A hybrid multi-objective data-driven approach towards safety stock and safety time optimization

Pedro Carvalho Malheiro da Silva

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"If I've seen further than others, it is by standing upon the shoulders of giants." – Isaac Newton

Big projects always ask for a lot of hard work and effort but also some inspiration and motivation from outside. I can say that I have realized that in the first place, recently. One year ago, I could not imagine myself working in a research team with such a big project in hands. Indeed, all these years of college were a complete surprise, filled with awesome people and memorable experiences that have been shaping the person and the Engineer I aim to become in the near future. Having now reached the end of a long and demanding stage, it is time to put into words my gratitude to those who inspired me to accomplish such an achievement as the conclusion of my master's degree.

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Perhaps by the time Newton uttered that quote, he was referring to other brilliant minds in the world of science. Although I do not forget the number of scientific works that allowed me to write this document, my biggest and most sincere acknowledgments go to the "giants" who made part of this journey.

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

Uma abordagem híbrida multiobjectivo orientada por dados com vista à otimização de stocks e tempos de segurança

Resumo

Os sistemas de planeamento de necessidades de materiais (MRP) são tipicamente afetados pela incerteza da procura e da oferta, pelo que as empresas normalmente implementam *stocks* de segurança e tempos de segurança como *buffers* de inventário para minimizar o impacto destas fontes de variabilidade, protegendo-se assim contra ruturas de *stock* inesperadas. Contudo, é de notar que a manutenção do *stock* representa um custo, por isso o desafio primordial deve passar por reduzir inventários sem que isso prejudique o nível de serviço para com o cliente.

Este projeto de dissertação, realizado no ambiente industrial da Bosch Car Multimédia Portugal S.A., visa otimizar o cálculo de *stocks* e tempos de segurança dos inúmeros componentes da fábrica. Atendendo aos inconvenientes apresentados pela estratégia atualmente adotada pela empresa, baseada em experiência passada, surge a necessidade de se criar um mecanismo mais eficaz, e capaz de lidar com grandes quantidades de dados, para determinar os níveis de *buffer* de inventário.

Adotando a metodologia *Cross-Industry Standard Processes for Data Mining* (CRISP-DM) e utilizando tecnologias de *Big Data*, é estudada e concebida uma nova abordagem baseada em dados para otimizar valores de *stocks* e tempos de segurança. Este estudo assenta num sistema de inventário multi-produto, com múltiplos fornecedores e sob procura determinística – mas dinâmica – e prazos de entrega estocásticos. Esta abordagem consiste na formulação de um modelo de otimização e simulação bi-objetivo para otimizar simultaneamente os custos de posse de inventário e os níveis de serviço, sugerindo múltiplas soluções ótimas de Pareto, não dominadas, aos decisores logísticos.

A técnica de solução proposta revela um bom funcionamento para uma vasta gama de componentes caracterizados por uma procura dinâmica, prazos de entrega incertos e planos de requisitos de produção com diferentes graus de esparsidade. Esta técnica apresenta também evidências de que estudos anteriores tendem a subestimar os potenciais benefícios da combinação de decisões de *buffers* de segurança. Uma vez que se pretende atingir níveis de serviço elevados, minimizando simultaneamente os custos relacionados com o inventário, os resultados deste trabalho sugerem que, em certos casos, aparenta ser mais rentável combinar o *stock* de segurança com o tempo de segurança, comparativamente a considerar apenas um ou o outro destes *buffers* de inventário.

Palavras-Chave: Extração de conhecimento de dados, Gestão de inventários, Otimização multi-objetivo, Stock de segurança, Tempo de segurança.

A hybrid multi-objective data-driven approach towards safety stock and safety time optimization

Abstract

As material requirements planning (MRP) systems are typically affected by demand and supply uncertainty, companies usually implement safety stock and safety time inventory buffers to minimize the impact of these sources of variability, thereby protecting themselves against unexpected disruptions. However, it is noteworthy that maintaining stock represents a cost, thus the ultimate challenge should be to reduce inventories without hurting the customer's service level.

This dissertation project, carried out within the industrial environment of Bosch Car Multimedia Portugal S.A., aims to optimize the estimation process of both safety inventory buffers for the multiple components. Considering the drawbacks presented by the experience-based strategy currently adopted by the company, there is a need to build a more effective mechanism, able of handling large amounts of data, for safety stock and safety time determination.

Following the well-grounded methodology of Cross-Industry Standard Processes for Data Mining (CRISP-DM) and taking advantage of Big Data technologies, it is studied and designed a novel data-driven approach to provide optimal values of safety stock and safety time. The supply chain topology underlying this study relies in a multi-item multi-supplier single-stage inventory system under deterministic - but dynamic - demands and stochastic lead times. The goal mainly consists in the formulation of a hybrid bi-objective optimization model to simultaneously optimize upstream inventory holding costs and service levels, suggesting multiple non-dominated Pareto-optimal solutions to logistics decision-makers.

The proposed solution technique has shown to work well across a wide range of components characterized by dynamic demand, uncertain lead-time, and requirements plans with different degrees of sparsity. It also provides evidence that previous studies tend to underestimate the potential benefits of combining safety-buffering decisions. Since it is intended to achieve high service levels while minimizing inventory-related costs, the results of this work suggest that, in certain cases, it appears to be more cost-effective to combine safety stock with safety time compared to considering these two inventory-buffers independently.

Keywords: Data mining, Inventory management, Multi-objective optimization, Safety stock, Safety time.

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Acronyms

AE Automotive Electronics.

AI Artificial Intelligence.

BOM Bill of Materials.

CM Car Multimedia.

CRISP-DM Cross-Industry Standard Processes for Data Mining.

DM Data Mining.

ERP Enterprise Resource Planning.

IT Information Technology.

KPIs Key Performance Indicators.

MRP Material Requirements Planning.

OR Operations Research.

SBX Simulated Binary Crossover.

SCD Shop Calendar Day.

SCOR Supply Chain Reference Model.

SCRM Supply Chain Risk Management.

SLR Systematic Literature Review.

VMI Vendor-managed Inventory.

Chapter 1

Introduction

This chapter begins with a brief overview of the topics covered in this dissertation, followed by a short description of the problem, the objectives and the research methodology used. At the end, the thesis structure is presented.

1.1 Background

In a business environment characterized by high complexity and uncertainty, manufacturing companies are encouraged to manage their supply chains effectively, aiming to increase efficiency and reactivity (Thun and Hoenig, 2011). Daily supply chain problems, such as supplier losses or quality issues enhance the importance of supply chain risk management (SCRM), which encompasses a wide variety of quantitative/qualitative strategies to identify, assess, mitigate and monitor unexpected events or conditions (Baryannis et al., 2019).

Although SCRM is a primary concern in many companies, it is limited supported by information technology (IT) systems, and disruptions in the supply chain are mostly treated reactively, missing ways to manage upcoming or future risks (Leveling et al., 2014). With the huge volume of data that companies have access to, digital and advanced analytic technologies play a critical role to accelerate operations and to minimize costs. Consequently, the use of data becomes more important as data-driven solutions start being adopted in this context (Kara et al., 2020).

By reducing vulnerability factors, companies decrease the likelihood of a disruption and increase their resilience – defined by Ponomarov and Holcomb (2009, p.131) as "*the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function*". The creation of a resilient supply chain can be achieved by creating redundancy, which means keeping some resources in reserve to be used in case of a disruption. One of the most common forms of redundancy are safety stocks (Sheffi and Rice Jr, 2005). Dolgui and Prodhon (2007) stand out this buffer strategy as exceptionally important for production since it circumvents the random factors whilst reducing the risk of shortages and increasing the holding costs. Indeed, no supply chain can operate without safety stocks (Syntetos et al., 2016). Likewise, other studies suggest the use of another inventory dampening strategy, known as safety time (Guide Jr and Srivastava, 2000), which is characterized for planning order releases earlier than what is indicated by the requirements plan and scheduling the corresponding receipts earlier than the required due date (Alves et al., 2004).

Material Requirements Planning (MRP) systems are usually affected by two basic sources of uncertainty (Whybark and Williams, 1976): demand and supply. The first source refers to changes in the gross requirements for a part. The second one exists in scheduled receipts for a part. Typically, companies implement inventory buffers to minimize the impact of these uncertainties. When creating these buffers in their stocks, they are protecting themselves against such unexpected disruptions. Nevertheless, it is well-known that maintaining stock represents a cost, and managers have been under increasing pressure to decrease inventories, as supply chains attempt to become leaner (Chopra et al., 2004). Hence, the goal is to reduce inventories without hurting the service level provided to customers. Adopting such a strategy often depends on rapid and flexible decision-making based on large, multidimensional data sources. These characteristics make SCRM a suitable area for the application of Artificial Intelligence (AI) techniques (Baryannis et al., 2019).

Yet, it is noteworthy that while large companies have access to large amounts of information, they are, in most cases, unable to process it intelligently. This dissertation, carried out in the Logistics department of Bosch Car Multimedia Portugal S.A., focuses on the development of a data-driven framework to optimize both safety stock and safety time levels for multiple components. Currently, the plant lacks a standardized and quantitative strategy for setting inventory buffers. The present approach adopted by the company is mainly based on experience rather than technique, considering several logistics criteria. In order to overcome the drawbacks presented by the current approach, there is a need to develop a more effective mechanism for dimensioning safety stock and safety time while coping with large amounts of data.

This project involves the development of a multi-objective simulation-based optimization approach that encompasses both demand and supply uncertainties to provide optimal values of safety stock and safety time while minimizing holding costs and shortfall quantities. Given the importance of Big Data in the context of supply chain management (Wang et al., 2016), managers tend to be increasingly reliant upon data to have a wider overview of their operations and make decisions. Thus, it becomes important, and in fact, a necessary condition, to verify and ensure the quality and accuracy of data inputs (Cai and Zhu, 2015) aiming to extract knowledge from data, bringing them together in a unified and accessible way (Korbel et al., 2019). At this point, the proposed approach is intended to be flexible enough to operate in supply chain contexts involving Big Data infrastructures, where data as an input to the developed multi-objective simulation-based optimization model is treated beforehand in such a way that it can generate valuable and reliable information.

1.2 Objectives

The main goal of this dissertation is to develop a data-driven framework for simultaneously optimize safety stock and safety time values in general supply chain contexts with assembly operations.

