essas decisões diferem em termos de periodicidade e frequência ao longo do horizonte de planejamento. No entanto, a integração dessas decisões há recebido atenção de acadêmicos e profissionais nos últimos anos, visando alcançar um nível de serviço adequado e desempenho eficiente, em termos de custos logísticos e vantagens competitivas. No entanto, ainda falta pesquisa nesta área. Assim, neste trabalho, estudamos o planejamento integrado em redes logísticas. Primeiro, realizamos uma revisão sistemática da literatura para entender as principais decisões no planejamento logístico, as estratégias de integração de decisões na modelagem matemática e os métodos de solução.

Em seguida, apresentamos um modelo matemático genérico para a integração do projeto de rede, gerenciamento de estoque e planejamento de transporte. Na modelagem matemática, se consideram características práticas, como variabilidade de demanda, prazos de entrega baseados em localização das instalações, restrições de capacidade de armazenamento em centros de distribuição (CDs), custos de transporte com descontos por quantidade (função linear por partes), em um contexto de múltiplos períodos e produtos. O modelo determina os locais do CD a serem alugados; a seleção do nível de capacidade nos CDs; a alocação de varejistas a CDs; os niveis de estoque antecipado, de ciclo, e de segurança nos CDs; a seleção da faixa/segmento de custo para transporte.

Além disso, investiga-se métodos de solução explorando características específicas do problema. Um algoritmo baseado em decomposição de Benders, *Logic-based Benders decomposition* (LBBD) que aprimora o problema mestre com uma decomposição não padrão e um limite inferior do estoque de segurança é proposta.

Além disso, abordamos o caso de uma rede logística farmacêutica no Brasil para propor modelagem matemática para planejamento de localização e transporte considerando características como medidas de segurança no transporte de carga e questões fiscais. Particularmente, abordamos o Imposto de Circulação de Mercadorias e Serviços (ICMS), um imposto relevante para cadeias produtivas no Brasil, mas pouco explorado na literatura. Também lidamos com a incerteza na demanda propondo um modelo de optimização robusta. Resolvemos instâncias baseadas em dados reais, para as quais um software de uso geral fornece soluções de baixa qualidade. Portanto, propomos uma heurística Fix-and-Optimize para obter soluções próximas à otimalidade. Também apresentamos análises de robustez e insights práticos sobre o problema.

Os resultados mostram o potencial dos modelos e métodos de solução para abordar problemas integrados em LNP. Portanto, ao estudar características práticas relevantes e sugerir métodos de solução eficazes, esta tese contribui para a literatura sobre otimização da cadeia de suprimentos e o desenvolvimento de ferramentas para apoiar a tomada de decisão na prática.

Palavras-chave: Logística; localização; política de estoque; estoque de segurança; transporte; *Logic-based Benders decomposition*; heurística *Fix-and-Optimize*; incerteza; otimização robusta.

Resumen

La planificación de la red logística (LNP en inglés) implica la toma de decisiones como la localización de instalaciones, la asignación de la demanda, a gestión del inventario y del transporte. Estas decisiones difieren en términos de periodicidad y frecuencia a lo largo del horizonte de planificación.

Sin embargo, la integración de estas decisiones ha recibido la atención de académicos y profesionales en los últimos años buscando lograr un nivel de servicio adecuado y un desempeño eficiente, en términos de costos logísticos y ventajas competitivas. Sin embargo, todavía falta investigación en esta área. Así, en este trabajo se estudia la planificación integrada en las redes logísticas. Primero, llevamos a cabo una revisión sistemática de la literatura para comprender las principales decisiones en la planificación logística, las estrategias de integración en el modelaje matemático y los métodos de solución.

Luego, se presenta un modelo matemático genérico para la integración de la configuración de redes, la gestión del inventario y la planificación del transporte. Se integran características del mundo real como la variabilidad de la demanda, los plazos de entrega basados en la ubicación de las instalaciones, las restricciones de capacidad de almacenamiento en los centros de distribución (CD), los costos de transporte con descuentos por cantidad (función lineal por partes), en un contexto de múltiples períodos y productos. El modelo determina los locales de los CD a rentar; la selección del nivel de capacidad en los CD; la asignación de minoristas a centros de distribución; los niveles de inventario anticipado, de ciclo y de seguridad en los centros de distribución; la selección del rango/segmento de costo para el transporte.

Además, se investigan métodos de solución explorando características del problema. Se propone una descomposición de Benders, *Logic-based Benders decomposition* que mejora el problema maestro con una descomposición no estándar y un límite inferior del inventario de seguridad.

Además, abordamos el caso de una red logística farmacéutica en Brasil para proponer modelos matemáticos para la planificación de localización y transporte con algunas características como medidas de seguridad en el transporte de carga y cuestiones fiscales. En particular, abordamos el Impuesto de Circulación de Bienes y Servicios (Imposto de Circulação de Mercadorias e Serviços - ICMS, en portugués), un impuesto relevante para las cadenas de suministro en Brasil, pero poco explorado en la literatura. También manejamos la incertidumbre en la demanda al proponer modelo de optimización robusta. Se resuelven instancias basadas en datos reales, para las cuales un software de propósito general no proporciona soluciones de buena calidad. Por lo tanto, se propone una heurística Fix-and-Optimize para resolver los modelos cerca de la optimalidad. También presentamos análisis de robustez y un análisis sobre el problema.

Los resultados muestran el potencial de los modelos y métodos de solución para abordar problemas integrados en LNP. Por lo tanto, al estudiar características prácticas relevantes y sugerir métodos de solución efectivos, esta tesis contribuye a la literatura sobre la optimización de la cadena de suministro y el desarrollo de herramientas para apoyar la toma de decisiones en la práctica.

Palabras clave: Logística; localización; política de inventario; inventario de seguridad; transporte; *Logic-based Benders decomposition*; heurística *Fix-and-Optimize*; incertidumbre; optimización robusta.

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Chapter 1

Introduction

1.1 Context

Logistics Network Planning (LNP) mainly involves four types of decisions that are strongly interrelated. The first deals with facility location and demand allocation to the facilities, the second deals with inventory management, the third includes production planning, and the fourth is transportation decisions, such as vehicle routing and transportation mode selection (Ballou and Masters, 1993; Liao et al., 2011a,b; Arabzad et al., 2014). These decisions are set in different scopes of the planning horizon and concern different levels of details. Due to the importance of the interactions among these decisions, important benefits can be obtained by approaching the network as a whole and integrating the decisions, such as responding quickly to changes in the business environment, eliminating conflicts and inconsistencies between decisions, and reducing costs (Cordeau et al., 2006). Some decisions such as facility location were made typically for the long-term. Nevertheless, currently, they are revisited more frequently and integrated problems is a major trend in supply chain management.

Mathematical models that integrate decisions in LNP can identify opportunities in which location decisions can be adapted to the variability that occurs at other hierarchical levels, tactical and operational. Nevertheless, decision timing and frequency, and the computational complexity of optimizing integrated problems are some challenges regarding integration (Liu et al., 2020). Due to the different planning horizon lengths for each level, the time periods used to model each decision level should also be different, adapted to each decision type and the interdependence among them (Brunaud and Grossmann, 2017; Biuki et al., 2020). Thus, LNP becomes more complicated, while it is essential to formulate representative models and apply appropriate solution methods to address the planning challenges arising from integration. Other important aspect to be considered in LNP is the variability and uncertainty in some information necessary for decision-making, such as retailer demand. Disregarding uncertainties can result in impractical solutions; solutions that deteriorate the service level; or solutions with high logistics costs and tax. Thus, it is important to deal with uncertainties in the planning parameters through methodologies that provide robust solutions that are little impacted by changes in the macroeconomic scenario.

In this thesis, we first investigate the integrated LNP, focusing on the development of mathematical models and solution methods for the integration of decisions under demand variability and uncertainty. This research is framed in the operational research area. Foremost, we carry out an extensive literature review to identify research gaps and opportunities. Based on our findings, we develop research on two fronts: normative-axiomatic research based on mathematical models and solution methods in the literature and empirical-normative research based on a real case study. These studies are not directly linked, since they were not developed sequentially, but in parallel, in order to fill different research gaps, such as considering the decision timing in the integration, addressing demand variability and uncertainty, dealing with discrete costs and mode selection in transportation planning, addressing real features in logistics planning (e.g., multiple products, location-based lead times, storage capacity constraints in DC, security measures and costs, and taxes), and proposing efficient solution methods.

1.2 Organization and contributions

In this section we present the organization of this thesis, briefly describing the contents of each chapter and highlighting their main contributions.

In Chapter 2, we present a systematic review to identify the main integrated decisions, their timing and planning horizon, the integration approaches, the solution methods, and mainly the opportunities to research all these features. The literature on LNP has considerably simplified data aggregation and some practical features are neglected. The studies presented elaborated models and solution methods. However, few studies applied the mathematical models in real cases. Regarding the solution methods, there is a predominance of heuristic approaches over exact ones, including methods based on decomposition or sequential procedures. Based on the findings of this systematic review, we outline a conceptual framework presenting the main modeling assumptions, integration strategies, and solution methods to the integrated problems, and we also discuss some promising research opportunities. This is a qualitative research because we aim to evaluate a significant sample (articles addressing the problem) in order to draw conclusions about that sample (Miguel and Ho, 2012).

In Chapter 3, we analyze an integrated location-inventory-transportation problem under demand uncertainty. We propose a generic modeling approach to integrate facility location with inventory and transportation decisions under demand uncertainty in a multi-period and multi-product context. Inventory planning decisions are made under a periodic review policy (T, S), consolidating the inventory of the retailers at distribution centers (DCs). Transportation decisions consider discrete costs by the selection of cost ranges/segments. Thus, the model determines the DC locals to rent, the assignment of retailers to DCs, the safety stock and anticipation inventory levels at DCs, aiming to minimize the total cost composed by rental costs, inventory costs, and transportation costs. The model is formulated as a nonlinear mixed-integer programming model. To solve the problem, we present a Logic-based Benders decomposition by exploiting the structure of the problem and obtain subproblems that preserve the characteristics of the original problem. To find a lower bound of safety stock in the master problem, we use a piecewise linear function. We also enhance the master problem including information about the subproblems and use a multi-cut to accelerate the convergence of the method. This is a normative axiomatic research because it is based on mathematical programming models that prescribe decisions for the problem. It is aiming to develop strategies and actions to improve the results available in the literature, to find an optimal solution for the problem, and to compare the performance of strategies that address the same problem (Morabito and Pureza, 2012).

In Chapter 4, we also address a LNP of a real case of a pharmaceutical company in Brazil. Most of the works in the literature about optimization models in the pharmaceutical industry focus on production planning. We describe practical features of the logistics context of the pharmaceutical industry in Brazil and propose a mathematical model that integrates network design and distribution planning decisions considering those features that have not been contemplated in the literature, such as safety measures in cargo transportation. We incorporate in the modeling tax aspects that are specific to the logistics networks in Brazil, such as the Tax of Circulation of Goods and Services (ICMS). This tax is little explored in the literature and is relevant for the decision-making of companies in Brazil. We also address variability and uncertainty in some problem parameters for decision-making in planning. A robust counterpart of the mathematical model is presented by using the robust optimization theory for handling the demand uncertainty. We investigate solution methods exploring specific characteristics of the problem, such as decomposition-based approaches, Fix-and-Optimize with partitions by period and arcs. The results show the potential of the models and solution methods to address some relevant problems in LNP, particularly in the context of the pharmaceutical industry in Brazil. This research has elements of empirical-normative research, because the modeling process considers the real characteristics of the problem and the main concern is to ensure that there is adherence between the real problem and the model elaborated for that reality, to develop policies, strategies, and actions that improve the existing situation (Morabito and Pureza, 2012; Bertrand and Fransoo, 2002).

Finally, in Chapter 5 we present an overall final discussion and concluding remarks together with perspectives for future research arising from the developments presented in this thesis.

Chapter 2

Literature review of integrated logistics network planning

This chapter presents a literature review about Logistics network planning (LNP). The objective is to identify the main integrated decisions, their scopes, integration approaches, and the solution methods used. Although this review addresses research with decisions at different hierarchical planning levels, we observed that integration of strategic and tactical decisions is more common and some of the integration approaches are single-level mono-period models, single-level multi-period models, multi-time scale models, and multi-level models. These models are defined and discussed in what follows. There is a predominance of aggregated data in these studies. Regarding the solution methods, there is a predominance of heuristic approaches over exact ones, including methods based on decomposition or sequential procedures. Based on the findings of this systematic review, we draw a conceptual framework presenting the main modeling assumptions, integration strategies, and solution methods to the integrated problems, and we also discuss some promising research opportunities.

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2.1 Logistics network planning

Logistics network planning (LNP) involves making decisions about the number, location, and capacity of the facilities (factories, warehouses, and distribution centers - DCs), as well as selecting suppliers, allocating products to plants, choosing distribution channels, and transportation modes, and determining flows of raw materials, semi-finished and finished products through the network. The aim is to meet customer demands and reduce fixed and variable costs of acquisition, production, storage, and transportation (Cordeau et al., 2006). These decisions are set in different scopes of the planning horizon and concern different levels of details, configuring the levels of strategic, tactical, and operational decisions. The strategic level involves long-term planning decisions that affect the structure and capacity of the network. The tactical level includes medium-term decisions related to the allocation and distribution of materials and products among the facilities. The operational level refers to decisions related to manufacturing, warehousing, distribution, and fulfilling demand operations (Gebennini et al., 2009).

The relationship between decision levels and planning horizons varies according to the supply chain (SC) context and planning concepts (Fleischmann et al., 2002). In practice, the decisions cross the boundaries of hierarchical levels and are associated with the various stages of the SC, therefore they have impacts on the overall performance of the SC (Manzini et al., 2008). Particularly in LNP, there are four types of decisions that are strongly interrelated (Ballou and Masters, 1993). The first deals with facility location (production or storage facilities) and demand allocation to the facilities. The second deals with inventory management decisions that concern inventory control. The third includes production planning at a tactical level and the main tasks are demand assignment to sites, process selection, and lot-sizing. The fourth is transportation decisions, such as vehicle routing and transportation mode selection. Most of the studies in LNP focus on economic objectives (e.g., minimizing costs), although service level is a growing concern in SC. Thus, some decisions include managing customer service levels (Ballou and Masters, 1993; Liao et al., 2011a,b; Arabzad et al., 2014). According to Cordeau et al. (2006), due to the importance of the interactions among these decisions, important benefits can be obtained by approaching the network as a whole and integrating the decisions. The integration allows the logistics networks to react to the dynamic conditions of the business environment, in addition to the potential cost reductions and improvements.

Mathematical models that integrate decisions in LNP can identify opportunities in which strategic decisions can be adapted to the variability that occurs at other hierarchical levels. Nevertheless, decision timing and frequency, and the computational complexity of optimizing integrated problems pose a challenges regarding integration (Liu et al., 2020). Due to the different planning horizon lengths for each level, the time periods used to model each decision level should be different, adapted to each decision type and the interdependence among them (Brunaud and Grossmann, 2017; Biuki et al., 2020). Thus, LNP becomes extremely complicated, while it is essential to formulate representative models and apply appropriate solution methods to address the planning challenges arising from integration.

In recent years, several authors have addressed different problems proposing models and solution methods to support decision-making in LNP considering the integration of different hierarchical levels (Manzini et al., 2008). In this context, our objective is to develop a systematic literature review focusing on two main questions from a broader perspective: (i) how did the authors integrate designing, planning, and operations decisions in logistics networks under a dynamic and uncertain environment, and (ii) what are the research gaps and opportunities in this area? To address these research questions, we developed a systematic review based on the protocol-driven methodology proposed by Denyer and Tranfield (2009). A systematic review enables us to identify relevant studies, evaluate their contributions, and summarize their results.

From this literature review, we aim to understand how the integration levels have been made by the operations management/operations research community. Therefore, the reference papers are analyzed in terms of different decision-making levels, integration strategies/approaches, and solution methods. Furthermore, we examine the planning horizons of the models and the timing of the decisions involved. Finally, we highlight some gaps and point out opportunities for future research. To present our research findings, we designed a conceptual framework with the challenges and benefits of the integrated LNP, the main characteristics and premises of the modeling, as well as the integration proposals and solution methods identified in the literature review. To the best of our knowledge, no review paper has examined the same aspects taken into account in this paper.

The rest of this chapter is structured as follows: Section 2.2 indicates the contribution of this work when compared to other reviews published on this topic. Section 2.3 describes the review methodology used in this article and Section 2.4, presents a descriptive analysis. Section 2.5 reports a detailed overview of the integrated decisions and strategies for integration in LNP. Section 2.6 discusses the solution methods and approaches used to solve the integrated models. Section 2.7 presents our conceptual framework and some research gaps. Finally, Section 2.8 presents our concluding remarks.

2.2 Recent related literature reviews

We initially searched for literature reviews and seminal works that have been published on integrated optimization problems in LNP, aiming to identify if these papers provide insights or address issues such as integrating decisions with different planning horizons, main integrated decisions, and methods to solve the integrated models. Analyzing these articles was an important step to define our literature review protocol. Table 2.1 shows the papers found and their scope in the period from 2000 to 2020. Integrated optimization in the field of network design has received more attention and there are several reviews addressing different integrated problems.

In the first decade of the 2000s, Melo et al. (2009) developed a literature review of facility location and SC management. The authors addressed the decisions in SC network design, solution approaches (exact/heuristics), and some modeling features, namely, the number of layers, commodities, the nature of the planning horizon (single/multi-period), and the type of

Table 2.1: Literature reviews in recent years on integrated optimization problems in LNP (2009 onwards).

Paper	Research focus	Is it a systematic review?	Number of papers	Time horizon
Melo et al. (2009)	Facility location models in SC	No	120	1997-2007
Farahani et al. (2014)	Location-inventory problem in SC	No	73	1976-2013
Prodhon and Prins (2014)	Location-routing problems	No	72	2007-2013
Drexl and Schneider (2015)	Variants of the location-routing problem	No	n/a	2006-2013
Govindan et al. (2015a)	Reverse logistics and closed-loop SC	Yes	382	2007-2013
Barbosa-Póvoa et al. (2018)	OR for sustainable SC	Yes	220	1999-2015
Farahani et al. (2018)	OR models in USFL	Yes	110	1970-2017

n/a: non applicable.

data (deterministic/stochastic). They concluded that tactical and operational decisions related to inventory and production were often integrated with location, while others such as vehicle routing and transportation mode selection were relatively neglected until that moment.

Farahani et al. (2014) presented a literature review of the Location-Inventory (LI) problems, which aims to integrate location with inventory management and control decisions. The review focuses on the key modeling attributes, the objective function cost components, the solution methods adopted, and the real-world applications investigated. The authors also verified the time structure of the models and concluded that most of the proposed models assume a planning horizon with a single period.

Taking into account that vehicle routing can improve transportation costs in facility location problems, Prodhon and Prins (2014) focus on location-routing problems (LR) in their review. According to these authors, several studies have already shown that although the location of facilities is a strategic decision and that vehicle routes must be built at the tactical and operational decision levels, these decisions are interdependent and the total cost of the system can be excessive if they are addressed separately. They also established that all LR problems with multiple periods were recently proposed, although the selection of clients to be served in each period shows the tactical dimension that was missing between the strategic decision level (location) and the operational decision level (route). The community has been proposing new variants of this problem, which include considering new characteristics (e.g., stochastic parameters, continuous location, multi-layers, multi-objectives) and the incorporation of other decisions, for example, *Inventory*-LR, *Pickup-and-delivery*-LR, and *Split-delivery*-LR (Drexl and Schneider, 2015). Farahani et al. (2018) developed a survey on the specific context of *Urban Service Facility Location* (USFL), concluding that routing decisions are often integrated into USFL models. However, other decisions, in particular, fleet sizing and inventory management decisions, are rarely addressed in these models.

Sustainability has been increasingly considered in SC management. Govindan et al. (2015b) and Barbosa-Póvoa et al. (2018) present literature reviews on sustainable SC, reverse logistics, and closed-loop SC. The reviews found that optimization models applied to strategic levels are the most preponderant studies. Barbosa-Póvoa et al. (2018) identified 59 out of 220 articles addressing the integration of strategic decisions (long-term planning) and tactical decisions concerning inventory, demand, and supply planning. Govindan et al. (2015b) concluded that strategic decisions, for example, designing and capacity, were successfully integrated with tactical decisions, for instance, network flows; however, operational decisions, such as production and inventory, remained separate. Both articles pointed out the need for approaches to integrate decisions of different levels into the sustainable SC. Other related integrated SC planning problems are production-routing problems (Adulyasak et al., 2015) and inventory with transportation issues (Engebrethsen and Dauzère-Pérès, 2018); however, these topics do not include network decisions and are out of the scope of the present review. The literature reviews in Table 2.1 show frequent decisions addressed in LNP studies and indicate trends and gaps in the integrated planning in SC. Nevertheless, these reviews did not particularly address our research question of how to deal with different planning horizons of decisions in the integration.

2.3 Literature review protocol

We performed an extensive literature review on models and solution methods to address the integrated planning of logistics networks, ranging from strategic to operational decisions. To ensure the consistency and quality of the work, we used a systematic research methodology (Tranfield et al., 2003; Jesson et al., 2011). We observe in Table 2.1 that this methodology was more used to develop literature revisions in LNP in recent years. The methodology was structured over three phases: planning, conducting and reporting. Table 2.2 presents a summary of the research protocol and the methods applied in each of these three phases.

Table 2.2: Research Protocol

Phases	Steps	Data
Planning	Study strategy	Definition of constructs, key words, research strings, database, and period
Conducting	Material collection	Analysis of inclusion and exclusion criteria Filter 1: title, abstracts and key-words assessment Filter 2: introduction and conclusion assessment Full reading
Reporting	Descriptive analysis	W's analysis (When, Who, What, and Where)
	Category selection	Classifications in groups
	Material evaluation	Answer questions, find relevant information and detect research gaps.

(Adapted from Denyer and Tranfield (2009); Jesson et al. (2011); Tranfield et al. (2003))

2.3.1 Planning

For the literature review, the constructs established were strategic, tactical, and operational planning, logistics network, integrated planning, and optimization. We did a survey regarding the most common words found in articles. A keyword-based bibliometric analysis on the initial sample was performed to better understand which keywords are usually used in papers addressing integrated decisions. Figure 2.1 presents a network visualization of the keywords using the VOSviewer® (van Eck and Waltman, 2010).

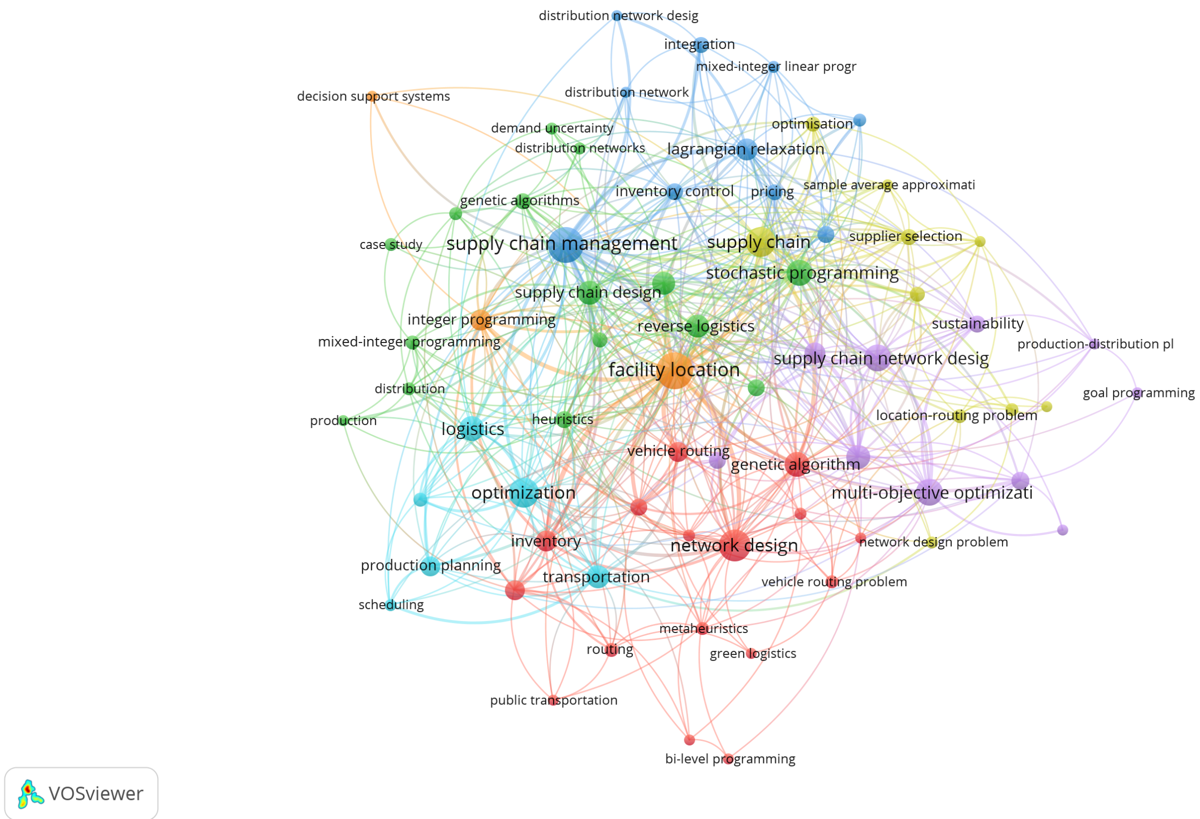


Figure 2.1: Keyword bibliometric analysis.

Thereafter, we constructed the search string by combining synonyms of the keywords, as shown in Table 2.3.

Table 2.3: Search string

((location* OR "network design" OR "network NEAR/2 configuration") AND (integrat* OR join OR simultaneous) AND (network OR "supply chain*" OR logistics) AND(decision* OR strategic OR tactical OR operational) AND (inventory OR transport* OR distribution OR production OR routing OR "fleet siz*") AND (optimiz* OR optimisation OR programming OR model* OR "mathematical formulation")).

We studied peer-reviewed articles published since 2000 to 2020 in the context of LNP indexed in international journals, searching among electronic bibliographical sources including Scopus® and Web of Science® and using a research string. We considered three criteria for these papers: (i) the paper should be written in English; (ii) the paper should address strategic decisions, such as network design or facility location; and (iii) the paper should include other decision variables related to tactical and operational planning, simultaneously.

2.3.2 Conducting

For the data collection, we applied the search string in the databases on 30 June 2020, covering the accepted papers (available online) from January 2000 to this date, resulting in 2894 papers (including duplicated papers in the databases). Then, the following filters were applied: (i) document type, including articles, articles in press, reviews, reiterations, excluding proceeding papers; (ii) areas, including Web of Science® categories: *Operations research management science, Engineering industrial, Engineering manufacturing, Multidisciplinary sciences, Management, Computer science interdisciplinary applications, Business or computer science information systems, Engineering multidisciplinary, Mathematics applied, Computer science artificial intelligence, Mathematics interdisciplinary applications, Transportation science technology, Transportation*; and Scopus® categories: *Engineering, Decision Sciences, Business, Management and Accounting, Computer Science, Mathematics, Multidisciplinary.* The information from the papers was exported (*Bib-Tex*) from databases to software *StArt® (State of the Art through Systematic Review).* After an initial review, duplicated articles (exported from the databases) were deleted, resulting in a sample of 778 documents. Afterwards, an article selection step was carried out, applying inclusion criteria related to alignment and scope. After reading the title, abstract, keywords, introduction and conclusions, a sample of 190 articles was selected. In the full reading stage, 131 papers were classified.

2.3.3 Reporting and disseminating results

To extract information from the papers, three steps were followed as shown in the stage reporting in Table 2.2, i.e., (i) a descriptive analysis, (ii) a category selection and (iii) a material evaluation. A descriptive analysis was made to obtain an understanding of integrated problems in LNP, a category selection was made using groups of similar articles in terms of decisions, model structure, integration approaches and solution methods. The following questions were used as motivation:

1. When were the articles published? From which countries are the authors' affiliations? What are the most used keywords?

2. What are the main decisions, assumptions, model structures and objectives functions?

3. How the time structure of decisions at different hierarchical levels has been addressed?

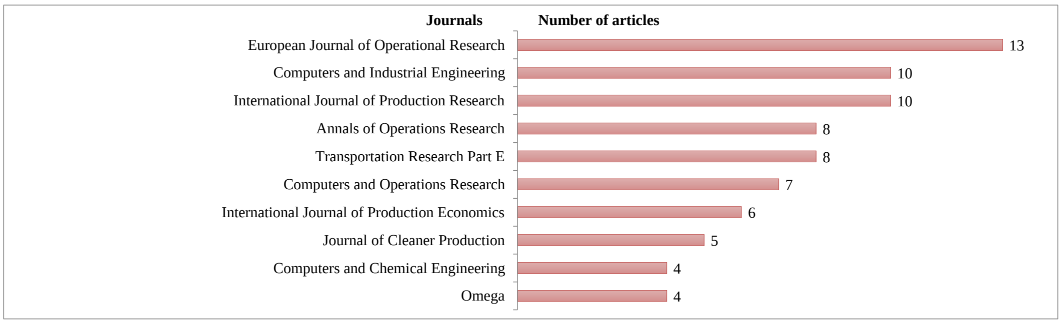
4. What are the modeling approaches used to integrate decisions at different levels?

5. What are the solution methods used?

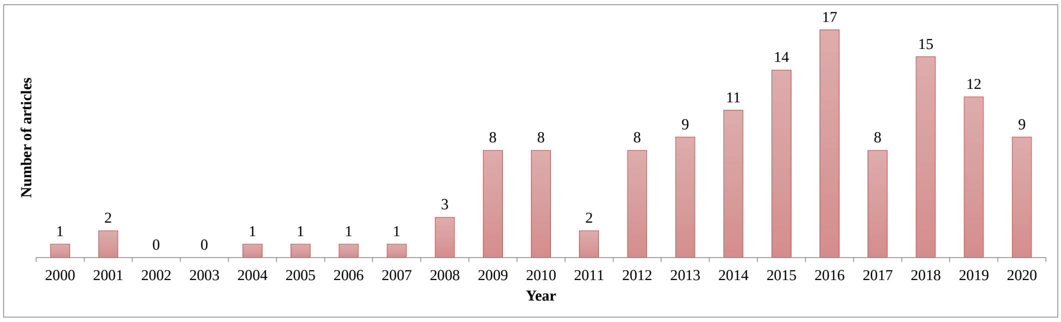
The following sections present discussions to cope the aforementioned questions and a conceptual framework that helps to visualize the main results of our literature review.

2.4 Description of selected sample

This section presents some statistics from the obtained sample applying our research protocol. Figure 2.2(a) shows the top 10 journals that published the articles. The distribution of these reference papers in terms of their publication date is shown in Figure 2.2(b). The number of articles exploring the integration of the decision levels has grown over the past 20 years, reaching its peak in 2016. Nevertheless, we found that more than 50% of these papers were published over a five-year period from 2015 to 2020. As this research was carried out in June 2020, it is expected that in 2020 the actual number of articles will be greater. The countries with more authors' affiliations are Iran, United States, China, United Arab Emirates, and Canada.



(a) Top 10 journals of the reference papers



(b) Publication date distribution of the reference papers

Figure 2.2: Statistics of the reference papers

2.5 Detailed analysis of the literature

In this section, a detailed analysis of the methodologies to integrate decisions, the main decisions and the main features of the integrated LNP are presented aiming to understand which decisions have been integrated and how the research community has been integrating these decisions.

2.5.1 Model structures to integrate decisions

An important issue in LNP concerns timing decisions, i.e., the coincidence of decisions with proper time horizons (Badri et al., 2013). The impact of strategic level decisions spans over a greater period than tactical level decisions, which could be even years as they deal with decisions that cannot change easily. Tactical decisions have time horizons of months and operational decisions are typically made on a daily basis (Hiassat et al., 2017). The timing among these decisions, as well as the distinct time-horizon granularity, should be taken into account when modeling integrated problems. Amiri-Aref et al. (2018) present a timing structure illustrated in Figure 2.3.

The lower layer of Figure 2.3 corresponds to the operational level, composed of a set of discrete periods where managers make daily or weekly decisions. At this level, information such as demands, lead-times, prices, capacities, costs and sourcing availability are less uncertain. The short-term operational decisions can be revised in each working period. The tactical level corresponds to the multi-period horizon illustrated by the intermediate layer. The granularity of

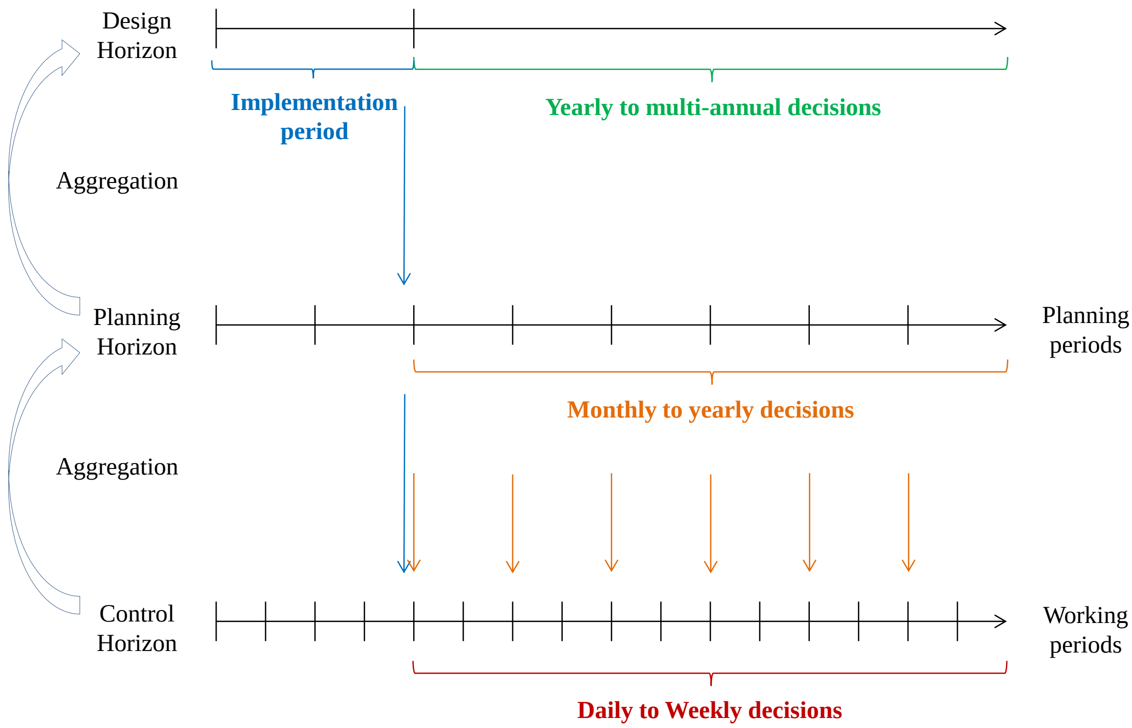


Figure 2.3: Decision-time hierarchy in the LNP (Amiri-Aref et al. (2018)).

the planning periods requires the aggregation of working periods and the operational decisions. These medium-term decisions are addressed from monthly to annual periods. At the upper layer, long-term decisions are made, which are generally decisions related to network design regarding yearly to multi-annual periods. The elapsed time between the network design and usage period implies that these decisions are made with partial information (Amiri-Aref et al., 2018).

We analyzed the techniques or strategies for integrating decisions in the mathematical modeling of the reference papers. Four groups were identified, namely: (i) single-level mono-period models, (ii) single-level multi-period models, (iii) multi-timescale models, and (iv) multi-level models. Figure 2.4 summarizes the time-horizon granularity for the strategic, tactical and operational levels, in agreement with different horizons: long-term (design) horizon, mid-term (planning) horizon and short-term (control) horizon, shown in Figure 2.3.

Single-level models integrate decisions at different planning levels through a mathematical model that incorporates all decisions simultaneously. These models can be mono or multi-period. Single-level mono-period models make decisions by aggregation of different problem parameters for the entire planning horizon, as shown in Figure 2.4. Govindan et al. (2019) develop a model to design a sustainable supply chain integrating location decisions of industrial plants and DCs with decisions of vehicle routing using a single-level mono-period model. Ahmadi-Javid and Azad (2010) propose a model that integrates location, inventory, and routing decisions using the same strategy. Generally, integrating decisions using a single-level mono-period model allow for making long-term decisions without the concern of variability in the mid and short-term decision making.

Single-level multi-period models take into account dynamic decisions according to problem

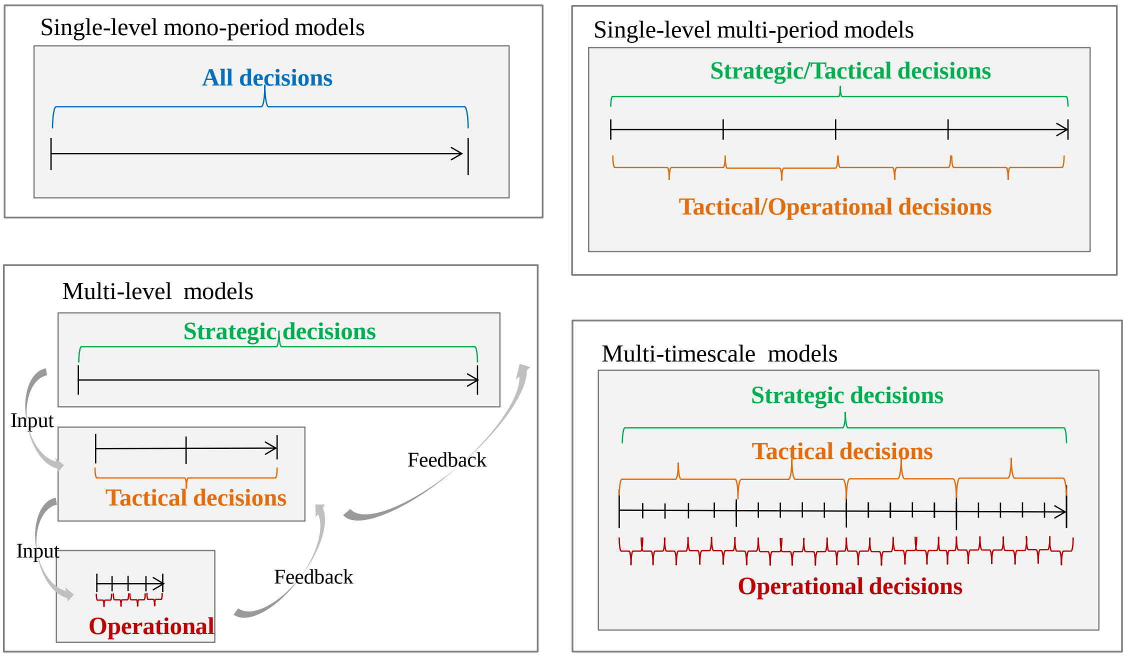


Figure 2.4: Decision-time in integration strategies in the LNP.

parameters that vary among periods. Network design decisions, such as location, are generally defined for the entire planning horizon and the tactical and/or operational decisions (e.g. production, inventory, and transportation) are addressed for each period, which enables us to differentiate decisions from strategic and tactical/operational levels. Rafie-Majd et al. (2018) consider this time granularity to address the inventory-location-routing problem, while Darvish and Coelho (2018) consider the DC location used for a specific number of periods joint with production, inventory, and transportation decisions. This approach also maintains the idea that location decision is valid for a longer period if compared to other decisions. Periodic decisions require detailed information about the parameters. Single-level multi-period models allow for making more accurate decisions by period; however, it takes more computational effort if compared to single period models.

In multi-timescale models, the planning horizon is divided into macro-periods in which strategic and/or tactical decisions are made. Each macro-period is divided into micro-periods, where tactical and/or operational decisions are regarded. Timescale models are also single-level models and have similar characteristics to multi-period models, since parameters and decisions are defined for distinct periods. However, this approach can be more advantageous when the decisions to be integrated differ in terms of periodicity and frequency over the planning horizon, enabling us to properly consider the timing of each decision. For instance, Salema et al. (2009, 2010) address location decisions for the entire horizon; demand allocation decisions in macro-period; and production, inventory, and product flow in micro-periods. Some articles consider lead time in operations, in particular, in production, transportation and supply activities. Authors have defined time operators for these activities that can locate the macro and micro periods at which each operation begins and ends, taking into account their lead time (Badri et al., 2013; Bashiri et al., 2012; Salema et al., 2009, 2010; Fattahi et al., 2016; Amiri-Aref et al., 2018). We note that timescale models present a time structure similar to the GLSP (General Lotsizing and Scheduling Problem) model proposed by Fleischmann and Meyr (1997), which integrates mid-term decisions (lot-sizing) and short-term decisions (sequencing).

Multi-level models consider two and three levels to integrate decisions of distinct hierarchical levels. At the first level, a model is solved and new information becomes available for the decision-maker. This solution is used as input parameters for the next level model. In the case of three-level models, for instance (Manzini et al., 2014), the solution of the second model feeds into the third model, that is, the multi-level models are solved hierarchically. Generally, the strategic decisions are addressed at the first level and then, tactical and operational decisions are considered. Thus, the solutions of some lower level models provide feedbacks to the upper level models, including information from the last solved models and, iteratively and interactively, searches for a better solution. This approach is obviously with loss of optimality. Commonly, the first level deals with location decisions in a single period, while the second and third levels (if there are any) deal with detailed decisions in multiple periods, for instance (Manzini et al., 2014). This enables us to differentiate the planning horizon for the different decision levels and, at the same time, reduce the computational effort by the model decomposition in two or three models.

Table 2.4 presents the approaches for integrating decisions in the mathematical modeling of the reference papers. Most of the papers (88%) integrate decisions at different levels through a single-level mathematical model. Notably, 53% of the reference papers consider single-level and mono-period models (i); 30% consider single-level and multi-period models (ii); and 5% use multi-timescale models (iii) to address different decision levels. Moreover, 12% of the papers are multi-level models with two and three levels, and almost 75% of the multi-level models address a multi-period context.

Table 2.4: Approaches for integrating decisions in the mathematical modeling of the reference papers

Mono period models	Multi-period models
4; 7; 6; 3; 5; 9; 14; 18; 20; 21; 22; 44; 46; 57; 227; 68; 80; 86; 88; 90; 95; 96; 98; 103; 104; 107; 118; 120; 122; 123; 126; 129; 131; 130; 134; 147; 149; 148; 151; 166; 167; 168; 170; 171; 177; 195; 178; 189; 190; 194; 197; 199; 200; 201; 203; 206; 208; 214; 215; 216; 217; 218; 219; 221; 222; 223; 226; 229; 232; 241.	2; 8; 15; 23; 39; 41; 47; 48; 59; 58; 67; 64; 65; 66; 73; 78; 84; 85; 93; 94; 97; 102; 121; 124; 132; 141; 150; 157; 158; 159; 172; 179; 188; 180; 209; 231; 236; 235; 238.
Multi-level models	**Multi-timescale models**
60; 91; 92; 110; 125; 137; 135; 136; 138; 160; 161; 184; 187; 207; 239.	17; 24; 28; 79; 193; 192.

See the author-date citation in Table A.1 in Appendix A.

Based on our review, single-level mono-period models can be effective to integrate strategic and tactical decisions in static situations where the data aggregation does not impact the tactical decisions. When data variability is significant, parameters can be described by a probability distribution function, as we will discuss this further. Single-level multi-period models are indicated when there is variability in parameters among periods affecting the periodical decisions (and the data aggregation is not recommended). Thus, more accurate decisions need to be made by the period which is usually related to tactical and operational ones. Timescales models can introduce more details by incorporating macro-periods and micro-periods, and addressing distinct decisions according to their timing. This integration approach corroborates the assumption that LNP decisions have different time-horizon length and granularity, according to Figure 2.3 proposed by Amiri-Aref et al. (2018). Thus, timescale models aim to optimize decisions from distinct hierarchical levels simultaneously. Multi-level models are also based on the same assumption. However, different from timescale strategies, multi-level models are optimized sequentially and, even using looping techniques to improve the solutions, it is more difficult to find an optimal solution. In either case, multi-level models can be very useful in many practical contexts when an optimal solution does not mean a substantial impact in LNP decisions that are not simultaneously made.

2.5.2 Main integrated decisions

LNP decisions addressed by the papers can be classified into four categories, namely, (i) location, (ii) inventory, (iii) production and (iv) transportation. As mentioned before, these decisions are typically established in different scopes of the planning horizons but they are interrelated. Several authors have addressed some interactions among these decisions, originating traditional problems in the literature that integrate different planning levels. Table 2.5 presents the integration of decisions in the reference papers: Location-Inventory (LI), Location-Transportation (LT), Location-Production (LP), Location-Inventory-Transportation (LIT), Location-Inventory-Production (LIP) and Location-Inventory-Production-Transportation (LIPT). A single article considered the intersection of location-transportation-production (LTP) (Govindan et al., 2019), as shown in Figure 2.5.

Table 2.5: Integration of decisions in reference papers

<table>
<tr><th>Location-transportation</th><th>Location-inventory</th><th>Location-production</th></tr>
<tr><td>3; 20; 22; 73; 86; 121; 125; 160; 167; 168; 197; 207; 208; 218.</td><td>2; 6; 5; 17; 21; 23; 44; 46; 47; 57; 227; 68; 67; 64; 65; 66; 80; 88; 118; 122; 123; 124; 126; 129; 131; 130; 132; 134; 147; 148; 159; 166; 170; 171; 195; 184; 189; 195; 199; 200; 203; 209; 215; 216; 217; 221; 223; 226; 229; 239.</td><td>45; 95; 222.</td></tr>
<tr><td colspan="2">4; 7; 14; 18; 39; 58; 84; 90; 93; 98; 102; 103; 110; 120; 141; 149; 150; 161; 172; 177; 178; 179; 180; 190; 194; 214; 232; 236; 238; 241.</td><td></td></tr>
<tr><td></td><td colspan="2">8; 9; 24; 28; 48; 59; 60; 79; 78; 85; 91; 92; 107; 137; 138; 158; 187; 193; 192; 206; 231; 235.</td></tr>
<tr><td colspan="3">15; 41; 94; 97; 135; 136; 151; 157; 188; 201; 219.</td></tr>
</table>

See the author-date citation in Table A.1 in Appendix A.

Figure 2.5 presents an overview in terms of the number of articles that address decisions of each category and the integration among them. All articles consider location decisions. The most frequent integration is location and inventory management, with 113 articles. In turn, 41 of these articles consider transportation decisions, and 11 of these articles also consider production decisions.

Table 2.6 presents more details about the decisions in each category, the number of articles considering each decision, the percentage in the sample, and their classification in static vs. dynamic and deterministic vs. stochastic. In this study, the classification of papers in static and dynamic refers to the consideration of the parameters and decisions in a single-period or multi-period horizon, respectively. On the other hand, the classification of papers in deterministic and stochastic refers to the consideration of known or uncertain parameters, respectively.

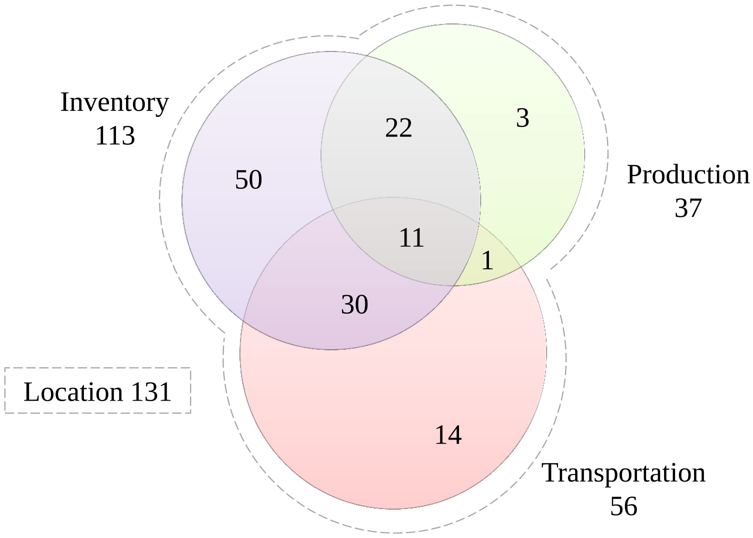


Figure 2.5: Number of publications covering the different decision categories in SC.

Table 2.6: Decisions and classification in static vs. dynamic and deterministic vs. stochastic

				Time		Uncertainty	
	Decisions	Number	%	Static(%)	Dynamic(%)	Deterministic(%)	Stochastic(%)
Location	DC location	131	100	56	44	51	49
	Plant location	34	26	41	59	47	53
	Demand allocation	95	73	73	27	49	51
	Capacity selection	37	28	32	68	54	46
	Supplier selection	9	7	78	22	67	33
	Technology selection	9	7	44	56	67	33
Inventory	Inventory level	84	63	45	55	48	52
	Order quantity	52	40	69	31	46	54
	Order point	26	20	77	23	54	46
	Safety stock	19	15	89	11	0	100
Production	Production quantity	37	28	30	70	65	35
	Production allocation	7	5	14	86	71	29
	Processes selection	6	5	17	83	83	17
Transportation	Routing	38	29	55	45	58	42
	Mode selection	20	15	45	55	70	30

According to Table 2.6, all the articles consider the location of intermediate facilities (e.g., DCs, hubs and collection centers) and 26% of them also consider the location of production/remanufacturing facilities. Despite the dynamic business environment and frequent changes (political, tributary, and social) that may arise over time, only a few articles cope with the network redesign, allowing for opening and closing facilities or allowing for expanding capacity on the planning horizon. Several articles take into account the location of collection facilities for processing post-consumer products, which lead to properly disposing of waste or integrating waste as raw materials in a circular economy (Barbosa-Póvoa et al., 2018). Other strategic decisions associated with facility location are defining, selecting or adding capacity to facilities (28%). Less explored decisions are supplier selection, fleet sizing, vehicle allocation, and pricing. According to Table 2.6, the decision concerning the location of intermediate facilities did not tend to be static or dynamic, deterministic or stochastic. However, some network design decisions, such as supplier selection, are made mainly in a static and also deterministic context. Other decisions, such as technology selection and capacity selection, are made mainly in a dynamic and deterministic context.

Concerning inventory management, some models deal with inventory decisions in several layers: plants, warehouses, and retailers. According to Table 2.6, a frequently integrated decision in LNP is the inventory level definition (63%). Other inventory decisions are order quantity (40%), replacement point (20%), and safety stock (15%), and these decisions are made mainly in a static way, according to Table 2.6. Moreover, 23% of articles that include inventory decisions consider lost sales, back order, or early delivery. Figure 2.6 presents the number of articles that address the three most frequent inventory decisions of Figure 2.5 and the intersections among them. Observe that 18 articles address only order quantity and 2 address only order point, but most decisions are combined.

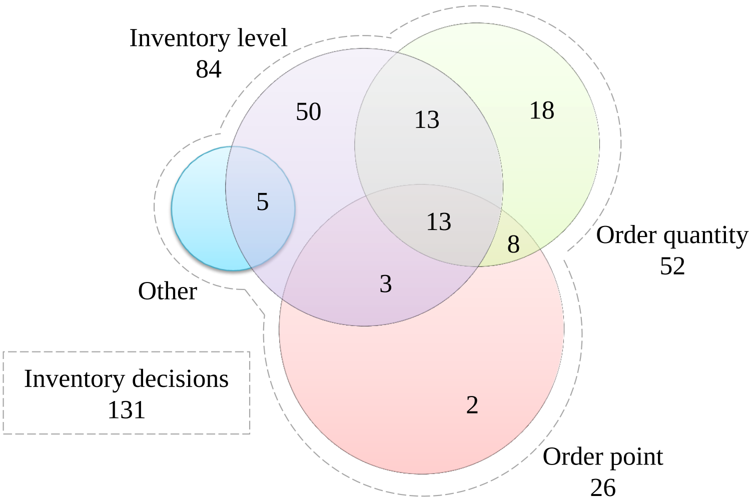


Figure 2.6: Number of publications covering the inventory decisions of Figure 2.5

Production decisions, in turn, include the amount to be produced (28%), allocation of production to facilities (5%), and selection of production processes or technologies (5%). According to Table 2.5, in LNP, production decisions are frequently integrated with inventory decisions, particularly the inventory level. In Table 2.6, the production category excels at making decisions in a dynamic and deterministic context. The 37 articles that consider the decision of production quantity definition are integrated with the different decision categories as shown in Figure 2.5.

The transportation decisions refer to the selection of transportation alternatives (modes) and vehicle routing. Only 15% of the studies incorporate the selection of transportation alternatives and 29% consider routing. Within vehicle routing problems, there are decisions associated with the definition of routes and the selection of predefined routes. Studies address both homogeneous and homogeneous vehicle fleets. According to Table 2.6, transportation decisions are made mainly in a deterministic context, i.e. mode selection (70%) and routing (58%).

A less addressed decision in LNP is to allow lost sales (14%) or even not fulfilled demand at the specified deadline, as well as backlogs/delays (11%) or advances (1%), considering penalties in both cases. These decisions appear in the reference papers which address location-inventory decisions.

Figure 2.7 presents the relations between the integrating approaches and the main integrated decisions in the reference papers. The strategy of a single-level model dominates in all types of integration, particularly LI integration. In these models, different decisions are made simultaneously considering aggregated data or average data (e.g., demand, capacity, costs). Some authors consider uncertainty in modeling, aiming to reduce the impact of this assumption over the decision-making process.

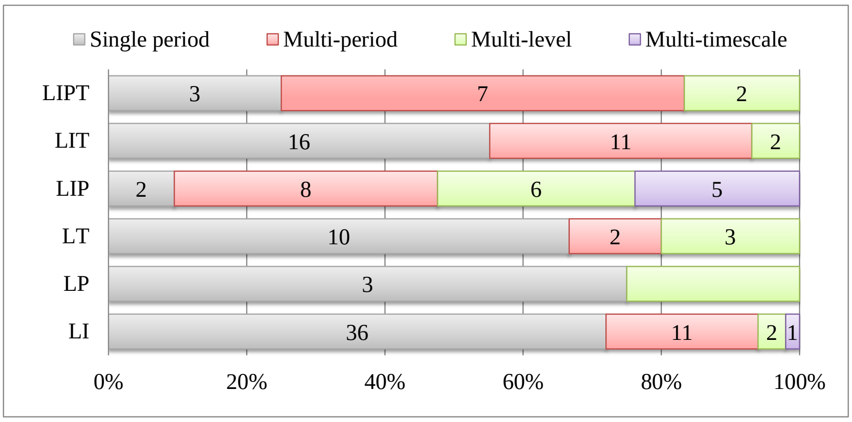


Figure 2.7: Relations between integrating strategies and main integration in reference papers.

2.5.3 Features of the integrated problems

This subsection presents a description of the main characteristics of the integrated problems related to data aggregation, data uncertainty and performance measures.

Data aggregation

As mentioned before, many articles (49.6%) deal with decisions in the same period, without taking into account the differences in nature and frequency of decision levels. This fact can lead to sub-optimal and even impractical decision making.

The most frequent decision addressed in the multi-period context is the DC location, however in most reference papers, this decision is made for the entire planning horizon. Production quantity is regarded predominantly for multi-period horizons represented by continuous variables, which are more treatable for solving integrated problems. Incorporating multiple periods usually increases the number of integer decision variables and constraints of the problem. Consequently, it increases the size of the problem and the time to solve it. To deal with this complexity, authors in the literature have devised different exact and heuristic solution methods. In this context, it is common to find sequential heuristics based on Lagrangian relaxation, Benders decomposition approaches, and metaheuristics.

In real contexts, the portfolio of a company often consists of different products with different physical characteristics, demand patterns, costs, among others. Despite this, only 42% (55 articles) of the articles propose models that consider multiple products. Depending on the context of the logistics network, different alternatives are available for transporting products: modal (railways, roadways, airways, waterways and pipelines), freight type (truckload and less-than-truckload) and different vehicle sizes. However, only 15% of the articles (19 articles) consider multiple transportation mode. Moreover, only 8 articles cope with a multi-period, multi-product and multi-modal context (Alshamsi and Diabat, 2018; Manzini et al., 2008; Manzini and Gebennini, 2008; Martins et al., 2017; Mota et al., 2018; Govindan et al., 2016; Sadeghi Rad and Nahavandi, 2018; Zeballos et al., 2014).

Figure 2.8 shows a relationship between the most frequent decisions in the sample and the data aggregation in periods, products and transportation modes. As expected, models with two categories of decision (LI, LP, LT) present more aggregated data, while models with more integrated decisions (LIPT) consider less aggregated data.

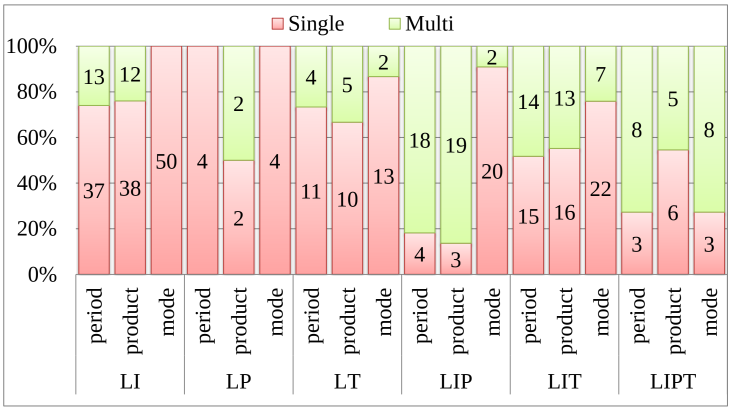


Figure 2.8: Time aggregation in the most frequent decisions of the sample

Logistics networks consist of different entities, such as suppliers, factories, warehouses, retailers and final consumers. The reference papers addressed networks mainly with three and two entities, i.e., with two echelons (60%, 78 articles) and one echelon (39%, 51 articles), respectively.

Data uncertainty

The input parameters of models in the reference papers are deterministic, stochastic, possibilistic and fuzzy. The terms fuzzy and possibilistic are often used in an equivalent way in the reference articles. 43% of the articles take into account variability and uncertainties in the parameters. The main uncertain parameter addressed is demand. LIP models also consider uncertainties in capacities, supply lead times and costs, while LIT models also consider uncertain costs and transportation times. LIPT models address uncertainty in facility opening and transportation costs, capacities and recovered products fraction in reverse logistics contexts.

According to Rabbani et al. (2019), uncertainty should be acknowledged to ensure reliability in the decision-making process. Uncertainties are addressed through different techniques. According to Rafie-Majd et al. (2018), there are three different and widely-used methods for dealing with uncertainty in modeling and optimizing the SC: (i) distribution-based approaches,

(ii) scenario-based approaches and (iii) fuzzy programming approaches.

In distribution-based approaches, probability distribution functions are used to model the uncertain parameters. Thus, several authors incorporate the parameters of the distribution function in the mathematical modeling. The Normal distribution is widely used to model uncertain demand as in (Alavi et al., 2016; Aryanezhad et al., 2010; Das and Sengupta, 2009; Liao et al., 2011b; Monteiro et al., 2010; Nakhjirkan and Rafiei, 2017; Nasiri et al., 2010; Puga and Tancrez, 2017; Rafie-Majd et al., 2018; Schuster Puga et al., 2019a; Shahabi et al., 2013; You and Grossmann, 2008), as well as lead-time (Alavi et al., 2016) and transportation time (Das and Sengupta, 2009). The Poisson distribution is also used to model uncertain parameters of demand and lead time (Gholamian and Heydari, 2017; Jeet and Kutanoglu, 2018). Sadjady and Davoudpour (2012) addressed uncertain demand and lead-time, which follow Poisson and Exponential distributions, respectively. They applied a queuing approach to obtain the annual quantities of ordering, purchase and shortage, and also the mean inventory in the steady-state condition.

In scenario-based approaches, some discrete scenarios with relevant levels of probability are used to describe the expected occurrence of specific results (Rafie-Majd et al., 2018). Some studies are framed in stochastic optimization methods, two-stochastic programming and multi-stage stochastic programming. Most authors addressed the uncertainty with two-stage scenario-based stochastic programming, separating the decision variables into two stages. First stage variables are decided upon before the realization of the stochastic parameters. Once the uncertain events have taken place, further adjustments can be made through the second-stage variables. Often, two-stage stochastic programming models assume that the stochastic parameters can be represented as random variables with a known probability distribution, or well approximated using a finite number of possible realizations, called scenarios. The number of scenarios should be appropriate to ensure both, the representativeness of the random variables and the computational tractability of the stochastic models. The objective is to identify decision variables at the first stage that seems to be balanced, with respect to all the possible scenarios of the stochastic parameters. This approach is used in several articles (Amiri-Aref et al., 2018; Angazi, 2016; Fattahi and Govindan, 2017; Ghaderi and Burdett, 2019; Khatami et al., 2015; Ghezavati et al., 2009; Shu et al., 2010; Tsiakis et al., 2001; Zeballos et al., 2014, 2018). There is a lack papers addressing the uncertainty using multi-stage stochastic optimization (for instance, Zeballos et al. (2013)), due to the complexity to solve the models.

In fuzzy-based approaches, parameters are regarded as fuzzy numbers with membership functions. Fuzzy programming can be applied when situations are not clearly defined and thus are uncertainty, or an exact value is not critical to the problem. Ahmadi et al. (2016) considered possibilistic demand and capacity, Dai et al. (2018) considered capacity and carbon emissions, Shavandi and Bozorgi (2012) and Govindan et al. (2020) considered demand, Zhalechian et al. (2016) consider demand, cost, distance, created job opportunities and regional development, and Sherafati and Bashiri (2016) proposed a fuzzy approach with all fuzzy parameters.

Robust optimization is another approach to deal with uncertain parameters in optimization problems. It constructs a solution that is feasible for any realization of the uncertainty in a given set. Akbari and Karimi (2015) used robust optimization and solved the models using general purpose optimization solvers.

It should be noted that, whereas stochastic programming approaches assume that there is a probabilistic description of the uncertainty, robust optimization works with a deterministic, set-based description of the uncertainty. In two-stage stochastic programming models, there is a challenge to define properly the number of scenarios in order to be appropriate to ensure both, the representativeness of the random variables and the computational tractability of the stochastic models. The difficulty of solving the robust optimization models does not rise compared with the stochastic models (Bertsimas and Sim, 2004). Regarding distribution-based approaches, the parameter of the distribution function can be used in modeling, but sufficient information about the parameters is needed to define an appropriate probability distribution function. Despite this, it is possible that the data does not adjust itself to any probability distribution function. On the other hand, the results of fuzzy-based approaches depend on choosing an appropriate membership function and basic rules, which is one of the most challenging aspects in this approach.

Table 2.7 shows the distribution of reference articles among deterministic and the different approaches to address uncertainty. It is remarkable that most articles use single-level models to integrate different decisions (LI, LT, LIP, LIT, LIPT) and these models are mainly deterministic.

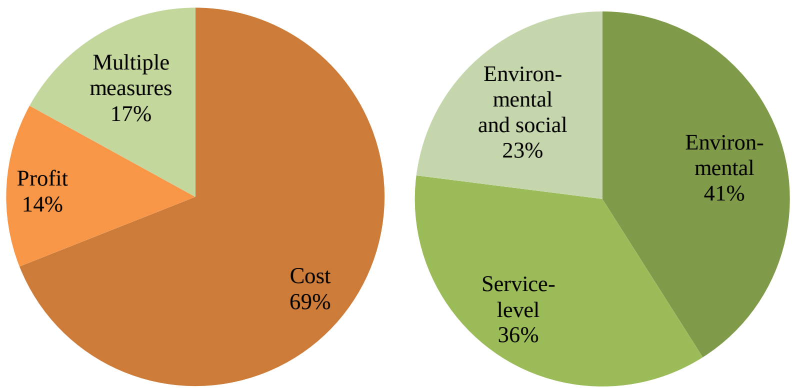
However, some of these integrations consider uncertainty through distribution-based, fuzzy-based, and robust optimization approaches. Multi-level models which integrate all decision categories (LIPT) are mainly deterministic models. In the same way, multi-timescale models to LIP are deterministic, but the different timescales address decisions in periods with less uncertainty.

Table 2.7: Modeling approaches to face data uncertainty

	Approach	Single-level mono-period	Single-level multi-period	Multi-level models	Timescale models
	Deterministic	12	7		
LI	Distribution-based	20	0	2	
	Fuzzy-based	2	1		
	Scenario-based	2		3	1
LP	Deterministic	1	0	1	
	Scenario-based	2	0		
	Deterministic	7	2	2	
LT	Distribution-based	2	0		
	Scenario-based	1		1	
	Deterministic	1	5	2	4
LIP	Distribution-based	1	0	2	
	Scenario-based		2	1	1
	Robust optimization	0	1	1	
	Deterministic	6	6	1	
LIT	Distribution-based	7	3	1	
	Fuzzy-based	1	1		
	Scenario-based	2	1		
	Deterministic	1	7	2	
LIPT	Distribution-based	1			
	Fuzzy-based	1			
	Total	70	39	16	6

Performance measures

We analyze the types of performance measures used in the integrated problems. Figure 2.9 depicts different objective functions that measure performances.



(a) Performance measures (b) Multiple objectives (17%)

Figure 2.9: Performance measures in integrated problems

Most articles have a single and economic objective, mainly minimizing total cost or maximizing profit. The minimization objective predominates with 69% of the studies (90 articles) minimizing the total cost, as shown in Figure 2.9(a), expressed through the sum of several cost components that depend on the modeled decisions. Some cost components are: facility opening, transportation, storage, routing and vehicle or technology acquisition. Some objective functions minimize total investment derived from a decision, for instance, investment in opening warehouses (Nasiri and Davoudpour, 2012). On the other hand, profit maximization objectives receive less attention, only 14% (18 articles) of the articles. Under profit maximization, it is not always attractive for a company to meet all demands of all customers. This occurs when serving certain customers generates additional costs higher than the corresponding revenues. Thus, some models include decisions such as delivery delays and lost sales, under penalties in the objective function.

Some papers propose models with multiple and conflicting objectives. This approach is especially useful for situations where objectives cannot be added because they have different units (Brunaud and Grossmann, 2017). Increasing environmental, legislative, and social concerns are forcing companies to take into account the impact of their operations on the environment and society. Thus, in addition to economic factors, objectives related to customer responsiveness and social and environmental impacts are taken into account in mathematical models. Among the articles studied, 17% (22 articles) are found in this category. All the multi-objective models have at least one economic objective. The pie-chart 2.9(b) is a sub-chart of 2.9(a) and out of the 17% of papers that consider multiple measures, 41% consider environmental measures in combination with economic measures, 36% consider service-level measures in combination with economic measures, and 23% consider environmental and social measures in combination with economic measures. Most multi-objective models integrate decisions through a single-model (91%). Multi-level models also address several objectives (9%). The main integration in multi-objective models is LIT with objectives related to environmental impacts, demand fulfillment, and delivery times (Biuki et al., 2020; Forouzanfar et al., 2018; Govindan et al., 2020; Mogale et al., 2019; Nekooghadirli et al., 2014; Qazvini et al., 2016; Rabbani et al., 2019; Zhalechian et al., 2016). Multi-objective LI models also concern objectives such as demand responses and delivery times (Ahmadi et al., 2016; Liao et al., 2011b,a; Naimi Sadigh et al., 2013; Nasiri and Davoudpour, 2012). LT and LIPT models consider environmental objectives, for instance, minimizing pollutant gas emissions (Govindan et al., 2014, 2016; Sadeghi Rad and Nahavandi, 2018; Govindan et al., 2019; Soleimani et al., 2018) and minimizing the environmental impacts through the life cycle analysis methodology (Mota et al., 2018).

Social objectives are more difficult to measure compared to economic objectives, therefore, they are more difficult to define and use. A social objective aims to maximize the social benefit measured through indicators. The main social indicator is creating job opportunities with different definitions, for instance, the number of jobs created by the SC in countries with less economic development (Mota et al., 2018). The maximization of job creation is also used by Biuki et al. (2020); Zhalechian et al. (2016). Govindan et al. (2016) proposed other social objectives in terms of economic welfare and growth, responsibilities towards stakeholders, extended producer responsibilities and employment practices. Govindan et al. (2019) presented several social indicators: variable and fixed job opportunities; equity between customers in terms of their access (distance); potential damage that may occur in the process of establishing facilities, shipment of products, manufacturing and handling; level of customer satisfaction in terms of time delivery; the equity of workers in terms of the standard deviation of distances passed by vehicles and the standard deviation of work-load in facilities; and the work damage during the manufacturing process. According to Farahani et al. (2014), the response time to the customer can be considered as a social objective, as the customer needs are primarily regarded despite the cost that the service may represent for the company. Some social and environmental objectives are used as constraints in other articles. Demand fulfillment policies derive constraints related to service levels, stock levels and safety stocks. Frequently, the consideration of service levels and safety stocks involve non-linear expressions. Most of the mathematical models in the sample show some non-linearity (89%), of which very few articles present strategies to linearize the non-linear models (9%).

A comparison of the performance measures between our analysis and the review presented by Melo et al. (2009) shows an increase in models considering multiple measures, particularly including environmental and social ones. This result seems to corroborate a tendency in the literature to incorporate sustainable issues in a multiple perspective of performance measures.

Applications

Regarding applications in the industrial sector, most applications of the proposed models and methods were made in European countries, including electronic, glass, pharmaceutical, consumer goods, and copier re-manufacturer companies. Moreover, there were applications in Iran in different companies, such as bread, filters, light automobile parts, and household goods. In Pakistan, an application was in a lube oil company. There is also a case in an Indian plastic manufacturer and other applications in cell phones, packaged gases, automotive timing belts, and steel pipe products. We also note that there are several applications in service parts logistics. The applications in industrial sectors represent only 30% of the reference articles. These articles present integrated problems based on case studies and also use real data or generated instances based on real data.

Most articles present axiomatic research assuming idealized problems, i.e., they are interested in developing approaches to improve addressed problems in the literature, to find better solutions to newly defined problems, or to compare various methods to solve a specific problem (Bertrand and Fransoo, 2002). These works consider generated data sets. We note that the mathematical formulations of these articles are inspired by other pieces of research that might have been originally motivated by real problems. However, the discussion about the model assumptions and data structure in practical contexts is frequently neglected in the revised papers. Most authors focus only on describing the main research contribution, which is often based on idealized problems. The lack of analysis about the fundamentals and premises to formulate LNP models can be a primary obstacle to the practitioners.

2.6 Solution methods for integrated problems in LNP

The methods used to solve the integrated LNP optimization models can be classified into exact and non-exact methods. Exact solution methods include techniques able to find optimal solutions: Benders decomposition (BD) (Benders, 1962), column generation (Ford and Fulkerson, 1958) branch-and-cut (B&C), branch-and-price (B&P) (Barnhart et al., 1998), and decomposition methods with exact solutions. Non-exact solution methods include heuristics and meta-heuristics. Taking into account that the integration of decisions suggests addressing problems simultaneously, an idea for solving the models is the decomposition of the integrated problem into sub-problems that are easier to solve with exact or heuristic methods, for instance, Benders decomposition based heuristics. Some heuristic methods explore features of mathematical programming with exact, heuristics, and meta-heuristics methods, called matheuristics. Table 2.8 presents the solution methods used in the articles of the sample.

2.6.1 Exact methods

About 35% of referenced articles use exact approaches to solve models for integrated problems, mainly BD and B&C as shown in Table 2.8. A well-known approach used in some revised papers is the BD method, a technique for partitioning variables aiming to solve large-scale problems with complicating variables. Alshamsi and Diabat (2018) proposed an accelerated BD algorithm to a large-scale reverse SC network design with production, inventory and transportation decisions. Azizi and Hu (2020) applied a BD algorithm for pickup and delivery SC design with LR and direct shipment. Wheatley et al. (2015) presented an exact solution methodology using logic-based BD for an LI problem with service constraints. Khatami et al. (2015) applied Benders' decomposition to solve a stochastic mixed integer programming model for the concurrent redesign of a forward and closed-loop SC network with demand and return uncertainties. Tapia-Ubeda et al. (2020)

Table 2.8: Solution methods found in the reference articles

Methods			Authors
Exact		BD	15; 22; 227; 124; 183; 216; 217; 241
		B&B	58
		B&P	3
		Column generation	203
		General purpose solvers (B&C)	2; 8; 22; 23; 28; 41; 48; 46; 60; 79; 85; 91; 92; 97; 98; 102; 107; 120; 135; 137; 138; 136; 141; 157; 158; 161; 169; 195; 178; 188; 187; 193; 192; 189; 199; 201; 209; 208; 222; 231; 236; 235
Non-exact	Heuristics	Specific/sequential heuristics	64; 149; 160; 177; 184; 197; 206; 214; 221; 223; 239
		LR based heuristics	6; 5; 14; 24; 47; 68; 67; 65; 73; 147; 148; 170; 180; 190; 229
		BD based heuristics	207
		Outer approximation method	18; 118; 151
		Sample average approximation	17; 86
	Meta-heuristics	Evolutionary algorithms	44; 45; 104; 131; 130; 132; 171; 218; 219; 226
		Genetic algorithm	20; 21; 66; 80; 84; 88; 110; 150; 166; 167; 168; 172; 179; 200; 215
		Imperialist competitive algo	9; 172
		Simulated annealing	78; 123; 172; 194
		Tabu search	125; 232
		Particle swarm algo	84; 94; 159; 150
		VNS	121
		Hybrid meta-heuristics	4; 39; 57; 93; 95; 96; 129; 134; 90; 103; 122; 238
		Matheuristics	7; 59; 126

Number and authors of articles are in Table A.1 in Appendix A.

proposed a generalized BD to spare parts SC network design problems and Zheng et al. (2019a) applied it to solve a location-inventory-routing problem.

Generally, in integrated models solved with BD, location and customer assignment decisions are temporarily fixed, while tactical and operational decisions are yielded in a sub-problem. Ramezani and Kimiagari (2016) fixed variables representing financial decisions to solve iteratively subproblems with logistics decisions (location, allocation, distribution) and other financial decisions in a closed-loop SC network. Darvish et al. (2019) proposed an exact method based on the interplay between two branch-and-bound algorithms that run in parallel called the enhanced parallel exact method.

Shu et al. (2010) developed a column generation method to solve the LI problem under uncertainty in the long life-cycles of warehouses. The authors explicitly model the possible combinations of retailers that can be served, and they solve the problem by initially considering only a subset of combinations and adding others iteratively, until the best allocation is found.

Ahmadi-Javid et al. (2018) addressed a location-routing-pricing problem, aiming at maximizing profit. The problem is reformulated to a set-packing master problem and elementary shortest path subproblems, by using the Dantzig-Wolfe decomposition. A branch-and-price algorithm is used as the solution method after reformulating the model. A location problem is addressed in the master problem with a subset of routes and new routes are added iteratively to this master problem using heuristic and exact label-setting algorithms.

Some articles solve problems using general purpose optimization solvers, such as CPLEX, GUROBI, LINGO and XPRESS, which are also considered here in the exact category, because an exact method is usually incorporated into these solvers, often a general-purpose B&C method. The main decisions integrated in these articles are location-allocation, flows and inventory levels.

2.6.2 Non-exact methods

Non-exact methods include algorithms that return a feasible solution in finite computational time with absent accuracy of such solution quality, i.e., without a certificate of optimality of the solution. Most of the articles studied (about 64%) present non-exact solution approaches, which is expected since location problems are difficult to solve (NP-hard). When location problems are combined with other problems, its resulting integrated mathematical model involves a greater number of constraints and complicating variables, and consequently it is also difficult to solve. In this case, authors often resort to heuristic methods that can find feasible solutions within acceptable run times to the integrated problems.

BD is an attractive methodology to develop heuristics because it can take advantage of problem structures Rahmaniani et al. (2017). Other sequential algorithms consist of separating decisions and solving parts of the problem sequentially (Diabat, 2016; Miranda et al., 2009; Rappold and Roo, 2009; Singh et al., 2015; Tsao et al., 2012; Zhang and Xu, 2014). Guerrero et al. (2015) proposed a relax-and-price heuristic for the location-inventory-routing problem, a hybridization between column generation, Lagrangian relaxation, and local search. Lagrangian relaxation (LR) is usually used as a decomposing strategy. This leads to relaxing some constraints of the problem, called coupling constraints, and are penalized (dualized) in the objective function and, generally, the resulting problem can be decomposed into independent problems. Heuristics based on Lagrangian relaxation are widely used in the sample, as shown in Table 2.8.

Some authors have also proposed algorithms inspired by metaheuristics, namely simulated annealing (Fattahi and Govindan, 2017; Keskin and Üster, 2012; Nekooghadirli et al., 2014; Saragih et al., 2019), tabu search (Kim and Lee, 2015; Yuchi et al., 2016), particle swarm optimization (Forouzanfar et al., 2018; Govindan et al., 2014; Mousavi et al., 2017; Mogale et al., 2019), and metaheuristics based on evolutionary algorithms (Cabrera et al., 2016; Calvete et al., 2014; Liao et al., 2011b,a; Lin et al., 2009; Nasiri et al., 2015; Tiwari et al., 2010; Wang et al., 2013). An evolutionary algorithm frequently used is the well-known genetic algorithm (Arabzad et al., 2014; Aryanezhad et al., 2010; Diabat and Deskoores, 2016; Firoozi et al., 2014; Ghezavati et al., 2009; Hiassat et al., 2017; Naimi Sadigh et al., 2013; Nakhjirkan and Rafiei, 2017; Shavandi and Bozorgi, 2012; Tang and Yang, 2008). Authors have also proposed hybrid metaheuristics, in particular, simulated annealing with tabu search (Ahmadi-Javid and Azad, 2010) and simulated annealing with genetic algorithm (Gholamian and Heydari, 2017; Guo et al., 2018). Some articles combine several meta-heuristics, such as simulated annealing, tabu search and genetic algorithm with variable neighborhood search (VNS) (Kaya and Urek, 2016). Some heuristic methods explore features of mathematical programming with exact, heuristics and meta-heuristics methods, called matheuristics. For instance, a hybrid Lagrangian relaxation and an ant colony optimization algorithm to solve a logistics network design problem (Lagos et al., 2015).

An idea for solving the integrated models is the decomposition into sub-problems that are easier to solve. Ahmadi-Javid and Seddighi (2012) presented a heuristic method in three phases: location, routing-1 and routing-2. After determining a suitable initial solution, a simulated annealing algorithm and a hybrid ant colony optimization algorithm are implemented to improve the solution in the first two phases and in the third phase, respectively. Darvish and Coelho (2018) proposed a matheuristic based on a hybrid of variable neighborhood search and exact methods. The problem is divided into two subproblems that are then solved in an iterative manner. In the first level, the authors apply a heuristic in order to decide location and production allocation. In the second level, transportation, inventory allocation at plants and rented DCs are determined exactly by solving an integer linear programming subproblem. Finally, they improve the obtained solution by solving the model presented with exact methods for a very short-time period.

Some optimization models have multiple objectives and are solved with methods that do not guarantee optimal solutions for each objective. This is the case when multiple objectives are transformed into a single objective by a weighted sum of each criterion (Naimi Sadigh et al., 2013) or by goal programming (Arabzad et al., 2014). Some authors also use an evolutionary approach (non-dominated sorting genetic algorithm) to deal with multiple objectives (Forouzanfar et al., 2018; Liao et al., 2011b; Mogale et al., 2019; Naimi Sadigh et al., 2013; Nekooghadirli et al., 2014). Govindan et al. (2014) proposed a hybrid metaheuristic, combining a particle swarm algorithm and an adapted multi-objective variable neighborhood search algorithm.

2.6.3 Analysis of solution methods for each type of integration

There is a predominance of non-exact methods over exact methods to solve LNP problems. In order to determine if there is some trend in the solution methods according to the decisions involved in the model and the integration strategies used, Figure 2.10 shows the participation of each category of method that involves these decisions.