In order to achieve this research objective, the following research questions (RQ) were proposed to be answered:

> **(RQ1)** *What operations research models and methods have been explored concerning the problem of setting safety stocks?*
>
> **(RQ2)** *How to design and implement a data-driven framework able to process large amounts of data towards safety stock and safety time optimization?*

While answering to the aforementioned questions, it is also intended to achieve sub-goals (SG) that could be perceived as success criteria, namely:

- (SG1) The proposed framework should minimize holding costs while maintaining desirable customer service levels;
- (SG2) The proposed framework should encompass the supplier delivery performance when suggesting safety stock and safety time values, by identifying which logistics variables should be taken into account for modeling supplier disruptions;
- (SG3) The proposed framework should act as a decision support system for logistics planners towards safety stock and safety time optimization.

Overall, this dissertation intends to propose a flexible decision support system able to allow business experts to generate cost-effective safety stocks and safety times, in a multi-item/multi-supplier supply chain context involving assembly operations.

1.3 Research methodology

According to Han et al. (2011), Data Mining (DM) can be described as the process of discovering valuable patterns and knowledge from large volumes of data. The data sources can include different types, such as databases, data warehouses, the Web or data that are dynamically streamed into a system. In this project, large amounts of data will be used and treated so they can be used as valuable inputs to achieve the expected objectives. Given the data-driven nature of this dissertation, the Cross-Industry Standard Processes for Data Mining (CRISP-DM) methodology (Chapman et al., 2000) will serve as basis for the development of the contents presented in subsequent chapters. It is noteworthy that the CRISP-DM methodology is commonly applied in real-world DM research projects (see, e.g., Moro et al., 2011) as it presents some parallels with well-grounded research methodologies (Moro, 2015). Apart from this, the choice of such methodology is also justified by its ability to provide a comprehensive and systematic way to conduct data analytics research studies (Oztekin et al., 2016), especially in real-world industrial contexts (Kharlamov et al., 2020). Hereinafter, the fundamental concepts related to this research approach are mainly retrieved from Chapman et al. (2000).

CRISP-DM encompasses a non-rigid sequence of six phases, together with their respective tasks and relationships (Fig. 1.1). This sequence allows to moving back and forward between the different phases whenever required. Depending on the outcome of each phase, it is decided which phase or which task of a phase has to be performed next. Note that the arrows indicate the most important and frequent dependencies between phases.

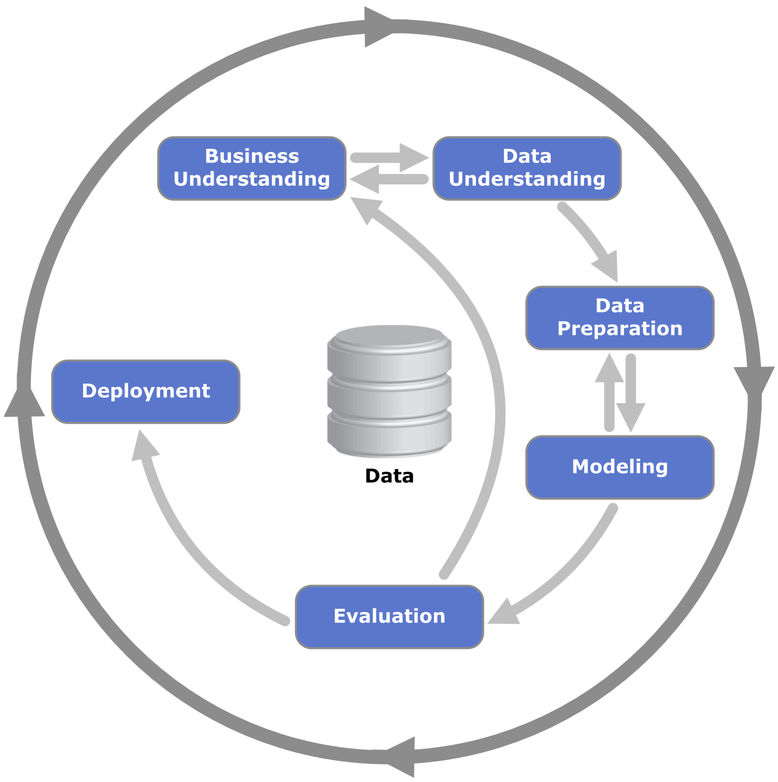

Figure 1.1: CRISP-DM reference model (adapted from Shearer, 2000).

Due to its cyclical nature, this methodology allows that the lessons learned during the development process usually trigger new and improved business-related outcomes. Following this reasoning, subsequent processes can benefit from the experience of previous ones. Each phase of the CRISP-DM methodology, is briefly described in Table 1.1. Such phases will serve as a basis to answer the investigation problem raised in Section 1.2. In particular, Chapter 4, in which is presented the proposed optimization framework, is organized according to the main phases of CRISP-DM.

Table 1.1: Summary of CRISP-DM phases.

	Description
Business Understanding	In this initial phase, project objectives, requirements and constraints are determined from the business perspective, and then converted to a DM problem. The business problem and the preliminary strategy to achieve the pretended goals are defined.
Data Understanding	The data understanding phase encompasses the initial data collection and the activities to get a closer overview of that data, such as data quality verification and data exploration.
Data Preparation	This phase covers all the activities to construct the dataset, which refers to the data that will feed the modeling tool. Such activities include table record, attribute selection and transformation, and data cleansing.
Modeling	In the modeling phase, various techniques are applied, such as algorithms to search, identify and display patterns or messages. Note that several approaches can be used for the same problem. Some of them have a specific set of requirements on the form of data, therefore it could be necessary to step back to the previous phase.
Evaluation	At this stage, the model applied and the steps followed to construct the model should be reviewed thoroughly in order to ensure it properly achieves the business objectives previously defined. It is important to verify if there is any important business issue that is not being considered. This phase ends with the decision on the use of the DM results.
Deployment	In this last phase, the obtained knowledge needs to be organized and presented in order to be employed by the end user. Usually, the deployment phase involves the application of models within an organization's decision-making processes. Depending on the requirements, this stage can include simple solutions, just by generating a report, or more complex ones such as implementing a repeatable DM process across the enterprise.

1.4 Dissertation structure

This dissertation is organized into 5 chapters, each one with one or more sections, as described below.

Chapter 1 highlights the purpose of this work, presenting a general overview of the project as well as its objectives and the followed research methodology.

In **Chapter 2**, a literature review is displayed in order to analyze previous Operations Research (OR) models and methods that have been explored to study the safety stock problem. As a result, potential research gaps and opportunities for future research on this topic are identified. In addition, it is intended that this dissertation allows to leverage the application and transfer of academic knowledge to the business reality, in which the project is developed.

Chapter 3 describes the business context in which this dissertation was carried out. It provides a brief presentation of the case company at hand, and gives special attention to the Logistics department and its respective dynamics.

Chapter 4 introduces the fundamental problem that motivates the development of this project and describes the proposed hybrid multi-objective data-driven approach for optimizing safety inventory buffers, according to the different phases of the CRISP-DM. Moreover, it presents some computational experiments to validate the performance of the designed approach within the considered industrial environment, and discusses the obtained results.

The dissertation concludes in **Chapter 5**, in which the outcomes of the research work are summarized, while answering the research questions, and identifying limitations and potential recommendations for future work on this subject.

Chapter 2

Literature Review

In this chapter, a systematic literature review (SLR) (Tranfield et al., 2003) is proposed to explore and identify relevant papers on OR-based models and methods for setting safety stocks, aiming to provide useful insights for the work developed throughout this dissertation. It is also intended that, as a result of this study, potential research gaps and opportunities for future research on these topics are uncovered.

This chapter intends to answer the first research question previously defined.

> **(RQ1)** *What operations research models and methods have been explored concerning the problem of setting safety stocks?*

With the purpose of deeply explore the previous studies on the safety stock problem, this question was subdivided in two additional research questions, as presented below:

> **(RQ1.1)** *What type of supply chain structures have been considered when developing OR models and methods for setting safety stocks?*
>
> **(RQ1.2)** *What industry sectors have been explored as applications domains of such operations research models and methods?*

In order to guarantee the reproducibility of the literature review, the following steps are considered: material collection (Section 2.2); descriptive analysis (Section 2.3); category selection and material evaluation (Section 2.4). These steps are developed along the subsequent sections. Before moving towards the details of the above-mentioned steps, some fundamental closed-form safety stock expressions, commonly adopted in practice, are briefly described as follows.

2.1 Standard closed-form safety stock stochastic expressions

The fundamental safety stock expressions are hereinafter recalled. For that, this work takes advantage of the research survey conducted by Schmidt et al. (2012).

Safety stock calculation is frequently performed by making use of a standard formula which, assuming that demand is typically modeled as normally distributed, multiplies a safety factor dependent on the service level with the standard deviation of the demand during the lead time:

$$SS = SF(SL) \cdot \sigma_D \cdot \sqrt{LT} \tag{2.1}$$

where SS is the safety stock level [units]; SF is the safety factor depending on service level [-]; SL is the service level [-]; σ_D is the standard deviation of demand in units per shop calendar day (SCD); and LT is the lead time [SCD]. Note that, in expression (2.1), safety stock is calculated as a function of the service level SL, which in turn is established as the percentage of the total demands served on time.

Equivalently, a similar rule is also provided in order to calculate safety stock (expression 2.2) as a function of the service level. Here it is used a forecast error derived from forecasting data as a stochastic component.

$$SS = SF(SL) \cdot \sigma_F \cdot \sqrt{LT} \tag{2.2}$$

with σ_F, standard deviation of the forecast error for the demand during LT [units/SCD].

The standard deviation of the expected error is calculated through historical data from the mean square deviation of the predicted demand from the actual one. Expression 2.2 is therefore applied regardless of a specific statistical distribution of demand.

The method presented bellow draws on the previous concepts and extends them by including a stochastic lead time.

$$SS = SF(SL) \cdot \sqrt{LT \cdot \sigma_D^2 + D^2 \cdot \sigma_{LT}^2} \tag{2.3}$$

with D, mean demand per period [units/SCD]; σ_{LT}, standard deviation of replenishment time [SCD].

In what follows it is intended to summarize the operations research models and methods that have been proposed in the scientific literature to extend or apply the above expressions in different inventory control settings and environments.