Studies on LI, LT, and LIT are addressed mainly by heuristics and metaheuristics. This is because models with decisions represented by integer variables and associated with nonlinear expressions in mathematical programming are difficult to approach with exact methods. In particular, models with decisions such as inventory policy definition, order point, and order number were mainly addressed through heuristics and meta-heuristics. Moreover, models with

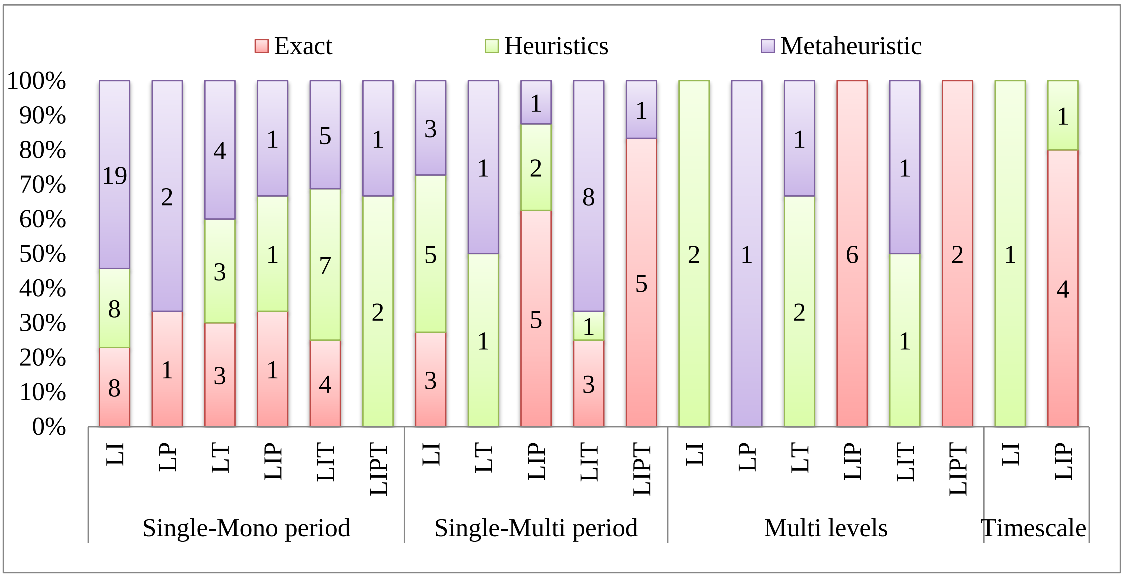


Figure 2.10: Participation of each category of method that involves these decisions

decisions represented by integer variables, such as demand allocation and vehicle routing, are largely addressed through heuristics and meta-heuristics. The LIP integration, that generally addressed inventory levels and production quantity decisions using continuous variables, is often solved by exact methods, predominantly by general purpose solvers. Models that additionally integrate transportation decisions, LIPT, are addressed more diversified solution methods, 64% by exact methods and 36% by non-exact methods.

The integration of decisions may increase the difficulty to solve the models. A strategy of a single-model is preponderant. To solve these models, heuristic methods are commonly used, customized heuristics, Lagrangian relaxation based heuristics, as well as meta-heuristics based on evolutionary algorithms, particularly genetic algorithm. Only 28% of the articles that use this strategy are solved with exact methods, predominantly solvers of general purpose (25%). Multi-level models use heuristic and exact solution approaches. Models with interconnected timescales use general purpose solvers.

2.7 Discussions about research gaps and opportunities

Researchers and practitioners of operations management and operations research communities often classify decisions into strategic, tactical, and operational, based on the time horizon of impact, therefore these decisions are dealt separately. When the members of the logistics network try to optimize their relative performance, the performance across the network might not be optimal. This is true also when each level is optimized regardless of the others, hence, this leads to a sub-optimality of decisions and excessive costs. Recently, many studies showed significant savings when regarding integration of decision levels (Hiassat et al., 2017).

In this context, the present study used a systematic literature review to better understand how this integration is developed in optimization models; what the main integrated decisions involved are; what types of problems are treated and what their main features are; how the data is addressed; which solution methods are used to solve the integrated problems; and what research gaps and opportunities are identified. Figure 2.11 summarizes the challenges and benefits of integrated planning, and also the main findings of the literature review, allowing a better overview of what has been done on this topic.

The integration of decisions levels in the network planning implies taking (some of) strategic, tactical and operational decisions simultaneously. Consequently, benefits can be obtained, as shown in Figure 2.11. The integration eliminates conflict and incompatibility among decisions and goals of different departments in a company. It also helps to react more quickly to the dynamic conditions of the environment. Moreover, the integrated planning reduces the logistics network costs and more information is exploited. Nevertheless, this integration presents challenges in modeling and solving problems, as pointed out in Figure 2.11. Integrated planning implies dealing with different decision timing (scope, periodicity, and frequency), as well as taking into account several logistics components and dealing with the variability and uncertainty of important problem parameters (Monteiro et al., 2010). Integrated planning also implies mathematical models with a greater number of variables (continuous and integer). It can increase the difficulty of solving the models, it is expressed in longer execution times. The requirements for large amounts of complex and hard to obtain data are other challenges (Miranda et al., 2009).

The reference papers of our review address the integration of: Location-Inventory (LI), Location-Transportation (LT), Location-Production (LP), Location-Inventory-Transportation (LIT), Location- Inventory-Production (LIP), location-transportation-production (LTP), and Location-Inventory-Production-Transportation (LIPT). Figure 2.11 presents the main decisions by hierarchical level. The studies have focused mainly on handling strategic and tactical decisions for the entire planning horizon. The main decisions addressed at the strategic level are facility location, network design, and demand allocation, generally defined for the entire planning horizon. Tactical and operational decisions are associated with production, inventory and transportation management. The main decisions in inventory management refer to inventory levels, order quantities and replacement points. Production decisions, in turn, include production quantities and production allocation which are typical master production planning (mid-term). In transportation management, the decisions considered are vehicle routing and transportation alternatives selection. Very few studies incorporate the selection of transportation alternatives, notwithstanding it is a common characteristic in real contexts.

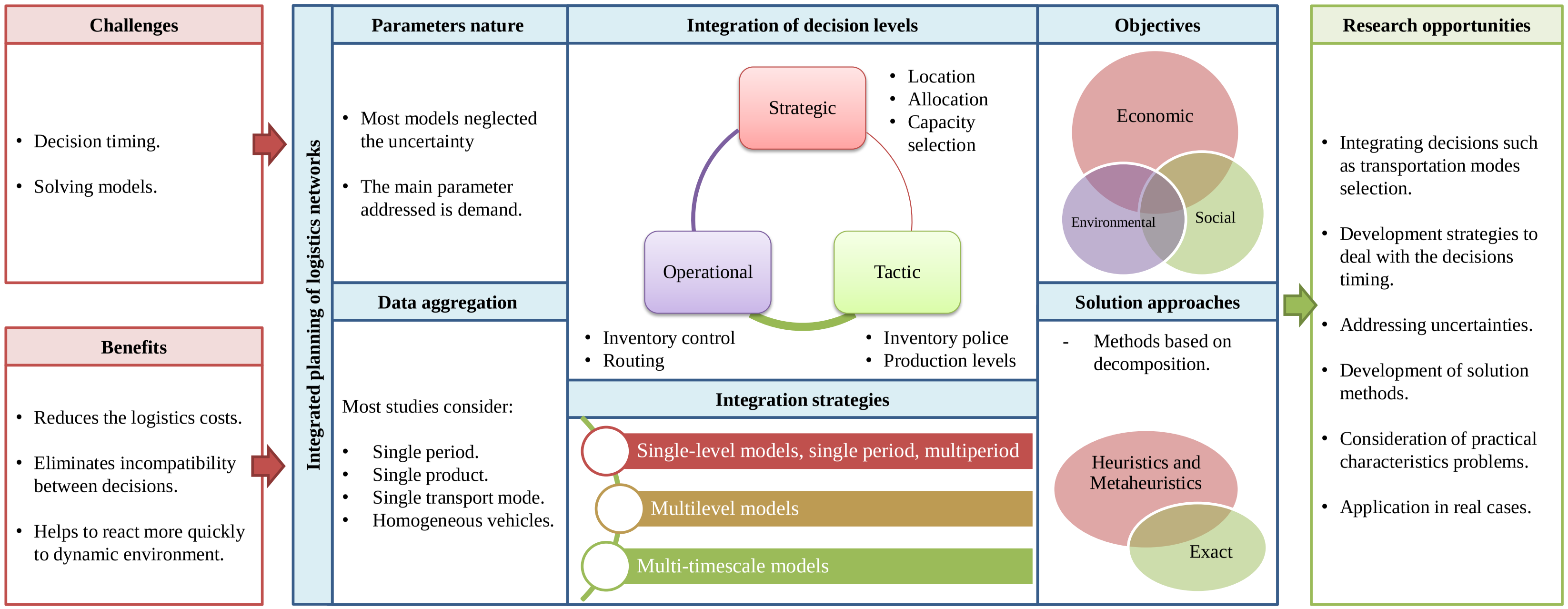


Figure 2.11: Conceptual framework of the main findings of the literature review towards research opportunities.

Regarding our main research question, the approaches to integrate decision levels can be classified into: (i) single-level and mono-period models; (ii) single-level and multi-period models; (iii) multi-level models; (iv) multi-time-scales models, as shown in Figure 2.11. Single-level, mono-period, and deterministic models integrate decisions of different hierarchical levels without taking into account the variability or uncertainties from the lower levels. These models can be effective when these variability and uncertainties are not significant for the planning results. To include these issues, some authors formulate similar models considering stochastic, possibilistic and fuzzy parameters.

The consideration of multiple periods when dealing with tactical decisions is the most common strategy identified. It allows re-evaluating the shorter-period decisions during the planning horizon, while strategic decisions are evaluated for the entire horizon or the macro-periods in the case of multi-scale models. This approach requires more computational effort to solve the problems. Other approaches are multi-level models that allow the consideration of further details and decisions. Some of these models used a feedback mechanism to pass information from the bottom to the top level.

Most articles have a considerably simplified data aggregation, as pointed out in Figure 2.11, which could means sub-optimal solutions of the models and in decision-making. Most companies have multiple products, however most studies aggregated them into a single product. Critical analysis about modeling assumptions and data generation aligned with practical problems could provide more interesting managerial insights. For models considering some inventory decisions (safety, replacement point, order point) historical data could be used to estimate the demand through probability distributions. However, this may not be effective if demand is seasonal, therefore these assumptions need to be carefully evaluated. In this same sense, in the practice of transport activities, different alternatives related to modal, freight type and vehicle capacity are available, however they are overlooked as they are considered a single mode of transportation. A possible reason is that taking into account multiple periods in modeling increases the difficulty of solving problems. Particularly, defining an appropriate transportation cost structure for different decision levels is very difficult. In a practical context, there are issues such as quantity discounts, which are established by the carriers to encourage organizations to transport larger quantities in order to reduce their fixed costs. These issues were neglected in the reference papers. Thus, a research opportunity is to incorporate these cost structures in the integrated models.

An important issue in LNP is the location problem that is NP-hard, and is integrated with other problems that can result in a mathematical model with greater number of constraints and complicating variables, consequently more difficult to solve. Most of the articles studied present non-exact solution approaches, as is presented in Figure 2.11. Many studies which use the single-level models, use decomposition strategies for solving them. In fact, most heuristics methods in the sample were based on the decomposition idea, thus several papers proposed customized sequential heuristics and Lagrangian relaxation based heuristics.

Regarding the relation between the integration strategies and the types of solution methods, to solve these single models were used non-exact methods; while multi-level models were solved with both exact and non-exact methods; and models with interconnected timescales were solved with general purpose solvers. Regarding the relation between the decisions and the type of solution methods, models with product flow, inventory levels and production quantity are often solved by purpose general solvers. However, models with decisions like inventory policies and routing decisions, are addressed mainly through meta-heuristics.

In the current business environment affected by uncertainties, LNP is a complex decision-making process. There are different sources of uncertainties as environmental changes (social, politics, economics, fiscal, etc.) and disruptions in supply chain operations. Thus, important information for decision-making such as customer demand, lead-times, sales prices, availability, and capacities are uncertain and could vary considerably along the planning horizon (Amiri-Aref et al., 2018). A few articles cope with stochastic/uncertain parameters through techniques such as representative scenarios, stochastic programming, robust optimization, and fuzzy programming.

Most articles have a single economic objective mainly minimizing total cost or maximizing profit. Few papers propose multi-objective models, considering environmental and social objectives. The environmental objectives aim to reduce the impacts of the decisions on the environment, and are measured through indicators such as gas emission. The social objectives aim to maximize the social benefit measured through indicators like the number of jobs created, and they are more difficult to measure, define and use.

Thereby, there are research gaps in the integrated planning of the logistics network, as pointed out in Figure 2.11. First, there is a gap in the consideration of some characteristics of the integrated problems, mainly parameter uncertainty. Thus, studies that propose appropriate techniques to address uncertainties in the problem parameters, as well as approaches to solving these problems can be interesting and promising. Other practical characteristics that could be regarded in the problem modeling would be multiple products and multiple transportation alternatives. Depending on the practical context, it would be interesting to look at environmental and social objectives, in addition to economic objectives. According to the product type, and responding to government legislation and social pressure, reverse logistics for the proper disposal or the re-manufacturing of used products should be also considered. Thus, there are important issues that decision-makers in LNP have to manage in the practice, which are neglected in the literature. At the same time, the studies presented elaborated models and solution methods. However, few studies applied the mathematical models in real cases. Thus, the questions raised by Bertrand and Fransoo in 2002 about the "gaps" between theory and practice in operations research remain as a gap in the literature.

Regarding the integration, there are gaps in the integration of relevant decisions, in particular the transportation mode selection. Moreover, there are opportunities to properly develop integration strategies for aggregate decisions, as well as propose representative mathematical models considering adequate time structure for decisions. It is also interesting to compare different strategies to address the integration of decisions. Most solution approaches of the articles are heuristic, thus there is an opportunity to develop efficient solution methods exploring the characteristics of the models and the integration of decisions.

The academic community on operations research is also called upon to go further, addressing diverse, practical, and relevant issues for the different supply chain networks and operations and proposing solutions for the last mile. There are research gaps in topics such as facility disruptions, e.g., power outages, poor weather conditions, natural disasters (Cheng et al., 2021); issues that affect transportation operations due to increases the time and costs, e.g., traffic congestion for commercial and humanitarian logistics (De Camargo and Miranda, 2012; Bayram and Yaman, 2018), disrupted road infrastructure (Moreno et al., 2020), security measures related to traffic accidents and cargo theft (Jalal et al., 2022b); and another disruptions and outbreaks in the supply chain as a consequence of social issues, e.g., pandemics, terrorism, and war.

2.8 Final remarks

Managers and researchers of the operations management/operations research community have noticed the importance of integration in logistics network design and planning, mainly because of the potential benefits obtained when addressing different decision levels. This chapter used a systematic literature review to better understand how decision level integration was developed in the optimization models of the literature. A set of articles on integrated planning of logistics networks published from 2000 to 2020 was reviewed. The growing number of publications in recent years indicates an increasing trend of research activities on this topic.

Based on this literature survey, we present a conceptual framework to highlight the challenges and benefits of integrated planning, and also the main characteristics of the reference papers regarding the integrated decisions, integrating strategies, and solution methods. We also discuss some research gaps in the literature. There are some interesting opportunities for future research in different directions, such as the development of integrated decision levels, development of integrating approaches, processing and aggregation data, incorporation of parameter uncertainties, development of exact solution methods, as well as applications to industrial and service settings.

Despite the growing literature in LNP integrated decisions, many studies do not differentiate the timing of the decisions. There is a predominance of simple data aggregation in the problem modeling, considering only a single period in the planning horizon with all decisions aggregated. Thus, a promising line of research would be to develop models for LNP carefully defining proper planning horizons, the time structure and the frequency in which decisions should be made or revised. Modeling assumptions should include the dynamism and variability presented in the current business contexts.

These research opportunities encourage collaboration and partnership between academia and organizations, particularly the industry. It can help to propose better problem descriptions and formulations, and better optimization approaches and tools, to effectively support decision-making in LNP. These tools can be useful in practice, contributing to the development of collaborative research. In SC networks, organizations should cooperate with each other to improve the performance of the whole SC, and this type of integration could be addressed in future studies.

Chapter 3

Integrated logistical planning: model formulation and solution method

In this chapter, we analyze an integrated location-inventory-transportation problem under demand uncertainty. We propose a generic modeling approach to integrate facility location with inventory planning decisions, made under a periodic inventory review policy, and transportation decisions considering volume-based costs. The model determines the DC locations to rent; the selection of the capacity level at the distribution centers (DCs); the assignment of retailers to DCs; the cycle, safety stock, and anticipation inventory levels at DCs; the selection of the correct discount segment for transportation, aiming to minimize the total cost composed of rental expenses, inventory costs, and transportation costs. Since this integrated problem is non-linear due to the presence of safety stock constraints, we leverage an enhanced Logic-based Benders decomposition (LBBD) with an initial solution derived from the problem structure, a piecewise linear lower bound function, and valid multiple cuts. Using the instances derived from the real data, we demonstrate the value of the integrated model in terms of feasible solutions and cost savings.

* A working paper based on the contents of this chapter is:

Aura Jalal, Yossiri Adulyasak, Raf Jans, Reinaldo Morabito, and Eli Toso (2021): Integrated planning of logistics network under demand uncertainty, Technical Report, *HEC Montreal*, Canada.

3.1 Introduction

Logistics network planning concerns several decisions, mainly related to location, production, inventory, and transportation management. Due to its complexity, these decisions are often made in a sequential fashion. Nevertheless, such a sequential approach can result in sub-optimal performance of the network (Üster et al., 2008; Bouchard et al., 2017; Darvish and Coelho, 2018). The integration of decisions in logistics network planning eliminates conflicts among decisions, helps to react more quickly to the changes in the environment, and reduces logistics network costs, as pointed out in the literature review of Chapter 2.

The main challenge of the integration network design and inventory management in the supply chain is its complexity and scalability issues (Farahani et al., 2014). Inventory management is an important part of supply chain performance, but most studies in the literature consider inventory management separately from the supply chain design. At the same time, most studies in network design do not consider inventory decisions or consider a simplistic form of inventory decisions rather than an explicit inventory policy. Furthermore, the safety stock level is not optimized and may lead to sub-optimal solutions (Chen et al., 2011; Sadjady and Davoudpour, 2012; Shavandi and Bozorgi, 2012). There are some studies (e.g., Üster et al. (2008); Ahmadi-Javid and Hoseinpour (2015a); Wheatley et al. (2015); Jeet and Kutanoglu (2018); Candas and Kutanoglu (2020)) that consider an integrated approach to supply chain network design and inventory management but most of them focus on a single-echelon network (You and Grossmann, 2010). The integration of transportation decisions is also an important issue in the problem. Most studies in the literature consider linear unit transportation costs, although realistic transportation costs typically comprise different structures and quantity discounts. Particularly, piecewise linear costs, which are frequently in transportation planning, are neglected in most of the related literature (Croxton et al., 2003; Engebrethsen and Dauzère-Pérès, 2018; Brunaud et al., 2018).

In this chapter, we address the integrated logistics planning of a network addressing real features. At the beginning of the year, it is necessary to decide in advance and simultaneously about the network design, inventory management, and transportation planning, to negotiate contracts with a third-party logistics partner. We assume that in the Enterprise Resource Planning system is used the periodic review (T, S) inventory policy to manage inventory at DCs, where the parameter T represents the review interval and the parameter S represents the target inventory level within the review interval. The period review interval T is an input parameter, but the target inventory level S is a decision, which can be different for each of the DCs and which can also vary over time since the average demand at the retailers can vary over time. As retailer demand is uncertain, safety stocks need to be maintained at DCs to provide an appropriate service level and to protect against short-term variations in retailer demand. We also consider anticipation inventory to address the seasonal expected demands. The company has a full coordination system, where all the DCs have the same review interval T.

We develop a mathematical model to determine the DC locations and capacity levels, shipment sizes from plants to DCs, assignment of retailers to DCs, and the target inventory, safety stock, and anticipation inventory levels at DCs by minimizing the facility location, transportation, and inventory holding costs. The model is formulated as a nonlinear mixed-integer programming problem. This is a single-level and multi-period model within the classification of integrated models in logistics network planning proposed in Chapter 2. Given that both the location/allocation and inventory problems are difficult to solve separately, it is not surprising that an integrated model that handles these problems simultaneously is hard to solve to optimality. Therefore, we propose an exact solution method using logic-based Benders decomposition and we address instances based on real data from the case of a pharmaceutical company. To the best of our knowledge, no previous work has jointly dealt with the same features present in our study.

This is normative axiomatic research since this is an idealized model proposed to contribute to the literature in different gaps identified in the literature review of Chapter 2. We integrate decisions related to network design, inventory management, and transportation planning, using multiple periods to address the decisions according to their timing, i.e., frequency and periodicity. This model addresses the variability of demand by a distribution-based approach.

The chapter is organized as follows: Section 3.2 presents the literature review. Section 3.3 details the problem description, model formulation, and linearization procedure. Section 3.4 presents the BD. Section 3.5 presents computational results and discussion. Finally, section 3.6 concludes with some directions for future research.

3.2 Literature review

Location and inventory decisions are related since inventory decisions depend on the location of the facilities (plants, DCs, and retailers) and the assignments of retailers to DCs and of DCs to plants. However, location and inventory management decisions have been commonly dealt with separately. We review studies that put forward this integration. Table 3.1 presents some characteristics of the relevant studies. Similarly, in Table 3.2 we present the review of the main decisions that are related to the context of our study (i.e., location-allocation, capacity selection, safety stock, anticipation inventory, and transportation decisions), as well as the data source of instances, model type, and solution method.

Since the firm must ensure sufficient inventory and safety stocks to deal with demand uncertainty, it is necessary to define the location with minimum costs, and also to define the inventory management decisions and inventory control policies based on a predefined service level. Under uncertain retailer demands, risk-pooling is a strategy to manage such demand uncertainty by consolidating inventory at DCs for achieving an appropriate service level. The transportation time from the pants to the DCs (lead time) is a relevant factor in the determination of the safety stock level under random retailer demands.

Lead times depend on several factors, such as the physical distance and transportation mode, as well as the product type, the production technologies, etc. Nevertheless, papers in the literature incorporating the risk-pooling strategy have not considered DC-to-plants dependent lead times in the network design problems. Most papers consider a single plant or supplier or source from which the DCs are supplied (Berman et al., 2012; Gzara et al., 2014; Zhang and Unnikrishnan, 2016; Amiri-Aref et al., 2018; Escalona et al., 2018; Schuster Puga et al., 2019b; Zheng et al., 2019b; Tapia-Ubeda et al., 2020). In this case, the lead time depends only on the DC location. Other works consider multiple plants but consider that the lead time is an average for all plant-DC pairs (Vidyarthi et al., 2007; You and Grossmann, 2008). In contrast, Park et al. (2010) and Yao et al. (2010) are the only studies that consider lead times from multiple plants to DCs, this consideration results in a problem more difficult to solve, but still solvable. Park et al. (2010) propose a two-phase heuristic solution algorithm based on the Lagrangian relaxation approach and Yao et al. (2010) develop an iterative heuristic method, both heuristics methods provide good solutions for the addressed problems.

Single-product (or single-commodity) problems cannot represent the cases when products have different characteristics (size, weight, price, demand patterns) and requirements (environmental conditions as temperature ranges). Moreover, considering multiple products allows considering by-products sourcing from plants and DCs as in Yao et al. (2010). Depending on the product, the lead times of production or transportation can be different and such characteristics should be considered jointly with the decisions of product assignments and inventory policies at different locations. Most papers in Table 3.1 consider an infinite planning horizon or single period planning that does not represent the contexts, when the demand varies over different periods in the planning horizon. These considerations of a single product and period can result in sub-optimal solutions (Jalal et al., 2022b).

Note that in Table 3.1 most papers do not consider capacity constraints. However, the capacity constraint of DCs and plants are a real feature. Without this consideration, solutions can be infeasible. The anticipation inventory is a decision to respond to capacity constraints. In this sense, the capacity selection decision is an important issue that helps to implement the solutions, by defining sizes for the different DCs. The DCs can assume different sizes according to the demand assignment. Addressing real transportation structures can reduce the overall costs of the network, but not many papers consider it.

The consideration of safety stocks made the problem non-linear and much more difficult to solve. To solve this complex problem, most articles present heuristics methods to solve the problems, such as heuristics based on Lagrangian relaxation (Vidyarthi et al., 2007; Park et al., 2010; You and Grossmann, 2010; Berman et al., 2012), Benders decomposition based on heuristics (Tapia-Ubeda et al., 2020), and approximation algorithms (Yao et al., 2010; Zhang and Unnikrishnan, 2016; Amiri-Aref et al., 2018). Few papers propose exact methods. Wheatley et al. (2015) present an exact solution method using logic-based Benders decomposition and Zheng et al. (2019b) propose an exact algorithm based on the Generalized Benders Decomposition method. However such methods are applied to tackle simpler problems compared to the application considered in our case which includes a multi-plant network and capacitated DCs in a multi-period problem.

Table 3.1 also presents the inventory policies used by the studies. A commonly used police in practice is the periodic review and order-up-to-level *(T,S)* inventory policy, where the product is replenished up to S whereas the ordering decision can be made periodically every T review interval. In the *(r,Q)* policy, when the inventory position falls below a reorder level r, a replenishment order for Q units is placed. In the minimum/maximum *(s,S)* inventory policy, when the inventory on-hand falls below a certain minimum s, a request for a replenishment order that will restore the on-hand inventory to a maximum number, S. The one-for-one *(S-1,S)* inventory policy, i.e., if one product is shipped, one is ordered to replenish, it is often advocated for controlling the stock levels of expensive, slow-moving items. The consideration of these policies implies the consideration of safety stock to deal with the uncertain demand.

Table 3.1: Literature review: problem characteristics

Article				Demand			Capacity	Inventory
	#Layers	#Plants	Lead times	Sourcing	#Products	#Periods	Constraints	Policy
Vidyarthi et al. (2007)	+Two	Multiple	Average	Single	Multiple	Single	Cap	
Park et al. (2010)	+Two	Multiple	Location based	Single	Single	Single	Cap	*(r,Q)*
Yao et al. (2010)	+Two	Multiple	Location based	R/C	Multiple	Single	Uncap	*(T,S)*
You and Grossmann (2010)	+Two	Multiple	Average	Single	Single	Single	Uncap	*(T,S)*
Berman et al. (2012)	+Two	Single	Location based	Single	Single	Single	Uncap	*(T,S)*
Gzara et al. (2014)	+Two	Single	Location based	Single	Multiple	Single	Uncap	*(S-1,S)*
Wheatley et al. (2015)	Two	None	Average	R/C	Multiple	Single	Uncap	*(S-1,S)*
Zhang and Unnikrishnan (2016)	+Two	Single	Location based	Single	Single	Single	Cap	*(T,S)*
Amiri-Aref et al. (2018)	+Two	Single	Location based	Multiple	Single	Multiple	Cap	*(s,S)*
Escalona et al. (2018)	+Two	Single	Location based	Single	Single	Single	Uncap	*(r,Q)*
Schuster Puga et al. (2019b)	+Two	Single	Location based	Single	Single	Single	Uncap	
Zheng et al. (2019b)	+Two	Single	Location based	Single	Single	Single	Uncap	*(T,S)*
Tapia-Ubeda et al. (2020)	+Two	Single	Location based	Single	Single	Single	Uncap	*(r,Q)(T,s,S)(S-1,S)*
Our article	+Two	Multiple	Location based	R/C	Multiple	Multiple	Cap	*(T,S)*

R/C: Retailer per commodity

Table 3.2: Literature review: decisions, model type, and solution method

Article	Decisions					Data	Model	Method
	Loc-alloc	Cap sel	Safety Stock	Ant inv	Transp			
Vidyarthi et al. (2007)	✓		✓		✓	Random data	MINLP	Heuristics
Park et al. (2010)	✓		✓			Random data	MINLP	Heuristics
Yao et al. (2010)	✓		✓			Random data	MINLP	Heuristics
You and Grossmann (2010)	✓		✓			Real data based	MINLP	Heuristics
Berman et al. (2012)	✓		✓			Random data	MINLP	Heuristics
Gzara et al. (2014)	✓		✓			Random data	MINLP	Solver
Wheatley et al. (2015)	✓		✓			Real data based	MINLP	Exact
Zhang and Unnikrishnan (2016)	✓		✓			Literature	CQMIP	Heuristics
Amiri-Aref et al. (2018)	✓		✓		✓	Generated data	MINLP	Heuristics
Escalona et al. (2018)	✓		✓			Random data	CQMIP	Solver
Schuster Puga et al. (2019b)	✓		✓			Literature	CQMIP	Solver
Zheng et al. (2019b)	✓		✓		✓	Real data based	CQMIP	Exact
Tapia-Ubeda et al. (2020)	✓		✓			Real data based	MINLP	Heuristics
Our article	✓	✓	✓	✓	✓	Real data	MINLP	Exact

All papers in Tables 3.1 and 3.2 and most of the studies on inventory planning simplify the transportation costs by considering linear unit transportation costs, although realistic transportation costs typically comprise different structures and discount schedules (Engebrethsen and Dauzère-Pérès, 2018). Particularly, piecewise linear costs, which are frequently in transportation planning (Croxton et al., 2003; Brunaud et al., 2018), are neglected in most of the related literature.

Our contribution is fourfold. First, we integrate important decisions in logistics network planning regarding network design, inventory management, and transportation planning. Second, we integrate features and characteristics of the real-world application in our problem, such as location-based lead times, storage capacity constraints in DCs, multi-period, multi-product, and single-sourcing per retailer and commodity. The safety stock is a function of the demand at each open DC and its lead time from plants. Hence, safety stock calculations must be simultaneously determined with the assignment and the location decisions. The inventory control decisions are made with a period review inventory policy, defining the amount of cycle inventory, safety stock, and anticipation inventory at open DCs. This work also addresses piecewise linear costs which are a real feature not often regarded in the literature. Third, since this integrated location-inventory-transportation model is highly complex, we propose an exact solution method using logic-based Benders decomposition. Fourth, we generate instances based on real data from the case of an international pharmaceutical company and carry out extensive computational experiments to analyze the performance of the decomposition framework.

3.3 Problem description and modeling

3.3.1 Problem definition

This study addresses logistics network planning at the tactical level. We study a network composed of plants, DCs, and retailers. The DCs are intermediate facilities between the plants and the retailers and facilitate the shipment of products between the two echelons, as shown in Figure 3.1. We consider the problem of defining which DCs of a third-party logistics (3PL) provider should be selected to distribute multiple products to a set of retailers. Moreover, the problem includes selecting the capacity level for the opened DCs. The capacity levels are defined in terms of volume. Hence, the DC location costs comprise contractual fixed costs (e.g., rental space/volume in DCs). The selected DCs must remain in operation until the end of the planning horizon. Plants also have limited capacity, but this is not a decision variable within the model.

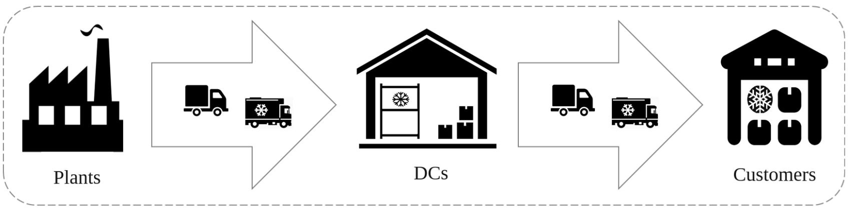


Figure 3.1: Logistics network

As in Zheng et al. (2019b), the retailers' demands are assumed to be independent, uncertain, and follow a normal distribution. Also, the expected demand per retailer can vary from period to period to represent seasonal demand. The inventory management at the DCs is executed by using a periodic review policy (T, S) that is presented in Figure 3.2. In the periodic review policy or reorder cycle policy, the stock level is kept under observation periodically. The parameter T represents the review interval and the parameter S is the target inventory level within the review interval, referred to as the order-up-to-level. At each time instant when the inventory is reviewed, the order quantity (from the plant to the DC) is determined based on this order-up-to level S and the available inventory I', $Q = S - I'$. The parameter S is determined as $S = \mu(T + \ell) + \Phi_\alpha \sigma \sqrt{(T + \ell)}$, where μ is the demand mean, σ is the standard deviation, and ℓ is the lead time, and Φ_α is the number of standard deviations related to the service level α such that $P(Z \leq \Phi_\alpha) = \alpha$. With this definition of S, the probability that there is a stockout is up to $(1 - \alpha)$. The difference between S and the average demand in $T + \ell$ makes up the safety stock $SS = \Phi_\alpha \sigma \sqrt{(T + \ell)}$. The periodic review policy involves a higher level of safety stock than a continuous policy. However, such a policy does not require continuous monitoring of the inventory level (Ghiani et al., 2005). In terms of coordinating the replenishment of the items, the (T, S) policy is highly preferred to the order points policies. This coordination can result in significant savings in ordering and transportation costs. Additionally, the (T, S) policy regularly provides the chance to update the order-up-to-level, a desirable property in context with demand variability (Berman et al., 2012).

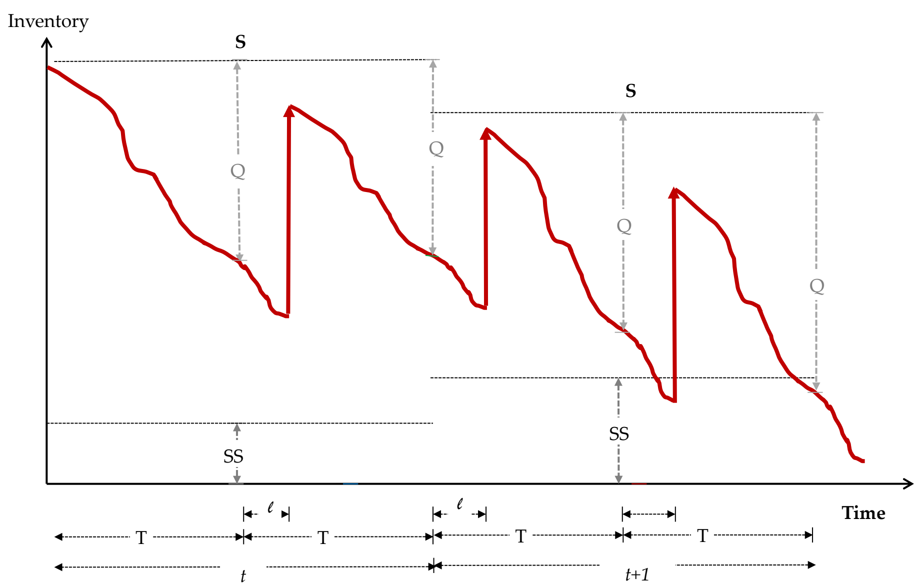


Figure 3.2: Periodic review policy (T, S)

In this work, we assume the consolidation of the cycle, safety stock, and anticipation inventory at DCs. We assume several review intervals T within the period t (e.g., if t is a month, T can be weekly or biweekly period) and retailer demands vary among periods, this can represent for example seasonal demand. We also assume the length of the review intervals T is known, thus the problem consists in determining the target inventory level or the order-up-to level S, depending on which retailers are assigned to a DC. The target level consists of both cycle inventory and safety stock. The cycle inventory is the stock expected to be used to meet normal demand during a review interval, while safety stock is extra stock to meet excess demand, to protect against uncertainty. We also consider the anticipation inventory that is built up to anticipate increased future retailer demands, due to the limited capacity in plants (Olhager et al., 2001). The anticipation inventory for every period is determined based on the total quantity ordered by DC to plants, the total demand allocated to the DC in the period, and the balance of safety stock. The total anticipation inventory is computed across several periods as $\sum_t \frac{I_{t-1}+I_t}{2}$, as shown in Figure 3.3. Finally, the total inventory cost is the sum of the costs of the target level, composed of the cycle and the safety stock, and the anticipation inventory.

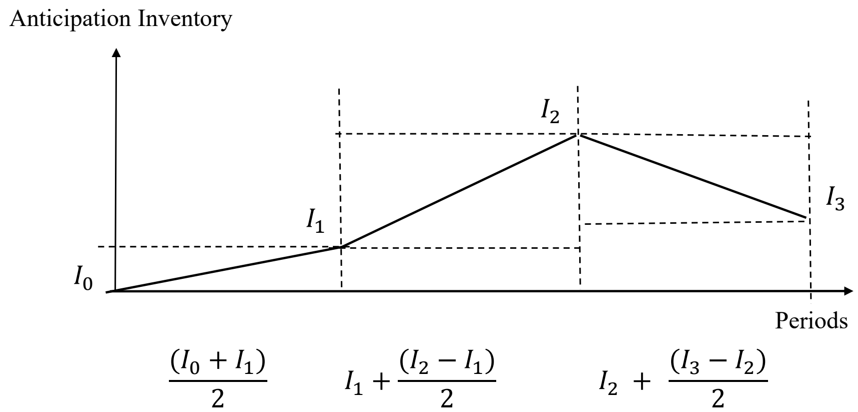


Figure 3.3: Anticipation inventory by period

The transportation costs depend on several factors such as transportation mode, distance, quantity (or weight), and commodity class. Most of the carriers usually offer shipment services depending on the shipment quantity. Less-than-truckload (LTL) freight rates are expressed as cost per shipping unit, however a real cost structure for LTL freight typically includes breakpoints, where the unit cost decreases for greater shipping quantities, and a minimum shipment cost is imposed to discourage small shipments (Engebrethsen and Dauzère-Pérès, 2018). In this problem, the transportation costs consist in applying different rates/values for different transport volumes, once a breakpoint b_s is reached. These breakpoints define different ranges or segments (in this work we use the term segments). Every segment has an associated fixed cost g_s and a variable cost c_s, this problem can be modeled as a Multiple Choice Model (Croxton et al., 2003). Figure 3.4 illustrates the transportation cost for different quantities of products: the x-axis is the load weight, thus the breakpoints are based on the weights, and the y-axis is the total transportation cost. Figure 3.4 also shows the impact of discounts among the segments. This transportation cost structure is applied for the transportation from the plants to DCs and from DCs to the retailers.

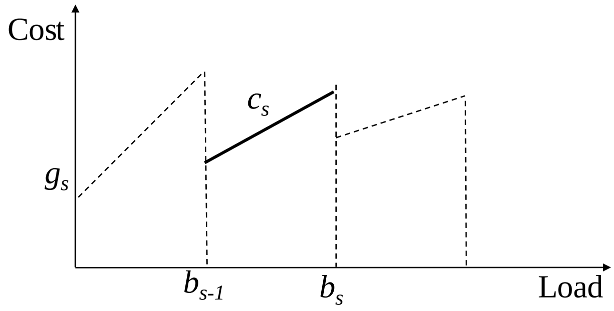


Figure 3.4: Discrete transportation costs

The carrier is responsible for the preservation of the goods from pick up to delivery. Thus, any damage that impairs the integrity of the cargo must be covered by the carrier. *Ad Valorem* is used to offset part of these costs. It is a component of the freight cost, charged to cover cargo security costs. It is a rate calculated on the value of the goods and in its composition can be considered all the measures that are taken to preserve the transported cargo, such as various insurances, investments for vehicle safety (including tracking and monitoring systems), operational costs, and security services. The *Ad Valorem* cost is explicitly modeled as part of the transportation cost in our model.

The problem is to minimize the total cost composed of DC location costs, transportation costs, and inventory costs.

3.3.2 Mathematical formulation

The notation used in the formulation is presented below.

Sets

$i, j, k \in \mathcal{I} = \mathcal{I}_f \cup \mathcal{I}_w \cup \mathcal{I}_c$	Facilities: plants, potential DCs, and retailers
$l \in \mathcal{L}$	Capacity levels at DCs
$p \in \mathcal{P}$	Products
$s \in \mathcal{S}$	Cost segments for transportation
$t, t' \in \Theta$	Time periods
$\mathcal{A}_{fw} = \{(i, j) : (i \in \mathcal{I}_f \wedge j \in \mathcal{I}_w)\}$	Available flows from plants
$\mathcal{A}_{wc} = \{(i, j) : (i \in \mathcal{I}_w \wedge j \in \mathcal{I}_c)\}$	Available flows from DCs
$\mathcal{A} = \mathcal{A}_{fw} \cup \mathcal{A}_{wc}$	Available network flows

Parameters

b_s Breakpoint at segment s for the transportation cost

cap_{ip} Production capacity of product p at plant i

c_{ijs} Variable cost of the segment s to transport cargo from entity i to entity j (per unit of weight)

c'_{ij} Variable security cost to transport cargo from entity i to entity j (per unit of value)

f_{jl} Fixed cost for opening DC j at capacity level l

g_{ijs} Fixed cost of the segment s to transport cargo from entity i to entity j

h_{pj} Unitary inventory holding cost of product p in DC j (per period)

ℓ_{ij} Lead time from entity i to entity j (in days)

q_l Storage capacity at level l

T_{jp} Prespecified review period at the DC j for the product p (in days)

η_{kt} Number of working days at retailer k in period t

μ_{pkt} Mean daily demand of product p at retailer k in period t

σ^2_{pkt} Variance of daily demand of product p at retailer k in period t

Parameters

ρ_p Price of product p

υ_p Volume of product p

ω_p Weight of product p

Φ_α Number of standard deviations related to the service level α such that $P(Z \leq \Phi_\alpha) = \alpha$

Continuous variables

I_{jpt} Anticipation inventory of product p at DC j at the end of the period t

Q_{ijpt} Total order quantity of product p from plant i to DC j in period t

S_{jpt} Target inventory of product p at DC j in each review period within period t

SS_{jpt} Safety stock of product p at DC j in each review period within period t

Z_{ijst} Auxiliary variable for cargo weight transported from entity i to entity j in period t in the segment s

Integer variables

Y_{jl} 1, if DC j is open at capacity level l; 0, otherwise

W_{ijst} 1, if the segment s is used to transport cargo between the entities i and j in period t; 0, otherwise.

X_{jkp} 1, if a demand of product p at retailer k is served from DC j; 0, otherwise

X'_{ijp} 1, if the product p at DC j is served from plant i; 0, otherwise

U_{ijkp} Binary auxiliary variable for the model linearization for product p from plant i to DC j and then to retailer k

The multi-echelon network design and inventory management and transportation planning model can be formulated as a mixed-integer nonlinear program (MINLP).

The objective function (3.1) consists in minimizing the total cost, given by the sum of opening costs, inventory holding costs, and transportation costs. The first term comprises the costs related to the selection of DC location and capacity levels. The second to fourth terms correspond to the safety stock, anticipation inventory, and cycle inventory costs, respectively. The total anticipation inventory is computed across several periods as $\sum_t \frac{I_{t-1}+I_t}{2}$, which implies that it is computed as the average of the inventory positions at the beginning and the end of each period as shown in Figure 3.3. In a periodic review system, the average order quantity is equal to the daily demand multiplied by the number of days in the review period. The cycle inventory level is half of this average order quantity. On the other hand, the transportation costs have two components, a variable cost associated with the cargo weight and a fixed cost associated with the segment cost corresponding to that weight as shown in Figure 3.3. The fifth and sixth terms represent the variable transportation costs, while fixed transportation costs are represented by the seventh and eighth terms, to both echelons, i.e., from plants to DCs, and from DCs to retailers. Finally, the last two terms of the objective function represent the transportation security costs to both echelons, these costs depend on the product price.

$$\begin{aligned}\min \Psi = \min \Bigg[& \sum_{j\in\mathcal{I}_w}\sum_{l\in\mathcal{L}} f_{jl}Y_{jl} + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(SS_{jpt} + \frac{I_{jpt-1}+I_{jpt}}{2} + \frac{1}{2}T_{jp}\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}\Big) \\ & + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c_{ijs}Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{jks}Z_{jkst}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} g_{ijs}W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{jks}W_{jkst}\Big) \\ & + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c'_{ij}\rho_p Q_{ijpt} + \sum_{k\in\mathcal{I}_c} c'_{jk}\rho_p\eta_{kt}\mu_{pkt}X_{jkp}\Big)\Bigg]\end{aligned} \tag{3.1}$$

Constraints (3.2) to (3.4) define the network structure. Constraints (3.2) guarantee that the demand of the product p at retailer k in period t is served by one DC. Constraints (3.3) set the relation among the two echelons, plants to DCs, and DCs to retailers. We guarantee single sourcing from plant to DC by constraints (3.4): if DC j is installed, it should be served by only one plant i, else if the DC is not installed, it is not assigned to any plant.

$$\sum_{j\in\mathcal{I}_w} X_{jkp} = 1,\ \forall k\in\mathcal{I}_c, p\in\mathcal{P}. \tag{3.2}$$

$$\sum_{i\in\mathcal{I}_f} X'_{ijp} \geq X_{jkp},\ \forall j\in\mathcal{I}_w, k\in\mathcal{I}_c, p\in\mathcal{P}. \tag{3.3}$$

$$\sum_{i\in\mathcal{I}_f} X'_{ijp} \leq \sum_{l\in\mathcal{L}} Y_{jl},\ \forall j\in\mathcal{I}_w, p\in\mathcal{P}. \tag{3.4}$$

We consider multiple plants in the network. As a result, it will become more difficult to model and solve the inventory management problem. Using the periodic review policy

(T,S), the target inventory level and the safety stock for product p at DC j in each review period within period t are defined by $\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}X'_{ijp}X_{jkp}+SS_{jpt}$ and $SS_{jpt}=\Phi_\alpha\sqrt{\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\sigma^2_{pkt}X'_{ijp}X_{jkp}}$, respectively. These equations are non-linear because of the product of two binary variables and the square root of the safety stock equation. To linearize the $X'_{ijp}X_{jkp}$ term, let $U_{ijkp}=X'_{ijp}X_{jkp}$. Notice U_{ijkp} can only be non-zero if both terms in the multiplication are equal to one. Thus $X'_{ijp}=0$ and/or $X_{jkp}=0$ implies that U_{ijkp} must equal zero. This is guaranteed by constraints (3.5) and (3.6). Otherwise, $U_{ijkp}=1$ if $X'_{ijp}X_{jkp}=1$, which only happens if both terms in the multiplication are equal to one. This is imposed by constraints (3.7).

$$\sum_{i\in\mathcal{I}_f}U_{ijkp}\le X_{jkp},\ \forall j\in\mathcal{I}_w,k\in\mathcal{I}_c,p\in\mathcal{P}. \tag{3.5}$$

$$U_{ijkp}\le X'_{ijp},\ \forall i\in\mathcal{I}_f,j\in\mathcal{I}_w,k\in\mathcal{I}_c,p\in\mathcal{P}. \tag{3.6}$$

$$\sum_{i\in\mathcal{I}_f}U_{ijkp}\ge\sum_{i\in\mathcal{I}_f}X'_{ijp}+X_{jkp}-1,\ \forall j\in\mathcal{I}_w,k\in\mathcal{I}_c,p\in\mathcal{P}. \tag{3.7}$$

The target inventory level and the safety stock for product p at DC j in each review period within period t are defined by constraints (3.8) and (3.9), respectively. S_{jpt} and SS_{jpt} are defined according to the review intervals T_{jp} within the periods t.

$$S_{jpt}=\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}U_{ijkp}+SS_{jpt},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.8}$$

$$SS_{jpt}=\Phi_\alpha\sqrt{\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\sigma^2_{pkt}U_{ijkp}},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.9}$$

Constraints (3.10) is the inventory balance for every product p, at every DC j in every period t. They define the order quantity and anticipation inventory for product p at DC j in period t. The anticipation inventory is determined based on the total quantity ordered by the DC from the plants, the total demand allocated to the DC in the period, and the balance of safety stock. Constraints (3.11) define the plant capacity constraints for product p at plant i in period t.

$$\sum_{i\in\mathcal{I}_f}Q_{ijpt}=\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}+I_{jpt}-I_{jpt-1}+SS_{jpt}-SS_{jp,t-1},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.10}$$

$$\sum_{j\in\mathcal{I}_w}Q_{ijpt}\le cap_{ip},\ \forall i\in\mathcal{I}_f,p\in\mathcal{P},t\in\Theta. \tag{3.11}$$

Constraints (3.12) represent the DC capacity constraint in period t, if the DC j is chosen to be opened at level l, considering the target inventory of the periodic review policy and the anticipation inventory. This constraint puts a limit on the maximum volume in a DC. Constraints

(3.13) ensure that only one level of capacity is selected for the DC j.

$$\sum_{p\in\mathcal{P}} \upsilon_p(S_{jpt} + I_{jpt}) \leq \sum_{l\in\mathcal{L}} q_l Y_{jl},\ \forall j \in \mathcal{I}_w, t \in \Theta. \tag{3.12}$$

$$\sum_{l\in\mathcal{L}} Y_{jl} \leq 1,\ \forall j \in \mathcal{I}_w. \tag{3.13}$$

Constraints (3.14) and (3.15) define the total cargo weight transported between the echelons (plant to DC, and DC to retailer) in every period. Constraints (3.16) guarantee that the cargo shipped between echelons corresponds to one of the segments s defined by the breakpoints b_{s-1} and b_s in period t. Constraints (3.17) guarantee that only one segment s is chosen in each period t between the echelons.

$$\sum_{p\in\mathcal{P}} \omega_p Q_{ijpt} = \sum_{s\in\mathcal{S}} Z_{ijst},\ \forall i \in \mathcal{I}_f, j \in \mathcal{I}_w, t \in \Theta. \tag{3.14}$$

$$\sum_{p\in\mathcal{P}} \omega_p \eta_{kt} \mu_{pkt} X_{jkp} = \sum_{s\in\mathcal{S}} Z_{jkst},\ \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, t \in \Theta. \tag{3.15}$$

$$b_{s-1} W_{ijst} \leq Z_{ijst} \leq b_s W_{ijst},\ \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}, t \in \Theta. \tag{3.16}$$

$$\sum_{s\in\mathcal{S}} W_{ijst} \leq 1,\ \forall (i,j) \in \mathcal{A}, t \in \Theta. \tag{3.17}$$

Finally, constraints (3.18) to (3.27) are integrality and nonnegativity constraints.

$$Y_{jl} \in \{0,1\},\ j \in \mathcal{I}_w, l \in \mathcal{L}. \tag{3.18}$$

$$X_{jkp} \in \{0,1\},\ \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, p \in \mathcal{P}. \tag{3.19}$$

$$X'_{ijp} \in \{0,1\},\ \forall i \in \mathcal{I}_f, j \in \mathcal{I}_w, p \in \mathcal{P}. \tag{3.20}$$

$$U_{ijkp} \in \{0,1\},\ \forall i \in \mathcal{I}_f, j \in \mathcal{I}_w, k \in \mathcal{I}_c, p \in \mathcal{P}. \tag{3.21}$$

$$Q_{ijpt} \geq 0,\ \forall i \in \mathcal{I}_f, j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.22}$$

$$Z_{ijst} \geq 0,\ \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}, t \in \Theta. \tag{3.23}$$

$$W_{ijst} \in \{0,1\},\ \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}, t \in \Theta. \tag{3.24}$$

$$I_{jpt} \geq 0,\ j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.25}$$

$$S_{jpt} \geq 0,\ j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.26}$$

$$SS_{jpt} \geq 0,\ j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.27}$$

If the network has a single plant or there is a pre-assignment of DCs to one plant for the planning horizon, the mathematical formulation is reduced to:

$$\min \Psi = \min\ (3.1) \tag{3.28}$$

$$\text{s.t. Constraints} : (3.2), (3.10) - (3.19), (3.22) - (3.27). \tag{3.29}$$

$$S_{jpt} = \sum_{i \in \mathcal{I}_f} \sum_{k \in \mathcal{I}_c} (T_{jp} + \ell_{ij}) u_{ijp} \mu_{pkt} X_{jkp} + SS_{jpt}, \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.30}$$

$$SS_{jpt} = \Phi_\alpha \sqrt{\sum_{i \in \mathcal{I}_f} \sum_{k \in \mathcal{I}_c} (T_{jp} + \ell_{ij}) u_{ijp} \sigma^2_{pkt} X_{jkp}}, \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.31}$$

where u_{ijp} is a parameter indicating if DC j obtains product p from plant i.

Moreover, for modeling single sourcing from plants and/or DCs, we can drop the product index on the allocation variables, i.e. X_{ij}, X'_{jk}.

Both versions of the problem are easier to solve compared with the addressed problem.

3.4 Solution method based on Benders decomposition

A well-known approach is the Benders decomposition (BD) method, a technique for solving large-scale problems with complicating variables. Instead of coping with all decision variables simultaneously, in the BD method, we decompose the problem into a relaxed master problem and smaller sub-problems that are easy to solve (Benders, 1962). Solving the problem by considering part of the decisions (e.g., location) and then fixing these decisions and solving smaller sub-problems (e.g., transportation) can help to solve the integrated model more efficiently than solving a single large model. The reader is referred to Rahmaniani et al. (2017) for a survey on the BD algorithm. BD method is limited to a variables partition that leads to linear subproblems. Several studies have been proposed strategies to deal with integer subproblems (Laporte and Louveaux, 1993; Sherali and Fraticelli, 2002; Angulo et al., 2016; Fakhri et al., 2017).

Logic-based Benders decomposition (LBBD) is an extension of the BD method, where the generation of the Benders cuts is not limited to solve the dual linear programs of the subproblems (Hooker and Ottosson, 2003). LBBD is a versatile decomposition technique applied successfully to a wide variety of mixed-integer problems. Similar to classical BD, LBBD assigns values to the complicating variables in the master problem and finds the best solution consistent with these values. Instead of solving the dual of the subproblems that remain when the complicating variables take fixed values, LBBD solves an inference dual, where proof of optimality within an appropriated logical formalism is derived based on the fixed values of some of the variables and the constraints of the original problem. Logic-based Benders decomposition provides no standard scheme to generate Benders cuts so they must be devised specifically for each problem class. There are two common implementations of the LBBD: the original LBBD implementation, which can be seen as a cutting plane approach, and the branch–and–check implementation (B&Ch), where the cuts are generated and added during the branch–and–bound process (Roshanaei et al., 2017; Martínez et al., 2019; Martínez et al., 2022).

3.4.1 Standard LBBD

We decompose the problem into a master problem (MP) and a subproblem (SP). In this framework, we identified as complicating variables the location Y_{jl} and allocation decisions,

$X_{jkp}, X'_{ijp}, U_{ijkp}$, to be defined in an MP with the estimation of the other continuous variables (I_{jpt}, Q_{ijpt}) in the constraints. The SP considers the other variables $(SS_{jpt}, S_{jpt}, I_{jpt}, Q_{ijpt}, Z_{ijst}, W_{ijst})$. After decomposing the problem, we obtain an MP and an SP with integer variables and linear constraints. The MP provides a lower bound for the problem. In this standard LBBD, the master problem (MPS) is modeled as follows:

$$\min \Psi^{MPS} = \min \Bigg[\sum_{j\in\mathcal{I}_w}\sum_{l\in\mathcal{L}} f_{jl}Y_{jl} + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(\frac{1}{2}T_{jp}\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta}\sum_{k\in\mathcal{I}_c} c'_{jk}\rho_p\eta_{kt}\mu_{pkt}X_{jkp} + \Delta\Bigg] \tag{3.32}$$

$$\text{s.t. Constraints}: (3.2)-(3.7), (3.11), (3.13), (3.18)-(3.22), (3.25). \tag{3.33}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp} + I_{jpt} - I_{jpt-1},\ \forall j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta. \tag{3.34}$$

$$\sum_{p\in\mathcal{P}} \upsilon_p\Big(\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}U_{ijkp} + I_{jpt}\Big) \le \sum_{l\in\mathcal{L}} q_l Y_{jl},\ \forall j\in\mathcal{I}_w, t\in\Theta. \tag{3.35}$$

$$\Delta \ge 0. \tag{3.36}$$

Notice that we drop the safety stock and transportation costs from the MPS and consider them only in the subproblem. To retrieve such costs to the MPS, we use the variable Δ. Initially, the lower bound for the Δ variable is zero in the MPS and is updated as optimality cuts are added to the problem. Thus, mathematical model (3.32) - (3.36) still lacks the feasibility and optimality cuts to be defined.

Then, the variables $\bar{Y}_{jl}, \bar{X}_{jkp}, \bar{U}_{ijkp}$ are temporarily fixed in the SP to determine the target inventory S_{jpt}, safety stock SS_{jpt}, anticipation inventory I_{jpt}, order quantity Q_{ijpt}, and segment selection Z_{ijst}, W_{ijst}. Notice that standard SP (SPS) is also a mixed-integer-linear model because $\bar{U}_{ijkp}$ is fixed.

$$\min \Psi^{SPS} = \min \Bigg[\sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(SS_{jpt} + \frac{I_{jpt-1}+I_{jpt}}{2}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c_{ijs}Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{jks}Z_{jkst}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} g_{ijs}W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{jks}W_{jkst}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c'_{ij}\rho_p Q_{ijpt}\Big)\Bigg] \tag{3.37}$$

$$\text{s.t. Constraints : } (3.11), (3.14), (3.16), (3.17), (3.22) - (3.27). \tag{3.38}$$

$$S_{jpt} = \sum_{i\in\mathcal{I}_f} \sum_{k\in\mathcal{I}_c} (T_{jp} + \ell_{ij}) u_{ijp} \mu_{pkt} \bar{U}_{ijkp} + SS_{jpt}, \; \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.39}$$

$$SS_{jpt} = \Phi_\alpha \sqrt{\sum_{i\in\mathcal{I}_f} \sum_{k\in\mathcal{I}_c} (T_{jp} + \ell_{ij}) \sigma^2_{pkt} \bar{U}_{ijkp}}, \; \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.40}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c} \eta_{kt} \mu_{pkt} \bar{X}_{jkp} + I_{jpt} - I_{jpt-1} + SS_{jpt} - SS_{jp,t-1}, \; \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.41}$$

$$\sum_{p\in\mathcal{P}} \upsilon_p (S_{jpt} + I_{jpt}) \leq \sum_{l\in\mathcal{L}} q_l \bar{Y}_{jl}, \; \forall j \in \mathcal{I}_w, t \in \Theta. \tag{3.42}$$

$$\sum_{p\in\mathcal{P}} \omega_p \eta_{kt} \mu_{pkt} \bar{X}_{jkp} \leq \sum_{s\in\mathcal{S}} Z_{jkst}, \; \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, t \in \Theta. \tag{3.43}$$

After solving the SPS, cuts are added to the MPS to update the cost of the location-allocation decisions in the MPS or to cut off the infeasible location-allocation solutions.

Feasibility and optimality cuts

Let $\bar{\beta} = (\bar{Y}, \bar{X})$ be a location-allocation solution for the MPS. Let

$$\Pi_{\bar{\beta}} = \sum_{j\in\mathcal{I}_w} \sum_{k\in\mathcal{I}_c} \sum_{\substack{p\in\mathcal{P}: \\ \bar{X}_{jkp}=1}} (X_{jkp} - 1) + \sum_{j\in\mathcal{I}_w} \sum_{\substack{l\in\mathcal{L}: \\ \bar{Y}_{jl}=1}} (Y_{jl} - 1) - \sum_{j\in\mathcal{I}_w} \sum_{k\in\mathcal{I}_c} \sum_{\substack{p\in\mathcal{P}: \\ \bar{X}_{jkp}=0}} X_{jkp} - \sum_{j\in\mathcal{I}_w} \sum_{\substack{l\in\mathcal{L}: \\ \bar{Y}_{jl}=0}} Y_{jl} \tag{3.44}$$

Note that for solution $\bar{\beta}$, $\Pi_{\bar{\beta}} = 0$. Moreover, note that if the solution $\bar{\beta}$ changes, i.e., if at least one variable with value 1 changes to 0 or one variable with value 0 changes to 1, $\Pi_{\bar{\beta}} < 0$. Consequently, if the solution $\bar{\beta}$ is infeasible in the SPS, valid feasibility cut to be added in the MPS to cut off this solution is:

$$\Pi_{\bar{\beta}} \leq -1 \tag{3.45}$$

Similarly, a valid optimality cut to be added to the MPS is:

$$\Delta \geq \bar{\Psi}^{SP} + \bar{\Psi}^{SP} \Pi_{\bar{\beta}} \tag{3.46}$$

Note that in this case, for solution $\bar{\beta}$, $\Delta \geq \bar{\Psi}^{SPS^*}$ ($\Pi_{\bar{\beta}} = 0$), updating the cost of the solution $\bar{\beta}$ in the MPS according to the real cost of the solution in the subproblem SPS^*. If at least one variable with value 1 changes to 0 or one variable with value 0 changes to 1, $\Pi_{\bar{\beta}} < 0$ and consequently $\bar{\Psi}^{SPS} + \bar{\Psi}^{SPS}\, \Pi_{\bar{\beta}} \leq 0$.

3.4.2 Enhanced LBBD

Due to the MPS losses a lot of variables and information in the decomposition, an infeasible or very bad solution can be frequently obtained. Since the safety stock level is not present in the master problem, the obtained location and allocation decisions may not be feasible for the original model. In this section, we present a piecewise linear lower bound function of safety stock, to enhance the master problem. Thus, we propose a second version of the master problem, that involves location, allocation, as well as order quantity based on demand and a piecewise linear lower bound function of safety stock.

Piecewise linear lower bound function of safety stock

The piecewise linear lower bound function of safety stock consists in estimating the curve of safety stock and describing the relationship between the x-axis and y-axis by a series of linear segments. Its accuracy is proportional to the number of segments used, and the number of segments used strongly influences the complexity of the problem. Since the segments are always under the curve to be approximated, the piecewise linear function underestimates the real values (Hamer-Lavoie and Cordeau, 2006).

We define a set $\mathcal{M}$ which contains all the points marking any bound for a segment. Consequently, there is a total of $|\mathcal{M}|$ points and $|\mathcal{M}| - 1$ segments. Every segment has an upper bound with variance value α_m and its corresponding real safety stock values $f(\alpha_m)$, as shown in Figure 3.5. We define the continuous variables λ_m and binary variables γ_m. Variables λ_m associated with every point $m \in \mathcal{M}$ represent the weight that the value of the variance of this point will have in the linear approximation of the segment m bounded by the points m and $m + 1$. The binary variables γ_m is associated to every segment m in the set $\{0, 1, ..., |\mathcal{M}| - 1\}$, taking the value 1 if the segment m is chosen for the linear approximation. A single γ_m, designating a segment, as well as two bounds λ_m and λ_{m+1} designating points must take a strictly positive value. In order to include the information concerning the DC, product, and period under consideration, the variables λ_{jptm} and $\gamma jptm + 1$ are defined.

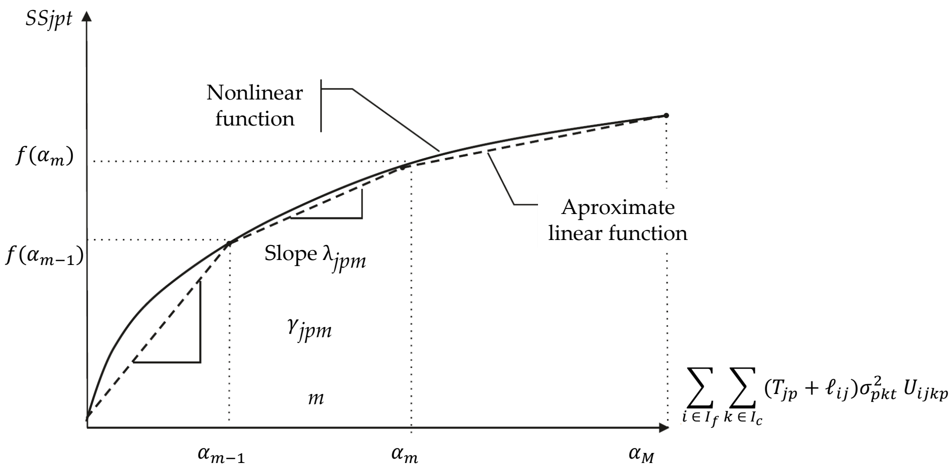


Figure 3.5: Piecewise linear lower bound function of safety stock

The piecewise linear lower bound function of safety stock can be expressed using the following set of constraints:

$$\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\sigma^2_{pkt}U_{ijkp}-\sum_{m\in\mathcal{M}}\alpha_m\lambda_{jptm}=0,\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.47}$$

$$\sum_{l\in\mathcal{L}}Y_{jl}\geq\sum_{m\in\mathcal{M}}\lambda_{jptm},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.48}$$

$$X_{jkp}\leq\sum_{m\in\mathcal{M}}\lambda_{jptm},\ \forall j\in\mathcal{I}_w,k\in\mathcal{I}_c,p\in\mathcal{P},t\in\Theta. \tag{3.49}$$

$$\sum_{l\in\mathcal{L}}Y_{jl}\geq\sum_{m\in\mathcal{M}}\gamma_{jptm},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.50}$$

$$X_{jkp}\leq\sum_{m\in\mathcal{M}}\gamma_{jptm},\ \forall j\in\mathcal{I}_w,k\in\mathcal{I}_c,p\in\mathcal{P},t\in\Theta. \tag{3.51}$$

$$\lambda_{jpt1}\leq\gamma_{jpt1},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.52}$$

$$\lambda_{jptm}\leq\gamma_{jptm-1}+\gamma_{jptm},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta,m\in\mathcal{M}\setminus\{0,|\mathcal{M}|\}. \tag{3.53}$$

$$\lambda_{jpt|\mathcal{M}|}\leq\gamma_{jpt(|\mathcal{M}|-1)},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.54}$$

$$\lambda_{jptm}\in[0,1],\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta,m\in\mathcal{M}. \tag{3.55}$$

$$\gamma_{jptm}\in\{0,1\},\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta,m\in\mathcal{M}\setminus\{|\mathcal{M}|\}. \tag{3.56}$$

A linear constraint used to calculate the approximate safety stock is:

$$SS^{prox}_{jpt}=\Phi_\alpha\sum_{m\in\mathcal{M}}\lambda_{jptm}f(\alpha_m),\ \forall j\in\mathcal{I}_w,p\in\mathcal{P},t\in\Theta. \tag{3.57}$$

Constraints (3.47) to (3.49) determine the value of variables λ_{jptm} corresponding to the obtained demand variance of product p in DC j. Constraints (3.48) and (3.50) state that the variables λ_{jptm} and γ_{jptm}, respectively, are equal to zero if the warehouse j is not open. Constraints (3.49) and (3.51) force the sum of λ_{jptm} and the sum of γ_{jptm}, respectively, to be one if at least one retailer demand of product p is allocated to a warehouse j in period t. Constraints (3.52) to (3.54) link the variables γ_{jptm} and λ_{jptm}. They ensure that λ_{jptm} are strictly positive only if at least one of the adjacent segments described by variables γ_{jptm} or/and γ_{jptm-1} is active. Finally, constraints (3.55) to (3.56) represent the domain of the variables.

Enhanced master problem (MPE)

The enhanced master problem MPE involves a piecewise linear lower bound function of safety stock, where the complicating nonlinear constraints are replaced by linear constraints (3.47) to (3.57). The variables of γ_{jptm} are relaxed in their integrality. Also, some variables of the subproblem are included in the MPE, auxiliary linear variables for calculating cargo weight Z_{ijst} and the cost/weight segment selection variables W_{ijst}. The MPE is formulated as follows:

$$\min\Psi^{MPE}=\min\ \Bigg[\sum_{j\in\mathcal{I}_w}\sum_{l\in\mathcal{L}}f_{jl}Y_{jl}+\sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}h_{pj}\Big(\frac{1}{2}T_{jp}\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}\Big)$$

$$+ \sum_{j\in\mathcal{I}_w}\sum_{k\in\mathcal{I}_c}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} c'_{jk}\rho_p\eta_{kt}\mu_{pkt}X_{jkp} + \Delta\Bigg] \tag{3.58}$$

$$\text{s.t. Constraints : (3.2)} - \text{(3.7), (3.11), (3.13)} - \text{(3.26), (3.47)} - \text{(3.57)}. \tag{3.59}$$

$$\sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(\mathrm{SS}^{prox}_{jpt} + \frac{I_{jpt-1}+I_{jpt}}{2}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c_{ijs}Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{ijs}Z_{ijst}\Big)$$

$$+ \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} g_{ijs}W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{ijs}W_{jkst}\Big) + \sum_{i\in\mathcal{I}_f}\sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} c'_{ij}\rho_p Q_{ijpt} \leq \Delta \tag{3.60}$$

$$S_{jpt} = \sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}U_{ijkp} + SS^{prox}_{jpt},\ \forall j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta. \tag{3.61}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp} + I_{jpt} - I_{jpt-1} + SS^{prox}_{jpt} - SS^{prox}_{jpt-1},\ \forall j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta. \tag{3.62}$$

$$\sum_{p\in\mathcal{P}}\upsilon_p\Big(\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}U_{ijkp} + \Delta SS_{jpt} + I_{jpt}\Big) \leq \sum_{l\in\mathcal{L}} q_l Y_{jl},\ \forall j\in\mathcal{I}_w, t\in\Theta. \tag{3.63}$$

$$SS^{prox}_{jpt} \geq 0,\ j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta. \tag{3.64}$$

$$\Delta \geq 0. \tag{3.65}$$

where Δ is a variable to update the real cost given the decisions considered in the subproblem, as indicated by constraints (3.60). Variable Δ is initially zero in the MPE and is updated as optimality cuts are added to the problem.

Enhanced subproblem (SPE)

One strategy to reduce the number of variables in the SP is to compute a priori the value of some variables. After solving the MPE, we can obtain the value of variables before solving the SP as follows. First, let $\bar{S}S_{jpt}$ and $\bar{S}_{jpt}$ be the value of the variables SS_{jpt} and S_{jpt}, respectively, for the location-allocation defined by the MPE. We can calculate $\bar{S}S_{jpt} = \Phi_\alpha\sqrt{\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\sigma^2_{pkt}\bar{U}_{ijkp}}$ and sequentially $\bar{S}_{jpt} = \sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}\bar{U}_{ijkp} + \bar{S}S_{jpt}$, $\forall j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta$. Second, we can also calculate the value of variables Z_{jkst} and W_{jkst}. Let $\bar{Z}_{jkst}$ and $\bar{W}_{jkst}$ be the value of the variables Z_{jkst} and W_{jkst}, respectively, for the location-allocation solution defined by the MPE. We compute the $\bar{Z}_{jkst}$ and $\bar{W}_{jkst}$ as follows:

$$\bar{Z}_{jkst} = \begin{cases} \kappa_{jkt}, s\in\mathcal{S}\wedge[b_{s-1}\leq\kappa_{jkt}\leq b_s], \forall j\in\mathcal{I}_w, k\in\mathcal{I}_c, t\in\Theta. \\ 0, \text{otherwise.}\end{cases}$$

$$\bar{W}_{jkst} = \begin{cases} 1, s\in\mathcal{S}\wedge[b_{s-1}\leq\kappa_{jkt}\leq b_s], \forall j\in\mathcal{I}_w, k\in\mathcal{I}_c, t\in\Theta. \\ 0, \text{otherwise.}\end{cases}$$

where κ_{jkt} is the total weight transported from j to k, defined as follows:

$$\kappa_{jkt} = \sum_{p \in \mathcal{P}} \omega_p \eta_{kt} \mu_{pkt} \bar{X}_{jkp}, \; \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, t \in \Theta.$$

In addition, given the single sourcing assumption from plants to DCs, we can express variable X_{jkp} in terms of variable U_{ijkp}, i.e., $\sum_{i \in \mathcal{I}_f} U_{ijkp} = X_{jkp}, \; \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, p \in \mathcal{P}$. Thus, we only need the value of the variables Y_{jl} and U_{ijkp} in the subproblem. The enhanced SP is modeled as follows:

$$\begin{aligned} \min \Psi^{SPE} = \min \Bigg[& \sum_{j \in \mathcal{I}_w} \sum_{p \in \mathcal{P}} \sum_{t \in \Theta} h_{pj} \Big(\bar{S}S_{jpt} + \frac{I_{jpt-1} + I_{jpt}}{2} \Big) \\ & + \sum_{j \in \mathcal{I}_w} \sum_{s \in \mathcal{S}} \sum_{t \in \Theta} \Big(\sum_{i \in \mathcal{I}_f} c_{ijs} Z_{ijst} + \sum_{k \in \mathcal{I}_c} c_{jks} \bar{Z}_{jkst} \Big) + \sum_{j \in \mathcal{I}_w} \sum_{s \in \mathcal{S}} \sum_{t \in \Theta} \Big(\sum_{i \in \mathcal{I}_f} g_{ijs} W_{ijst} + \sum_{k \in \mathcal{I}_c} g_{jks} \bar{W}_{jkst} \Big) \\ & + \sum_{i \in \mathcal{I}_f} \sum_{j \in \mathcal{I}_w} \sum_{p \in \mathcal{P}} \sum_{t \in \Theta} \Big(c'_{ij} \rho_p Q_{ijpt} \Big) \Bigg] \end{aligned} \tag{3.66}$$

$$\text{s.t. Constraints} : (3.11), (3.14), (3.16) - (3.17), (3.22) - (3.25). \tag{3.67}$$

$$I_{jpt} - I_{jpt-1} = \sum_{i \in \mathcal{I}_f} Q_{ijpt} - \Bigg[\Big(\sum_{i \in \mathcal{I}_f} \sum_{k \in \mathcal{I}_c} \eta_{kt} \mu_{pkt} \bar{U}_{ijkp} + \bar{S}S_{jpt} - \bar{S}S_{jp,t-1} \Big) \Bigg], \; \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.68}$$

$$\sum_{p \in \mathcal{P}} \upsilon_p (\bar{S}_{jpt} + I_{jpt}) \leq \sum_{l \in \mathcal{L}} q_l \bar{Y}_{jl}, \; \forall j \in \mathcal{I}_w, t \in \Theta. \tag{3.69}$$

Modified combinatorial cuts

The single-sourcing assumption from plants to DCs, $\sum_{i \in \mathcal{I}_f} U_{ijkp} = X_{jkp}, \; \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, p \in \mathcal{P}$, allows to define the SP in terms of $\bar{Y}_{jl}, \bar{U}_{ijkp}$. Thus it is possible to define combinatorial cuts using these variables.

Let $\bar{\beta}' = (\bar{Y}, \bar{U})$ be a location-allocation solution for the MPE and let

$$\Pi_{\bar{\beta}'} = \sum_{i \in \mathcal{I}_f} \sum_{j \in \mathcal{I}_w} \sum_{k \in \mathcal{I}_c} \sum_{\substack{p \in \mathcal{P}: \\ \bar{U}_{ijkp}=1}} (U_{ijkp} - 1) + \sum_{j \in \mathcal{I}_w} \sum_{\substack{l \in \mathcal{L}: \\ \bar{Y}_{jl}=1}} (Y_{jl} - 1) - \sum_{i \in \mathcal{I}_f} \sum_{j \in \mathcal{I}_w} \sum_{k \in \mathcal{I}_c} \sum_{\substack{p \in \mathcal{P}: \\ \bar{U}_{ijkp}=0}} U_{ijkp} - \sum_{j \in \mathcal{I}_w} \sum_{\substack{l \in \mathcal{L}: \\ \bar{Y}_{jl}=0}} Y_{jl} \tag{3.70}$$

If the solution $\bar{\beta}'$ is infeasible in the subproblem, a valid feasibility cut to be added in the master problem to cut off this solution is:

$$\Pi_{\bar{\beta}'} \leq -1 \tag{3.71}$$

Similarly, a valid optimality cut to be added to the master problem is:

$$\Delta \geq \bar{\Psi}^{SP} + \bar{\Psi}^{SP}\Pi_{\bar{\beta}'} \tag{3.72}$$

Logic-based cuts

Cuts (3.71) and (3.72) are enough to update the real cost of the solution and to cut off infeasible solutions. However, we also introduce additional logic–based inequalities to strengthen the bounds in MP. Let $\bar{Z}_{jkst}$ and $\bar{W}_{jkst}$ be the value of the variables Z_{jkst} and W_{jkst}, respectively, for a given solution. The additional cuts are formulated as follows:

$$Z_{jkst} \geq \bar{Z}_{jkst} - \bar{Z}_{jkst}\Big(\sum_{\substack{p\in\mathcal{P}:\\ \bar{X}_{jkp}=1}}(1 - X_{jkp}) - \sum_{\substack{p\in\mathcal{P}:\\ \bar{X}_{jkp}=0}} X_{jkp}\Big), \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, s \in \mathcal{S}, t \in \Theta. \tag{3.73}$$

$$W_{jkst} \geq \bar{W}_{jkst} - \bar{W}_{jkst}\Big(\sum_{\substack{p\in\mathcal{P}\\ \bar{X}_{jkp}=1}}(1 - X_{jkp}) - \sum_{\substack{p\in\mathcal{P}:\\ \bar{X}_{jkp}=0}} X_{jkp}\Big), \forall j \in \mathcal{I}_w, k \in \mathcal{I}_c, s \in \mathcal{S}, t \in \Theta. \tag{3.74}$$

Unlike cuts (3.71) and (3.72), that apply to only one solution in the MPE, the multiple cuts (3.73) and (3.74) apply to every DC, retailer, cost segment, and period. In cut (3.73), the second term of the right-hand side is equal to zero for the current solution. In this case, the cut forces the Z_{jkst} variable in the MPE to take its real cost. If at least one of the allocation decisions changes, the right-hand side is less or equal to zero. In that case, cuts (3.73) do not eliminate any feasible solutions to the original problem. Similarly, we add cuts (3.74) to strengthen the estimation of W_{jkst} based on the allocation decisions. These cuts are based only on the allocation variables X_{jkp} due to this information is enough to define the real safety stock levels at DCs.

B&Ch algorithm and LBBD implementation

The B&Ch algorithm is implemented using the branch–and–bound callbacks of a MIP solver as follows. At each node, we solve the linear relaxation of the current MP. If it is infeasible or the objective value solution is higher than or equal to the objective value of the incumbent solution, then node is pruned. Otherwise, integrality constraints are checked, and if the solution is not integer feasible, then branching is performed. If the solution is integer feasible, we solve the subproblem SP to verify the violation of constraints (3.71) and (3.72). Constraint (3.71) is violated if the subproblem SP is infeasible. If no constraint is violated, then the solution is feasible for the original LBBD and is set as the new incumbent solution. Constraints (3.73) - (3.74) are used to strengthen the bounds of the MP. Otherwise, the MPE is modified by the addition of Benders cuts, the linear relaxation of the current MP is resolved, and the described steps are applied again. General-purpose optimization software may additionally rely on automated cuts. Algorithm 1 presents a pseudo-code for the B&Ch algorithm.

Algorithm 1: B&Ch algorithm

```
1  Initialization: Initial solution; set UB = inf, LB = 0, gap = inf, ε = 10^{-4} ;
2  Solve the linear relaxation of MPE and obtain LB = the best overall lower bound of
     the problem MPE ;
3  Calculate gap = (UB − LB)/UB ;
4  if gap ≥ ε & an integer solution β̄ is found then
5  |   Go to step 9 ;
6  else
7  |   Go to step 15 ;
8  end
9  if the solution β̄ violate feasibility or optimality cuts then
10 |   Generate and add feasibility or optimality cuts ;
11 |   Go to step 2 ;
12 else
13 |   Update UB ;
14 end
15 if gap ≤ ε then
16 |   Stop ;
17 end
18 The algorithm is repeated in the next node selected by the Branch-and-bound ;
```

3.4.3 Initial solution approach

In addition, we initialized the method with part of an initial solution: the location and capacity selection provided by a part of the model. The reduced relaxed model is as follows:

$$\min \Psi = \min \Bigg[\sum_{j\in\mathcal{I}_w}\sum_{l\in\mathcal{L}} f_{jl}Y_{jl} + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(\frac{I_{jpt-1}+I_{jpt}}{2} + \frac{1}{2}T_{jp}\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}\Big)$$
$$+ \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c_{ijs}Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{jks}Z_{jkst}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} g_{ijs}W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{jks}W_{jkst}\Big)$$
$$+ \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c'_{ij}\rho_p Q_{ijpt} + \sum_{k\in\mathcal{I}_c} c'_{jk}\rho_p\eta_{kt}\mu_{pkt}X_{jkp}\Big)\Bigg] \tag{3.75}$$

$$\text{s.t.Constraints}(3.2) - (3.7), (3.11), (3.13) - (3.25). \tag{3.76}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp} + I_{jpt} - I_{jpt-1},\ \forall j\in\mathcal{I}_w, p\in\mathcal{P}, t\in\Theta. \tag{3.77}$$

$$\sum_{p\in\mathcal{P}}\upsilon_p\big(\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\mu_{pkt}U_{ijkp} + I_{jpt}\big) \le \sum_{l\in\mathcal{L}} q_l Y_{jl},\ \forall j\in\mathcal{I}_w, t\in\Theta. \tag{3.78}$$

The solution given by this model is verified, calculating the safety stock and verifying DC capacity. If the DC capacity is not sufficient, the problem is solved again by imposing a safety stock based on the previous solution and the maximum safety stock. This is done progressively until reaches 100% of the maximum safety stock which always is a feasible solution. The maximum safety stock is computed as the maximum safety stock (for every DC, product, and period), considering the DC has to attend to the demand of all retailers and it is supplied from the plant with the largest lead time.