2.2 Material collection

The publications here presented and analyzed were collected as a result of a set of searches on the Scopus[1] database. In order to define the appropriate search terms, a two-level keyword assembly structure was design, aiming to accommodate a broad range of search terms for capturing published OR models and methods towards safety stock optimization. Table 2.1 shows the keyword assembly structure where the first level defines the search context and the second level contains the modeling keywords.

[1]Scopus is considered a more comprehensive research database when compared to Web-of-science (see Fahimnia et al., 2015, and references cited therein). Furthermore, it has been used and recommended as a reliable source of peer-reviewed articles within the supply chain literature (Wilding et al., 2012)

The modeling keywords are kept at a general level to cover a broader range of studies. These terms, according to INFORMS organization[2], include a wide range of problem solving techniques and methods applied towards decision making and efficiency, encompassed by OR.

Table 2.1: The proposed keyword assembly structure.

Research query	("safety time" OR "safety stock" OR "safety inventory") AND ("supply chain management" OR "inventory management") AND (simulation OR "mathematical optimization" OR optimization OR optimisation OR "queuing theory" OR "Markov decision processes" OR "economic methods" OR "data analysis" OR statistics OR "neural networks" OR "expert systems" OR "decision analysis")
Time span	All papers published up to September 2020
Article type	Peer-reviewed scientific journals and conference proceedings
Language	English
Hits in Scopus	170

This resulted in an initial set of 170 publications. To better define the papers that should be the focus of analysis, articles with the following conditions were further considered:

- Only publications published in peer-reviewed journals are included.
- Only publications published in top quartiles journals (Q1 and Q2) are included.
- Only articles that directly address the safety stock optimization problem in a quantitative fashion are included.

A content analysis of each paper, through the reading of respective abstracts, allowed the intersection with the established conditions and, consequently, made possible to identify their relevance for the purpose of this dissertation. This resulted in a more restricted set of publications: 81 papers in total.

In order to validate the adopted filtering process and papers selection criteria, a keyword bibliometric analysis based on co-occurrence data was performed in both initial (170 papers) and final (81 papers) sets of papers, by using the software VOSviewer (Van Eck and Waltman, 2010). The left and right of Fig. 2.1 show co-occurrence maps of keywords present in the papers of the initial and final samples, respectively. In both maps, the bigger the circle of a keyword, the more frequently that keyword occurs in the respective sample. Furthermore, the smaller the distance between two or more keywords, the larger the number of co-occurrences of such keywords in the same paper. A comparison between both maps of Fig. 2.1 reveals that the papers included in the final sample comply with the objective of this systematic review. At this point, note that fundamental keywords, such as "safety stock", "supply chain management" and

[2] https://www.informs.org/Explore/What-is-O.R.-Analytics/What-is-O.R.(Last accessed on November, 2020)

"inventory control", are not excluded during the content analysis of each paper and application of the aforementioned inclusion criteria. In particular, this validates the filtering process from the initial to the final sample of papers included in the subsequent analyses.

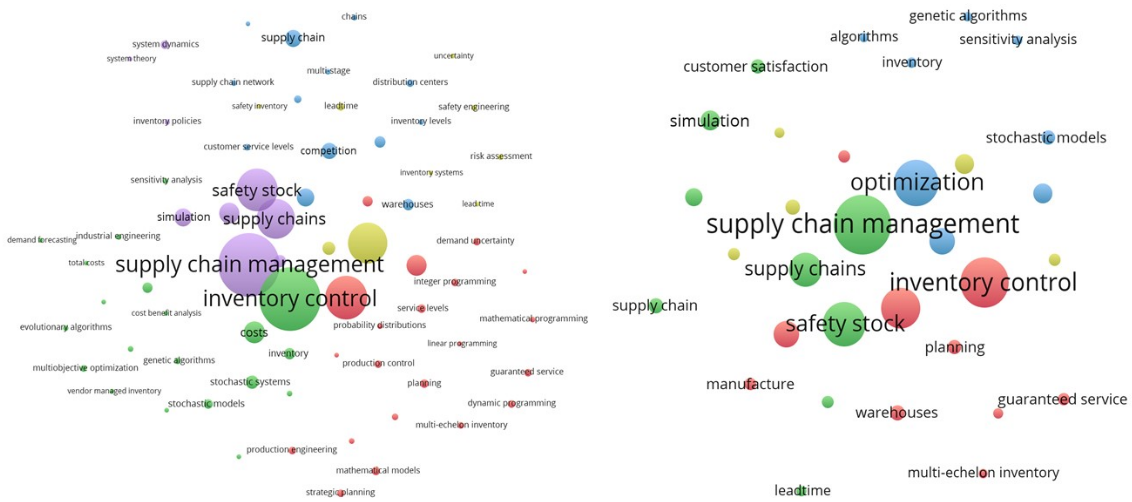

Figure 2.1: Co-occurrence maps for author and indexed keywords.

2.3 Descriptive analysis

The selected papers were descriptively characterized according to the following criteria: the number of publications over time and per international peer-reviewed journal; the modeling approach employed; and the supply chain structure type.

Regarding the evolution of the number of published articles from 1986 and 2020, there appears to be an upward trend over the considered time window (see Fig. 2.2).

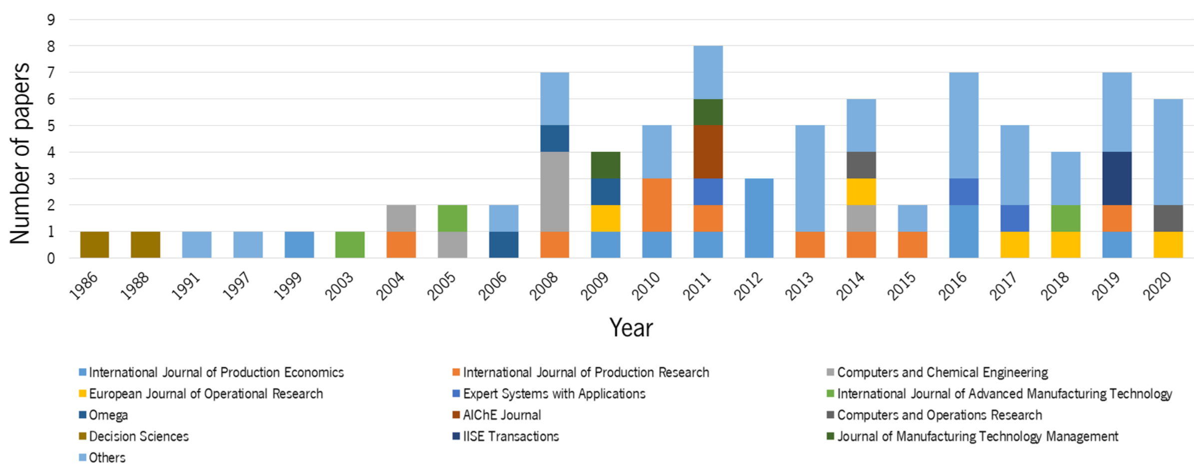

Figure 2.2: Papers distribution by peer-reviewed international journal from 1986 to 2020.

It is noticeable from Fig. 2.2 that there is a significant increase in the number of published articles from the year 2006 onwards, being 2011 the year with most identified publications. The years of 2008, 2014, 2016, 2019, and 2020 also reveal a significant number of published papers.

The sample here collected is distributed in 44 different journals, where a higher number of publications do not mean a higher relevance within the set. The International Journal of Production Economics lists the maximum number of published papers over the time window considered (10 papers) followed by the International Journal of Production Research (9 papers), the Computers and Chemical Engineering (6 papers) and the European Journal of Operations Research (5 papers). Other journals such as Expert Systems with Applications, Omega, and International Journal of Advanced Manufacturing Technology, also contain a considerable number of publications on the topic of OR models and methods for safety stock optimization.

In what concerns to the distribution of papers according to the modeling approach employed, this research found that the problem of setting optimal values of safety stocks is usually addressed by using analytical/optimization models, simulation models or hybrid models (Fig. 2.3). It is noteworthy that analytical/optimization techniques play a major role on the study of safety stock optimization, since it is represented in the great majority of techniques intended for this purpose (71%). Simulation methodologies are present in 16% of the papers while hybrid approaches are employed by the remaining 12%.

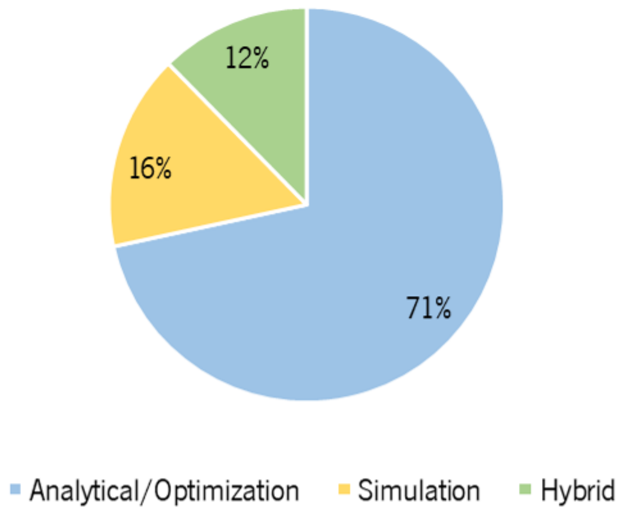

Figure 2.3: Papers distribution by modeling approach.

As to the different OR methods applied in the studied context, from Fig. 2.4 it can be concluded that optimization based methods, where the development of a mathematical programming model is observed, are the most used methods (46 papers), followed by simulation models, presented in 14 papers.