3.4.4 Linearized model APXM

We also test a mathematical model using the piecewise linear lower bound function of safety stock. This model can be initialized with part of an initial solution, the location and capacity selection, provided by the relaxed model, as presented in Section 3.4.3. APXM is solved directly using CPLEX, without any tailored algorithm.

$$\min \Psi = \min \Bigg[\sum_{j\in\mathcal{I}_w} \sum_{l\in\mathcal{L}} f_{jl} Y_{jl} + \sum_{j\in\mathcal{I}_w} \sum_{p\in\mathcal{P}} \sum_{t\in\Theta} h_{pj} \Big(SS^{prox}_{jpt} + \frac{I_{jpt-1} + I_{jpt}}{2} + \frac{1}{2} T_{jp} \sum_{k\in\mathcal{I}_c} \eta_{kt} \mu_{pkt} X_{jkp} \Big) + \sum_{j\in\mathcal{I}_w} \sum_{s\in\mathcal{S}} \sum_{t\in\Theta} \Big(\sum_{i\in\mathcal{I}_f} c_{ijs} Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{jks} Z_{jkst} \Big) + \sum_{j\in\mathcal{I}_w} \sum_{s\in\mathcal{S}} \sum_{t\in\Theta} \Big(\sum_{i\in\mathcal{I}_f} g_{ijs} W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{jks} W_{jkst} \Big) + \sum_{j\in\mathcal{I}_w} \sum_{p\in\mathcal{P}} \sum_{t\in\Theta} \Big(\sum_{i\in\mathcal{I}_f} c'_{ij} \rho_p Q_{ijpt} + \sum_{k\in\mathcal{I}_c} c'_{jk} \rho_p \eta_{kt} \mu_{pkt} X_{jkp} \Big) \Bigg] \tag{3.79}$$

$$\text{s.t.Constraints}(3.2) - (3.7), (3.11) - (3.25), (3.47) - (3.57). \tag{3.80}$$

$$S_{jpt} = \sum_{i\in\mathcal{I}_f} \sum_{k\in\mathcal{I}_c} (T_{jp} + \ell_{ij}) \mu_{pkt} U_{ijkp} + SS^{prox}_{jpt}, \ \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.81}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c} \eta_{kt} \mu_{pkt} X_{jkp} + I_{jpt} - I_{jpt-1} + SS^{prox}_{jpt} - SS^{prox}_{jp,t-1}, \ \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.82}$$

$$SS^{prox}_{jpt} \geq 0, \ j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.83}$$

3.4.5 Sequential approach SQAP

The problem can be solved sequentially, first the location problem and then the inventory management and transportation planning. The upper level or location problem has information about the original problem such as cycle inventory, anticipation inventory, variable transportation costs, and capacity constraints to select the location and capacity levels of DCs. The second level fixes these decisions and defines the allocation, order quantity, anticipation inventory, the cargo weight. Finally, the bottom level defines the safety stock and the target inventory level. Because the upper level does not consider all the problem constraints, the upper decisions can be infeasible at the bottom levels.

Upper level

$$\min \Psi = \min \Bigg[\sum_{j\in\mathcal{I}_w}\sum_{l\in\mathcal{L}} f_{jl}Y_{jl} + \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}\Big(\frac{I_{jpt-1}+I_{jpt}}{2} + \frac{1}{2}T_{jp}\sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp}\Big)$$
$$+ \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c_{ijs}Z_{ijst} + \sum_{k\in\mathcal{I}_c} c_{jks}Z_{jkst}\Big) + \sum_{j\in\mathcal{I}_w}\sum_{s\in\mathcal{S}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} g_{ijs}W_{ijst} + \sum_{k\in\mathcal{I}_c} g_{jks}W_{jkst}\Big)$$
$$+ \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta}\Big(\sum_{i\in\mathcal{I}_f} c'_{ij}\rho_p Q_{ijpt} + \sum_{k\in\mathcal{I}_c} c'_{jk}\rho_p\eta_{kt}\mu_{pkt}X_{jkp}\Big)\Bigg] \tag{3.84}$$

$$\text{s.t.Constraints}(3.2) - (3.7), (3.11) - (3.25), (3.47) - (3.57). \tag{3.85}$$

$$\sum_{i\in\mathcal{I}_f} Q_{ijpt} = \sum_{k\in\mathcal{I}_c}\eta_{kt}\mu_{pkt}X_{jkp} + I_{jpt} - I_{jpt-1}, \ \forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta. \tag{3.86}$$

Bottom level: Mathematical model (3.66) - (3.69).

3.5 Computational results

In this section, we report the computational performance of the proposed solution method. The aim is to calculate the efficiency of the tailored solution methods in providing good-quality solutions within a plausible running time.

The models were coded in C++ programming language and solved using the general-purpose optimization software IBM CPLEX version 20.10, with its default configuration. A Linux PC with a CPU Intel Core i7 3.4 GHz and 16.0 GB of memory was used to run the experiments. The stopping criterion was due to either the elapsed time exceeding the time limit of 3600 seconds or the optimality gap becoming smaller than 10^{-4}.

3.5.1 Data description

This section presents the instances derived from the real-world data obtained from the pharmaceutical company. The company produces part of its commercialized products in a plant. Other products are imported from foreign plants and packed in the plant. From this plant, products are sent to DCs managed by logistics operators, from which the company fulfills the demand of retailers all over the country. The company groups the retailers according to demand areas, it can be the capital and countryside of each state. Table 3.3 presents the cardinality of the sets.

Table 3.3: Data set

Data set	Cardinality
Number of plants	$\|\mathcal{I}_f\| = 1, 2$
Number of potential DCs	$\|\mathcal{I}_w\| = 3$
Number of retailers	$\|\mathcal{I}_c\| = 5, 10, 15, 30$
Number of capacity levels at DCs	$\|\mathcal{L}\| = 3$
Number of cost segments	$\|\mathcal{S}\| = 5$
Number of products	$\|\mathcal{P}\| = 7, 10, 20, 30, 40$
Number of time periods	$\|\Theta\| = 12$ months

We assume that a one-year planning horizon is appropriate to evaluate the DC location since DC rental agreements are made annually. Hence, we consider 12 periods to address tactical decisions of inventory management and transportation planning.

We consider the review intervals T_{jp} at all DCs to be 10 days. The lead-time ℓ_{ij} was calculated considering the distance and the mean velocity of trucks on roads. The portfolio of the company is composed of a large number of products, but we built instances with up to 40 products. The products cost ρ_p was assumed to be 40% of the product's price. The mean and variance of the daily demand, μ_{pkt} and σ^2_{pkt}, were defined according to the data provided by the company. We assume the same number of selling days at each retailer $\eta_{kt} = 30$ days.

The storage capacity levels q_l were estimated based on the total demand volume, and the opening costs f_{jl} were estimated based on the fixed and operational costs of the installed DCs, i.e. inventory insurance and rental space/volume in DCs that depend on selected capacity level. The holding costs were calculated based on the cost of \$53.45 per month to store a pallet (120x100x25 cm^3) at room temperature. From this information, the unit cost of inventory per product (h_{pj}) was calculated. Without loss of generality, the initial stocks were considered null at the beginning of the planning horizon. We assume a service level of 95%, this corresponds to $\Phi_\alpha = 1.64$. The fixed and variable costs of transportation g_{ijs} and c_{ijs} respectively, as well as the breakpoints b_s were defined based on the transportation tables from carriers.

Finally, for the piecewise linear function of safety stock, we define the number of segments, as well as the values of α_m based on the variance from retailer demand, and $f(\alpha_m)$ values are the square root of α_m values. Because the different products do not have the same scale of demand and variance, we define α_m $\forall j \in \mathcal{I}_w, p \in \mathcal{P}, t \in \Theta$, which results in the parameters α_{jptm} and f_{jptm}. With this definition, it is possible to reduce the number of segments, which impacts the solution time, we test 5 and 10 segments.

Table 3.4 presents the instance names; the number of binary and continuous variables; and the number of constraints.

Table 3.4: Instances

Name	Decision variables: Binary	Decision variables: Continuous	Constraints
i1-j3-k5-p7	2,580	3,348	7,151
i1-j3-k5-p10	3,219	4,320	9,551
i1-j3-k10-p10	4,419	5,220	15,061
i1-j3-k10-p20	6,849	8,460	27,311
i1-j3-k15-p10	5,619	6,120	20,571
i1-j3-k15-p20	8,349	9,360	37,071
i1-j3-k30-p20	12,849	12,060	66,351
i1-j3-k30-p30	16,479	15,300	95,601
i1-j3-k30-p40	20,109	18,540	124,851
i2-j3-k5-p7	2,886	3,780	7,592
i2-j3-k5-p10	3,579	4,860	10,073
i2-j3-k10-p10	4,929	5,760	15,733
i2-j3-k10-p20	7,689	9,360	28,403
i2-j3-k15-p10	6,279	6,660	21,393
i2-j3-k15-p20	9,489	10,260	38,463
i2-j3-k30-p20	14,889	12,960	68,643
i2-j3-k30-p30	19,449	16,560	98,913
i2-j3-k30-p40	24,009	20,160	129,183

3.5.2 Performance of the solutions approaches

In this section, we present and discuss the numerical results obtained, in terms of the performance of the proposed algorithms. The list of the different approaches compared in this section is presented in Table 3.5. IloPieceLinear method from CPLEX creates and returns a numeric expression representing a piecewise linear function.

Table 3.5: Solution approaches

SLBBD	Standard decomposition method of Section 3.4.1.
ELBBD	Enhanced LBBD method of Section 3.4.2.
ELBBDi	ELBBD + initial solution described in Section 3.4.3
ELBBDi+IPLf	ELBBDi + IloPieceLinear method from CPLEX.
APXM	Approximated-safety stock model of Section 3.4.4.
APXMi	APXM + initial solution described in Section 3.4.3.
APXMi+IPLf	APXMi + IloPieceLinear method from CPLEX.

Performance of the decomposition approaches

Table 3.7 presents the upper bound (UB), lower bound (LB), the optimality gap computed as $Gap = 100\frac{UB-LB}{UB}$, the time and number of iterations (#iter) for the SLBBD, the ELBBD, and ELBBDi. Table 3.6 summarizes the performance of methods presenting the best UB among the three methods and the gaps computed as $\%LB = 100\frac{Best\ UB-LB}{Best\ UB}$.

Table 3.6: Performance of the decomposition methods

Instance	Best UB	SLBBD LB(%)	ELBBD LB(%)	ELBBDi LB(%)
i1-j3-k5-p7	17,709,700	55.27	7.59	0.87
i1-j3-k5-p10	20,586,850	52.67	17.04	3.08
i1-j3-k10-p10	25,710,285	46.23	13.97	1.73
i1-j3-k10-p20	27,498,682	37.10	5.22	2.28
i1-j3-k15-p10	29,943,327	35.61	18.84	1.53
i1-j3-k15-p20	32,778,192	46.11	5.59	3.28
i1-j3-k30-p20	48,471,115	38.81	5.43	8.15
i1-j3-k30-p30	61,927,334	48.26	8.14	8.10
i1-j3-k30-p40	73,245,412	53.46	4.49	5.29
i2-j3-k5-p7	17,357,831	55.13	41.23	5.34
i2-j3-k5-p10	17,709,700	46.70	0.87	3.53
i2-j3-k10-p10	24,269,853	50.02	9.00	9.14
i2-j3-k10-p20	28,659,565	55.37	22.06	27.85
i2-j3-k15-p10	28,291,455	48.42	8.89	8.91
i2-j3-k15-p20	31,305,383	50.35	10.31	20.65
i2-j3-k30-p20	45,869,986	39.05	21.61	13.40
i2-j3-k30-p30	60,920,789	51.95	25.96	20.77
i2-j3-k30-p40	65,702,679	52.56	10.51	11.82
Average	36,553,230	47.9	13.2	8.7

Table 3.7: Performance of the decomposition methods

	SLBBD					ELBBD					ELBBDi				
Instance	UB	LB	Gap(%)[1]	Time	#iter	UB	LB	Gap(%)[1]	Time	#iter	UB	LB	Gap(%)[1]	Time	#iter
i1-j3-k5-p7	17,709,700	7,921,612	55.3	3,600	14,300	17,709,700	16,365,409	7.6	3,600	10,671	17,709,700	17,555,735	0.9	3,600	8,895
i1-j3-k5-p10	20,586,850	9,743,810	52.7	3,600	10,470	20,586,850	17,078,012	17.0	3,600	7,828	20,586,850	19,951,829	3.1	3,600	9,983
i1-j3-k10-p10	26,259,414	13,824,488	47.4	3,600	9,400	26,259,414	22,119,051	15.8	3,601	10,404	25,710,285	25,265,418	1.7	3,600	7,892
i1-j3-k10-p20	28,038,725	17,297,558	38.3	3,600	5,800	28,038,725	26,062,724	7.0	3,600	1,807	27,498,682	26,871,608	2.3	3,600	2,229
i1-j3-k15-p10	30,647,840	19,281,376	37.1	3,600	7,693	30,773,017	24,302,472	21.0	3,601	8,981	29,943,327	29,485,518	1.5	3,600	6,775
i1-j3-k15-p20	33,050,022	17,663,482	46.6	3,600	5,053	33,050,022	30,947,042	6.4	3,600	986	32,778,192	31,702,931	3.3	3,600	603
i1-j3-k30-p20	49,023,641	29,660,137	39.5	3,600	3,339	48,826,261	45,837,189	6.1	3,600	115	48,471,115	44,518,778	8.2	3,600	1,283
i1-j3-k30-p30	61,927,334	32,039,748	48.3	3,601	2,624	62,815,563	56,888,494	9.4	3,600	468	62,013,797	56,908,278	8.2	3,600	976
i1-j3-k30-p40	74,357,129	34,089,888	54.2	3,601	2,371	73,245,412	69,960,097	4.5	3,601	28	77,543,104	69,373,241	10.5	3,600	5
i2-j3-k5-p7	17,499,095	7,788,293	55.5	3,601	12,843	18,422,681	10,201,783	44.6	3,600	12,057	17,357,831	16,431,242	5.3	3,600	10,271
i2-j3-k5-p10	28,362,562	9,439,444	66.7	3,600	10,806	17,709,700	17,555,735	0.9	3,600	8,991	19,262,305	17,084,040	11.3	3,600	8,158
i2-j3-k10-p10	25,221,741	12,130,134	51.9	3,601	9,297	24,269,853	22,084,861	9.0	3,601	7,457	24,410,516	22,052,432	9.7	3,600	5,460
i2-j3-k10-p20	28,659,565	12,791,547	55.4	3,600	5,949	30,207,042	22,338,471	26.0	3,600	1,382	30,627,173	20,677,853	32.5	3,600	2,765
i2-j3-k15-p10	29,655,644	14,593,215	50.8	3,600	7,713	28,291,455	25,776,474	8.9	3,600	5,995	28,291,455	25,771,093	8.9	3,601	6,028
i2-j3-k15-p20	37,293,578	15,541,600	58.3	3,600	5,044	NA	28,078,825	NA	3,600	NA	31,305,383	24,842,381	20.6	3,600	1,263
i2-j3-k30-p20	47,508,474	27,957,772	41.2	3,601	3,272	46,438,140	35,959,662	22.6	3,600	2,268	45,869,986	39,721,452	13.4	3,600	1,036
i2-j3-k30-p30	NA	29,274,100	NA	3,601	NA	60,920,789	45,103,577	26.0	3,600	1,439	65,639,098	48,269,258	26.5	3,600	537
i2-j3-k30-p40	99,572,557	31,170,681	68.7	3,601	2,086	NA	58,795,500	NA	3,600	NA	65,702,679	57,938,974	11.8	3,601	31
Average		19,011,605					31,969,743				37,262,304	33,023,448	10,0		

[1] Gap=$100\times\frac{UB-LB}{UB}$

* NA: No solution provided.

Note in Table 3.7 that the ELBBDi outperforms the other methods in the number of feasible solutions and quality of the solutions. It can solve all solutions, while SLBBD fails in solving one instance and ELBBD fails in solving two instances. Moreover, the average LB of ELBBDi is better compared with SLBBD and ELBBD, 42.4% and 3.2% higher than these methods. Table 3.6 shows that ELBBDi provides on average best LBs for the problem. Note that for some instances, ELBBD finds solutions with better UB compared with the ELBBDi method, due to for these instances the ELBBDi method does not improve significantly the provided initial solutions.

We develop additional experiments with ELBBDi using a different number of segments for the piecewise linear function of safety stock, 5 and 10 segments as shown in Table B.1 in Appendix. The average gap of solutions considering 5 segments is higher than considering 10 segments since the UB and the LB are better. It can explain because, with 5 segments, there are fewer variables and constraints, and consequently it is easier to be solved. Solutions for 5 and 10 segments with lower gaps have similar bounds, so 5 segments is a good choice for the number of segments. These results were expected because the piecewise linear function of safety stock is considered only in the master problem to approximate the safety stock costs, then the safety stock is properly defined in the subproblem. Thus, it is not necessary for a larger number of segments to approximate the safety stock and obtain a good solution using LBBDi. We also develop computational experiments with the method ELBBDi changing the computational times, i.e., half-hour, one hour, and 2 hours, as shown in Table B.3 in Appendix. The results show that with half-hour the performance is worse, and with 2 hours the performance does not improve concerning the results with one hour. Thus, one hour is a reasonable time to solve the problem. Furthermore, we develop experiments using the Special Order Sets (SOS1) from CPLEX for the variables W and Y aiming to improve the solutions. However, the incorporation of the CPLEX function of SOS1 does not improve them, as shown in Table B.2 in Appendix.

Table 3.8 presents the results of using the IloPieceLienear method from CPLEX, instead of using the explicit constraints of the piecewise linear lower bound function of safety stock in the master problem, and the comparison with the ELBBDi. The positive ratios of improvement indicate a larger value of the ELBBDi+IPLf. Notice that the incorporation of the IloPieceLienear method can reduce the average gap slightly (1%), despite the UB is higher since it provides an average LB that is 2.8% higher than the LB of the ELBBDi.

Table 3.8: Results of the impact of IloPieceLinear method from CPLEX in ELBBDi

	ELBBDi + IPLf					Ratio of improvement[1]				
Instance	UB	LB	Gap(%)[2]	Time	#iter	UB	LB	Diff(%)[3]	Time	#iter
i1-j3-k5-p7	17,709,700	17,703,574	0.03	3,600	9,601	0.00	0.84	-0.83	0.00	7.94
i1-j3-k5-p10	20,586,850	20,569,984	0.1	3,600	4,047	0.00	3.10	-3.00	0.00	-59.46
i1-j3-k10-p10	25,627,116	25,580,095	0.2	3,600	4,676	-0.32	1.25	-1.55	0.00	-40.75
i1-j3-k10-p20	28,038,725	26,945,655	3.9	3,600	31	1.96	0.28	1.62	0.00	-98.61
i1-j3-k15-p10	30,124,060	29,863,365	0.9	3,600	398	0.60	1.28	-0.66	0.00	-94.13
i1-j3-k15-p20	32,778,192	31,943,106	2.6	3,600	27	0.00	0.76	-0.73	0.00	-95.52
i1-j3-k30-p20	48,471,115	46,332,449	4.4	3,600	12	0.00	4.07	-3.74	0.00	-99.06
i1-j3-k30-p30	61,886,915	56,991,268	7.9	3,600	23	-0.20	0.15	-0.32	0.00	-97.64
i1-j3-k30-p40	77,543,101	69,369,383	10.5	3,600	7	0.00	-0.01	0.00	0.00	40.00
i2-j3-k5-p7	17,357,831	17,333,804	0.1	3,600	11,759	0.00	5.49	-5.20	0.00	14.49
i2-j3-k5-p10	19,262,305	19,180,885	0.4	3,600	7,573	0.00	12.27	-10.89	0.00	-7.17
i2-j3-k10-p10	24,444,672	23,723,312	3.0	3,600	613	0.14	7.58	-6.71	0.00	-88.77
i2-j3-k10-p20	32,858,210	23,150,651	29.5	3,600	62	7.28	11.96	-2.94	0.00	-97.76
i2-j3-k15-p10	28,793,683	26,155,413	9.2	3,600	166	1.78	1.49	0.25	-0.03	-97.25
i2-j3-k15-p20	32,135,264	25,716,594	20.0	3,600	120	2.65	3.52	-0.67	0.00	-90.50
i2-j3-k30-p20	47,650,414	38,621,200	19.0	3,600	79	3.88	-2.77	5.54	0.00	-92.37
i2-j3-k30-p30	65,443,042	48,319,570	26.2	3,600	24	-0.30	0.10	-0.30	0.00	-95.53
i2-j3-k30-p40	75,699,849	57,372,623	24.2	3,600	13	15.22	-0.98	12.39	-0.03	-58.06
Average	38,133,947	33,604,052	9.0	3,600	2,180	1.82	2.80	-0.99	0.00	-63.90

[1] Ratio $=100\times\frac{\text{ELBBDi+IPLf}\ -\ \text{ELBBDi}}{\text{ELBBDi}}$

[2] Gap$=100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

[3] Diff=ELBBDi+IPLf gap − ELBBDi gap

Performance based on APXM approaches

Table 3.9 presents the impact of the initial solution on APXM method. The warm-up of the APXM method with an initial solution has a positive impact on the performance of the method. APXMi provides a solution for all instances, in fact, it provides a lower average gap and higher LB compared with the ELBBDi+IPLf, despite the bigger instances having a larger gap.

Table 3.9: Initial solution effect in APXM

	APXM					APXMi				
Instance	UB	O.F. value	LB	Gap(%)[1]	Time	UB	O.F. value	LB	Gap(%)[1]	Time
i1-j3-k5-p7	17,709,670	17,703,574	17,703,419	0.0	5	17,709,700	17,703,574	17,701,843	0.0	7
i1-j3-k5-p10	20,586,790	20,569,984	20,569,781	0.1	127	20,586,790	20,569,984	20,568,393	0.1	183
i1-j3-k10-p10	25,626,858	25,580,095	25,576,342	0.2	529	25,626,858	25,580,095	25,577,849	0.2	446
i1-j3-k10-p20	NA	NA	25,395,173	NA	3,601	27,481,953	27,465,998	27,191,636	1.1	3,600
i1-j3-k15-p10	29,943,068	29,894,106	29,891,189	0.2	1,242	29,943,068	29,894,106	29,891,151	0.2	416
i1-j3-k15-p20	NA	NA	29,602,291	NA	3,600	32,758,543	32,719,279	32,020,394	2.3	3,600
i1-j3-k30-p20	NA	NA	44,041,835	NA	3,600	48,470,734	48,411,047	46,489,952	4.1	3,600
i1-j3-k30-p30	NA	NA	57,067,853	NA	3,600	62,302,971	62,227,646	58,641,971	5.9	3,605
i1-j3-k30-p40	NA	NA	69,393,180	NA	3,600	77,539,557	77,251,502	69,413,298	10.5	3,600
i2-j3-k5-p7	17,357,472	17,334,589	17,331,778	0.1	51	17,357,472	17,334,589	17,332,871	0.1	31
i2-j3-k5-p10	19,263,172	19,230,560	19,223,703	0.2	3,600	19,263,172	19,230,560	19,224,995	0.2	3,600
i2-j3-k10-p10	24,312,322	24,218,590	24,163,274	0.6	413	24,269,633	24,175,299	24,172,882	0.4	2,258
i2-j3-k10-p20	27,482,784	27,453,407	23,359,880	15.0	3,600	26,569,533	26,461,043	23,982,511	9.7	3,600
i2-j3-k15-p10	28,855,278	28,742,816	26,505,978	8.1	3,600	28,290,714	28,176,103	26,422,314	6.6	3,600
i2-j3-k15-p20	NA	NA	25,010,964	NA	3,600	31,155,957	31,120,739	27,912,331	10.4	3,600
i2-j3-k30-p20	43,477,716	43,295,632	38,397,414	11.7	3,600	53,204,602	52,987,354	38,890,302	26.9	3,602
i2-j3-k30-p30	NA	NA	56,978,753	NA	3,600	65,549,584	65,387,747	48,162,989	26.5	3,600
i2-j3-k30-p40	NA	NA	59,360,422	NA	3,601	75,566,261	75,330,735	57,048,611	24.5	3,600
Average			33,865,179			37,980,395	37,890,411	33,924,794	7.2	

[1] Gap=100$\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

[*] NA: No solution provided.

Performance of ELBBDi+ILPf and APXMi

In this section, we present the bests versions of the methods in the two previous sections, the ELBBDi+IPLf and the APXMi. The APXMi offers solutions with a piecewise linear lower bound function of safety stock. Consequently, in the APXMi, the safety stock costs are an approximation of the real safety stock costs and the objective function value is an approximation of the total cost. Thus, after solving the APXMi, we compute the real safety stock costs by using the allocation of the optimal (or last incumbent) solution provided by the solver, i.e., $\bar{U}_{ijkp}$ as $SS_{jpk} = \sum_{j\in\mathcal{I}_w}\sum_{p\in\mathcal{P}}\sum_{t\in\Theta} h_{pj}(\Phi_\alpha\sqrt{\sum_{i\in\mathcal{I}_f}\sum_{k\in\mathcal{I}_c}(T_{jp}+\ell_{ij})\sigma^2_{pkt}\bar{U}_{ijkp}})$. Finally, we compute the real total costs that we call as upper bound by updating the safety stock costs. Table 3.10 presents the upper bound "UB", lower bound "LB", the "Gap" computed as $Gap = 100\frac{UB-LB}{UB}$, and the "Time" for the methods. Also, the number of iterations "#iter" to the ELBBDi+ILPf and the objective function value "O.F. value" to the APXMi. Table 3.10 also presents the best (or lowest) UB and the best (or highest) LB for each instance provided by the methods, the ELBBD+ILPf or the APXMi, and the gap computed with these bounds.

Notice in Table 3.10 that the proposed methods can provide good solutions to the addressed problem in a computational time of one hour, with an average gap of 6.7%. Most instances with one plant have good solutions with gaps until 5.2%, just one instance (biggest instance with one plant with 30 retailers and 40 products) presents a gap of 10.5%. Instances with high gaps (i.e., $\geq$ 18%) have two plants, 30 retailers, and at least 20 products.

Table 3.10: Comparison between ELBBDi+IPL and APXMi

Instance	ELBBDi+IPLf					APXMi							
I-J-K-P	UB	LB	Gap(%)[1]	Time	#it	UB	O.F. value	LB	Gap(%)[1]	Time	Best UB	Best LB	Gap(%)[1]
i1-j3-k5-p7	17,709,700	17,703,574	0.0	3,600	9,601	17,709,700	17,703,574	17,701,843	0.0	7	17,709,700	17,703,574	0.0
i1-j3-k5-p10	20,586,850	20,569,984	0.1	3,600	4,047	20,586,790	20,569,984	20,568,393	0.1	183	20,586,790	20,569,984	0.1
i1-j3-k10-p10	25,627,116	25,580,095	0.2	3,600	4,676	25,626,858	25,580,095	25,577,849	0.2	446	25,626,858	25,580,095	0.2
i1-j3-k10-p20	28,038,725	26,945,655	3.9	3,600	31	27,481,953	27,465,998	27,191,636	1.1	3,600	27,481,953	27,191,636	1.1
i1-j3-k15-p10	30,124,060	29,863,365	0.9	3,600	398	29,943,068	29,894,106	29,891,151	0.2	416	29,943,068	29,891,151	0.2
i1-j3-k15-p20	32,778,192	31,943,106	2.6	3,600	27	32,758,543	32,719,279	32,020,394	2.3	3,600	32,758,543	32,020,394	2.3
i1-j3-k30-p20	48,471,115	46,332,449	4.4	3,600	12	48,470,734	48,411,047	46,489,952	4.1	3,600	48,470,734	46,489,952	4.1
i1-j3-k30-p30	61,886,915	56,991,268	7.9	3,600	23	62,302,971	62,227,646	58,641,971	5.9	3,605	61,886,915	58,641,971	5.2
i1-j3-k30-p40	77,543,101	69,369,383	10.5	3,600	7	77,539,557	77,251,502	69,413,298	10.5	3,600	77,539,557	69,413,298	10.5
i2-j3-k5-p7	17,357,831	17,333,804	0.1	3,600	11,759	17,357,472	17,334,589	17,332,871	0.1	31	17,357,472	17,333,804	0.1
i2-j3-k5-p10	19,262,305	19,180,885	0.4	3,600	7,573	19,263,172	19,230,560	19,224,995	0.2	3,600	19,262,305	19,224,995	0.2
i2-j3-k10-p10	24,444,672	23,723,312	3.0	3,600	613	24,269,633	24,175,299	24,172,882	0.4	2,258	24,269,633	24,172,882	0.4
i2-j3-k10-p20	32,858,210	23,150,651	29.5	3,600	62	26,569,533	26,461,043	23,982,511	9.7	3,600	26,569,533	23,982,511	9.7
i2-j3-k15-p10	28,793,683	26,155,413	9.2	3,600	166	28,290,714	28,176,103	26,422,314	6.6	3,600	28,290,714	26,422,314	6.6
i2-j3-k15-p20	32,135,264	25,716,594	20.0	3,600	120	31,155,957	31,120,739	27,912,331	10.4	3,600	31,155,957	27,912,331	10.4
i2-j3-k30-p20	47,650,414	38,621,200	19.0	3,600	79	53,204,602	52,987,354	38,890,302	26.9	3,602	47,650,414	38,890,302	18.4
i2-j3-k30-p30	65,443,042	48,319,570	26.2	3,600	24	65,549,584	65,387,747	48,162,989	26.5	3,600	65,443,042	48,319,570	26.2
i2-j3-k30-p40	75,699,849	57,372,623	24.2	3,600	13	75,566,261	75,330,735	57,048,611	24.5	3,600	75,566,261	57,372,623	24.1
Average	38,133,947	33,604,052	9.0	3,600	2,180	37,980,395	37,890,411	33,924,794	7.2	2,586	37,642,747	33,951,855	6.7

[1] Gap=$100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

3.5.3 Comparison between the integrated and the sequential model

We carry out computational experiments to study the impact of integrating inventory decisions with the network design problem. We compare the sequential and integrated approaches in terms of cost and computational time. Table 3.11 presents, for three approaches: ELBBDi, SQAP, and SQAP*, the costs of location, inventory, transportation, and total costs, as well as the computational time and the ratio between the total costs of the approaches that are computed as $ratio = 100\frac{SQAP-ELBBDi}{ELBBDi}$. ELBBDi represents the integrated approach, SQAP represents the sequential approach, in which the location decision is fixed in the inventory-transportation problem as described in Section 3.4.5. SQAP* represents the sequential approach, in which the location decision is fixed in the inventory-transportation problem, however, is possible to open other DCs if it is necessary. In the sequential approaches, the location decision results in an infeasible solution (INF) for some instances, and for others, the solver does not provide a solution (NA) within one hour of the time limit. Table 3.12 shows the average results of the feasible solutions for the approaches SQAP* and ELBBDi.

Notice in Table 3.11 that the integrated approach decreases the total solution cost by an average between 0.4% and 15.7% even if the instances were not solved optimally by the ELBBDi. Notice in Table 3.11 that big instances can be solved with SQAP* compared with SQAP. According to Table 3.12, the average costs are lower in the integrated problem. However, the integrated model is slightly difficult to solve, because all instances report a computational time of one hour, while SQAP* has an average time of 2,038 seconds.

Table 3.11: Comparison between the sequential SQAP and integrated approach ELBBDi

Instance	ELBBDi				SQAP					SQAP*				
	Location	Inv+Transp	Total cost	Time	Location	Inv+Transp	Total cost	Time	Ratio[1]	Location	Inv+Transp	Total cost	Time	Ratio[1]
i1-j3-k5-p7	13,050,000	4,659,700	17,709,700	3,600	INF			3,600		13,100,000	4,771,167	17,871,167	4	0.9%
i1-j3-k5-p10	13,050,000	7,536,850	20,586,850	3,600	INF			3,600		13,100,000	7,687,331	20,787,331	119	1.0%
i1-j3-k10-p10	13,050,000	12,660,285	25,710,285	3,600	INF			3,600		14,430,000	15,325,493	29,755,493	2,351	15.7%
i1-j3-k10-p20	13,100,000	14,398,682	27,498,682	3,600	INF			3,600		13,100,000	14,020,519	27,882,688	3,582	1.4%
i1-j3-k15-p10	12,110,000	17,833,327	29,943,327	3,600	INF			3,600		14,430,000	20,548,288	34,978,288	3,582	16.8%
i1-j3-k15-p20	13,050,000	19,728,192	32,778,192	3,600	INF			3,600		13,050,000	18,335,816	33,050,022	3,205	0.8%
i1-j3-k30-p20	13,050,000	35,421,115	48,471,115	3,600	NA			3,600		NA			3,600	
i1-j3-k30-p30	13,050,000	48,963,797	62,013,797	3,600	NA			3,600		NA			3,600	
i1-j3-k30-p40	13,050,000	64,493,104	77,543,104	3,600	NA			3,600		NA			3,600	
i2-j3-k5-p7	13,050,000	4,307,831	17,357,831	3,600	13,100,000	4,375,385	17,475,385	1	0.7%	13,100,000	4,375,385	17,475,385	2	0.7%
i2-j3-k5-p10	12,067,500	7,194,805	19,262,305	3,600	13,100,000	7,095,981	20,195,981	92	4.8%	13,100,000	7,032,842	20,132,842	193	4.5%
i2-j3-k10-p10	12,067,500	12,343,016	24,410,516	3,600	13,100,000	12,234,374	25,334,374	457	3.8%	13,100,000	12,378,434	25,478,434	694	4.4%
i2-j3-k10-p20	13,050,000	17,577,173	30,627,173	3,600	13,100,000	14,020,519	27,120,519	3,582	-11.4%	13,050,000	14,017,061	27,373,742	3,570	-10.6%
i2-j3-k15-p10	13,050,000	15,241,455	28,291,455	3,600	13,100,000	16,522,649	29,622,649	2,380	4.7%	13,100,000	16,549,340	29,649,340	3,570	4.8%
i2-j3-k15-p20	13,050,000	18,255,383	31,305,383	3,600	13,100,000	18,335,816	31,435,816	3,205	0.4%	13,100,000	18,477,660	31,577,660	3,582	0.9%
i2-j3-k30-p20	19,650,000	26,219,986	45,869,986	3,600	NA			3,600		NA			3,600	
i2-j3-k30-p30	13,100,000	52,539,098	65,639,098	3,600	NA			3,600		NA			3,600	
i2-j3-k30-p40	13,100,000	52,602,679	65,702,679	3,600	NA			3,600		NA			3,600	

* NA: No solution provided in 3,600 s, INF: infeasible.

[1] Ratio=$100 \times \frac{\text{SQAP UB} - \text{ELBBDi UB}}{\text{ELBBDi UB}}$

Table 3.12: Average of costs and time for sequential SQAP and integrated approach ELBBDi for feasible solutions

Approach	Location	Inv+Transp	Total costs	Time	Ratio
ELBBDI	12,812,083	12,644,725	25,456,808	3,600	
SQAP*	13,313,333	12,793,278	26,334,366	2,038	3.4%

3.5.4 Sensitivity analysis

In this section, we present a sensitivity analysis to observe the impact of variations in some parameters (coefficient of variation, opening, inventory, and transportation costs) over the network structure , i.e., on the number of facilities and their location, and other planning decisions. In this context, we perform sensitivity analysis over the coefficient of variation and for the decision costs. For the sensitivity analysis, we present the average optimality gap, the average objective function costs, the average inventory levels, Key Performance Indicators (KPI) for inventory and location decisions, and some statistics about transportation decisions. The inventory KPIs are turnover and days in inventory. The turnover is calculated as the number of units sold over the average number of units stocked, and the days in inventory are calculated as 365 over the turnover.

Coefficient of variation

This analysis is related to the parameter coefficient of variation, i.e. the ratio of the standard deviation to the mean demand. Table 3.13 presents the average gap and costs, KPIs, and statistics for different values of the coefficient of variation.

Table 3.13: Variation on the coefficient of variation

		Coefficient of variation				
		20%	50%	80%	100%	150%
	Optimality gap	4%	8%	14%	17%	22%
Objective function costs	Location costs	14,198,056	14,089,583	13,499,861	13,557,222	13,364,444
	Inventory costs	9,385,262	10,222,213	11,350,525	11,957,753	13,667,098
	Transportation costs	10,192,781	10,064,407	9,986,370	9,942,510	9,698,388
	Security costs	3,110,502	3,092,524	3,085,067	3,061,364	3,013,060
	Total costs	36,886,601	37,468,726	37,921,823	38,518,848	39,742,991
Inventory costs	Safety stock costs	746,167	1,646,922	2,746,145	3,346,773	5,077,640
	Anticipation inv costs	56,368	23,825	9,319	5,783	3,821
	Cycle inv costs	8,582,727	8,551,467	8,595,061	8,605,197	8,585,637
Inventory levels	Safety stock units	31,700	75,493	121,270	151,041	223,973
	Anticipation inv units	1,263	523	222	172	51
	Cycle inv units	412,976	412,976	412,976	412,976	412,976
	Total units	445,939	488,992	534,467	564,189	637,000
Inventory KPIs	Turnover	71	37	25	21	16
	Days in inventory	5	10	14	17	23
Location KPIs	Total Opened DCs	45	43	39	39	38
	% Used capacity	63%	60%	61%	61%	59%
Transportation statistics	Avg weight plant-DC	9,015,031	9,028,566	9,043,192	9,052,237	9,075,324
	Max weight plant-DC	6,299,624	5,714,120	5,768,223	5,541,415	5,056,923
	Min weight plant-DC	888,214	1,535,870	1,608,854	1,922,310	3,826,892
	Avg weight DC-retailer	9,004,880	9,004,880	9,004,880	9,004,880	9,004,880
	Max weight DC-retailer	476,237	475,966	476,237	476,237	476,237
	Min weight DC-retailer	102,496	157,934	153,537	241,002	253,205

Notice in Table 3.13 that the coefficient of variation increases the average optimality gap, thus the problem seems to be more difficult to solve. The total objective cost also increases considering a higher coefficient of variation. This increase in the total cost is observed because of an increment in the inventory cost, while we have a reduction in location and transportation costs.

As expected, the safety stock units increase and consequently the safety stock costs increase. On the other hand, the anticipation inventory costs decrease. However, the anticipation inventory represents only a very small portion of the total inventory. The turnover decreases due to more units being stocked, and consequently, the days in inventory increase. Notice in Table 3.13 that opening costs decrease because fewer DCs are opened, however, the percentage of used capacity decreases slightly from 63% to 59%, which indicates that the total installed capacity increases to keep the growing safety inventory with the coefficient of variation.

Table 3.13 also shows that the average and minimum weight among plants and DCs increase, which suggests the use of transportation segments with higher capacity, taking advantage of scale economies. It can explain the reduction in transportation costs. Although the retailer demand does not change, the average minimum weight among DCs and retailers increases. It can be explained due to the location decisions change, fewer DCs are opened, so the transported cargo weight among arcs increases.

Opening costs variation

This analysis is related to the parameter of opening costs. The model is tested for this parameter on +/- 50% of its initial value. Table 3.14 presents the average gap and costs, KPIs, and statistics for different values of opening costs.

As expected, the variation of opening costs affects directly the total opening costs, increasing and changing the location decisions. With higher opening costs, fewer DCs are opened, in turn, it also generates changes in inventory levels and costs. However, turnover and days in inventory are not significantly affected. Transportation decisions also are affected and the total transportation costs decrease.

Inventory costs variation

This analysis is related to the parameter of inventory costs. The model is tested for this parameter on +50% and +100% of its initial value. Table 3.15 presents the average gap and costs, KPIs, and statistics for different values of inventory costs. The variation of inventory costs affects directly the total inventory costs and also affects slightly the location costs that increase and the transportation costs that decrease.

Table 3.14: Variation on Opening costs

		Variation of opening costs		
		50%	100%	150%
	Optimality gap	14%	14%	15%
Objective function costs	Location costs	6,895,515	13,499,861	20,386,875
	Inventory costs	11,945,449	11,350,525	11,385,789
	Transportation costs	10,175,723	9,986,370	9,740,650
	Security costs	3,201,717	3,085,067	3,072,762
	Total costs	36,886,601	37,468,726	44,586,076
Inventory costs	Safety stock costs	2,945,089	2,746,145	2,773,902
	Anticipation inv costs	8,597	9,319	5,122
	Cycle inv costs	8,991,763	8,595,061	8,606,766
Inventory levels	Safety stock units	126,627	121,270	123,594
	Anticipation inv units	70	222	73
	Cycle inv units	414,043	412,976	412,976
	Total units	540,740	534,467	536,642
Inventory KPIs	Turnover	25	25	25
	Days in inventory	15	15	15
Location KPIs	Total Opened DCs	54	39	39
	% Used capacity	57%	61%	62%
Transportation statistics	Avg weight plant-DC	9,532,588	9,043,192	9,043,892
	Max weight plant-DC	5,406,369	5,768,223	5,647,928
	Min weight plant-DC	2,649,236	1,608,854	1,979,132
	Avg weight DC-retailer	9,490,925	9,004,880	9,004,880
	Max weight DC-retailer	494,602	476,237	476,237
	Min weight DC-retailer	234,780	153,537	188,994

Table 3.15: Sensitivity analysis: variation on inventory costs

		Variation of inventory costs		
		100%	150%	200%
	Optimality gap	14%	16%	17%
Objective function costs	Location costs	13,499,861	13,553,333	13,694,861
	Inventory costs	11,350,525	16,696,443	22,444,492
	Transportation costs	9,986,370	9,935,971	9,893,070
	Security costs	3,085,067	3,090,424	3,073,465
	Total costs	36,886,601	37,468,726	49,105,888
Inventory costs	Safety stock costs	121,270	122,151	123,306
	Anticipation inv costs	222	126	43
	Cycle inv costs	412,976	412,976	412,976
Inventory levels	Safety stock units	126,627	121,270	123,594
	Anticipation inv units	70	222	73
	Cycle inv units	414,043	412,976	412,976
	Total units	534,467	535,253	536,324
Inventory KPIs	Turnover	25	25	25
	Days in inventory	15	15	15
Location KPIs	Total Opened DCs	39	39	39
	% Used capacity	61%	59%	57%
Transportation statistics	Avg weight plant-DC	9,043,192	9,043,513	9,043,610
	Max weight plant-DC	5,768,223	5,568,788	5,474,688
	Min weight plant-DC	1,608,854	1,851,617	2,054,622
	Avg weight DC-retailer	9,004,880	9,004,880	9,004,880
	Max weight DC-retailer	476,237	475,832	476,237
	Min weight DC-retailer	153,537	251,415	221,551

Transportation costs variation

This analysis is related to the parameter of transportation costs. The model is tested for this parameter from 0% to 200% of its initial value by increments of 50%. Table 3.16 presents the average gap and costs, KPIs, and statistics for different values of transportation costs. The variation of transportation costs affects directly the total transportation costs. It also affects directly other decisions, such as the total inventory units which increase. It can explain because the total installed capacities increase even if the number of DCs does not increase.