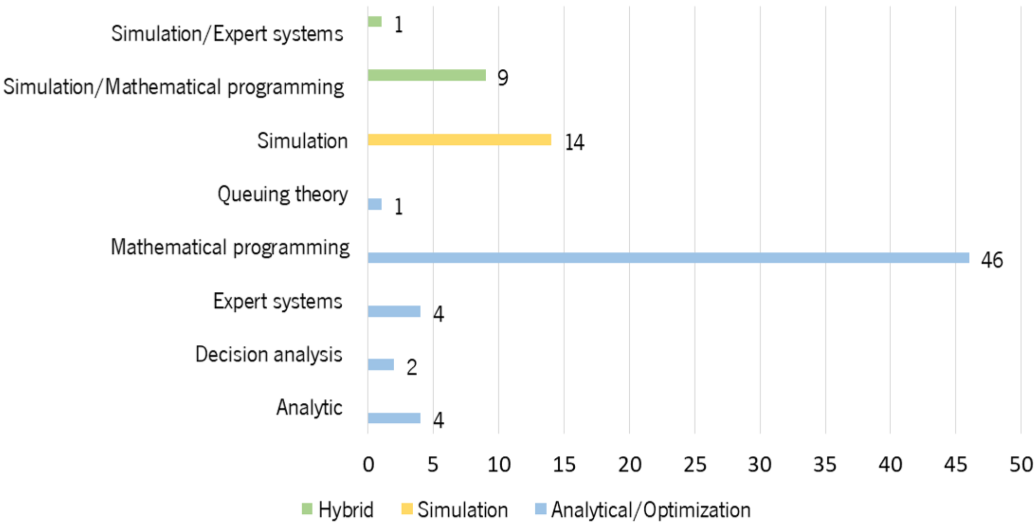

Figure 2.4: Publications distributed by OR technique employed.

On the subject of supply chain type, this investigation made possible to infer that 44 of the 81 articles analyzed (54%) were referred to a multi-echelon supply chain type, while 37 publications mentioned a single-echelon context, corresponding to 44% of the total sample. Table 2.2 presents the final amount of selected papers according to the modeling technique embraced and is subdivided by the two considered types of supply chain.

Table 2.2: Summary of the research studies based on modeling approach employed and type of supply chain structure considered.

Supply chain	Modeling approach		
	Analytical/Optimization	Simulation	Hybrid
Single-echelon	Badinelli (1986), Das and Tyagi (1997), Hung and Chang (1999), Chandra and Grabis (2008), Louly and Dolgui (2009), Ruiz-Torres and Mahmoodi (2010), Kanet et al. (2010), Teimoury et al. (2010), Sediri and Nakade (2010), Vargas and Metters (2011), Janssens and Ramaekers (2011), Jeong et al. (2013), Carlsson et al. (2014), Srivastav and Agrawal (2016), Bimpikis and Markakis (2016), Braglia et al. (2016), Yue et al. (2016), Albrecht (2017), Kang et al. (2018), Turgut et al. (2018), Tasdemir and Hiziroglu (2019), Chowdhury et al. (2019), Yang et al. (2020)	McClelland and Wagner (1988), Benton (1991), Yeh and Yang (2003), Thiel et al. (2010), Choy et al. (2011), Bam et al. (2017), Jonsson and Mattsson (2019), Aljanabi and Ghafour (2020)	Koo et al. (2008), Feng et al. (2011), Avci and Selim (2017), Cai et al. (2017), Aiassi et al. (2020), Buschiazzo et al. (2020)
Multi-echelon	Dominguez and Lashkari (2004), Kim et al. (2005), You and Grossmann (2008), Graves and Willems (2008), Jung et al. (2008), Sitompul et al. (2008), Gebennini et al. (2009), Manikas et al. (2009), You and Grossmann (2011b), Taleizadeh et al. (2011), You and Grossmann (2011a), Funaki (2012), Osman and Demirli (2012), Jeong and Leon (2012), Humair et al. (2013), Tempelmeier (2013), Rodriguez et al. (2013), Rodriguez et al. (2014), Berling and Marklund (2014), Amirjabbari and Bhuiyan (2014), Albrecht (2014), Chen and Li (2015), Shu et al. (2015), Glock and Kim (2016), Lowe and Mason (2016), Hua and Willems (2016), Cheaitou and Cariou (2017), Hong et al. (2018), Derakhshi et al. (2018), Tempelmeier and Fischer (2019), Bayram et al. (2019), Li and Wu (2019), Ghadimi et al. (2020), Ghadimi and Aouam (2020)	Zhang et al. (2006), Reichhart et al. (2008), Beaumont and Schmidt (2009), Cattani et al. (2011), Mendoza et al. (2014), Strohhecker and Größler (2019)	Jung et al. (2004), Wan et al. (2005), Schwartz et al. (2006), Chen et al. (2013),

2.4 Category selection and material evaluation

This section provides details on the studies that have been explored when applying OR methods to safety stock optimization. The information from the analyzed publications must be grouped in order to be possible to retrieve valuable knowledge from a wide set of sources and thus respond accurately to the research questions raised at the beginning of this chapter. The selected papers were characterized according to five distinct categories: industry sector; OR method and employed technique; main performance criteria; and type of uncertainty in the supply chain. These categories were applied for each modeling methodology referred in the previous section.

2.4.1 Analytical/optimization models

A great part of the sampled papers (71%) addresses the problem of setting optimal values of safety stock by applying analytical/optimization methods, such as mathematical programming, analytic, expert systems, among others. This subsection focuses on studies that have adopted several OR techniques encompassed by these methods. Table 2.3 summarizes the findings regarding the use of analytical/optimization techniques in setting optimal values of safety stock.

Table 2.3: A literature overview of analytical/optimization models for setting safety stocks.

References	Industry Sector	OR method/Technique(s)	Main performance criteria	Type of uncertainty
(Badinelli, 1986)	–	MP/Quadratic prog.	1. Holding costs; 2. Ordering costs; 3. Stockout costs	Demand
(Das and Tyagi, 1997)	–	MP/NLP	1. Inventory costs; 2. Transportation costs	Demand
(Hung and Chang, 1999)	Electronic	Analytic/Inventory theory	1. On-time delivery; 2. Costumer service level	Other
(Dominguez and Lashkari, 2004)	Appliance manufacturing	MP/MIP	1. SC costs	Demand/ Lead time
(Kim et al., 2005)	Retail	Expert systems/Reinforcement learning; Inventory theory	1. Service level	Demand
(You and Grossmann, 2008)	Chemical	MP/MINLP	1. NPV	Demand
(Graves and Willems, 2008)	–	MP/Dynamic prog.	1. Holding costs	Demand
(Chandra and Grabis, 2008)	–	MP/Heuristic	1. Holding costs; 2. Procurement costs	Demand
(Jung et al., 2008)	Chemical	MP/LP	1. Holding costs; 2. Service level	Demand
(Sitompul et al., 2008)	–	MP/Heuristic	1. SC costs	Demand/ Lead time
(Gebennini et al., 2009)	Electronic	MP/MINLP	1. SC costs	Demand
(Louly and Dolgui, 2009)	Electronic/ Automotive	MP/Combinatorial optimization	1. Holding costs; 2. Service level	Demand

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Table 2.3 – *Continued from previous page*

References	Industry Sector	OR method/Technique(s)	Main performance criteria	Type of uncertainty
(Manikas et al., 2009)	Construction	MP/Heuristic	1. Profit	Demand
(Ruiz-Torres and Mahmoodi, 2010)	Electronic	Decision analysis/Decision tree; Inventory theory	1. Holding costs; 2. Service level	Demand/ Lead time
(Kanet et al., 2010)	Automotive	MP/LP	1. Shortage Freq.; 2. Fill rate	Demand/ Lead time
(Teimoury et al., 2010)	Chemical	MP/MIP	1. SC costs	Demand/ Lead time
(Sediri and Nakade, 2010)	Retail	Decision analysis/Game theory; Inventory theory	1. Profit	Demand
(You and Grossmann, 2011b)	Chemical	MP/MINLP	1. Total costs	Demand/ Lead time
(Taleizadeh et al., 2011)	–	MP/INLP	1. SC costs	Demand/ Lead time
(You and Grossmann, 2011a)	Chemical	MP/MINLP	1. SC costs; 2. SC responsiveness	Demand/ Lead time
(Vargas and Metters, 2011)	–	MP/Heuristic	1. SC costs	Demand
(Janssens and Ramaekers, 2011)	–	MP/LP	1. Shortage freq.; 2. Stockout prob.	Demand
(Funaki, 2012)	Machinery	MP/Dynamic prog.	1. SC costs	Demand
(Osman and Demirli, 2012)	–	MP/MINLP; BD	1. SC costs	Demand/ Lead time
(Jeong and Leon, 2012)	–	MP/Convex prog.	1. Profit	Demand
(Humair et al., 2013)	–	Analytic/Closed-form expressions	1. Inventory levels	Demand/ Lead time
(Jeong et al., 2013)	Manufactured Housing	MP/–	1. Holding costs; 2. Stockouts	Demand/ Lead time
(Tempelmeier, 2013)	–	Queuing theory/Probability theory	1. SC costs	Demand/ Lead time
(Rodriguez et al., 2013)	Electric motors	MP/MINLP	1. SC costs	Demand
(Rodriguez et al., 2014)	Electric motors	MP/MINLP; MILP	1. SC costs	Demand
(Carlsson et al., 2014)	Pulp	MP/Robust optimization	1. SC costs	Demand/ Lead time
(Berling and Marklund, 2014)	Retail	MP/Heuristic	1. Holding costs; 2. Fill rate; 3. Shortage costs	Demand/ Lead time
(Amirjabbari and Bhuiyan, 2014)	Aerospace	MP/NLP	1. Logistics costs	Demand
(Albrecht, 2014)	–	MP/Heuristic	1. Holding costs; 2. Back-order costs	Demand

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Table 2.3 – *Continued from previous page*