Table 3.16: Sensitivity analysis: variation on transportation costs

		Variation of transportation costs				
		0%	50%	100%	150%	200%
	Optimality gap	15%	21%	14%	13%	11%
Objective function costs	Location costs	13,382,500	13,494,445	13,646,528	13,755,000	13,948,750
	Inventory costs	11,058,594	11,670,048	11,434,477	11,488,870	11,449,809
	Transportation costs	0	5,201,176	9,936,835	14,509,316	19,169,481
	Security costs	3,002,966	3,202,805	3,061,952	3,034,954	3,028,631
	Total costs	27,444,060	33,568,474	38,079,792	42,788,140	47,596,671
Inventory costs	Safety stock costs	105,760	124,807	123,925	125,994	127,675
	Anticipation inv costs	105	56	170	76	43
	Cycle inv costs	414,043	427003	412976	412976	412976
Inventory levels	Safety stock units	31,700	75,493	121,270	151,041	223,973
	Anticipation inv units	1,263	523	222	172	51
	Cycle inv units	412,976	412,976	412,976	412,976	412,976
	Total units	445,939	488,992	534,467	564,189	637,000
Inventory KPI	Turnover	28	25	25	25	25
	Days in inventory	13	15	15	15	15
Location KPI	Total Opened DCs	39	39	39	39	39
	% Used capacity	64%	67%	60%	57%	54%
Transportation statistics	Avg weight plant-DC	9,062,155	9,332,215	9,044,076	9,044,697	9,045,197
	Max weight plant-DC	6,109,022	5,581,178	5,780,324	5,025,569	5,023,278
	Min weight plant-DC	1,405,570	2,149,665	1,922,754	2,602,967	2,854,274
	Avg weight DC-retailer	9,028,603	9,293,049	9,004,880	9,004,880	9,004,880
	Max weight DC-retailer	455,284	477,738	476,237	476,237	476,237
	Min weight DC-retailer	32,676	214,700	151,958	197,160	261,931

3.6 Conclusions

In this study, we addressed some decisions of logistics network planning under demand uncertainty. We have presented an MINLP model that determines the optimal network structure, transportation, and inventory levels of a multi-echelon supply chain. Real data from a pharmaceutical supply chain was used to illustrate the applicability of the proposed model. The model determines the plant and DC locations, shipments from plants to the DCs, and the assignment of retailers to DCs. The model considers the periodic review policy (T, S) to control the inventory at the DCs. The objective is to minimize the location costs, transportation costs, and safety stock costs.

To solve the problem, we present an LBBD by exploiting the structure of the problem and obtaining subproblems that preserved the characteristics of the original problem. We also enhanced the master problem including information about the subproblems and use a multi-cut to accelerate the convergence of the method. We also propose a model with a piecewise linear lower bound function of safety stock. To validate the proposed approaches, real data was examined and used to construct realistic instances. The method provides good solutions for most instances.

We compare the integrated model with a sequential approach, the results evidence the importance of having an integrated approach. We also perform a sensitivity analysis aiming to understand how each parameter influences the supply chain design and planning problem. We find that the network design is sensitive to the coefficient of variation and the opening costs.

Therefore, we focus on several research opportunities pointed out in Chapter 2, i.e., considering the decision timing in the integration, addressing the uncertainty in problem parameters, considering discrete transportation costs, and proposing efficient solution methods.

For future work, it is interesting to analyze the impact of considering different length of the review interval in the periodic review policy (T, S) over the inventory decisions. Additionally, it is interesting to consider other inventory policies in the model, and compare the implications of different policies on logistics network planning. Also, to address capacity planning in networking by decisions of closing and opening DCs or expanding or reducing capacity DCs.

Chapter 4

A location-transportation problem under demand uncertainty for a pharmaceutical network in Brazil

Logistics Network Planning (LNP) concerns facility location and transportation decisions, among others. Traditionally these decisions are handled separately and hierarchically. However, the integration of these decisions has been receiving attention from academics and practitioners in the last years aiming to achieve an adequate service level, efficient performance in terms of costs of the network logistics and competitive advantages. In this work, we study the integrated location-transportation problem under demand uncertainty. We address the case of a pharmaceutical logistics network in Brazil and propose mathematical modeling for location and transportation planning with practical features, such as fleet sizing, safety measures in cargo transportation, and tax issues. We propose a mathematical model with multi-time scales for the addressed decisions. Moreover, we address demand uncertainty for decision-making by proposing a robust counterpart. We also investigate solution methods exploring specific characteristics of the problem. We explicitly propose a Fix-and-Optimize heuristics. We develop computational experiments using real data from a partner company and evaluate the impact of the uncertainty over the problem. The heuristics method performs the MIP model by reducing the average costs by 40%. The results showed that demand uncertainty and variability affect the problem decisions significantly. The robust model reduces the expected solution costs. Thus, these models and solution methods can support the decision-making process on location-transportation problems in Logistics Network Planning (LNP), particularly in the context of the pharmaceutical industry in Brazil.

* A working paper based on the contents of this chapter is:

Aura Jalal, Reinaldo Morabito, and Eli Toso (2021): Optimization approach for the integrated planning of logistics network, Technical Report, *Federal University of Sao Carlos*, Brazil.

4.1 Introduction

The pharmaceutical industry faces several challenges, one of which is that its supply chains are usually large and complex with sites in several locations, forcing companies to deal with different regional policies and tax structures. Adding to this already complex network, there should be coordination with the other actors of the network, including third-party logistics providers. The literature on supply chain problems to the pharmaceutical industry addresses different decision levels; however, it is poor at addressing the interaction between levels. Additional, the pharmaceutical sector is exposed to different sources of uncertainties that can be grouped into strategic (changes in the socio-political context and disruptions) and operational (changes in supply chain operations) uncertainties. Moreover, uncertainty and modeling approaches in global supply chain operations should be better exploited (Marques et al., 2020). Jalal et al. (2022b) address some of these issues, however, this study does not consider demand uncertainty. Therefore, in this study, we analyze the case study of the pharmaceutical logistics network in Brazil, taking into account demand uncertainty.

At the beginning of the year, the company decision-makers have to decide in advance and simultaneously about the network design, inventory management, and transportation planning, to negotiate contracts with a third-party logistics provider. Thus, a relevant issue for planning the network refers to the outsourcing of warehousing activities, such as storage, handling, and shipping of products. The logistics operators that carry out these activities have warehouses already established in different locations that can be shared among several companies, offering a reduction in fixed installation costs and greater flexibility for the planning of logistics networks. Thus, DC location decisions can become more dynamic and re-evaluated more frequently, emphasizing the importance of evaluating location decisions and transportation decisions simultaneously. In the pharmaceutical sector, this is common practice, which allows companies to focus on their core business.

Another important aspect of distribution planning for the company is security. Shipments of high-added-value products, such as medicines, are a frequent target for theft in some countries. Thus, it is necessary to take out insurance for product transportation. Insurance companies impose limits on the value of cargo that can be transported without using of escort vehicles and maximum limits on the value of the cargo, even using security services. Particularly in Brazil, distribution planning poses additional challenges, as the distribution of goods is subject to the Circulation Tax on Goods and Services, ICMS. According to (Shah, 2004), tax implications frequently take precedence over logistics issues, resulting in cost-effective but complicated networks. This is the case of ICMS, which depends on the origin-destination of the transportation and, therefore, decisions on the location and choice of DCs, as well as the definition of product flows, significantly impacting the amount to be paid for this tax.

Most of the existing papers on pharmaceutical distribution planning focus on supply chain planning in a broader scope (Sousa et al., 2011; Susarla and Karimi, 2012; Uthayakumar and Priyan, 2013). Sousa et al. (2011) addressed a global supply chain for a pharmaceutical company and proposed a model to decide where to produce and how to distribute it to maximize the net profit value. Susarla and Karimi (2012) developed a MIP model integrating procurement, production, distribution, and several other real-life issues adopting a multi-period approach and a global perspective. In a more specific context, Uthayakumar and Priyan (2013) approached an inventory problem integrating production and distribution considering multiple products for a pharmaceutical company and a hospital supply chain; and Amaro and Póvoa (2008) focused on an integrated production planning and scheduling problem, considering reverse flows. Liu and Papageorgiou (2013) proposed a multiobjective mixed-integer linear programming approach for production, distribution, and capacity planning of global supply chains. On the other hand, few studies specifically addressed the network design. Sousa et al. (2008) address the location, production, and distribution problem by solving the integrated decisions in two stages for a pharmaceutical and agro-chemical industry. Jalal et al. (2022b) propose a multi-product, multi-period, and multi-modal mathematical model integrating network design and distribution planning decisions, such as product flow, transportation modes, type of freight shipping, fleet sizing, and security services for high-value cargo. Moreover, the mathematical formulation takes into consideration realistic features such as value-added tax, whose rate varies among locations.

Uncertainty is inherent in the planning process. Much relevant information to decision-making is not available or may vary over the time horizon, such as retailer demand. Demand uncertainty is an unavoidable issue for most pharmaceutical products because of the uncertainties associated with healthcare providers' decisions, competitor actions, impacts of the entry of a new product, and the launching of a generic version of a product (Laínez et al., 2012). Therefore, a particular problem faced by the pharmaceutical industry in logistics network planning is to balance a capacity network with a demand under such significant uncertainty (Shah, 2004). In most cases, it is reasonable to consider retailer demand uncertain within the planning horizon (of one year, for instance), as it can be known only when the retailer places the order, and at which time the products must be available in the DC to meet the demand. Disregarding uncertainties can result in impractical solutions, or solutions that deteriorate the service level, or solutions with high logistics costs and tax. Thus, it is important to deal with uncertainties in the planning parameters through methodologies that provide robust solutions that are little impacted by changes in the macroeconomic scenario.

Two-stage stochastic programming is an approach that assumes the probability distributions of uncertain data that must be known or considers a set of discrete scenarios to represent the possible realizations of the random variable. The resulting mathematical model increases with the number of scenarios, making it more difficult to solve the problem (Ben-Tal et al., 2009). Robust optimization is a mathematical programming technique to address uncertainties in optimization problems, which bypasses the difficulties involved in stochastic programming (Ben-Tal et al., 2015; Bertsimas and Goyal, 2012; Bertsimas et al., 2015). In robust optimization, random parameters are represented as limited and symmetric random variables, whose possible realizations are contained in a set that, in general, is called an uncertainty set (Bertsimas and Sim, 2003). The objective is to find feasible solutions for all possible realizations of the data within the uncertainty set. Robust optimization has been applied to other problems in the supply chain such as hub network design (Martins de Sá et al., 2018a,b), vehicle routing (De La Vega et al., 2017; Munari et al., 2019), production planning (Alem and Morabito, 2012, 2013, 2015; de Paiva and Morabito, 2011; Munhoz and Morabito, 2012, 2014; Jalal et al., 2022a) and humanitarian logistics (Moreno, 2020; Caunhye et al., 2020).

Particularly, in pharmaceutical network planning, Mousazadeh et al. (2015) considered the pharmaceutical supply chain network design with tactical decisions of production, inventory, and material flows over a mid-term to minimize the total costs and unmet demand. The parameter of demand, manufacturing and transportation cost parameter and safety stock were considered uncertain. A robust possibilistic programming approach is used to handle uncertain parameters. The model was tested on a real case study in the Islamic Republic of Iran, which regards the supply chain network design of amoxicillin. The same methodology, robust possibilistic programming, was used by Zahiri et al. (2018) to propose a mathematical model for the network design of a pharmaceutical supply chain, addressing uncertainties in costs and demand. The authors performed a case study of Rebif supply chain, that is a medicine used to treat patients with recurrent multiple sclerosis. Zahiri et al. (2017) proposed a sustainable-resilient mixed-integer linear programming model for designing a pharmaceutical supply chain network under uncertainty. To cope with the uncertainty in logistics costs, purchasing and selling price of carbon credit, and environmental impact of shipping, a fuzzy possibilistic-stochastic programming approach is developed. The authors presented a case study of the HIV medicines supply chain in France.

In this chapter, we present a mathematical model that addresses the described characteristics and challenges faced by the pharmaceutical distribution planning in Brazil. The model evaluates decisions for the location of DCs, selecting locations of existing DCs of a logistics operator to be rented, taking into account installation costs, inventory decentralization costs, and tax issues associated with ICMS. Simultaneously, flow decisions of multiple products (with different characteristics of weight, volume, price, and temperature condition) between facilities are addressed considering the generation of ICMS, and the cost of transportation through various transportation alternatives that are differentiated by the type of freight, temperature conditioning, and vehicle capacity. In transportation, decisions on the use of escort vehicles for cargo with a monetary value above the established limit are also considered. The objective is to meet the demand of geographically dispersed retailers with minimal logistical costs and minimal tax generation while respecting existing logistical constraints. This is a mathematical model with multi-time scales for the addressed decisions, according to the classification of integrated models presented in Chapter 2. Moreover, we address demand uncertainty for decision-making planning by proposing a robust counterpart for the deterministic model. We also investigate solution methods exploring specific characteristics of the problem such as decomposition-based approaches, Fix-and-Optimize heuristics method using partition criteria by periods and/or arcs is proposed. We develop computational experiments using real data from a partner company and evaluate the impact of the uncertainty on the problem. From this data, we also generate random instances considering different variabilities of the demand in time and quantity. In addition, we compare the integrated model with a sequential approach in terms of total cost and network structures. We also analyze some scenarios with different ICMS rates to understand the sensitivity of solutions to this parameter.

The logistical cost plays an important role in the value of medicines, and the inefficiency in the medicines distribution is reflected in the quality and cost of the products. Therefore, the proposal of using tools to improve the performance of the pharmaceutical logistics network can contribute to reducing the cost of products and, consequently, increasing access to medicines.

We aim to contribute to the literature in different gaps identified in the literature review of Chapter 2. Thus, we address the real problem of a pharmaceutical company. We integrate decisions related to location and transportation using multi-timescales. This model addresses the uncertainty of demand by robust optimization technique. This research has elements of empirical-normative research because the modeling process considers the real characteristics of a problem.

The rest of this chapter is structured as follows: Section 4.2 presents the pharmaceutical sector in Brazil and worldwide. Section 4.3 details the problem description and case study. Section 4.4 presents the model formulation. Section 4.5 presents the heuristics approach. Section 4.6 presents computational results and discussion. Finally, section 4.7 draws the conclusions with some remarks.

4.2 Pharmaceutical sector in Brazil and worldwide

The pharmaceutical industry's supply chain involves several companies, from suppliers in the chemical and packaging industry to retailers that sell the products. The logistics networks are characterized by being comprehensive, comprising industrial plants, warehouses, distributors, and wholesalers (pharmacies, hospitals, purchasing centers of government entities), and geographically dispersed. This spatial distribution is intensified by company acquisition and merger processes, which are very frequent in the pharmaceutical sector.

The pharmaceutical industry's global sales are expected to reach US$1.5 trillion in 2021 (INTERFARMA, 2018). Brazil stands out on the world stage, as it occupies the 8th position in the world ranking of medicine sales and it continues to grow. Regarding job creation, estimates are that the Brazilian pharmaceutical industry in 2015 offered more than 680,000 direct and indirect jobs (SINDUSFARMA, 2017). It is estimated that the Brazilian pharmaceutical industry groups around 600 companies, including suppliers, laboratories, importers, and distributors, and more than 70,000 pharmacies. It is higher than the recommendation of the Worldwide Health Organization, and Brazil is the country with the highest rate of pharmacies per inhabitant in the world (Graciani and Ferreira, 2014). The Brazilian hospital network comprises more than 11,000 establishments distributed in 6,422 hospitals, 774 emergency care units, and 4,346 polyclinics (Hiratuka et al., 2013). This universe of entities, added to the country's territorial extension, means that the medicine supply chain in Brazil has broad capillarity and, in turn, high complexity.

In the characterization of the pharmaceutical chain in Brazil, there is an increasing trend in the outsourcing activities such as storage, shipping, and marketing. Thus, logistics operators gain importance. These have structures for DCs that can be shared among several companies, offering reduced logistics costs and flexibility in planning logistics networks.

The main mode used to transport medicines in Brazil is by road. The general condition of the roads is poor, and leads to high operating costs for transportation services, given the frequent maintenance of vehicles and increased fuel consumption (Confederação Nacional do Transporte, 2016a). The distribution of medicines requires even more attention, as the products are sensitive to mechanical shock and environmental conditions. Depending on their composition, medicines must be kept at different temperature intervals specified by the manufacturers. Maintaining controlled temperature or refrigeration throughout the entire chain generates high costs for energy and fuel consumption (Saif and Elhedhli, 2016).

As mentioned, another factor that deserves attention refers to the fact that vehicles are exposed to frequent theft. The southeast of Brazil concentrates 85.7% of theft cases. The state of Sao Paulo leads the list, accounting for 44.1% of the occurrences. Pharmaceutical products are among those most targeted, in fact, they are the fourth most stolen cargo in Brazil (Confederação Nacional do Transporte, 2016b). Due to this, companies are investing in systems for hiring security services of pilot/escort companies, services provided by insurance companies, and risk managers, to preserve the physical integrity of drivers, vehicles, and transported cargo, which implies even higher transportation costs (Corrêa and Aguiar, 2012). The value of insurance reaches about 15% of the cost of the product.

Another aspect to highlight is the Brazilian tax context. There are several taxes levied on the pharmaceutical sector at federal, state, and municipal levels, therefore the taxes correspond on average to 31.3% of the price of medicines for humans, one of the highest averages in the world (SINDUSFARMA, 2017). In fact, a survey on health policies analyzed the tax burden on medicines in 38 countries, finding that in Brazil it is three times higher than the average of the other countries analyzed (INTERFARMA, 2018). Due to its incidence in all phases of the chain, ICMS is one of the taxes that has the greatest impact on the pharmaceutical chain (Hiratuka et al., 2013). ICMS consists of intrastate and interstate tax rates applied to the value of the goods when leaving the establishment of origin. Thus, when transporting goods between facilities of the same company (for example, from the plant to the DC), the rates are applied to the cost of the goods; and in sales operations (for example, from the DC to the retailer), the rates are applied to the sale price of the merchandise. ICMS rates are defined by state governments, therefore, they vary among different Brazilian states. Thus, moving the same cargo to the same destination state from different origin states implies different amounts of ICMS payable. Consequently, in addition to the costs associated with installation and operation, in location decisions, it is important to consider tax issues that affect the supply chain logistics. For more details on ICMS, see Appendix B.

In this context, the distribution of medicines in Brazil needs to be carefully planned, to deliver quality products to the retailer, within the established deadlines, that is, with high service levels and with the lowest logistics and tax costs to facilitate medicine access for the population. Shortage or inadequate procedures in the medicines distribution can lead to irreparable consequences for final consumers, especially for medicines used in the treatment of serious illnesses. Moreover, any type of failure can negatively affect the image of companies in the market.

4.3 Problem description and case study

This research is motivated by a real problem of one of the largest pharmaceutical companies in the world, which is present in more than 100 countries, and Brazil is one of them. For reasons of confidentiality of the information provided, the company is not identified (Jalal et al., 2022b).

In Brazil, the studied company has industrial plants where a part of its products is produced. Most of the products are imported from foreign plants. The products are imported in bulk, and are packaged in national plants. After that, the medicines are taken to storage in a DC, as the industrial plants do not store the products.

Storage and distribution operations are outsourced, and are performed by a highly specialized logistics operator, who has national and international experience in the logistics of the pharmaceutical sector. The logistics operator already has facilities in many cities around the country and offers shared warehousing services under annual contracts. The logistics operator receives products at the DC, stores, dispatches, and transports the products to retailers, ensuring the conditions required by the products and the requirements of the sector's regulatory entities. Currently, the company centralizes its warehousing and distribution operations in DCs located close to the factories. Since the storage is outsourced, locating new DCs does not entail incurring construction and equipment purchase costs. The company must only assume contractual commitments with the logistics operator, cost of rental of the DC, storage of products, and insurance for the stock. Therefore, DC location decisions may be reassessed from time to time to take advantage of changes or opportunities in the environment. On the other hand, industrial plant location decisions involve high costs and complexity, due to the high investment in technology, and adjustment to the broad and rigorous applicable legislation, among other factors, and are not of interest in this study.

The company's retail portfolio is made up of public and private institutions: pharmaceutical chains, independent pharmacies, health centers, hospitals, and clinics, spread across all the states of the country.

The company's product portfolio is quite broad, offering more than 250 different items, ranging from over-the-counter medications without medical indication, such as antipyretic pills, to highly specialized medications for rare diseases. Medicines have different characteristics of weight, volume, price, demand, and temperature conditions required for product conservation, that is, room temperature or cold chain. These characteristics interfere in the planning of logistical operations because issues such as temperature conditions in storage and transport, selection of transportation alternatives, and the maximum quantity of products transported in one shipment, among others, depend on them. Figure 4.1 shows a representation of the logistics network, showing the echelons and the storage and transportation of products at room temperature and cold chain.

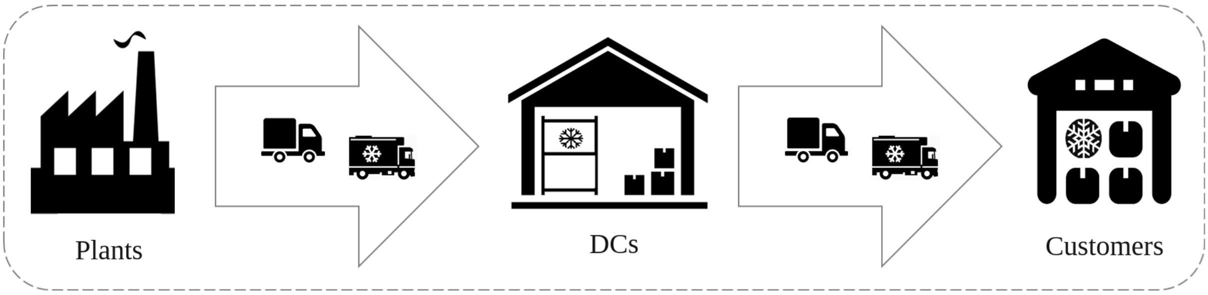


Figure 4.1: Logistics network

The cost of stocking products on the DCs depends on the conditions under which the drugs must be stored, room temperature or cold room, and the quantity of products stored.

The transportation cost is defined by previously negotiated price lists for the different available alternatives. According to Hiratuka et al. (2013), transportation costs vary mainly as a result of the conditions of the network, the average age of the truck fleet, and the high levels of vehicle traffic in large urban centers. In the case of the studied company, the cost of transportation alternatives varies depending on the following factors:

- Types of freight: complete/dedicated or fractional;
- Vehicle load capacity;
- Cargo conditioning: handling dry or cold cargo;
- Other factors such as access, state, and security of highways or airports.

Regarding the type of cargo, the company considers the alternative of sending a full load (*Full truckload*-FTL), which can use vehicles of different capacity in volume, and the alternative of fractional loading (*Less Than Truckload*-LTL), for smaller volume shipments, sharing the freight with products from other companies. Transporting smaller quantities leads to reduced costs associated with retailers' inventories, but requires additional freight costs.

The cost of fractional cargo depends on the weight of the goods, and it is only possible to ship products at room temperature. The full load cost, on the other hand, depends on the capacity of the vehicle used, which can be in weight or volume, depending on the characteristics of the products. Through these aspects, the logistics operator defines a price structure for the company, by cargo weight ranges, in the case of fractional alternatives, and by type of vehicle used, in the case of dedicated transportation alternatives. The number of dedicated vehicles to be hired must be adequately defined by the company. If it is underestimated, the company will pay a high price on the spot market (out of contract) for a dedicated vehicle. However, if the number of vehicles is overestimated, part of the rented vehicles will remain idle.

Due to the high rates of cargo theft and accidents during transport, there are restrictions on the flow of products associated with the monetary value of the cargo. That is, insurance companies establish limits for the total value of the transported cargo, after which they do not provide coverage for eventualities such as accidents, losses, or theft; therefore, cargo transportation with a value above the limit is undesirable. In addition, there is a monetary value limit for the cargo, above which vehicles must be escorted by a pilot/escort car during the journey, incurring extra costs for transportation because medicines are high added-value products and the *Ad Valorem* rates are not enough to cover the safety costs.

Products in addition to being stocked on DCs can be placed in stock at retailers as consignment inventory to meet the demand for future periods. It means the products are sold by the retailers, but ownership is retained by the company until the products have been sold, and unsold products can be returned from retailer to company. Thus, a large inventory at the retailer is undesirable due to the uncertainty in demand, risks of expiration and damage of products, and limited space at retailers. Consequently, the inventory at the retailer is highly penalized with a unitary early delivery cost proportional to the product price. These products can also be delivered late at the cost of delayed delivery proportional to the product price. Backlogging is also undesirable because it affects the service level, which is a priority for the company.

In the operational planning of distribution, as the company receives orders from retailers, it assesses the feasibility of meeting delivery terms and conditions, considering the transportation alternatives previously negotiated. Thus, both the physical structure of the network, more specifically the location of the DC, as well as the planned transportation structure, affect the entire dynamics of the operation. In other words, tactical planning decisions are determining factors for good performance at the operational level. In this context, the challenges for planning the logistics network observed in the company involve integrating decisions at the tactical level. Figure 4.2 presents the proposed decision timing of the location-transportation problem.

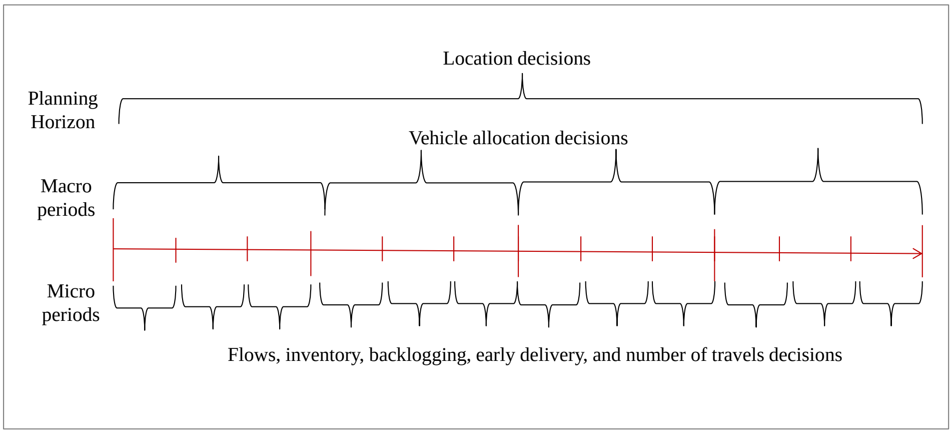


Figure 4.2: Proposed decision timing of the location-transportation problem

4.4 Mathematical formulation

The notation used in the formulation is presented below.

Sets

$i \in \mathcal{I}$	Industrial plants
$j \in \mathcal{J}$	Potential locations for DCs
$k \in \mathcal{K}$	Retailers
$l \in \mathcal{L}$	Transportation alternatives
$\mathcal{L}_{DV} \subset \mathcal{L}$	Dedicated vehicles
$\mathcal{L}_{LTL} \subset \mathcal{L}$	LTL transportation alternatives
$p \in \mathcal{P}$	Products
$t \in \mathcal{T}$	Time periods
$\theta \in \Theta$	Macro time periods
$\mathcal{T}(\theta) \subseteq \mathcal{T}$	Subset of the periods within macro period θ.

Parameters

d_{pkt}	Demand of product p in retailer k in period t
c_{ijl}, c'_{jkl}	Transportation cost (per unit of weight) from plant i to DC j and from DC j to retailer k using transportation $l \in \mathcal{L}_{LTL}$
f_{ijl}, f'_{jkl}	Transportation cost from plant i to DC j and from DC j to retailer k using transportation $l \in \mathcal{L}_{DV}$
g_l	Fixed cost of hiring dedicated vehicle $l \in \mathcal{L}_{DV}$
h_{pj}	Unitary inventory cost of product p in DC j
o_j	Opening cost of DC j

Parameters

q_l	Volume capacity of transportation alternative $l \in \mathcal{L}_{DV}$
r^A_{pk}	Unitary early delivery cost of product p at retailer k
r^B_{pk}	Unitary backlogging cost of product p at retailer k
$\alpha_{ij}, \alpha^{'}_{jk}$	ICMS tax from plant i to DC j and from DC j to the retailer k
$\epsilon_{ij}, \epsilon^{'}_{jk}$	Cargo security cost for shipping from plant i to DC j and from DC j to retailer k
λ_{ij}, λ'_{jk}	Distance from plant i to DC j and from DC j to retailer k.
Λ^{max}_l	Limit for distance traveled for each vehicle $l \in \mathcal{L}_{DV}$ in one period
γ_l	Limit on the monetary value of the load per truck in alternatives $l \in \mathcal{L}_{DV}$
σ	Limit on the monetary value of the load per truck in alternatives $l \in \mathcal{L}_{DV}$ without pilot/escort vehicle
π_p	Production cost of product p
ρ_p	Price of product p
υ_p	Volume of product p
ω_p	Weight of product p
M	Large number

Continuous variables

A_{pkt}	Inventory of product p at the retailer k in period t
B_{pkt}	Amount of product p backlogging to the retailer k in period t
I_{pjt}	Inventory of product p at DC j in period t
Q_j	ICMS payable by DC j
X_{pijlt}, X'_{pjklt}	Flow of product p from plant i to DC j and from DC j to retailer k using transportation alternative $l \in \mathcal{L}$ in period t

Integer variables

Y_j	1, if DC j is open; 0, otherwise
$W_{jl\theta}$	Number of dedicated vehicle $l \in \mathcal{L}_{DV}$ hired and allocated to DC j in macro period θ
Z_{ijlt}, Z'_{jklt}	Trips from plant i to DC j and from DC j to retailer k using alternatives $l \in \mathcal{L}_{DV}$ in period t
E_{ijlt}, E'_{jklt}	Trips with pilot/escort vehicles from plant i to DC j and from DC j to retailer k using alternative $l \in \mathcal{L}_{DV}$ in t; 0, otherwise

4.4.1 Deterministic mathematical model

The location and transportation problem can be formulated as a mixed-integer linear programming model. Jalal et al. (2022b) address the same case study, however in this formulation the escort vehicle trips are modeled in a more realistic and understandable way, and ICMS is also calculated in a comprehensible fashion, as follows:

$$
\begin{aligned}
\min \Psi_2 = \min \Bigg[& \sum_{j \in \mathcal{J}} o_j Y_j + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \sum_{p \in \mathcal{P}} h_{pj} I_{pjt} \\
& + \sum_{\theta \in \Theta} \sum_{l \in \mathcal{L}_{DV}} \sum_{j \in \mathcal{J}} g_l W_{jl\theta} + \sum_{t \in \mathcal{T}} \sum_{p \in \mathcal{P}} \sum_{l \in \mathcal{L}_{LTL}} \sum_{j \in \mathcal{J}} \Big(\sum_{i \in \mathcal{I}} c_{ijl} \omega_p X_{pijlt} + \sum_{k \in \mathcal{K}} c'_{jkl} \omega_p X'_{pjklt} \Big) \\
& + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}_{DV}} \Big(\sum_{i \in \mathcal{I}} f_{ijl} Z_{ijlt} + \sum_{k \in \mathcal{K}} f'_{jkl} Z'_{jklt} \Big) + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}_{DV}} \Big(\sum_{i \in \mathcal{I}} \epsilon_{ij} E_{ijlt} + \sum_{k \in \mathcal{K}} \epsilon_{jk} E'_{jklt} \Big) \\
& + \sum_{j \in \mathcal{J}} Q_j + \sum_{t \in \mathcal{T}} \sum_{k \in \mathcal{K}} \sum_{p \in \mathcal{P}} \Big(r^A_{pk} A_{pkt} + r^B_{pk} B_{pkt} \Big) \Bigg]
\end{aligned}
\tag{4.1}
$$

Subject to:

$$
\sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjklt} + A_{pkt-1} - A_{pkt} - B_{pkt-1} + B_{pkt} = d_{pkt}, \ \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}. \tag{4.2}
$$

$$\sum_{i\in\mathcal{I}}\sum_{l\in\mathcal{L}} X_{pijlt} + I_{pj(t-1)} = \sum_{k\in\mathcal{K}}\sum_{l\in\mathcal{L}} X'_{pjklt} + I_{pjt},\ \forall j \in \mathcal{J}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{4.3}$$

$$\sum_{i\in\mathcal{I}}\sum_{p\in\mathcal{P}}\sum_{l\in\mathcal{L}_{DV}}\sum_{t\in\mathcal{T}} X_{pijlt} \le MY_j,\ \forall j \in \mathcal{J} \tag{4.4}$$

$$\sum_{l\in\mathcal{L}}\sum_{\theta\in\Theta} W_{jl\theta} \le M'Y_j,\ \forall j \in \mathcal{J} \tag{4.5}$$

$$\sum_{p\in\mathcal{P}_l} \upsilon_p X_{pijlt} \le q_l Z_{ijlt},\ \forall i \in \mathcal{I}, j \in \mathcal{J}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.6}$$

$$\sum_{p\in\mathcal{P}_l} \upsilon_p X'_{pjklt} \le q_l Z'_{jklt},\ \forall j \in \mathcal{J}, k \in \mathcal{K}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.7}$$

$$\sum_{p\in\mathcal{P}_l} \rho_p X_{pijlt} \le \gamma_l Z_{ijlt},\ \forall i \in \mathcal{I}, j \in \mathcal{J}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.8}$$

$$\sum_{p\in\mathcal{P}_l} \rho_p X'_{pjklt} \le \gamma_l Z'_{jklt},\ \forall j \in \mathcal{J}, k \in \mathcal{K}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.9}$$

$$\sum_{p\in\mathcal{P}_l} \rho_p X_{pijlt} - \sigma Z_{ijlt} \le (\gamma_l - \sigma) E_{ijlt},\ \forall i \in \mathcal{I}, j \in \mathcal{J}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.10}$$

$$\sum_{p\in\mathcal{P}_l} \rho_p X'_{pjklt} - \sigma Z'_{jklt} \le (\gamma_l - \sigma) E'_{jklt},\ \forall j \in \mathcal{J}, k \in \mathcal{K}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.11}$$

$$\sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}(\theta)} \lambda_{ij} Z_{ijlt} + \sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}(\theta)} \lambda'_{jk} Z'_{jklt} \le \Lambda_l^{max} W_{jl\theta},\ \forall j \in \mathcal{J}, l \in \mathcal{L}_{DV}, \theta \in \Theta. \tag{4.12}$$

$$\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}}\sum_{p\in\mathcal{P}}\sum_{i\in\mathcal{I}} \alpha_{ij}\pi_p X_{pijlt} \le Q_j,\ \forall j \in \mathcal{J}. \tag{4.13}$$

$$\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}}\sum_{p\in\mathcal{P}}\sum_{k\in\mathcal{K}} \alpha'_{jk}\rho_p X'_{pjklt} \le Q_j,\ \forall j \in \mathcal{J}. \tag{4.14}$$

$$Y_j \in \{0,1\},\ j \in \mathcal{J}. \tag{4.15}$$

$$W_{jl\theta} \in \{0,1\},\ j \in \mathcal{J}, l \in \mathcal{L}, \theta \in \Theta. \tag{4.16}$$

$$Z_{ijlt}, Z'_{jklt}, E_{ijlt}, E'_{jklt} \in \{0,1\},\ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, l \in \mathcal{L}_{DV}, t \in \mathcal{T}. \tag{4.17}$$

$$X_{pijlt}, X'_{pjklt}, A_{pkt}, B_{pkt}, I_{jpt}, Q_j \ge 0,\ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, p \in \mathcal{P}, l \in \mathcal{L}, t \in \mathcal{T}. \tag{4.18}$$

The objective function (4.1) minimizes the distribution costs, early delivery, and backlogging costs. The first term comprises DC opening costs and the second term represents the inventory costs. The allocation costs of the vehicles to opened DCs among the macro periods are represented by the third term. Shipment costs for LTL freights are represented by the fourth and fifth terms. Note that the costs of LTL alternatives depend on product weight and the flow of products. Shipment costs for TL freights are represented by the sixth and seventh terms that depend on the number of trips. The eighth and ninth terms represent the security costs for TL freight with escort/pilot vehicles, these costs depend on the number of trips for which the cargo value exceeds the limit imposed by insurance companies. Finally, the tax costs are represented by the tenth term, and the eleventh and twelfth costs represent the penalties for early delivery and backlogging at retailers.

The balance constraints (4.2) are required to guarantee demand satisfaction. For each period, product and retailer, if the amount delivered (i.e., transportation from DCs plus early delivery in $t-1$) is less than the products demand to the actual period, there is backlogging, $B_{pkt} > 0$. If the amount delivered is more than the demand for the actual period, there is an early delivery, $A_{pkt} > 0$. Constraints (4.3) ensure the flow balance of products in each DC considering $I_{pj0} = 0$. Constraints (4.4) ensure a flow of products only to open DCs, and the parameter M is estimated as the total demand required by the retailers in the planning horizon. Constraints (4.5) ensure that vehicles are allocated only to open DCs, and the parameter M' is estimated based on the total demand, the volume of products, and the capacity of vehicles, ensuring that this parameter is slack. Constraints (4.6) and (4.7) relate the flow of products and the number of trips required for each TL shipping alternative, respecting the capacity of vehicles (q_l). In addition, to determine the number of required trips, there are also limits to the load value, according to the insurance values agreed upon by the carrier. Constraints (4.8) and (4.9) ensure that the value of load does not exceed the value covered by the insurance. For LTL transportation alternatives, the costs of insurance and cargo security services are embedded in transportation costs. Moreover, due to the high value of the pharmaceutical cargo, security services are used when the value of the cargo exceeds the prescriptive limit σ. For load values above the limit σ, constraints (4.10) and (4.11) make it mandatory to use escort vehicles. Constraints (4.12) ensure the maximum distance allowed to vehicles. Constraints (4.13) and (4.14) calculate the ICMS payable by the DCs. Lastly, constraints (4.15)–(4.18) are domain variables.

4.4.2 Uncertainty set

This section presents a robust counterpart of the proposed mathematical model. We assume that the demand d_{pkt} is uncertain. The uncertain parameters are modeled as independent, limited and symmetric random variables that assume values in the intervals $\tilde{d}_{pkt} \in [d_{pkt} - \hat{d}_{pkt}, d_{pkt} + \hat{d}_{pkt}]$ for demand. Here, d_{pkt} represents the expected (nominal) value, and $\hat{d}_{pkt}$ represents the maximum deviation of the random variable allowed from its corresponding nominal value. To deal with these uncertainties, we propose a robust optimization model assuming that the uncertain demands belong to the convex uncertainty set $\mathcal{U}^d_{pkt}$. The aim is to find the best solution that satisfies every realization of the uncertain parameter that belongs to $\mathcal{U}^d_{pkt}$. We consider the budgeted uncertainty set proposed by Bertsimas and Sim (2004). This set provides robust counterparts as tractable as their original deterministic formulations (Bertsimas and Sim, 2003). Let $\tilde{d}_{pkt}$ be rewritten as $\tilde{d}_{pkt} = d_{pkt} + \hat{d}_{pkt}\xi_{pkt}$, where ξ_{pkt} is a random variable that assumes values in the interval $[-1, 1]$. The uncertainty set $\mathcal{U}^d_{pkt}$ is defined as follows for all product p, retailer k, and period t:

$$\mathcal{U}^d_{pkt} = \left\{ \boldsymbol{\xi} \in \mathbb{R}^{|\mathcal{P}||\mathcal{K}||\mathcal{T}|} : \sum_{\tau=1}^{t} |\xi_{pk\tau}| \leq \Gamma^d_{pkt} \ \wedge \ -1 \leq \xi_{pk\tau} \leq 1, \ \forall \tau = 1, \ldots, t \right\} \tag{4.19}$$

where the cumulative uncertainty of the random variables is bound by their budget of uncertainty

Γ^d_{pkt}.