References	Industry Sector	OR method/Technique(s)	Main performance criteria	Type of uncertainty
(Chen and Li, 2015)	–	MP/Dynamic prog.	1. Holding costs; 2. Ordering costs	Demand/ Lead time
(Shu et al., 2015)	Retail	MP/MIP	1. SC costs	Demand/ Lead time
(Srivastav and Agrawal, 2016)	–	Expert systems/MOPSO; MOGA	1. Inventory costs; 2. Stockout units; 3. Stockout freq.	Demand
(Glock and Kim, 2016)	–	MP/Integer prog.	1. SC costs	Demand/ Lead time
(Bimpikis and Markakis, 2016)	DVD's	Analytic/Closed-form expressions	1. SC costs	Demand
(Braglia et al., 2016)	–	MP/Heuristic	1. SC costs	Demand
(Lowe and Mason, 2016)	Electronic	MP/MIP	1. SC costs	Demand
(Hua and Willems, 2016)	IT	Analytic/Inventory theory	1. Holding costs	Demand/ Lead time
(Yue et al., 2016)	Retail	Expert systems/ABC algorithm	1. Total inventory costs; 2. Total gross profit	Demand
(Albrecht, 2017)	–	MP/Heuristic	1. Service level; 2. Inventory costs	Demand
(Cheaitou and Cariou, 2017)	Shipping	MP/Heuristic	1. Costs; 2. Profit	Demand
(Hong et al., 2018)	–	Expert systems/Spanning tree; PSO	1. SC costs	Demand
(Kang et al., 2018)	–	MP/–	1. SC costs	Other
(Turgut et al., 2018)	Retail	MP/MILP	1. SC costs	Demand
(Derakhshi et al., 2018)	–	MP/MILP	1. SC costs	Demand
(Tasdemir and Hiziroglu, 2019)	Wood	MP/Heuristic	1. Inventory costs	Demand
(Tempelmeier and Fischer, 2019)	–	MP/Heuristic	1. Holding costs; 2. Waiting costs; 3. Service level	Demand/ Lead time
(Chowdhury et al., 2019)	Additive Manufacturing	MP/Stochastic prog.	1. SC costs	Demand
(Bayram et al., 2019)	Electronic	MP/MIP	1. SC costs	Demand/ Lead time
(Li and Wu, 2019)	–	MP/Dynamic prog.	1. Inventory costs; 2. Service level; 3. Fill rate	Demand
(Ghadimi et al., 2020)	–	MP/MINLP	1. Holding costs	Demand
(Yang et al., 2020)	Food	MP/MILP	1. Fill rate	Demand
(Ghadimi and Aouam, 2020)	Electronic	MP/Heuristic	1. SC costs	Demand

Nomenclature: MP: Mathematical programming; SC: Sypply Chain; NLP: Non-Linear Programming; MIP: Mixed-Integer Programming; MINLP: Mixed-Integer Non-linear Programming; NPV: Net present value; LP: Linear Programming; INLP: Integer Non-Linear Programming; MILP: Mixed-integer Linear Programming; MOPSO: Multi-Objective Particle Swarm Optimization; MOGA: Multi-Objective Genetic Algorithm; IT: Information technology; ABC: Artificial Bee Colony; PSO: Particle Swarm Optimization; BD: Benders Decomposition; –: Not reported.

2.4.1.1 Mathematical programming

Mathematical programming appears to be the most used method among the various OR analytical/optimization methods. Moreover, nearly 50% of the total sampled papers implemented mathematical programming models to address the safety stock problem.

Combinatorial optimization. Louly and Dolgui (2009) introduced a novel approach for components safety stock calculation for one level just-in-time assembly system with random lead times. The authors use a branch and bound algorithm to determine the optimal value of safety stock for each type of component, minimizing average holding cost whilst meeting a given service level.

Robust optimization. Carlsson et al. (2014) designed a model to handle the uncertainty and to establish a distribution plan, together with related inventory management. In this research work, there was no need for explicit safety stock levels since it was taken into account directly through the robust solution.

Convex programming. Considering that information sharing among the different elements in a supply chain appears to be an effective way to mitigate the bullwhip effect, Jeong and Leon (2012) suggested an alternating direction method and a diagonal quadratic approximation method to coordinate a supply chain under partial information-sharing environments. The proposed cost model is similar to the newsvendor problem, though it also considers safety stocks.

Dynamic programming. Dynamic programming models have been established essentially to address the problem of where to place safety stock in a multi-echelon supply chain structure, under demand uncertainty (Graves and Willems, 2008; Funaki, 2012; Li and Wu, 2019). This process is commonly referred to as safety stock placement (Graves and Willems, 2000). In contrast, a study carried out by Chen and Li (2015) considered both types of uncertainties when solving a deterministic mathematical programming model for the optimization of an (R, Q) policy with given a cycle service level.

Integer non-linear programming. Taleizadeh et al. (2011) investigated a multi-buyer multi-vendor supply chain problem with several products and constraints. The objective was to determine the reorder point, the safety stock, the amount of shipments, and the number of packages in each shipment of each product ordered by each buyer to the vendors while minimizing the expected total costs of the chain.

Integer programming. The mathematical programming model constructed by Glock and Kim (2016) helps to determine optimal safety stock levels and optimal safety return times for returnable transport items, which, in turn, help to reduce stockout risks and the consequences associated therewith.

Linear programming. Jung et al. (2008) proposed a linear programming model to optimally solve the problem of the safety stock placement in a multi-stage supply chain. The model incorporates the nonlinear performance functions, the interdependence between the service level at different stages of the supply chain, and capacity constraints. In a study elaborated by Kanet et al. (2010), in an automotive equipment industry, the authors made use of the same technique to provide a model for the problem of minimizing inventory given a set of safety stock targets. On the other hand, Janssens and Ramaekers (2011) formulated an optimization model in order to determine a safety stock level which guarantees the performance measure under the worst case of uncertain lead-time demand.

Mixed-integer linear programming. Recent studies have adopted data-driven approaches based on MILP models in optimizing safety stock levels (Turgut et al., 2018; Yang et al., 2020). Curiously, the former study produced a model in which incorporated the backroom effect, described as the handling effort of a replenishment that does not fit on the shelf of a retailer. In a separate work produced by Derakhshi et al. (2018), a multi-stage stochastic mixed-integer programming model was implemented, including several realistic constraints. In addition, through the integration of a safety stock policy in the model, it was transformed into a bi-objective optimization problem, and a hybrid exact-approximate approach was used to generate solutions.

Mixed-integer non-linear programming. F. You and I. Grossmann developed some studies (2008; 2011b; 2011a) on the safety stock problem, in which mixed-integer non-linear programming (MINLP) models are applied in the chemical industry. On the other hand, the same problem has been considered in electronic industry supply chains using MINLP approaches to deal with uncertainties on the demand side (Gebennini et al., 2009; Rodriguez et al., 2013, 2014). Moreover, in a study authored by Osman and Demirli (2012), the safety stock placement problem was tackled through the development of two different models, each one of them aiming to establish a different inventory policy. More recently, Ghadimi et al. (2020) combined the present technique with a mixed-integer linear program to build up a framework able to redesign an optimal supply chain for the spare parts. The proposed framework allowed to minimize costs as well as to make several management decisions to overcome an uncertain demand (e.g., where to place assets, which installed warehouses and factories should be eliminated, what were the stock capacities and safety stocks required, and how to connect the different echelons of the supply chain).

Mixed-integer programming. Dominguez and Lashkari (2004) proposed with a capacitated, multi-stage, multi-period, multi-commodity, and multi-facility inventory planning model in the context of a major household appliance manufacturer. The model employed the strategy of risk pooling or time postponement as a cost-reduction driver to account for the provision of safety stocks in the system. Teimoury et al. (2010) suggested, in turn, a production-inventory planning model aiming to minimize the supply chain's total cost. This dynamic framework was built upon a combination of two separate models: an inventory control system and a production planning model with safety stocks and setup times. Shu et al. (2015) studied an integrated supply chain network design problem that involved an external supplier, a set of potential distribution center locations, and a set of retail outlets. The goal was to serve all the retailers at the total minimum system-wide cost and the specified service levels. Due to the complex trade-offs among the various costs and multiple non-linear terms in the mixed-integer programming (MIP) model, traditional solution techniques were inadequate for this problem. Hence, it was outlined a polymatroid cutting-plane approach based on the sub-modular property of the cost terms. Lowe and Mason (2016) detailed a high fidelity mixed-integer programming model to schedule wafer, package, and device starts across an entire supply chain. The model took into consideration costs to qualify assembly and test locations; capacity limits at the available unit level, assembly, and test; and minimum inventory requirements as a hedge against unexpected demand. Here, safety stocks were referred to as minimum inventory levels and had been treated as settings specified in the model.

In a work developed by Bayram et al. (2019), it was considered an integrated capacity, inventory, and demand allocation decision problem, faced by a manufacturing firm with a single large production facility, multiple inventory locations, and different markets. A new linear and efficient MIP model for the demand and inventory allocation problem that exactly accounts for safety stocks was introduced. The results showed that as capacity costs increased, more distribution centers were opened and higher levels of safety stock were required to meet demand. In addition, as capacity became more expensive, it was necessary to use capacity more effectively.

Non-linear programming. In a study published by Das and Tyagi (1997), the authors determine the optimal degree of centralization as a trade-off between inventory and transportation costs, by analyzing the impact of different factors. Expressions for various elements of total system costs were formulated and their individual and combined effects on centralization were then analyzed through an optimization model. Later, Amirjabbari and Bhuiyan (2014) build up a model consisting of an optimization phase that sets the optimal safety stock value as well as its location across the supply chain and a simulation phase, in which the results of the previous phase could be sustained.

Quadratic programming. An early research carried out by Badinelli (1986) introduced an optimization procedure to determine safety stock levels under stochastic demand patterns. The suggested approach involved the estimation of a disvalue function, an optimization method to derive stockout performance, and the definition of bounds on the optimal solution.

Stochastic programming. In an additive manufacturing supply chain, a two-stage stochastic programming model was described by Chowdhury et al. (2019) for the design and management of the network, under customer demand uncertainty. While the first stage of the model determines the location and production capacity to open the additive manufacturing facilities, in the second objective function constraints guarantee a minimum raw material safety stock level for each facility.

Heuristics. Several authors applied heuristics attending to optimize safety stocks in environments affected by demand and supply uncertainties (Sitompul et al., 2008; Berling and Marklund, 2014; Tempelmeier and Fischer, 2019). Interestingly, Berling and Marklund (2014) presented a flexible heuristic for determining near-optimal reorder points at all locations of a multi-stage retail supply chain. However, the majority of the studies applying heuristics in this context have only focused on demand uncertainty (Chandra and Grabis, 2008; Manikas et al., 2009; Vargas and Metters, 2011; Cheaitou and Cariou, 2017). For instance, M. Albrecht provided two studies employing heuristics to determine the optimal safety stock levels (2014; 2017). While the former study was conducted in a multi-echelon supply chain, in the latter one, a single-stage structure was considered. On the other hand, Tasdemir and Hiziroglu (2019) structured a six-step systematic optimization approach in order to optimize a raw material inventory management system of a wood company. In a different industrial setting, Ghadimi and Aouam (2020) used a nested Lagrangian relaxation heuristic to address the problem of jointly optimizing capacity planning and safety stock placement for a production-distribution system, consisting of one manufacturer, one warehouse with capacity constraints, and one retailer.