4.4.3 Deterministic reformulation

Note that the uncertain demand is only considered in constraints (4.2) of the deterministic model, i.e., there is only one demand parameter in these constraints. It means that the equality constraints (4.2) are not appropriate for implementing static robust optimization (RO) methodology, which requires that the model must continue to be feasible for all realizations of the uncertainty set because the inventory variables are not realization-dependent. To obtain a robust counterpart formulation for the problem, we must introduce constraints that can be met for all realizations of uncertain parameters within the uncertainty set, i.e., it is necessary to reformulate the deterministic counterpart. To do that, an aggregate formulation is required to express the cumulative demand over time in the same constraint (Alem and Morabito, 2012; Alem et al., 2018; Jalal et al., 2022a). In the reformulation, we rewrite Equation (4.2) in terms of the difference between the inventory and the backlogging at retailer k in period t, as shown in Equation (4.20).

$$A_{pkt} - B_{pkt} = A_{pkt-1} - B_{pkt-1} + \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjklt} - d_{pkt} \, \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}. \tag{4.20}$$

Then, we obtain the aggregate form in terms only of the initial inventory/backlogging at retailers, as follows:

$$A_{pkt} - B_{pkt} = A_{pk0} - B_{pk0} + \sum_{\tau=1}^{t} \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjklt} - \sum_{\tau=1}^{t} d_{pkt} \, \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}. \tag{4.21}$$

Let $S_{pkt} = A_{pkt} - B_{pkt}$ be the net inventory, an unrestricted variable able to represent inventory or backlogging at the retailer. Then, we have:

$$S_{pkt} = S_{pk0} + \sum_{\tau=1}^{t} \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjklt} - \sum_{\tau=1}^{t} d_{pkt} \, \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}. \tag{4.22}$$

We consider a convex and piecewise linear inventory/backlogging cost function of the form:

$$R_{pkt} = \max\{r^A_{pk} \; S_{pkt}, -r^B_{pk} \; S_{pkt}\} \, \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}. \tag{4.23}$$

Finally, based on the piecewise linearity and convexity of the inventory/backlogging cost function, and assuming that initial inventory and backlogging quantities are zero without loss of generality, we have the following pair of inequalities that replace equality (4.2):

$$R_{pkt} \geq r^A_{pk} \; S_{pkt} = r^A_{pk} \left(\sum_{\tau=1}^{t} \left(\sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) \right), \qquad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.24}$$

$$R_{pkt} \geq r^B_{pk} \; (-S_{pkt}) = r^B_{pk} \left(- \sum_{\tau=1}^{t} \left(\sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) \right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.25}$$

In this case, we have obtained a deterministic equivalent reformulation with the cumulative demand over time in constraints (4.24) and (4.25). Considering the demand uncertainty, these constraints can be expressed, as follows:

$$R_{pkt} \geq r^{A}_{pk}\ S_{pkt} = r^{A}_{pk} \left(\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - \tilde{d}_{pk\tau} \right) \right), \qquad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.26}$$

$$R_{pkt} \geq r^{B}_{pk}\ (-S_{pkt}) = r^{B}_{pk} \left(-\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - \tilde{d}_{pk\tau} \right) \right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.27}$$

Then,

$$R_{pkt} \geq r^{A}_{pk}\ S_{pkt} = r^{A}_{pk} \left(\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} - \hat{d}_{pk\tau}\xi_{pk\tau} \right) \right), \qquad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.28}$$

$$R_{pkt} \geq r^{B}_{pk}\ (-S_{pkt}) = r^{B}_{pk} \left(-\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} - \hat{d}_{pk\tau}\xi_{pk\tau} \right) \right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.29}$$

4.4.4 Robust optimization counterpart

We now develop a robust optimization counterpart for the deterministic reformulation, i.e., the objective function (4.1) presented below subject to constraints (4.3) to (4.18) and (4.28) to (4.29). Considering the uncertainty budget $\Gamma^{d}_{pkt} \in [0, t]$ and the variable $\xi_{pk\tau}$, we apply the robust optimization technique developed in Bertsimas and Sim (2003). We have to maximize the right-hand side of constraints (4.28) and (4.29) over the set of all admissible realizations of the uncertain demands. As robust optimization is based on an optimization of worst-case perspective, the auxiliary problem results in minimizing $\sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau}$ in constraint (4.28) and maximizing $\sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau}$ in constraint (4.29), as follows:

$$R_{pkt} \geq r^{A}_{pk} \left(\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) - \min \sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau} \right), \qquad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.30}$$

$$R_{pkt} \geq r^{B}_{pk} \left(-\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) + \max \sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau} \right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.31}$$

that is equivalent to:

$$R_{pkt} \geq r^{A}_{pk} \left(\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) + \max \sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau} \right), \qquad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.32}$$

$$R_{pkt} \geq r^{B}_{pk} \left(-\sum_{\tau=1}^{t} \left(\sum_{j\in\mathcal{J}} \sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) + \max \sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau} \right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.33}$$

Then, for a given p, k and t, we have to solve the following auxiliary problem:

$$\max \sum_{\tau=1}^{t} \hat{d}_{pk\tau}\xi_{pk\tau} \tag{4.34}$$

$$\text{s.t.} \quad \sum_{\tau=1}^{t} \xi_{pk\tau} \le \Gamma^d_{pkt}, \tag{4.35}$$

$$0 \le \xi_{pk\tau} \le 1, \qquad \forall \tau \le t. \tag{4.36}$$

Using the duality technique, we have the dual problem of the primal problem (4.34) - (4.36). For each p, k and t:

$$\min \; (\Gamma^d_{pkt}\lambda^d_{pkt} + \sum_{\tau=1}^{t} \mu^d_{pkt\tau}) \tag{4.37}$$

$$\text{s.t.} \quad \lambda^d_{pkt} + \mu^d_{pkt\tau} \ge \hat{d}_{pk\tau}, \; \forall \tau \le t, \tag{4.38}$$

$$\lambda^d_{pkt} \ge 0, \tag{4.39}$$

$$\mu^d_{pkt\tau} \ge 0, \; \forall \tau \le t. \tag{4.40}$$

Now, we have:

$$R_{pkt} \ge r^A_{pk}\left(\sum_{\tau=1}^{t}\left(\sum_{j\in\mathcal{J}}\sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau}\right) + \min\left(\Gamma^d_{pkt}\lambda^d_{pkt} + \sum_{\tau=1}^{t}\mu^d_{pkt\tau}\right)\right), \quad \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.41}$$

$$R_{pkt} \ge r^B_{pk}\left(-\sum_{\tau=1}^{t}\left(\sum_{j\in\mathcal{J}}\sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau}\right) + \min\left(\Gamma^d_{pkt}\lambda^d_{pkt} + \sum_{\tau=1}^{t}\mu^d_{pkt\tau}\right)\right), \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.42}$$

Since the objective function aims to minimize R_{pkt}, the inner problem of minimizing in the constraints can be removed, and we obtain the following robust model for the addressed problem under uncertainty:

$$\begin{aligned} \min \Psi_2 = \min \Bigg[& \sum_{j\in\mathcal{J}} o_j Y_j + \sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}} h_{pj} I_{pjt} \\ & + \sum_{\theta\in\Theta}\sum_{l\in\mathcal{L}_{DV}}\sum_{j\in\mathcal{J}} g_l W_{jl\theta} + \sum_{t\in\mathcal{T}}\sum_{p\in\mathcal{P}}\sum_{l\in\mathcal{L}_{LTL}}\sum_{j\in\mathcal{J}}\Big(\sum_{i\in\mathcal{I}} c_{ijl}\omega_p X_{pijlt} + \sum_{k\in\mathcal{K}} c'_{jkl}\omega_p X'_{pjklt}\Big) \\ & + \sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}}\sum_{l\in\mathcal{L}_{DV}}\Big(\sum_{i\in\mathcal{I}} f_{ijl} Z_{ijlt} + \sum_{k\in\mathcal{K}} f'_{jkl} Z'_{jklt}\Big) + \sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}}\sum_{l\in\mathcal{L}_{DV}}\Big(\sum_{i\in\mathcal{I}} \epsilon_{ij} E_{ijlt} + \sum_{k\in\mathcal{K}} \epsilon_{jk} E'_{jklt}\Big) \\ & + \sum_{j\in\mathcal{J}} Q_j + \sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{K}}\sum_{p\in\mathcal{P}} R_{pkt}\Big) \Bigg] \end{aligned} \tag{4.43}$$

Subject to (4.3) to (4.18)

$$R_{pkt} \ge r^A_{pk}\left(\sum_{\tau=1}^{t}\left(\sum_{j\in\mathcal{J}}\sum_{l\in\mathcal{L}} X'_{pjkl\tau} - d_{pk\tau}\right) + \Gamma^d_{pkt}\lambda^d_{pkt} + \sum_{\tau=1}^{t}\mu^d_{pkt\tau}\right), \; \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.44}$$

$$R_{pkt} \geq r_{pk}^{B} \left(- \sum_{\tau=1}^{t} \left(\sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} X'_{pjkl\tau} - d_{pk\tau} \right) + \Gamma_{pkt}^{d} \lambda_{pkt}^{d} + \sum_{\tau=1}^{t} \mu_{pkt\tau}^{d} \right), \ \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T} \tag{4.45}$$

$$\lambda_{pkt}^{d} + \mu_{pkt\tau}^{d} \geq \hat{d}_{pk\tau}, \ \forall p \in \mathcal{P}, k \in k, t \in \mathcal{T}, \tau \leq t, \tag{4.46}$$

$$\mu_{pkt\tau}^{d}, \lambda_{pkt}^{d} \geq 0, \ \forall p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}, \tau \leq t, \tag{4.47}$$

where λ_{pkt}^{d}, μ_{pkt}^{d} are the dual variables associated with the constraints of the primal problem (4.34) - (4.36).

4.5 Solution methods

Facility location problems are NP-hard, and as they are integrated with other decisions (such as vehicle allocation, and mode selection) can result in a mathematical model with a greater number of constraints and variables, and consequently, it can be more difficult to solve. The uncertainty in input data of this location problem may reduce the importance of attempting to find the best solution in real and large problems when multiple high-quality solutions can be found (Guazzelli and Cunha, 2018). Mixed-integer programming heuristics, based on decomposition schemes and taking advantage of the model's structure that involves multiple periods, have been proposed in the literature in an attempt to obtain good solutions by solving smaller and easier subproblems. Relax-and-Fix and Fix-and-Optimize heuristics have been successfully used in location and transportation problems (Moreno et al., 2016, 2018), Location and routing problem (Rieck et al., 2014), location and network design problem (Rahmaniani and Ghaderi, 2013; Ghaderi and Jabalameli, 2013), and hub location (He et al., 2015; Etemadnia et al., 2015). We developed Relax-and-Fix and Fix-and-Optimize heuristics and carried out preliminary experiments, and the Fix-and-Optimize heuristics was the most promising method. Thus, in this section, we present a Fix-and-Optimize heuristics for the addressed problem.

Fix-and-Optimize heuristics (*F&O*) starts with an initial feasible solution and tries to improve it iteratively by solving the subproblems generated by the partition criteria that we defined in Table 4.1. A pseudo-code for the *F&O* algorithm based on dividing the problem by periods and arcs is outlined in Algorithm 1. The basic idea is to compare the current solution to the incumbent one as the subproblems are successively solved. If the current solution is better than the incumbent, we need to update the former according to the new MIP solution. Otherwise, the current solution is equal to the incumbent one.

To obtain an initial feasible solution, a relaxed problem considering the variables associated with the number of trips as continuous variables is solved. Then, the solution obtained from the first step is adapted to be feasible in the original integrated model by simply approximating the number of trips to the nearest higher integer value.

Table 4.1: Summary of the proposed strategies.

Partition criteria	Variable fixing criteria	Strategy name
By period	Z_{ijlt}, Z'_{jklt}	*F&O*1
	$Z_{ijlt}, Z'_{jklt} > 0$	*F&O*2
By period and arc	Z_{ijlt}, Z'_{jklt}	*F&O*3
	$Z_{ijlt}, Z'_{jklt} > 0$	*F&O*4
By period (two periods)	Z_{ijlt}, Z'_{jklt}	*F&O*5
	$Z_{ijlt}, Z'_{jklt} > 0$	*F&O*6
By period and arc (two periods)	Z_{ijlt}, Z'_{jklt}	*F&O*7
	$Z_{ijlt}, Z'_{jklt}, > 0$	*F&O*8

In Table 4.1, strategies *F&O*1 to *F&O*4 consider subproblems of one period, while strategies *F&O*5 to *F&O*8 consider subproblems of two periods. On the other hand, strategies *F&O*1, *F&O*3, *F&O*5, *F&O*7, after solving the subproblems, fix all variables, while the other strategies fix only the variables with values larger than zero.

Algorithm 2: Fix-and-Optimize - *F&O*4

Initialization: Initial solution. ;
Fix the variables larger than zero in their current values ;
Incumbent solution := initial solution, OF_incumbent := objective function of the initial solution, OF_MIP := objective function of the subproblem ;
for $t = 1$ ***to*** $|\mathcal{T}|$ **do**
    Unfix the discrete variables Z_{ijlt} ;
    Solve the resulting subproblem ;
    if *OF_MIP* $<$ *OF_incumbent* **then**
        Incumbent solution := MIP solution ;
        OF_incumbent:= OF_MIP ;
        Fix variables larger than zero according to the incumbent solution.
    end
    Unfix the discrete variables Z'_{jklt} ;
    Solve the resulting subproblem ;
    if *OF_MIP* $<$ *OF_incumbent* **then**
        Incumbent solution := MIP solution ;
        OF_incumbent:= OF_MIP ;
        Fix variables larger than zero according to the incumbent solution.
    end
end

4.6 Computational experiments and discussion

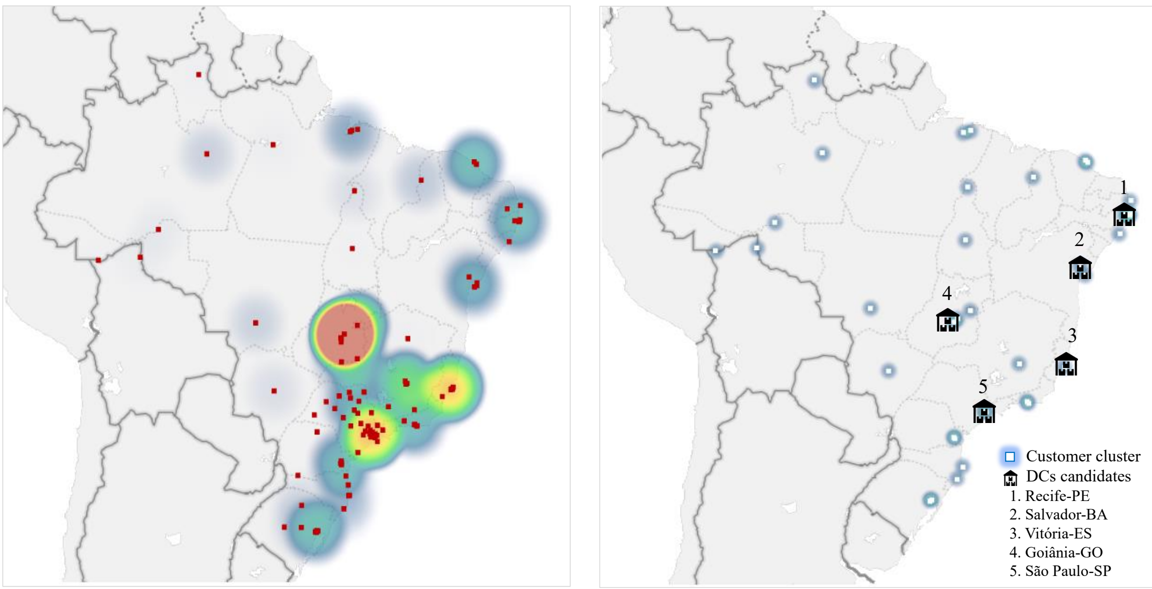
This section presents the results of the computational experiments carried out according to the proposed mathematical models, deterministic model (4.1) to (4.18) and robust model (4.43) - (4.47), and solution method, *F&O*, of previous section. The purpose is to evaluate our approach to modeling and solving the integrated location-transportation problem. Thus, we organize this section as follows: Subsection 4.6.1 presents the data and instances description. Subsection

4.6.2 compares the results achieved by *F&O* with those obtained by the solver CPLEX (IBM, 2019), when solving the deterministic and robust models. In Subsection 4.6.3, we carried out tests to study the impact of integrating decisions into the problem. Subsection 4.6.4 presents some cases with different ICMS contexts to be analyzed. Subsection 4.6.5 analyzes the impact of the uncertainties and the quality of the robust solutions, obtained by solving the robust model (4.43) - (4.47) and applying the *F&O* heuristics.

The models were coded in C++ programming language and solved using the general-purpose optimization software IBM CPLEX version 20.10, with its default configuration. A Linux PC with a CPU Intel Core i7 3.4 GHz and 16.0 GB of memory was used to run the experiments. The stopping criterion was due to either the elapsed time exceeding the time limit of 3600 seconds or the optimality gap becoming smaller than 10^{-4}.

4.6.1 Case study and instances generation

The data set used in the computational test is based on the current operations of a pharmaceutical company with operations in Brazil. The logistics network comprises three entities: plants, DCs, and retailers. Due to the tactical nature of the study, retailers are grouped into 54 clusters and assigned to the capital and countryside of each Brazilian state. This company has a plant and a DC operating in Sao Paulo. From the plant, products are sent to DC managed by logistics operators, from which the company meets the demand of retailers all over the country. The management board has decided to open new DCs, and five cities were chosen as candidates: Sao Paulo, Goiania, Vitoria, Recife e Salvador. Figure 4.3 presents maps based on the Brazilian political and administrative division: Figure 4.3(a) shows a heat map with client demands whereas Figure 4.3(b) shows retailer groups and DC candidates.



(a) Demand distribution

(b) Candidate locals

Figure 4.3: Heat map of client demands and candidate locations for DCs (Jalal et al., 2022b)

Simultaneously, managers have to make transportation decisions regarding demand fulfillment and transportation mode selection, considering the insurance measures and restrictions. The carriers offer transportation alternatives that differ in freight type and temperature conditions. Thus, there are four transportation options: less-than-truckload alternative, truckload with tree vehicle types, i.e., mid-size truck, large truck, and large-and-refrigerated truck.

Due to the tactical nature of the problem, we aggregated the wide portfolio of the company into product families, based on similar characteristics. We employed the *K-Means* method to group products into 30 product families. The *K-Means* method aims to divide M points in N dimensions into K clusters so that the within-cluster sum of squares is minimized (Hartigan and Wong, 1979). We consider the dimensions or attributes of temperature conditions, size, weight, price, and demand patterns of products to cluster the products. Since DC rental agreements are made annually, we assume a one-year planning horizon to evaluate the DC location, but transportation decisions should be considered in shorter periods. We divided the planning horizon into 12 periods and 4 macro-periods.

The product costs ρ_p were assumed as 40% of the product price. The early delivery costs r_{pk}^{A} were estimated as 25% of the product price. As the company's service policy is geared towards maintaining a high service level, delivery delays r_{pk}^{B} are not desirable and are penalized with very high values, 5 times the product price, respectively. Regarding ICMS, the current tax rates were considered, α_{ij} and $\alpha^{'}_{jk}$ vary among 7%, 12%, 17%, and 18%.

We consider different variabilities of the demand in time and quantity to generate instances. Smooth demand has low variability both in time and magnitude; intermittent demand has demand magnitude relatively constant, but there are large and irregular gaps between non-zero demand values; erratic demand does not have a lot of gaps on time, but the magnitudes vary significantly and irregularly; finally, lumpy demand is both intermittent and erratic, with irregular gaps and sharp changes in the magnitude (Syntetos et al., 2005). Thus, we consider instances where all products present the same variability, i.e. smooth, intermittent, erratic, and lumpy demand, and an instance with regular demand, based on the real data of the company with products with different demand variabilities at the same time. Table 4.2 presents the number of binary and continuous variables; and the number of constraints, of model (4.43) - (4.47). Note that the size of the MIP model is huge, with thousands of variables and constraints.

Table 4.2: Instances

Model	Instance	Decision variables		Constraints
		Binary	Continuous	
Deterministic	Each instance	19,865	436,685	51,020
Robust	Each instance	19,865	1,953,005	1,586,780

To incorporate uncertainty into the instances, we define the deviations of the demand $\hat{d}_{pkt}$ as $\beta \in \{0.1, 0.2, 0.3\}$. The robust model was solved using combinations of 6 different values for the parameters of the budget of uncertainty Γ_{pkt}^{d}. The Γ_{pkt}^{d} values were generated based on preliminary computational experiments and related works in the literature (Alem et al., 2018), the values are $0.1t + 0.5$, $0.25t + 0.5$, $0.5t + 0.5$, $0.75t + 0.5$, and t. These budgets of uncertainty represent different attitudes towards risk. For instance, $\Gamma^d_{pkt} = 0$ represents the deterministic case while $\Gamma^d_{pkt} = t$ represents a robust approach where all the uncertain parameters are allowed to assume their worst-case values. A total of 640 experiment settings were obtained from combining the five instances with the six different Γ^d_{pkt} and three deviation values β, considering that the deterministic case (i.e., $\Gamma^d_{pkt} = 0$) is not combined with the different deviation values β.

4.6.2 Computational performance of the proposed heuristics

Table 4.3 summarizes for all instances the performance of the Fix-and-Optimize heuristics. Columns in Table 4.3 refer to the *F&O* strategies, the percentage of instances for which the strategies provide the best solution (% Best UB), and the percentage of instances for which the strategies provide a solution with a cost no higher than 1% and 5% of the best cost (%Best+1% and %Best+5%), the average upper bound (UB), the average gap ($\frac{\text{UB } F\&O - \text{LB MIP}}{\text{UB } F\&O}$, similar to CPLEX gap calculation), and the average elapsed time. The gap values for the different solution strategies (including MIP) were calculated using the same lower bound value (LB MIP), that is, the one obtained by CPLEX when solving the original (deterministic and robust) models within 3,600 seconds.

Table 4.3: Average results of the different solution strategies for the all test with the five instances.

F&O strategy	%Best UB	%Best+1% UB	%Best UB +5%	Avg. UB	[1]Avg. Gap(%)	[2]Avg. UB ratio(%)	Avg. Time
MIP	3.75	23.75	56.25	1,848,071,830	14.32	438.36	3,601
1	0.00	13.75	55.00	797,939,324	7.17	8.55	3,561
2	15.00	93.75	98.75	770,753,943	2.40	8.47	3,598
3	8.75	52.50	85.00	774,743,223	3.43	3.71	**2,716**
4	**23.75**	**100.00**	**100.00**	**760,955,056**	**1.27**	**1.31**	3,486
5	0.00	35.00	81.25	780,344,457	5.19	8.66	3,598
6	16.25	92.50	97.50	766,668,399	2.39	5.13	3,601
7	8.75	48.75	90.00	771,838,558	2.93	3.10	3,530
8	**23.75**	97.50	100.00	761,335,088	1.32	1.35	3,544

[1] Gap=$100\times\frac{\text{UB } F\&O - \text{LB MIP}}{\text{UB } F\&O}$

[2] UB ratio=$100\times\frac{\text{UB } F\&O - \text{LB MIP}}{\text{LB } MIP}$

Note that *F&O*4 and *F&O*8 present the best performance compared with the other strategies. These strategies have a partition by period and arc and partially fix the variables, those larger than zero. Both of them find the %Best UB for 23.75% of instances; in the worst case, the obtained UB is 5% of the best solution. The *F&O*4 provides the lower average gap and UB and *F&O*3 provides the lower average elapsed time. Note that the *F&O*4 provides an average gap of 1.27% and an average UB ratio of 1.31%, while the MIP scales from an average gap of 14.32% to an average ratio of more than 400%. *F&O*4 outperforms the heuristics with respect to UBs and gap.

Table 4.4 shows the average results of the robust optimization counterpart with instances according to the type of demand for MIP and *F&O*4 heuristics. Columns in Table 4.4 refer to: method type, instances, the average UB, the average gap ($\frac{\text{UB } F\&O - \text{LB MIP}}{\text{UB } F\&O}$), and the average elapsed time. The gap values for the different instances solved with MIP and *F&O*4 were calculated using the same lower bound value (LB MIP) obtained by CPLEX for the different instances with the original models within 3,600 seconds. Table 4.4 also shows the Ratio, the relative difference between the solutions (in terms of average UB, gap, and elapsed time) of MIP and *F&O*4, computed as $100 \times \frac{\text{MIP} - F\&O4}{\text{MIP}}$. A relative difference larger than zero indicates that *F&O*4 obtained a value lower than the upper bound of the MIP (UB MIP), whereas a relative difference lower than zero indicates that *F&O*4 obtained a value larger than the MIP upper bound.

Table 4.4: Average results of *F&O*4 strategy and MIP

	Instance	Avg. UB	Avg. Gap(%)	[1]Avg. UB ratio(%)	Avg. Time (sec)
MIP	Regular	4,478,493,225	12.03	1,349.53	3,601
	Smooth	1,763,932,763	25.10	693.36	3,600
	Erratic	914,207,684	13.42	65.10	3,601
	Intermittent	1,185,125,363	17.30	79.74	3,601
	Lumpy	898,600,115	3.74	4.09	3,600
	Avg	1,848,071,830	14.32	438.36	3,601
F&O4	Regular	725,084,301	1.36	1.39	3,502
	Smooth	651,258,590	1.54	1.58	3,518
	Erratic	717,009,596	1.47	1.51	3,520
	Intermittent	839,099,970	0.98	0.99	3,457
	Lumpy	872,322,822	1.02	1.04	3,434
	Avg	760,955,056	1.27	1.31	3,486
Ratio(%)[2]	Regular	83.81	88.70	99.90	2.75
	Smooth	63.08	93.86	99.77	2.29
	Erratic	21.57	89.06	97.68	2.24
	Intermittent	29.20	94.35	98.75	4.00
	Lumpy	2.92	72.62	74.47	4.61
	Avg	40.12	87.72	99.70	3.18

[1] UB ratio=$100 \times \frac{\text{UB } F\&O - \text{LB MIP}}{\text{LB MIP}}$

[2] Ratio=$100 \times \frac{\text{MIP} - F\&O4}{\text{MIP}}$

Notice that the best improvement for the Avg. UB was obtained for the Regular instance with a ratio of 83.81% in average UB. The instance with less variability, smooth, has a high ratio, and the instance with more variability, lumpy, has a lower ratio, 3%. It is clear that *F&O*4 improves the quality of the solution and elapsed times for all instances. The average UB decreased from 1,848,071,830 to 760,955,056 , from MIP to *F&O*4. The strategy *F&O*4 reduced the average cost, the average optimality gap, and the average UB ratio of the solutions by 40.12%, 87.72%, and 99.70% respectively, when compared to MIP. It is worth highlighting that in almost all instance classes, *F&O*4 outperformed MIP regarding the UB and computational elapsed times.

4.6.3 Integrated approach vs Sequential approach

The studied problem integrates location and transportation decisions, which are commonly addressed hierarchically by practitioners in companies. Thus, another approach to dealing with these decisions is to solve the problem sequentially. Therefore, we solve a relaxed version of the original problem, ignoring decisions concerning the number of trips as we are interested in the location decisions in the first stage problem. Since the security costs also directly depend on the number of trips, these decisions are also not considered in this first stage problem. Then, in the second stage, we fix the location decisions to address the transportation planning decisions, regarding the transportation alternatives selection, the number of trips, and the number of trips with escort vehicles.

We compare the integrated model with this Sequential approach (SEQ) in terms of total cost and network structures. Both methods spent one hour of elapsed time. Table 4.5 presents the results for the sequential and integrated (*F&O4*) solutions for different instances, in terms of number of DCs (#DCs) and allocated vehicles (*Veh*), percentage of participation of LTL and TL freight on total transported units ($U_{LTL}(\%)$ and $U_{TL}(\%)$, respectively), percentage of participation in transportation costs of LTL and TL freight ($C_{LTL}(\%)$ and $C_{TL}(\%)$, respectively), the UB, and backlogging/delivery costs. Table 4.5 also shows the relative difference between the solutions (UB, backlogging and delivery costs, number of DCs and allocated vehicles) of MIP and *F&O4*, computed as $100\times\frac{\text{SEQ}-F\&O4}{\text{SEQ}}$.

Table 4.5: Comparison between the sequential and integrated solutions

	Instance	#DCs	*Veh*	$U_{LTL}(\%)$	$U_{TL}(\%)$	$C_{LTL}(\%)$	$C_{TL}(\%)$	UB	Back/Early delivery costs
SEQ	Regular	4	143	9.74	90.26	8.63	91.37	140,090,849	1,355,578
	Smooth	5	246	20.33	79.67	51.90	48.10	217,730,057	58,384,416
	Erratic	4	145	15.82	84.18	51.90	48.10	215,924,809	69,389,213
	Intermtt	4	141	8.96	91.04	9.88	90.12	144,744,603	6,400,140
	Lumpy	4	62	24.83	75.17	90.24	9.76	2,790,927,873	2,634,288,695
F&O4	Regular	2	166	9.01	90.99	4.79	95.21	139,029,082	422,666
	Smooth	2	193	8.53	91.47	2.68	97.32	139,666,461	289,069
	Erratic	2	197	8.46	91.54	2.42	97.58	139,929,994	195,455
	Intermtt	2	166	8.69	91.31	4.32	95.68	137,798,352	448,347
	Lumpy	3	170	8.56	91.44	4.35	95.65	138,816,594	365,179
Ratio(%)*	Regular	50	-16.08	7.50	-0.81	44.45	-4.20	0.76	68.82
	Smooth	60	21.54	58.06	-14.82	94.84	-102.32	35.85	99.5
	Erratic	50	-35.86	46.52	-8.75	95.34	-102.86	35.2	99.72
	Intermtt	50	-17.73	2.97	-0.29	56.25	-6.16	4.8	92.99
	Lumpy	25	-174.19	65.54	-21.65	95.18	-880.21	95.03	99.99

* Ratio $=100\times\frac{\text{SEQ}-F\&O4}{\text{SEQ}}$

The decisions of location and allocation vehicle to open DCs change significantly, in the integrated model the number of DCs decreases from 25% to 60%, and the allocated vehicle number increases for most instances from 16% to 174%. It happens because the first level of the sequential approach considers only opening decisions in terms of ICMS and unitary transportation costs, i.e. LTL freight. Since the unitary transportation costs by LTL freight are higher than TL costs, this approach opens more DCs to reduce the total transportation costs for retailers. With this configuration, the sequential approach has higher participation of LTL freight than the TL freight compared with the integrated approach. Nevertheless, the total transportation costs in the sequential approach are lower than in the integrated one. However, the difference is compensated in the integrated approach by the location costs.

Note that the freight selection decisions of the integrated approach are robust for different demand variabilities because the participation of the freight type in terms of the number of transported units and cost is similar among the instance. While the sequential approach changes with the demand variabilities. The integrated model reduces the UB for all instances in the same elapsed time as the sequential model. The high value of lumpy instances for the sequential model is because of the high Backlogging/Early delivery cost. The Backlogging/Early delivery cost is lower in the integrated approach for all instances.

4.6.4 Analysis of ICMS impact over decisions

ICMS can have a large impact on the location and product flow definition. In some cases, ICMS can be passed to the retailer, and it is not a relevant issue for companies. Nevertheless, fiscal incentives and negotiations should be evaluated in the long term, with caution regarding the well-known “Tax War” among the federal states. Thus, the use of the model makes it possible to evaluate different scenarios to support decisions related to the physical structure of the logistics network (Jalal et al., 2022b). Aiming to understand how ICMS influences the presented network design and planning problem, four cases with different ICMS values are studied:

- Case A: corresponds to the context without ICMS.
- Case B: corresponds to the current context of ICMS.
- Case C: corresponds to the context with the same rates of ICMS 12%.
- Case D: corresponds to the context with the same rates of ICMS 7%.

Table 4.6 presents the UB, total costs, ICMS, distribution costs, Number of DCs, and allocated vehicles for the different cases. For case A, ICMS is calculated after solving the problem based on the flow decisions. It is important to mention that there is a credit of ICMS for the importation of the products and raw materials, which is not countable in this problem because we do not have information about the added value of the product at plants.

For the cases with different ICMS contexts, the network structure changes with different numbers of DCs and allocated vehicles. Note that, for the same ICMS context, instances with regular, smooth, and erratic demand present the same number of opened DCs; while, the instances of intermittent and lumpy demand present changes in the network structure. Both instances present variability in demand timing, and that characteristic can explain the change in the network structure. Thus, the network configuration is also sensitive to the demand variability.

Table 4.6: Impact of ICMS over costs and decisions

Instance	Case	UB	Total costs	ICMS	Distr. costs	#DCs	#Vehicles
Regular	A	15,919,771	171,525,931	155,770,148	15,755,782	5	140
	B	139,029,082	138,606,416	122,243,968	16,362,448	2	166
	C	220,756,360	191,578,974	165,869,886	25,709,088	5	206
	D	173,545,941	123,280,418	96,757,434	26,522,984	5	198
Smooth	A	16,407,192	174,272,399	157,990,354	16,282,045	5	144
	B	139,666,461	139,377,391	121,856,659	17,520,733	2	193
	C	183,789,116	183,749,953	165,872,206	17,877,747	5	174
	D	177,343,556	123,658,371	96,758,787	26,899,584	5	207
Erratic	A	54,113,164	196,604,534	170,603,767	26,000,767	5	219
	B	139,929,994	139,734,539	121,783,551	17,950,988	2	197
	C	325,908,891	192,479,997	165,549,679	26,930,318	5	176
	D	114,197,798	114,061,496	96,754,345	17,307,151	5	167
Intermittent	A	2,178,984,335	178,940,420	143,766,390	35,174,030	3	132
	B	137,798,352	137,350,005	121,800,415	15,549,590	2	166
	C	180,091,569	179,873,909	165,872,297	14,001,612	3	130
	D	112,144,422	111,910,984	96,758,840	15,152,144	5	129
Lumpy	A	83,325,636	198,301,984	172,694,242	25,607,742	5	195
	B	138,816,594	138,451,415	121,909,096	16,542,319	3	170
	C	180,593,145	180,341,910	165,866,313	14,475,597	5	117
	D	112,195,985	111,983,998	96,754,842	15,229,156	4	140

Case A is similar to Cases B and D, considering that all rates are 0%. Notice that for these cases, regular, smooth, and erratic demand presents the same number of opened DCs, i.e., five DCs. Since there are no advantages of the DCs in terms of ICMS rates, the decision is to open all DCs and optimize the product flow in terms of logistics (opening, inventory, and transportation) costs. Notice that, although the network does not change in these cases, the number of vehicles does. It implies that there are still changes in the alternative transportation selection and flow definition.

Nevertheless, for case B, which considers the current tax structure with different rates according to the definition of state governments, only two DCs are opened. It is because the model selects the DCs considering both logistics costs and tax. The ICMS participation in total costs is higher than logistics costs, therefore the model selects the DCs with lower origin-destination tax rates to take advantage of these differences in the definition of product flows. For the considered data, it implies in opening just two DCs. We confirm that the taxation consideration can easily dominate the network configuration as set by Shah (2004). Comparing cases A and B, notice that for all instances the ICMS costs (calculated in post-process) are higher in case A than case

B, i.e. when they are ignored. These results show that this model represents a tool to support the decision-making process with different scenarios of ICMS and demand variability.

4.6.5 Robustness analysis

We designed a robustness analysis based on a Monte Carlo simulation to evaluate the quality of solutions resulting from our robust optimization counterpart. The simulation was performed by generating 1000 random uniform realizations for demands in the interval $[d_{pkt} - \hat{d}_{pkt}, d_{pkt} + \hat{d}_{pkt}]$ for all $p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}$, respectively. In the simulation, the solution to the robust problem, and the decisions were fixed (except backlogging and early delivery) and the performance of the solution is evaluated with the random demand generated by the instances with different demand variabilities.

We analyze the behavior of the robust solutions when the Γ^d_{pkt} values increase. Figure 4.4 shows, for different Γ^d_{pkt}, the average relative difference of the cost components of all the robust solutions with respect to the deterministic solution.

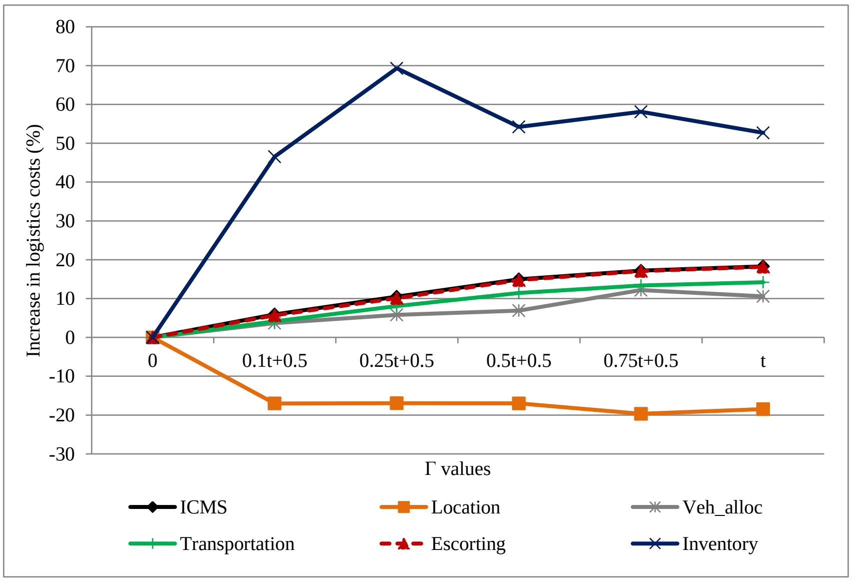


Figure 4.4: Cost increases (%) for different Γ values in costs

As expected, the total costs increase for different values of deviation and budget of uncertainty. It can be observed that ICMS, transportation, security, and vehicle allocation costs tend to increase in similar proportion along with Γ^d_{pkt}. While the location and inventory cost present an erratic behavior compared with the deterministic case (i.e., with $\Gamma^d_{pkt} = 0$). Intuitively, one way to protect the solutions against demand uncertainty is to increase the inventory levels of the items.

Table 4.7 presents, for different Γ^d_{pkt} values, the average values of total costs, distribution costs, backlogging/early delivery, number of opened DCs, and allocated vehicles.

Table 4.7: Average results of the robust solutions for different Γ values

Γ	Avg. UB	%*	Distr. costs	%*	Backlogging/ Early delivery	%*	#DCs	#Vehicles
0	195,851,244	0.00	142,503,086	0.00	53,348,158	0.00	3	173
0.1t+0.5	460,085,261	134.92	150,035,464	5.29	310,049,797	481.18	2	178
0.25t+0.5	673,981,156	244.13	156,174,491	9.59	517,806,665	870.62	2	181
0.5t+0.5	880,438,298	349.54	162,110,289	13.76	718,328,008	1,246.49	2	183
0.75t+0.5	985,681,145	403.28	165,402,402	16.07	820,278,742	1,437.60	2	187
t	1,031,375,360	426.61	166,863,933	17.09	864,511,427	1,520.51	2	187

* Increase of the value respect to the deterministic solution.

Note in Figure 4.4 that some terms in the objective function (inventory cost) increase until 70%. Intuitively, a way to protect the solutions against demand uncertainty is to increase the inventory levels of the items. Nevertheless, the total distribution cost increases just until 17% with respect to the deterministic solution, as shown in Table 4.7. Backlogging/early delivery costs increase as high as 1520% with $\Gamma^d_{pkt} = t$. Thus, a higher impact on uncertainty is noticed in these Backlogging/early delivery costs. If the demand is lower than expected, products are stored (anticipated) at retailers, thus leading to high early delivery costs. On the other hand, if the demand is higher than expected, items are backlogged, thus leading to high backlogging costs. Both, backlogging and surplus of products significantly affect the cost of robust solutions. The decision on DC location was not significantly affected by the uncertainty. Nevertheless, the allocation of vehicles to the opened DCs was affected. In this case, more vehicles are allocated to DCs as higher values of Γ^d_{pkt} are considered.

Though robust solutions present high backlogging/delivery costs when these solutions are evaluated in the simulation (with demand generated in the interval $[d_{pkt} - \hat{d}_{pkt}, d_{pkt} + \hat{d}_{pkt}]$), it can observe that the expected backlogging/delivery costs decrease when Γ^d_{pkt} values increase, as shown in Table 4.8. This result indicates that as higher Γ^d_{pkt} values are considered, the solutions are more robust to the different realization of the demand, i.e., they are more protected against uncertainties.