Besides the aforementioned techniques, other mathematical programming approaches were also proposed. By way of example, Jeong et al. (2013) designed an optimization framework of an industry-specific supplier relationship management, composed of six modules, in which one of them calculates the optimal safety stock for the desired service level. Kang et al. (2018) developed a mathematical model that considers, as decision variables, safety stock, lot size, and planned backorders for a single-stage imperfect production setup. The presented model allowed the authors to tackle the uncertainty caused by product imperfection.

2.4.1.2 Analytic

Another type of approach to establish safety stock levels is based on analytic techniques. In a study conducted by Humair et al. (2013), the authors extended the guaranteed service model for safety stock optimization to incorporate stochastic lead times in multi-echelon networks. This work on lead-time variability was critical to adopt the guaranteed service approach in a generalized way. Bimpikis and Markakis (2016) provided simple closed-form expressions that determine the benefit from inventory pooling, in terms of both the expected cost and the safety stock. In a two-stage network environment, Hua and Willems (2016) analytically characterized the impact of lead time and cost allocation on safety stock placement. In their model, lead times are independent of the production plan and can be interpreted as control parameters.

In an earlier study, Hung and Chang (1999) proposed a safety stock estimation method to mitigate the uncertainties caused by the variability of both flow times and production rates in available-to-promise environments. Safety levels are presented as a linear function of the yield rate and can be determined according to a given on-time-delivery specification.

2.4.1.3 Expert systems

The willingness to develop advanced decision models, with higher capabilities to support decision-making in a wide range of applications, boosts the integration of multiple criteria decision analysis techniques with efficient systems such as intelligence and expert systems (Zyoud and Fuchs-Hanusch, 2017). Studies have been applying this type of approach in the context of retail supply chains. Kim et al. (2005) proposed two adaptive inventory control models for a supply chain consisting of one supplier and multiple retailers, in which safety lead time and safety stock were the control parameters of the supplier and the retailers, respectively. The objective of the models was to satisfy a target service level predefined for each retailer. A demand forecasting method was further presented by

Yue et al. (2016), based on the product life cycle and taking into consideration the characteristics of fashion products. The employed method is based on the Artificial Bee Colony algorithm combined with polynomial regression and intended to optimize safety stocks, total inventory costs, and gross profit.

In a separate context, Srivastav and Agrawal (2016) developed a multi-objective hybrid backorder inventory model for monopolistic items using a multi-objective Particle Swarm Optimization (MOPSO) algorithm. Later, Hong et al. (2018) combined the latter algorithm with a spanning-tree based approach to solve a supply chain configuration problem for a green product family, where safety stock is adopted to satisfy stochastic demands.

2.4.1.4 Other models

This sections intends to provide a general overview on other analytical/optimization models that differ from those presented before. Ruiz-Torres and Mahmoodi (2010) applied decision analysis when presented with an alternative re-ordering point model, based on historical data, to determine the possible outcomes of the replenishment cycle. By taking advantage of Game Theory, Sediri and Nakade (2010) studied a buyback contract model of the competitive newsvendor problem between a single supplier and multiple retailers under simultaneous price and safety stock competition. In their approach, the authors computed Nash equilibrium prices, safety stocks, optimal wholesale, optimal supplier, and retailers' profits, numerically. On the other hand, one study was found applying queuing theory in this context, in which Tempelmeier (2013) developed a multi-level inventory optimization model that uses a discrete-time reorder point-order quantity policy for the central warehouses and a base-stock policy for distribution centers. The results have focused on optimized values of decision variables at the factory, warehouse, and distribution center.

2.4.2 Simulation models

Another approach for optimizing safety stock values is through the application of simulation models. Although the use of this type of methods is relatively lower, compared to the analytical/optimization ones, a significant amount of studies made use of simulation based models as a solution technique (16%).

This subsection presents the studies that apply such techniques. Table 2.4 provides an overall characterization of the papers hereinafter described.

In the study conducted by Beaumont and Schmidt (2009), discrete-event simulation was applied, resulting in performance improvements through the exchange of order data, once it enhanced the stock calculations without hurting the service levels. By adopting the same technique, Thiel et al. (2010)

Table 2.4: A literature overview of simulation models for setting safety stocks.

References	Industry Sector	OR method/Technique(s)	Main performance criteria	Type of uncertainty
(McClelland and Wagner, 1988)	–	Simulation/–	1. SC costs	Demand/ Lead time
(Benton, 1991)	–	Simulation/–	1. Service level	Demand
(Yeh and Yang, 2003)	Clothing	Simulation/–	1. Inventory costs	Demand
(Zhang et al., 2006)	Retail	Simulation/–	1. Holding costs; 2. Backorder costs; 3. Fill rate	Demand
(Reichhart et al., 2008)	–	Simulation/Monte Carlo	1. Operational costs	Demand
(Beaumont and Schmidt, 2009)	–	Simulation/DES	1. Average Inventory level; 2. Average SS; 3. Service level	Demand
(Thiel et al., 2010)	–	Simulation/DES	1. SC costs	Demand
(Cattani et al., 2011)	Home improvements	Simulation/Monte Carlo	1. Inventory levels; 2. Service levels	Demand
(Choy et al., 2011)	–	Simulation/System dynamics	1. Inventory costs	Demand
(Mendoza et al., 2014)	–	Simulation/System dynamics	1. SC costs; 2. Service level	Demand
(Bam et al., 2017)	Pharmaceutical	Simulation/System dynamics	1. SC costs; 2. Shortage freq.	Demand/ Lead time
(Jonsson and Mattsson, 2019)	Miscellaneous	Simulation/DES	1. Ordering costs; 2. Service level	Demand
(Strohhecker and Größler, 2019)	Pharmaceutical	Simulation/System dynamics	1. Profit	Demand/ Lead time
(Aljanabi and Ghafour, 2020)	Cement	Simulation/–	1. SC costs	Demand/ Lead time

Nomenclature: SC: Sypply chain; DES: Discrete-event simulation; –: Not reported.

simulated the impact of inventory record inaccuracy on service level quality, based on a (Q, R) continuous-review lost-sales inventory model. Their research focused on determining the required buffer size to minimize shortage costs. Additionally, under a similar context of demand uncertainty, Jonsson and Mattsson (2019) explained the effects of inherent differentiation and system level throughput assessment in inventory management, by testing the performance of adopting a safety time margin when replenishing inventory on-hand, as an alternative to the safety stock approach based on a targeted demand.

Other works have been applying Monte Carlo simulation in multi-echelon supply chain systems. For instance, Reichhart et al. (2008) proposed a novel safety stock formula for multi-variant products and responsive systems, by taking advantage of this simulation process. Cattani et al. (2011), in turn, have used the same approach to model a company's decentralized system and therefore determine the expected inventory and service levels.

System dynamics have also been explored to optimize safety stock levels, mainly in the context of pharmaceutical industry supply chains. Bam et al. (2017) combined supplier characteristics, inventory management strategies and demand forecasting methods, and simulate several scenarios to identify an optimal set of management policies that minimizes supply chain costs. Strohhecker and Größler (2019), under a similar industrial environment, used simulation experiments to build up inventory policies on handling critical failures in the production process. In a different context, Choy et al. (2011) assessed the need for safety stock at the customer order decoupling point. In their work, it is presented a model capable of testing how configurations with differently located customer oder decoupling points respond to two different demand signals. Moreover, Mendoza et al. (2014) demonstrated the use and application of a systems dynamics-based simulation approach as a research methodology (Forrester, 1997) for aggregate production planning policies in a two-level, multi-product and work force intensive supply chain.

Apart from the techniques mentioned above, other models were found in this context. By way of example, McClelland and Wagner (1988) showed, in his simulation study, that the best level of the product structure where to concentrate inventory depends on how the variance of end-item demand interacts with the Bill of Materials (BOM) structure. Some of the complexities of safety stock were further explored by Benton (1991) that addressed the problem of whether to place a replenishment order to achieve a predetermined service level. The main feature of their model is to generate several periods of planned and actual requirements, and to account for the safety stock levels that resulted from a specific service level and lot size methodology. Later, Yeh and Yang (2003) incorporated several factors such as lead times, ordering policies and inventory holding costs and, by making use of data obtained from a garment manufacturer, established a process sequence that minimized the total expected costs. In another study, Zhang et al. (2006) evaluated a three-stage linear supply chain model and provided an approach to quantify the value of shared shipment information. Their model aimed to support supply chain managers assessing cost–benefit trade-offs during information system construction. More recently, Aljanabi and Ghafour (2020) applied simulation to generate demand during lead-time probability distribution data. The distribution parameters was then extracted and used to establish the safety factor of the safety stock.

2.4.3 Simulation-based optimization models

As discussed in previous sections, many studies apply optimization or simulation methods to address the safety stock optimization problem. However, 12% of the sampled papers combine these two modeling approaches in simulation-based optimization models, or the so-called hybrid models. This combination is used quite often for optimizing model inputs, computing model parameters, or sampling of scenarios for mathematical programming models (Figueira and Almada-Lobo, 2014).

Table 2.5 briefly presents some representative works on this subject and that will be discussed throughout this subsection.

The most part of the studies that apply hybrid methodologies brings mathematical programming together with simulation techniques. For instance, Jung et al. (2004) proposed a computational

Table 2.5: A literature overview of simulation-based optimization models for setting safety stocks.

References	Industry Sector	OR method/Technique(s)	Main performance criteria	Type of uncertainty
(Jung et al., 2004)	Chemical	Simulation; MP/Monte Carlo; LP	1. Customer satisfaction level; 2. SC costs	Demand
(Wan et al., 2005)	–	Simulation; Expert Systems/Monte Carlo; LSSVM; Bayesian evidence framework; DACE	1. Holding costs; 2. Backlogging costs	Demand/ Lead time
(Schwartz et al., 2006)	Electronic	Simulation; MP/SPSA	1. Profit margin	Demand/ Lead time
(Koo et al., 2008)	Chemical	Simulation; MP/DES; Genetic algorithm	1. Profit margin; 2. Customer satisfaction level index	Demand
(Feng et al., 2011)	–	Simulation; MP/DES; Stochastic prog.; Heuristic	1. Holding costs; 2. Shortage costs	Demand
(Chen et al., 2013)	Pharmaceutical	Simulation; MP/DES; MILP	1. Operational costs	Demand
(Avci and Selim, 2017)	Automotive	Simulation; MP/ MOEA/D	1. Holding costs; 2. Premium freights ratio	Demand/ Lead time
(Cai et al., 2017)	Refrigeration Unit	Simulation; MP/Monte carlo; Genetic algorithm	1. Cost rate	Demand
(Aiassi et al., 2020)	–	Simulation; MP/DES; Multi-objective optimization	1. Logistics costs; 2. Customer experience level	Demand
(Buschiazzo et al., 2020)	Healthcare	Simulation; MP/System dynamics; MILP	1. SC costs	Demand

Nomenclature: MP: Mathematical programming; LP: Linear programming; SC: Sypply chain; LSSVM: Least square support vector machine; DACE: Design and analysis of computer experiment; SPSA: Simultaneous perturbation stochastic approximation; DES: Discrete-event simulation; MILP: Mixed-integer linear programming; MOEA/D: Multi-objective evolutionary algorithm based on decomposition; –: Not reported.

approach to determine safety stock levels for different products at each stage of the supply chain. Through the application of a multi-stage stochastic program integrated with Monte Carlo simulation, this study intended to minimize the expected supply chain costs, taking into account the stochastic nature of the customer satisfaction level. Schwartz et al. (2006) presented a framework involving simultaneous perturbation stochastic approximation (SPSA) for optimally specify parameters of two decision policies for inventory management. The application of such method allowed to both reduce safety stock levels and to achieve financial benefits without compromising the supply chain operating performance. Feng et al. (2011) presented an approach that employs simulation and a linear search process in order to determine the best constant safety stock level to hedge against demand uncertainty. Later, Aiassi et al. (2020) extended an innovative model introduced by Lim et al. (2017) to find a trade-off between minimizing logistics costs and enhancing customers' experience level. Their approach initially evaluates the performance of two different inventory policies and, thereafter, calculates the optimized values of flexibility degree and safety stock fraction for each strategy, using a multi-objective simulation-optimization method.

Apart from the aforementioned strategies, safety stock solutions are, oftentimes, derived via evolutionary computation approaches. Koo et al. (2008) developed a technique for supporting decisions related to supply chain design and operations, with the purpose of maximizing profits and customer satisfaction. Optimization was performed using a non-dominated sorting genetic algorithm (NGSA-II) linked to an integrated stochastic supply chain simulator, where product safety stock as well as other operations decisions were jointly considered. Avci and Selim (2017) introduced a decomposition-based multi-objective differential evolution algorithm (MOEA/D) for inventory optimization, which operates in a simulation-based optimization fashion. In the simulation phase, safety stocks are evaluated in terms of holding costs and premium freights ratio, and in the optimization phase, the outputs from the previous phase are considered to generate new safety stock levels. In addition, Cai et al. (2017) combined a genetic algorithm with Monte Carlo simulation to obtain the optimal safety inventory level, at the lowest cost rate.

Safety stocks decisions have also been explored in the context of healthcare supply chains, either via heuristics-driven simulation-optimization approaches (Chen et al., 2013) or via system dynamics (Buschiazzo et al., 2020). Interestingly, the latter work proposed a reproducible model able to anticipate possible requirements in the supply chain configuration and to analyze the expected service level according to a desired confidence interval.

On the other hand, to a lesser extent, research has been conducted combining simulation techniques with expert systems. By way of example, Wan et al. (2005) extended the concept of simulation-based optimization by introducing a model that integrates least square support vector machine (LSSVM), Bayesian evidence framework, and design and analysis of computer experiment (DACE), aiming to optimize safety stock levels, among other supply chain decision variables. The main purpose of this extension was to mitigate the computational burden of the already existing methods.

2.5 Literature summary and discussion

Throughout this chapter, a SLR was carried out aiming to identify the existing works on OR-based models and methods for setting safety stocks, as well as to understand the development progress of these quantitative approaches to support inventory-buffering decisions. Descriptive analyses illustrated that extensive research has been conducted to address this problem, which is far from being a closed field of research. A detailed content analysis to the collected papers allowed to describe safety stock optimization strategies from three types of modeling approaches, applied in different supply chain structures. In each one of them, each paper was further characterized according to OR method, modeling technique, industry sector, performance criteria employed, and the type of uncertainty in the supply chain.

Recall that, as stated at the beginning of this chapter, this SLR intended to answer the following research question:

(RQ1) *What operations research models and methods have been explored concerning the problem of setting safety stocks?*

In what follows, the answers to this main research question **(RQ1)** and the sub-questions (**RQ1.1** and **RQ1.2**) derived therefrom are provided.

(ARQ1) By the end of this literature review, it became evident that a wide range of different models and techniques were applied with the purpose of optimizing safety stocks, whilst taking into consideration other decision variables such as costs, profits, or service levels.

- **(ARQ1.1)** In what concerns the type of supply chain structure that has been considered on the development of OR models and methods for setting safety stocks, it had been clear that the majority of the studies have employed such techniques in multi-echelon supply chain structures. This conclusion could be confirmed through the analysis displayed in Table 2.2, in Section 2.3, "Descriptive analysis".
- **(ARQ1.2)** With regard to the industry sectors, which have been explored as application domains of such OR models and methods, this study allowed to acknowledge that several branches of industry have been considered, giving particular emphasis to the fields of chemical processing, electronic semiconductors manufacturing, and retail. These last outcomes were drawn from the content analysis developed in Section 2.4, "Category selection and material evaluation".

Overall, within the analyzed literature, it was possible to retrieve relevant insights from the safety stock optimization problem and, consequently, drawn conclusions regarding both the adopted modeling approaches and the supply chain environment in which the problem was addressed.

Nevertheless, it is also possible to identify a few research gaps and opportunities for future work on the present topic. In what follows, some shortcomings are outlined and future directions in this domain are discussed.

On the lack of data-driven approaches in the context of Big Data. An informed decision-making process is only as good as the data on which it is based. Considering the different approaches encompassed in this research, only a small part of them were performed in contexts embracing large amounts of data while accounting for data quality issues. In this context, alongside business analytics technologies, Big Data has been highly adopted by companies to sustain their supply chain operations decisions (demand planning, procurement, inventory, and logistics, to name a few) (Wang et al., 2016), while guaranteeing data availability and quality (Roßmann et al., 2018). Hence, it becomes clear that safety stock decisions could be enhanced through the application of such techniques within a Big Data environment.

On the lack of supply chain contexts involving assembly operations in automotive electronics industry. From the literature analyzed it can be stated that approaches for setting optimal values safety stock were applied over a wide range of empirical contexts. Although several branches of industry were encompassed within the scope of the present research, automotive industry is still a domain in this matter that is far from being well explored. Therefore, as estimates point to an 8% growth of the automotive electronics market in a foreseen future (PRNewswire, 2017), the application of data analytics in this context becomes particularly interesting.

On the lack of non-parametric demand/lead-time modeling approaches. The findings generated from this study shown that several authors have generally been assuming normally distributed lead time demands. In addition, other approaches for setting optimal values of safety stocks have considered constant or even known lead times. In general, these assumptions and considerations do not reflect the reality of multi-item supply chain contexts, which are typically characterized by volatile and non-stationary demands. Therefore, there is a need to produce studies capable of going beyond these assumptions, for instance, through the development of non-parametric approaches, which reveal to be more suitable to address the inherent dynamics of supply chain lead time demand.

On the lack of joint optimization approaches using safety stock and safety time. The present research has allowed concluding that, although many different solution techniques have been adopted to address the safety stock problem, only a few consider safety time as a decision variable in their models. Besides, in the analyzed sample, there were not found any studies considering both safety stock and safety time combined in a single optimization approach. At a first glance, the simultaneous use of both strategies may seem redundant. Yet, note that the effectiveness of a safety time buffer is highly dependent on the supplier delivery performance. In fact, despite the existence of a safety time margin, there is a probability that the order arrives after the expected date. In these cases, the safety time margin is insufficient to cover the supply uncertainty. Instead of increasing the safety time values (which could imply bringing forward the scheduled delivery well ahead of time, and thereby a dramatic increase in holding costs), it would be interesting to evaluate the potential of maintaining (or decreasing) safety time and introduce suitable quantities of safety stock such that the overall levels of holding costs are minimized and the manufacturer's service level is not damaged. Alternatively, one could also reduce the use of safety time and take fully advantage of safety stock to cope with demand and supply variability.

Nevertheless, the holding costs derived from this strategy might be very high and, depending on the levels of uncertainty, some part of this safety stock may never be used. All of these arguments motivate the interest of combining both buffers in a multi-objective optimization approach.

In short, this review allows concluding that safety stock optimization is a topic that continues challenging both academics and practitioners in supply chain management. This dissertation intends to propose a hybrid data-driven multi-objective approach to meet these gaps while contributing to the existing literature on this subject.

Chapter 3

Case company overview

This chapter depicts the corporate environment in which this research project was developed. Initially, a brief description of the group to which the case company belongs is made, referring to its main business sectors and highlighting the division that comprises the scope of this dissertation. Following this, it is presented the plant in Braga, as well as its Logistics department.

3.1 Bosch Group

Robert Bosch GmbH is a German multinational engineering and technology company, founded by Robert Bosch in Stuttgart in 1886. It contains subsidiaries and regional companies in over 60 countries, and sales and service partners in roughly 150 locations worldwide, having approximately 400 000 associates.

The main goal of this leading global supplier of technology and services is to guarantee the future of the company, ensuring its strong and meaningful development whilst preserving its financial independence. To this end, Bosch Group is driven towards the creation of technology "invented for life", which stands for developing products able to inspire people, enhance the quality of life and contribute to the conservation of natural resources. In particular, it envisions a sustainable future, aiming to become a world reference in the electronics sector with regard to sustainability.