Table 4.8: Average distribution, backlogging/early delivery costs over the 1000 runs of the simulation for different Γ values

Γ	Distr. Cost	%*	Backlogging/ Early delivery cost		Backlogging cost		Early costs	
0	142,503,086	-	1,079,648,065	0.00	1,027,676,288	0.00	51,971,777	-94.94
0.1t+0.5	150,035,464	5.29	316,905,492	-70.65	161,163,511	-84.32	155,741,981	-84.85
0.25t+0.5	156,174,491	9.59	276,793,159	-74.36	28,785,290	-97.20	248,007,870	-75.87
0.5t+0.5	162,110,289	13.76	344,088,941	-68.13	2,339,869	-99.77	341,749,072	-66.75
0.75t+0.5	165,402,402	16.07	391,033,853	-63.78	924,460	-99.91	390,109,393	-62.04
t	166,863,933	17.09	411,931,627	-61.85	893,708	-99.91	411,037,919	-60.00

* Increase of the value with respect to the deterministic solution.

Figure 4.5 presents the robust solution costs (distribution), as well as the backlogging and early delivery costs over the 1000 runs of the simulation for different Γ_{pkt} values.

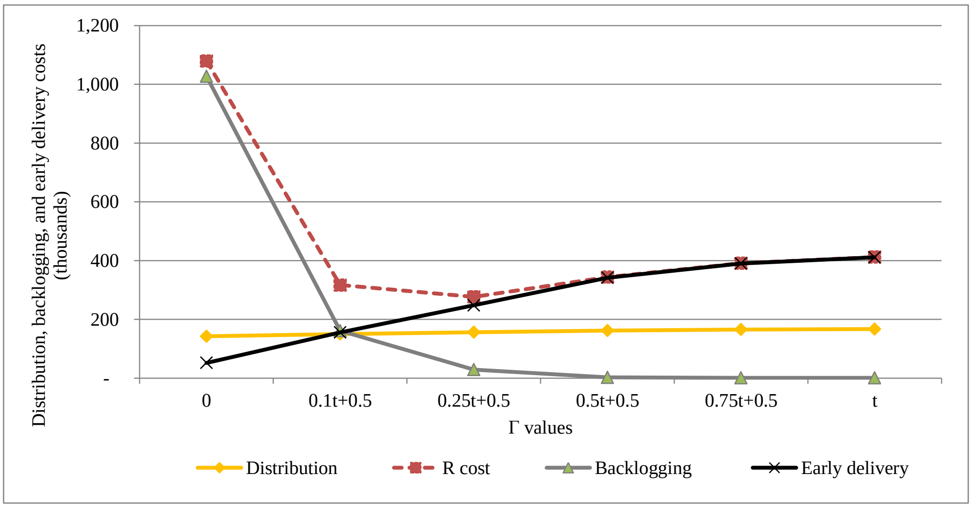


Figure 4.5: Backlogging and early delivery costs over the 1000 runs of the simulation for different Γ values.

Figure 4.5 shows that the average backlogging cost decreases significantly when the Γ_{pkt} values grow, while early delivery costs increase to protect the solutions against demand uncertainty, increasing the early delivery to retailers. The distribution costs of the robust solutions (ICMS, location, transportation, etc.) increase in a smaller proportion than the reduction in the expected backlogging costs. Figure 4.5 indicates that at some point when Γ_{pkt} is increased, it found a minimum value for the sum of backlogging/early delivery costs, presenting a lower total cost, e.g., $\Gamma_{pkt} = 0.25t + 0.5$.

4.7 Remarks

We addressed the integrated location-transportation problem of a pharmaceutical company using robust optimization to deal with the demand uncertainty. First, we presented a deterministic mixed-integer linear programming model that integrates network design and distribution planning decisions. Practical features of the logistics context of the pharmaceutical industry are considered. We also proposed a robust counterpart of the mathematical model, a mixed-integer linear programming model, for handling the inherent uncertainty of input data in logistics network planning. Instances of the deterministic formulation and its robust counterpart cannot be solved optimally by general-purpose software, such as CPLEX, i.e. high-quality solutions cannot be found within reasonable elapsed times using this software. Thus, we proposed a Fix-and-Optimize heuristic, using partition criteria by periods and/or arcs, to solve the models.

We developed computational experiments using real data from a partner company and evaluated the impact of the uncertainty on the problem. The proposed heuristics method is able to obtain solutions near optimality, outperforming the MIP model. The costs of the solutions provided by the MIP model are at least two times higher than the ones provided by the heuristics strategies. Comparing the MIP model and the best heuristics strategy, the average costs decrease by more than 40%.

To assess the robustness of the solutions obtained by the robust optimization counterpart, they were compared to those generated by the deterministic model. Therefore, we proposed solution methods to solve the deterministic and robust models. We designed and proposed a robustness analysis based on a Monte Carlo simulation to evaluate the quality of solutions resulting from our RO model. The simulation was performed by generating random uniform realizations for demands in the interval $[d_{pkt} - \hat{d}_{pkt}, d_{pkt} + \hat{d}_{pkt}]$ for all $p \in \mathcal{P}, k \in \mathcal{K}, t \in \mathcal{T}$, respectively. Because the aim of the robust optimization models is to find solutions that are immunized against uncertainty, the corresponding decisions reduce the expected costs of backlogging and early delivery. As expected, the total costs increase for different values of deviation and budget of uncertainty. The ICMS, transportation, security, and vehicle allocation costs tend to increase in a similar proportion along with the uncertainty budget, while the DC inventory cost also increases significantly. Moreover, the backlogging/early delivery costs increase more than 1500% for the worst case. Intuitively, one way to protect the solutions against demand uncertainty is to increase the inventory levels of the items. Regarding the network structure, the number of opened DCs was not significantly affected by the uncertainty. Nevertheless, the allocation of vehicles to the opened DCs was affected, more vehicles are allocated to DCs with higher values of deviation and uncertainty budget.

In addition, we compared the integrated model with a Sequential approach in terms of total cost and network structures. We found that the integrated model reduces the total costs, reduces the number of DCs, and increases the number of allocated vehicles. We also analyzed some scenarios with different ICMS rates to understand the sensitivity of solutions to this parameter. ICMS influences the presented network design and planning problem, changing the number of DCs and allocated vehicles. It is interesting that, for the same ICMS context, the instances of intermittent and lumpy demand present changes in the network structure, and both instances present variability in demand timing.

Therefore, we fill several research gaps pointed out in Chapter 2, i.e., considering the decision timing in the integration, addressing practical features of a real case, taking into account the uncertainty in problem parameters, and proposing efficient solution methods to solve the problem.

Future research could address other methodologies to consider the uncertainties in this problem such as stochastic programming or adjustable robust optimization. Other solution methods could be developed to solve instances of the problem, such as methods based on Benders decomposition. Also, it is interesting the proposition of a solution method using ICMS as generator of solutions since ICMS can dominate the location and flow decisions.

Chapter 5

Remarks and future steps

5.1 Remarks

In the previous chapters, we have studied the integration of decisions in the context of LNP and presented different formulations and methods to solve them. In this section, we summarize the major findings and contributions of each chapter of this thesis. The final section of this chapter concludes with the identification of possible interesting directions for this research.

In Chapter 2, a detailed literature review of the LNP was provided to identify the main decisions, their scope, integration approaches, and solution approaches. Integrating decisions is a trend in the literature because of its advantages. It eliminates conflict and incompatibility among decisions and goals of different departments in a company; enables faster response to dynamic environmental conditions, reduces logistics network costs and further information is explored. Integrated planning implies managing different scopes, periodicity, and frequency, as well as considering several logistics components and dealing with the variability and uncertainty of important parameters of the problem. In addition, data aggregation is an important aspect as well. Nevertheless, most studies consider integration decisions within a single time frame and consider a single commodity and transportation mode. Also, studies neglected the uncertainty in several parameters of the decision-making process. Furthermore, many models and methodologies are sophisticated, but few case studies are taken into account. As a result, there are important issues that LNP decision-makers must deal with in practice and that are overlooked in the literature. Building on this, in this thesis we approached the integration of the main decisions on LNP through a generic framework and a case-based mathematical formulation in Chapter 3 and Chapter 4, respectively.

In Chapter 3, we presented the integration of three important decisions on the logistics network, i.e., location, inventory, and transportation. We proposed a generic modeling approaching location-allocation decisions; inventory planning decisions, made under a periodic review (T, S) policy, defining the amount of cycle inventory, safety stock, and anticipation inventory at open DCs; and transportation decision from the cost segment selection. We addressed features such as location-based lead times, storage capacity constraints in DCs, multi-period and multi-product context, and single sourcing per retailer and commodity. The objective is to minimize the total cost composed of rental costs, inventory costs, and transportation costs. To solve the problem, we proposed two methods, an exact method and an approximated method. First, we developed a Logic-based Benders decomposition by exploiting the structure of the problem and obtained subproblems that preserved the characteristics of the original problem. To approximate safety stock in the master problem, we used a piecewise linear lower bound function of safety stock. We also enhanced the master problem including information about the subproblems and used a multi-cut to accelerate the convergence of the method. Second, we presented a MIP model with the same idea of a piecewise linear lower bound function of safety stock. Both methods provide good solutions for most instances. We compared the integrated model with a sequential approach, and the results confirm the importance of having an integrated approach that integrates decisions at the various levels of the supply chain. We also performed a sensitivity analysis aiming to understand how each parameter influences the supply chain design and planning problem. We found that the network design is sensitive to the coefficient of variation and the opening costs.

In Chapter 4, we addressed the integration of location and transportation decisions on a pharmaceutical network in Brazil. We outlined practical features of the pharmaceutical industry's logistics environment in Brazil. Thus, we proposed a mathematical model that assesses DC's location and transportation decisions by considering rental costs, inventory decentralization costs, transportation costs, and ICMS tax issues. The flow of products (with different characteristics of weight, volume, price, and temperature condition) was addressed with several transportation alternatives, which were differentiated by the type of freight, the temperature conditioning, and the capacity of the vehicles. Also, the use of escort vehicles for freight whose monetary value exceeds the established limit was considered. In addition, we addressed variability and uncertainty in demand for decision-making in planning. Thus, a robust optimization counterpart considering demand uncertainty was proposed. To solve the problem, we developed Fix-and-Optimize heuristics method that solves the instances near the optimality. We performed computation experiments using data from a pharmaceutical company. Results show that ICMS has a significant influence over the location and product flow definition. This finding underscores the importance of taking into account the fiscal structure in the issue of DC location in global supply chains, particularly for the distribution of high-value products in countries with similar tax systems. The advantage of the integration over the sequential approach has been confirmed. Finally, the robustness analysis evidenced that the deterministic approach fails in protecting against uncertainty for the considered instances. Based on the research results, some relevant problems in LNP, especially those related to the Brazilian pharmaceutical industry, can be solved by these models and solution methods.

5.2 Future research

There are several possible future research directions for the continuity of this study, some of them are described as follows:

- Uncertainty and variability in other parameters of the problem. Other parameters such as lead time could preset variability. Moreover, retailer demand can be correlated. These issues can have a significant impact on the decisions of the problem. Hence, an interesting topic of research is to consider them and extend the proposed mathematical formulation and solution methods of Chapter 3 to deal with them.

- Uncertainty methodologies. Robust static optimization has a high level of conservatism. Studying strategies to reduce this conservatism of the static approach is an interesting prospect for future research. Other methodologies such as Adjustable Robust Optimization or Distributionally Robust Optimization are alternative and promising methodologies that can be also explored for the analysis of the mathematical model of Chapter 4.

- Solution methods. Alternative decomposition methods of the problem could be explored. For the location-transportation problem of Chapter 4, it is interesting to consider Benders decomposition. Also, heuristics can be explored for the location-inventory-transportation problem of Chapter 3.

- Explore other integration and modeling strategies such as multi-level models.

- Use the generic approach of Chapter 3 to address and compare tax structures of different counties, e.g., Brazil, Canada, United States, China, and countries of the European Union.

- Other features. Considering other inventory policies in the model of Chapter 3, and compare the implications of different policies on the logistics network planning. Addressing capacity planning in networking by decisions of closing and opening DCs or expanding or reducing capacity of the DCs.

- Application in a real case. Applying the proposed approaches in a real case study, to better analyze the benefits of these approaches in the practice of a company.

Appendix A

Sample articles

Table A.1: Sample articles

No.	Authors	No.	Authors
2	Ahmadi et al. (2016).	131	Liao et al. (2011b).
4	Ahmadi-Javid and Azad (2010).	130	Liao et al. (2011a).
7	Ahmadi-Javid and Seddighi (2012).	132	Lin et al. (2009).
6	Ahmadi-Javid and Hoseinpour (2015b).	134	Liu et al. (2020).
3	Ahmadi-Javid et al. (2018).	137	Manzini et al. (2008).
5	Ahmadi-Javid and Hoseinpour (2015a).	135	Manzini (2012).
8	Akbari and Karimi (2015).	136	Manzini et al. (2014).
9	Alavi et al. (2016).	138	Manzini and Gebennini (2008).
14	Alenezi and Darwish (2014).	141	Martins et al. (2017).
15	Alshamsi and Diabat (2018).	147	Miranda and Garrido (2004).
17	Amiri-Aref et al. (2018).	149	Miranda et al. (2009).
18	Angazi (2016).	148	Miranda and Garrido (2006).
20	Arabzad et al. (2014).	150	Mogale et al. (2019).
21	Aryanezhad et al. (2010).	151	Monteiro et al. (2010).
22	Azizi and Hu (2020).	157	Mota et al. (2018).
23	Azizi et al. (2020).	158	Motaghedi-Larijani et al. (2012).
24	Badri et al. (2013).	160	Mousavi et al. (2013).
28	Bashiri et al. (2012).	161	Mousavi et al. (2014).
39	Biuki et al. (2020).	159	Mousavi et al. (2017).
41	Brahimi and Khan (2014).	166	Naimi Sadigh et al. (2013).
44	Cabrera et al. (2016).	167	Nakhjirkan and Rafiei (2017).
45	Calvete et al. (2014).	168	Nakhjirkan et al. (2019).
46	Candas and Kutanoglu (2007).	170	Nasiri et al. (2010).
47	Candas and Kutanoglu (2020).	171	Nasiri et al. (2015).
48	Cardoso et al. (2013).	172	Nekooghadirli et al. (2014).
57	Dai et al. (2018).	177	Puga and Tancrez (2017).
59	Darvish and Coelho (2018).	195	Schuster Puga et al. (2019a).
58	Darvish et al. (2019).	178	Qazvini et al. (2016).
60	Das and Sengupta (2009).	179	Rabbani et al. (2019).
227	Wheatley et al. (2015).	188	Sadeghi Rad and Nahavandi (2018).
68	Diabat et al. (2013).	180	Rafie-Majd et al. (2018).
67	Diabat and Richard (2015).	184	Rappold and Roo (2009).
64	Diabat (2016).	187	Sabri and Beamon (2000).
65	Diabat et al. (2015).	189	Sadjadi et al. (2016).
66	Diabat and Deskoores (2016).	190	Sadjady and Davoudpour (2012).
73	Etebari (2019).	193	Salema et al. (2009).
79	Fattahi et al. (2016).	192	Salema et al. (2010).
78	Fattahi and Govindan (2017).	194	Saragih et al. (2019).
80	Firoozi et al. (2014).	197	Schwardt and Dethloff (2005).
84	Forouzanfar et al. (2018).	199	Shahabi et al. (2013).
85	Gebennini et al. (2009).	200	Shavandi and Bozorgi (2012).
86	Ghaderi and Burdett (2019).	201	Sherafati and Bashiri (2016).
88	Ghezavati et al. (2009).	203	Shu et al. (2010).
90	Gholamian and Heydari (2017).	206	Singh et al. (2015).
91	Ghomi-Avili et al. (2018).	207	Solak et al. (2014).
92	Ghomi-Avili et al. (2020).	209	Soleimani et al. (2016).
93	Ghorbani and Akbari Jokar (2016).	208	Soleimani et al. (2018).
94	Govindan et al. (2014).	214	Tancrez et al. (2012).
95	Govindan et al. (2015a).	215	Tang and Yang (2008).
97	Govindan et al. (2016).	216	Tapia-Ubeda et al. (2018).
96	Govindan et al. (2019).	217	Tapia-Ubeda et al. (2020).
98	Govindan et al. (2020).	218	Tavakkoli-Moghaddam et al. (2010)
102	Guerrero et al. (2015).	219	Tiwari et al. (2010)
103	Guo et al. (2018).	221	Tsao et al. (2012).
104	Guo et al. (2019)	222	Tsiakis et al. (2001)
107	Hammami et al. (2017).	223	Üster et al. (2008).
110	Hiassat et al. (2017).	226	Wang et al. (2013).
118	Jeet and Kutanoglu (2018).	229	You and Grossmann (2008).
120	Kabadurmus and Erdogan (2020).	231	Yu et al. (2015).
121	Karakostas et al. (2019).	232	Yuchi et al. (2016).
122	Kaya and Urek (2016).	236	Zeballos et al. (2014).
123	Keskin and Üster (2012).	235	Zeballos et al. (2018)
124	Khatami et al. (2015).	238	Zhalechian et al. (2016).
125	Kim and Lee (2015).	239	Zhang and Xu (2014).
126	Lagos et al. (2015).	241	Zheng et al. (2019a)
129	Li et al. (2013).		

Appendix B

Additional computational results

Table B.1 presents a comparison of results for the different number of segments for the piecewise linear lower bound function of safety stock. The average gap of solutions considering 5 segments is higher than considering 10 segments since the UB and the LB are better. It can explain because the instances have less number of variables and constraints, and consequently are easier to be solved. Solutions for 5 and 10 segments with lower gaps have similar bounds, so 5 segments is a good choice for the number of segments.

Table B.1: Impact of number of segments: ELBBDi with 5 and 10 segments

	5 segments					10 segments				
Instance	UB	LB	Gap(%)[1]	Time	#iter	UB	LB	Gap(%)[1]	Time	#iter
i1-j3-k5-p7	17,709,700	17,555,735	0.9	3,600	8,895	17,709,700	17,555,735	0.9	3,601	8,874
i1-j3-k5-p10	20,586,850	19,951,829	3.1	3,600	9,983	20,586,850	19,951,829	3.1	3,600	8,808
i1-j3-k10-p10	25,710,285	25,265,418	1.7	3,600	7,892	25,722,883	25,262,375	1.8	3,600	7,093
i1-j3-k10-p20	27,498,682	26,871,608	2.3	3,600	2,229	27,720,327	25,796,396	6.9	3,600	2,373
i1-j3-k15-p10	29,943,327	29,485,518	1.5	3,600	6,775	29,943,327	29,485,518	1.5	3,600	5,645
i1-j3-k15-p20	32,778,192	31,702,931	3.3	3,600	603	32,778,192	30,931,814	5.6	3,600	2,644
i1-j3-k30-p20	48,471,115	44,518,778	8.2	3,600	1,283	48,471,115	46,116,865	4.9	3,600	62
i1-j3-k30-p30	62,013,797	56,908,278	8.2	3,600	976	61,811,610	58,375,540	5.6	3,600	72
i1-j3-k30-p40	77,543,104	69,373,241	10.5	3,600	5	77,543,104	69,346,518	10.6	3,600	4
i2-j3-k5-p7	17,357,831	16,431,242	5.3	3,600	10,271	17,821,710	16,393,989	8.0	3,601	8,366
i2-j3-k5-p10	19,262,305	17,084,040	11.3	3,600	8,158	20,085,796	17,066,704	15.0	3,600	6,162
i2-j3-k10-p10	24,410,516	22,052,432	9.7	3,600	5,460	31,000,062	21,145,732	31.8	3,600	5,300
i2-j3-k10-p20	30,627,173	20,677,853	32.5	3,600	2,765	32,140,709	21,416,983	33.4	3,601	2,124
i2-j3-k15-p10	28,291,455	25,771,093	8.9	3,601	6,028	28,295,011	25,236,038	10.8	3,601	7,038
i2-j3-k15-p20	31,305,383	24,842,381	20.6	3,600	1,263	31,380,410	24,653,323	21.4	3,601	2,144
i2-j3-k30-p20	45,869,986	39,721,452	13.4	3,600	1,036	44,844,759	38,816,302	13.4	3,600	559
i2-j3-k30-p30	65,639,098	48,269,258	26.5	3,600	537	59,036,992	48,291,288	18.2	3,600	263
i2-j3-k30-p40	65,702,679	57,938,974	11.8	3,601	31	65,767,492	57,252,388	12.9	3,600	10
Average	37,262,304	33,023,448	10.0			37,370,003	32,949,741	11.4		

[1] Gap=$100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

Table B.3 presents the results of the ELBBD warm started with an initial solution for different computational times: half-hour, one hour, and 2 hours.

Table B.2 presents the results of using the Special Order Sets (SOS1) of CPLEX for the variables W and Y. The incorporation of the CPLEX function of SOS1 does not affect significantly the solutions.

Table B.2: SOS1 function effect

	ELBBDi +SOS1 for variables W and Y					Ratio of improvement[1]				
Instance	UB	LB	Gap(%)[2]	Time	#iter	UB	LB	Diff(%)[3]	Time	#iter
i1-j3-k5-p7	17,709,700	17,555,735	0.87	3,600	11,877	0.00	0.00	0.00	0.00	33.52
i1-j3-k5-p10	20,586,850	19,951,829	3.08	3,600	9,756	0.00	0.00	0.00	0.00	-2.27
i1-j3-k10-p10	25,627,484	25,265,418	1.41	3,600	6,135	-0.32	0.00	-0.32	0.00	-22.26
i1-j3-k10-p20	28,038,725	25,686,574	8.39	3,600	3,330	1.96	-4.41	6.11	0.00	49.39
i1-j3-k15-p10	29,943,327	29,485,518	1.53	3,600	5,428	0.00	0.00	0.00	0.00	-19.88
i1-j3-k15-p20	32,388,205	31,768,272	1.91	3,600	1,835	-1.19	0.21	-1.37	0.00	204.31
i1-j3-k30-p20	48,471,115	46,185,066	4.72	3,601	271	0.00	3.74	-3.44	0.03	-78.88
i1-j3-k30-p30	62,303,729	57,036,520	8.45	3,600	797	0.47	0.23	0.22	0.00	-18.34
i1-j3-k30-p40	73,897,676	69,509,393	5.94	3,600	17	-4.70	0.20	-4.60	0.00	240.00
i2-j3-k5-p7	17,357,831	16,400,831	5.51	3,600	13,941	0.00	-0.19	0.18	0.00	35.73
i2-j3-k5-p10	19,320,134	17,042,538	11.79	3,600	9,476	0.30	-0.24	0.48	0.00	16.16
i2-j3-k10-p10	24,269,853	22,037,121	9.20	3,601	7,257	-0.58	-0.07	-0.46	0.03	32.91
i2-j3-k10-p20	31,284,413	21,806,677	30.30	3,600	3,444	2.15	5.46	-2.19	0.00	24.56
i2-j3-k15-p10	29,663,714	24,722,117	16.66	3,600	6,330	4.85	-4.07	7.75	-0.03	5.01
i2-j3-k15-p20	33,807,758	27,326,714	19.17	3,600	2,341	7.99	10.00	-1.47	0.00	85.35
i2-j3-k30-p20	46,091,230	40,186,378	12.81	3,600	1,128	0.48	1.17	-0.59	0.00	8.88
i2-j3-k30-p30	65,588,883	48,983,964	25.32	3,600	432	-0.08	1.48	-1.15	0.00	-19.55
i2-j3-k30-p40	75,573,770	57,274,504	24.21	3,603	134	15.02	-1.15	12.40	0.06	332.26
Average	37,884,689	33,234,732	10.63	3,600	4,663	1.46	0.69	0.64	0.00	50.38

[1] Ratio $=100\times\frac{\text{ELBBDi+SOS1} - \text{ELBBDi}}{\text{ELBBDi}}$

[2] Gap$=100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

[3] Diff=ELBBDi+SOS1 gap − ELBBDi gap

Table B.3: ELBBDi with different computational time

	1/2 hour					1 hour					2 hours				
Instance	UB	LB	Gap(%)[1]	Time	#iter	UB	LB	Gap(%)[1]	Time	#iter	UB	LB	Gap(%)[1]	Time	#iter
i1-j3-k5-p7	17.709.700	17.555.735	0,9	1.800	6.070	17.709.700	17.555.735	0,9	3.600	8.895	17.709.700	17.555.735	0,9	7.200	10.885
i1-j3-k5-p10	20.586.850	19.951.829	3,1	1.800	6.716	20.586.850	19.951.829	3,1	3.600	9.983	20.586.850	19.951.829	3,1	7.201	11.814
i1-j3-k10-p10	25.710.285	25.265.418	1,7	1.800	4.575	25.710.285	25.265.418	1,7	3.600	7.892	25.709.726	25.265.418	1,7	7.200	9.314
i1-j3-k10-p20	27.498.177	26.842.501	2,4	1.800	1.453	27.498.682	26.871.608	2,3	3.600	2.229	27.507.990	26.928.738	2,1	7.200	4.573
i1-j3-k15-p10	29.943.327	29.485.518	1,5	1.800	4.624	29.943.327	29.485.518	1,5	3.600	6.775	29.943.327	29.485.518	1,5	7.201	9.661
i1-j3-k15-p20	32.778.192	30.513.316	6,9	1.800	440	32.778.192	31.702.931	3,3	3.600	603	32.778.192	31.784.527	3,0	7.200	3.409
i1-j3-k30-p20	48.471.115	44.501.164	8,2	1.800	995	48.471.115	44.518.778	8,2	3.600	1.283	48.471.115	46.106.258	4,9	7.200	1.780
i1-j3-k30-p30	62.303.730	56.836.665	8,8	1.800	179	62.013.797	56.908.278	8,2	3.600	976	62.303.730	57.028.924	8,5	7.200	1.007
i1-j3-k30-p40	77.543.104	69.323.266	10,6	1.800	6	77.543.104	69.373.241	10,5	3.600	5	77.543.104	69.556.853	10,3	7.200	665
i2-j3-k5-p7	17.357.831	16.428.765	5,4	1.800	8.276	17.357.831	16.431.242	5,3	3.600	10.271	17.357.831	16.431.242	5,3	7.200	16.275
i2-j3-k5-p10	19.262.305	17.080.654	11,3	1.800	6.727	19.262.305	17.084.040	11,3	3.600	8.158	19.262.305	17.094.668	11,3	7.201	13.881
i2-j3-k10-p10	24.410.516	22.046.680	9,7	1.800	4.755	24.410.516	22.052.432	9,7	3.600	5.460	24.410.516	22.100.426	9,5	7.200	10.819
i2-j3-k10-p20	31.506.658	20.533.519	34,8	1.800	1.962	30.627.173	20.677.853	32,5	3.600	2.765	29.092.252	20.870.770	28,3	7.200	3.340
i2-j3-k15-p10	28.291.455	25.761.372	8,9	1.800	3.855	28.291.455	25.771.093	8,9	3.601	6.028	28.291.455	25.787.490	8,9	7.201	8.998
i2-j3-k15-p20	31.305.385	24.786.319	20,8	1.800	906	31.305.383	24.842.381	20,6	3.600	1.263	31.305.382	24.912.465	20,4	7.200	1.447
i2-j3-k30-p20	54.277.960	39.648.044	27,0	1.800	691	45.869.986	39.721.452	13,4	3.600	1.036	49.435.882	39.788.521	19,5	7.200	2.182
i2-j3-k30-p30	65.694.016	48.260.512	26,5	1.800	123	65.639.098	48.269.258	26,5	3.600	537	65.443.397	48.278.656	26,2	7.200	652
i2-j3-k30-p40	76.117.443	57.280.353	24,7	1.800	9	65.702.679	57.938.974	11,8	3.601	31	75.573.770	57.438.257	24,0	7.200	288
Average	38.376.003	32.894.535	11,8			37.262.304	33.023.448	10,0			37.929.251	33.131.461	10,5		

[1] Gap=$100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

Table B.4 presents the results of using the IloPieceLinear method from CPLEX on APXMi. The incorporation of the CPLEX function, IloPieceLienear, deteriorates the average gap slightly (1%), different from ELBBDi which is improved by IloPieceLinear method from CPLEX.

Table B.4: Results of the impact of IloPieceLinear method from CPLEX in APXMi

	APXMi+IPLf					Ratio of improvement [1]				
Instance	UB	O.F. value	LB	Gap(%)[2]	Time	UB	O.F. value	LB	Diff(%)[3]	Time
i1-j3-k5-p7	17,709,670	17,703,574	17,702,293	0.1	6	0.00	0.00	0.00	0.00	-14.29
i1-j3-k5-p10	20,586,790	20,569,984	20,569,099	0.1	85	0.00	0.00	0.00	0.00	-53.55
i1-j3-k10-p10	25,626,858	25,580,095	25,577,734	0.2	184	0.00	0.00	0.00	0.00	-58.74
i1-j3-k10-p20	27,484,378	27,431,992	27,207,578	1.0	3,600	0.01	-0.12	0.06	-0.05	0.00
i1-j3-k15-p10	29,943,068	29,894,106	29,891,126	0.2	706	0.00	0.00	0.00	0.00	69.71
i1-j3-k15-p20	32,777,931	32,719,280	32,112,406	2.0	3,600	0.06	0.00	0.29	-0.22	0.00
i1-j3-k30-p20	48,470,734	48,411,047	47,092,078	2.8	3,600	0.00	0.00	1.30	-1.24	0.00
i1-j3-k30-p30	61,876,652	61,800,380	57,170,825	7.6	3,600	-0.68	-0.69	-2.51	1.73	-0.14
i1-j3-k30-p40	77,169,092	77,060,061	69,595,137	9.8	3,600	-0.48	-0.25	0.26	-0.67	0.00
i2-j3-k5-p7	17,357,472	17,334,589	17,332,893	0.1	10	0.00	0.00	0.00	0.00	-67.74
i2-j3-k5-p10	19,263,172	19,230,560	19,228,638	0.2	344	0.00	0.00	0.02	-0.02	-90.44
i2-j3-k10-p10	24,269,633	24,175,299	24,172,883	0.4	451	0.00	0.00	0.00	0.00	-80.03
i2-j3-k10-p20	34,641,330	34,529,757	22,967,988	33.7	3,600	30.38	30.49	-4.23	23.96	0.00
i2-j3-k15-p10	28,473,899	28,346,642	26,769,029	6.0	3,600	0.65	0.61	1.31	-0.62	0.00
i2-j3-k15-p20	36,961,536	36,739,858	25,586,829	30.8	3,600	18.63	18.06	-8.33	20.36	0.00
i2-j3-k30-p20	43,618,154	43,351,166	41,803,335	4.2	3,600	-18.02	-18.19	7.49	-22.74	-0.06
i2-j3-k30-p30	65,534,732	65,372,907	48,849,413	25.5	3,600	-0.02	-0.02	1.43	-1.06	0.00
i2-j3-k30-p40	75,305,997	75,098,511	57,743,686	23.3	3,600	-0.34	-0.31	1.22	-1.18	0.00
Average	38,170,617	38,074,989	33,965,165	8.2		1.68	1.64	-0.09	1.01	

[1] Ratio $=100\times\frac{\text{APXMi+IPLf} - \text{APXMi}}{\text{APXMi}}$

[2] Gap$=100\times\frac{\text{UB}-\text{LB}}{\text{UB}}$

[3] Diff=APXMi+IPLf gap − APXMi gap

Appendix C

ICMS in logistics network planning in Brazil

In addition to the costs associated with installation and operation, in location decisions, it is important to consider tax issues that affect the supply chain logistics. The movement of goods in Brazil is taxed by ICMS, which together with the Tax on Industrialized Products - IPI, represents in Brazil the equivalent of the Value Added Tax (VAT) in other countries. Most pharmaceutical products are exempt from the IPI. However, ICMS is the tax that most influences medicine costs, given its incidence in all stages of the supply chain, and is therefore addressed in this study as a tactical cost element.

ICMS consists of intrastate and interstate tax rates applied to the value of the goods when leaving the establishment of origin. Thus, when transporting goods between facilities of the same company (for example, from the plant to the DC), the rates are applied on the cost of the goods; and in sales operations (for example, from the DC to the retailer), the rates are applied to the sale price of the merchandise.

Thus, ICMS is levied on the entire supply chain, but it has a debit and credit structure that allows the payment of tax from previous stages to be discounted in subsequent stages of the logistics network. Figure C.1 illustrates the structure of ICMS. The DC tax balance can be calculated by Equation (C.1). Another simple way to calculate ICMS is the multiplication of cargo value times ICMS rate.

$$\begin{aligned} DC\ tax\ balance &= debit - credit \\ &= \left(\frac{product\ price}{1-tax\ rate} - product\ price\right) - \left(\frac{product\ cost}{1-tax\ rate} - product\ cost\right) \end{aligned} \tag{C.1}$$

In each transaction, the balance of ICMS is paid. However, if the balance is negative, no amount must be paid, is called 'dead credit' because it is not returned by the State, that is, it cannot be recovered by the company, which implies that the ICMS credit for previous transactions does not was taken advantage of.

ICMS rates are defined by state governments, therefore, they vary among different Brazilian

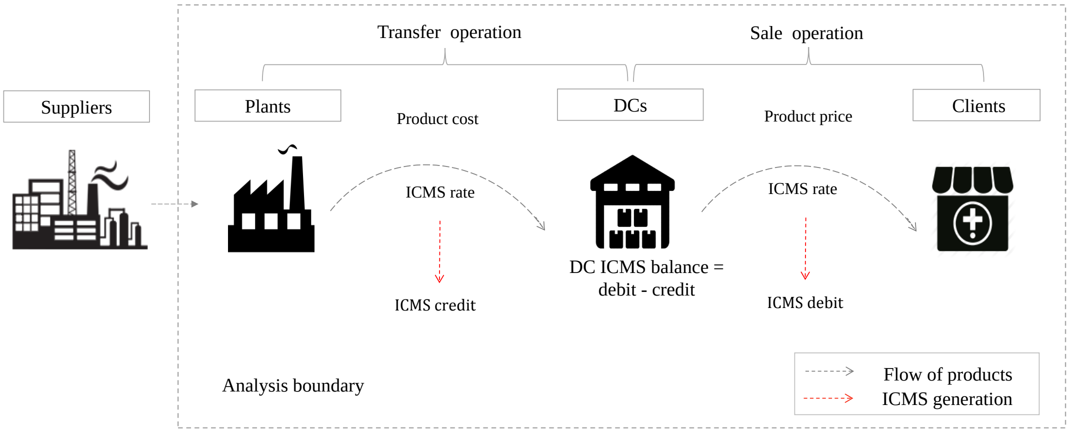


Figure C.1: Tax calculation (Jalal et al., 2022b)

states. Thus, moving the same cargo to the same destination state from different origin states implies different amounts of ICMS payable. To attract investment, some state governments offer low ICMS rates or offer tax benefits that allow companies to reduce their tax burden, such as the presumed ICMS credit, through which the state grants a reduction in the amount of ICMS to pay in transactions made from the state.

To understand the impact of taxation on logistics planning, consider that a company with a plant in the state of Sergipe (SE) is planning to open a new DC to serve its retailers in the state of Espirito Santo. Possible locations for the DC are the states of Espirito Santo (ES), Bahia (BA) and Minas Gerais (MG). Figure C.2 illustrates the differences between flows and rates for the three candidates.

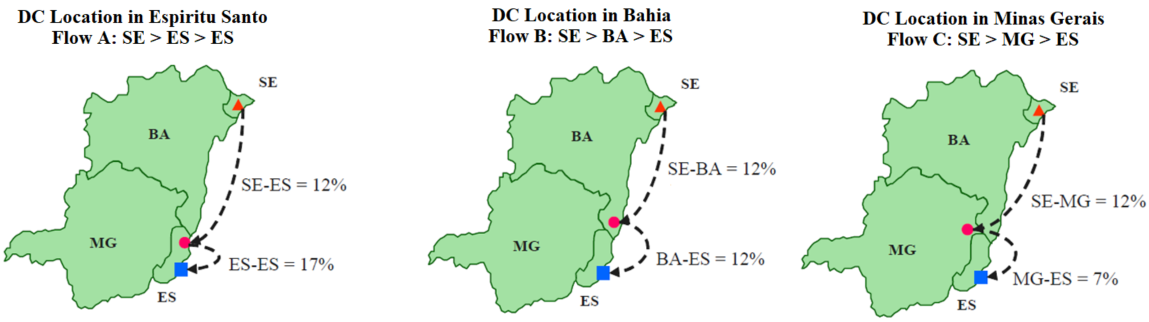


Figure C.2: ICMS flow and rates for candidate locations of the example of Silva (2007)

Suppose a retailer in ES has a demand for goods with a cost of \$100 and a sale price of \$150. In the transfer of goods from the plant in SE to the DCs (ES, BA, or MG), the ICMS rates coincide at 12%, generating an ICMS amount of \$13.64 in the three cases, as shown in Table C.1. In the sale operation from the DC-ES, a rate of 17% is levied, generating an amount of \$30.72, while the service from the DC-BA generates an amount of \$20.45, since the rate is 12%. However, suppose that the state of Bahia offers a presumed ICMS credit of 3%, and the amount is reduced by \$4.64, so the final amount is \$15.82. Finally, in the sale operation from DC-MG, an ICMS rate of 7% is levied, generating a debit of \$11.29. These three values represent the ICMS debit, from which the credit for the transfer operation (between the plant and the DC) is subtracted (\$13.64), obtaining the balance or balance payable of \$17.08, \$2.18 and -\$2.35 for DC-ES, DC-BA and DC-MG, respectively. The operation in DC-MG generated dead credit, as the amount paid in the transfer to the DC (\$13.64) is greater than the amount due in the sale operation (\$11.29). The ICMS amounts paid for each option are shown in Table C.1.

Table C.1: ICMS payable by the candidates in each echelon

	DC-ES	DC-BA	DC-MG
Credit: Plant > DC	\$13,64	\$13,64	\$13,64
Debit: DC > Retailer	\$30,72	\$15,82	\$11,29
Balance at DC	\$17,08	\$2,18	-\$2,35
ICMS payable on the network	\$30,72	\$15,82	\$13,64

Note that DC-MG generates a lower amount of ICMS payable by the network, followed by DC-BA. The location of a DC in the State of ES to serve retailers in ES is attractive from the perspective of transportation costs, but it is the least attractive location in terms of ICMS tax costs.

Now, suppose a logistics network for any product (for example, medicines) with a plant and a DC in the State of Sao Paulo (SP) in different municipalities and another DC in the State of Goias (GO). Also suppose the demand for several products of a retailer located in the State of SP, which consolidated represents a load with a weight of 10 kg, a cost of \$100, and a sale price of \$200. The service can be done through one of the DCs, generating ICMS and transport costs, the latter being calculated based on the weight and distance covered. The State of GO offers a presumed ICMS credit of 5.6% on the movement of products. Transportation cost, considering a unit cost of \$0.05/kg.km; and ICMS amount, considering the applicable origin-destination rates and the tax benefits offered.

The total cost to meet the demand from the GO and SP DC is \$803.4 and \$190.9, respectively, as shown in Table C.2. Therefore, the demand is allocated to the SP DC. Assume increases in the total value of the retailer's order (Table C.2). The allocation of demand to the DC corresponds to a trade-off between transportation cost and ICMS payable. When the ICMS value is considerably high, it pays to pay a higher transportation cost and reduce the amount of ICMS generated, taking advantage of presumed credit rates, or lower ICMS rates.

Table C.2: sensitivity of demand allocation to variation in the cargo value

	Variation of cargo costs/prices							
	$100 - $200		$1.000 - $2.000		$10.000 - $20.000		$100.000 - $200.000	
DCs	GO	SP	GO	SP	GO	SP	GO	SP
ICMS Transfer ($)	7,5	22,0	75,3	219,5	752,7	2.195,1	7.526,9	21.951,2
ICMS Sales ($)	15,4	43,9	154,1	439,0	1.540,8	4.390,2	15.408,3	43.902,4
ICMS Balance ($)	7,9	22,0	78,8	219,5	788,1	2.195,1	7.881,4	21.951,2
ICMS PAyable ($)	15,4	43,9	154,1	439,0	1.540,8	4.390,2	15.408,3	43.902,4
Transp. in transfer ($)	453,5	21,0	453,5	21,0	453,5	21,0	453,5	21,0
Transp. in sell ($)	334,5	126,0	334,5	126,0	334,5	126,0	334,5	126,0
Transp. Total ($)	788,0	147,0	788,0	147,0	788,0	147,0	788,0	147,0
ICMS + Transportation ($)	803,4	190,9	942,1	586,0	2.328,8	4.537,2	16.196,3	44.049,4
Selection de DC		✓		✓	✓		✓	

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