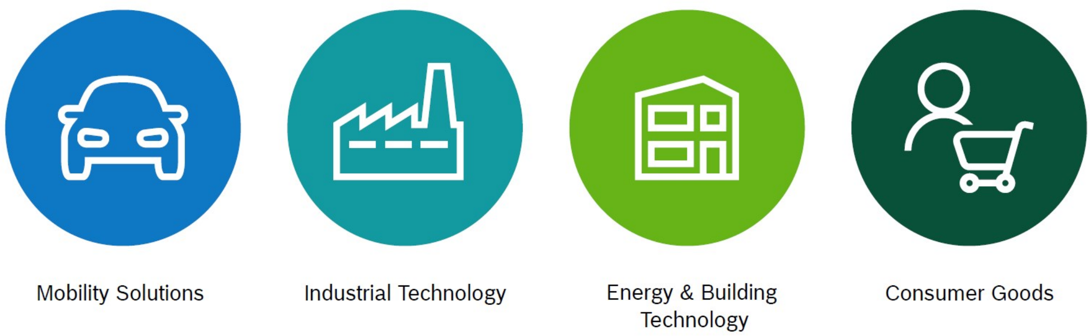

Figure 3.1: Bosch Group business sectors (Bosch, 2019).

Bosch Group comprises four business sectors: Mobility Solutions; Industrial Technology; Energy and Building Technology; and Consumer Goods (see Fig. 3.1). In 2019, the Bosch Group's total sales revenue was 77.9 billion euros, being 60% for Mobility Solutions. Each above-mentioned business sectors encompasses cross-functions, divisions, subsidiaries and business units.

3.2 Bosch Car Multimedia

Bosch Car Multimedia (CM) is one of the divisions of the Mobility Solutions sector of the Robert Bosch GmbH. This business sector offers customers and partners all over the world a portfolio that includes consulting, system development, high-volume production, and services. Whether for private and commercial vehicles, multi-modal transport services, or smart traffic infrastructure, Bosch merges vehicle technology, the data cloud, and services into complete mobility solutions.

Throughout its intelligent solutions, Bosch CM contributes to making the integration of in-car entertainment, navigation, telematics and driver-assistance systems more flexible and efficient, while keeping it easier to operate. CM develops hardware and software of the present and actively shapes the future of connected mobility. This division has 3 production plants: Braga Plant (BrgP); Penang Plant (PgP); and Wuhu Plant (WhuP), being one of the smallest divisions of its business sector.

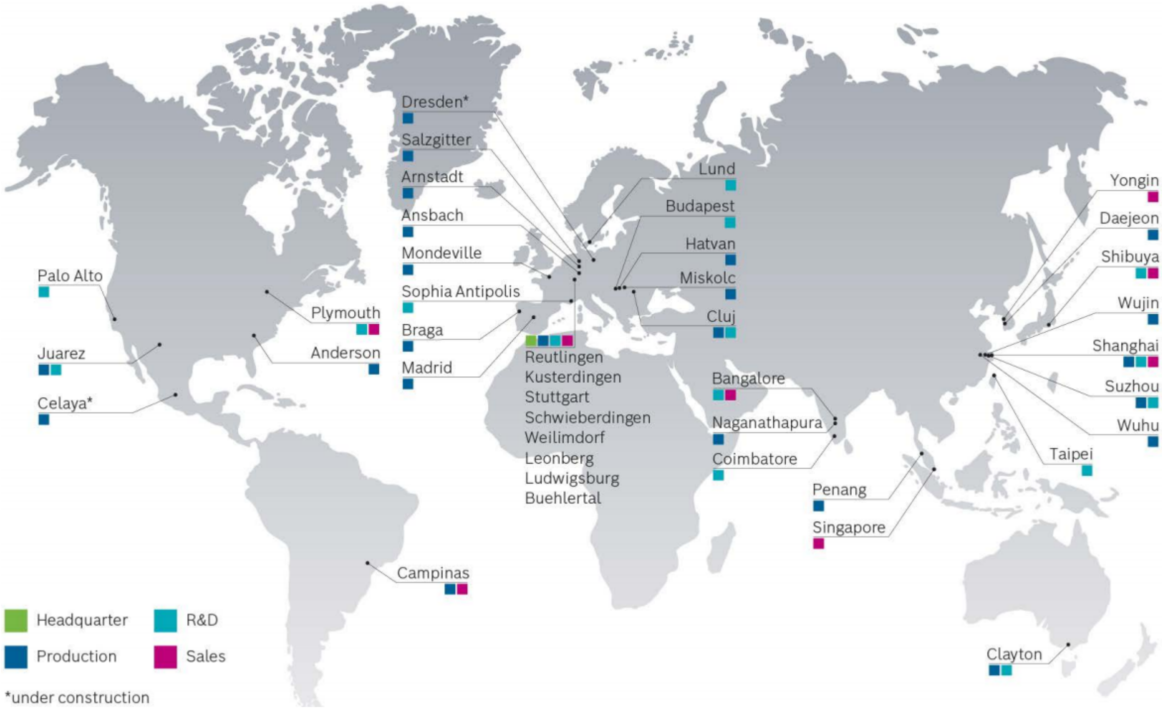

Figure 3.2: Bosch CM and AE plants (Bosch, 2019).

Rapid changes in the automotive sector are occurring and the Mobility Solutions sector is adapting itself to those changes. To reinforce this sector, divisions CM and Automotive Electronics (AE), both from Mobility Solutions, are in a merging project, becoming a division with 17 total plants (see Fig. 3.2).

3.3 Bosch Braga Plant

Bosch in Braga was founded in 1990, under the name Blaupunkt Auto-Radio Portugal, Lda. In 2009, a CM division was restructured and the Blaupunkt brand was sold together with the radio aftermarket business. Since then, the plant has focused only on original equipment for industry and automobiles and has changed its name to Bosch Car Multimedia Portugal, S.A.

Over the years, the company's know-how has become a benchmark, building a solid reputation in the electronic market, for being able to produce increasingly complex products with high quality and flexibility. In these last five years, Bosch Braga Plant (Bosch BrgP) had a significant increase, forcing it to reinforce its physical infrastructures (see Fig. 3.3). Currently, the plant is the biggest one in the CM division and the biggest Bosch location in Portugal.

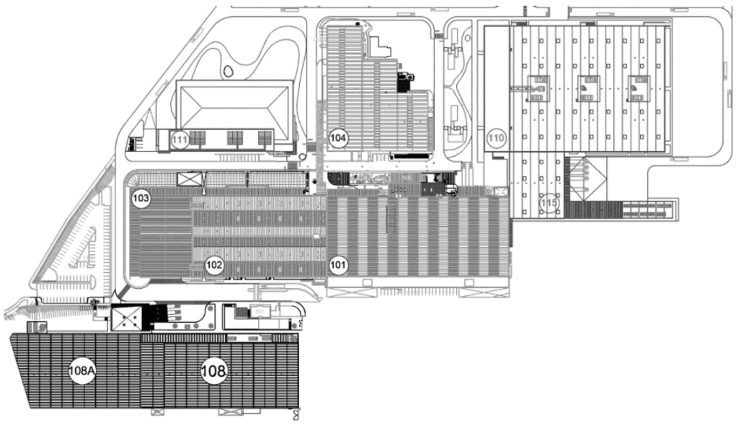

Figure 3.3: Bosch BrgP building layout (Bosch, 2019).

Bosch BrgP produces a broad product portfolio that includes navigation systems, instrumentation systems and high-level car radios for the automotive industry, steering angle sensors for the electronic stability control system, electronic controllers for heating equipment, and electronic controls for home. Bosch's portfolio in Braga also offers services from a Research and Development Center, an Engineering Competence Center specialized in production, a Service and Repair Center, as well as an IT Service Center for Iberia.

With regard to the products exported, around 95% of them are to destinations in Europe and abroad. The company sells to about 181 customers worldwide, for approximately 800 products. In what concerns the supply of raw material, Bosch BrgP relies on more than 350 suppliers, both located in Europe and the Far East. Its purchasing strategy is based on a structure that encompasses three levels, such as National suppliers, European suppliers and Asian suppliers.

3.4 Logistics at Bosch Braga Plant

Logistics, in general, ensures the existence of materials, in the right quantity, with the quality assured, in the right place at the right time, for the right customer, at the right cost. For these purposes, Bosch BrgP uses the Supply Chain Reference Model (SCOR) model.

The SCOR model has been developed to describe the business activities associated with all phases of satisfying a customer's demand. The model itself contains several sections and it is organized around six primary management processes (shown in Fig. 3.4):

- **Plan** – processes that describe the activities associated with developing plans to operate the supply chain;
- **Source** – processes that describe the ordering (or scheduling of deliveries) and receipt of goods and services;
- **Make** – processes that describe the activities that encompass the conversion of materials or creation of the content for services;
- **Deliver** – processes that describe the activities linked to the creation, maintenance and fulfillment of customer orders;
- **Return** – processes that describe the activities attached to the reverse flow of goods;
- **Enable** – processes that describe the activities related to the management of the supply chain.

Figure 3.4: SCOR six major management processes (Bosch, 2012).

Bosch BrgP has a strong commitment to these principles and tries to ensure the satisfaction of all parties involved, with the help of the most current technologies and tools. The vision of Logistics of BrgP (BrgP/LOG) is to design and manage agile logistics processes for customers. The business partners of BrgP/LOG ensure a fast, stable and synchronized flow of materials throughout the supply chain. In this way, BrgP/LOG is able to ensure a performance at the level of quality, cost and supervision. BrgP/LOG is organized by the Logistics sections listed and explained in Table 3.1.

Table 3.1: BrgP/LOG sections.

	Functions and responsibilities
Logistics Controlling (BrgP/LOC)	Links cost controlling with the various areas of Logistics. Some of their responsibilities are making forecasts of the evolution of logistics costs, cost monitoring, stock analysis, cost reporting and coordinating the process of debits to suppliers and customers.
Material flow and Internal Logistics (BrgP/LOM)	Manages all the internal logistics flow and processes, such as productions lines supply, material receipt, product shipment, internal stock control or warehouse management.
Customer Order Management and Production Planning (BrgP/LOP)	Deals with customer orders, production planning, Key Performance Indicators (KPIs) monitoring and control.
Supplier Interface (BrgP/LOS)	Responsible for material supply and purchasing. They plan necessities and order materials according to production plan, dealing daily with suppliers, to guarantee the availability of raw materials. It is also their responsibility to monitor and track KPIs such as raw material stocks, supplier delivery performance and transportation costs.
Transport Management (BrgP/LOT)	Manages and organizes transports. It is also responsible for freight control (import/export), organizing urgent transports and provide support for all shipments that require customs services.
Logistics Innovation, IT Systems and Processes and Logistics Quality (BrgP/LOI)	Manages and develops projects for the all the Logistics Sections, as well as process improvement. They also manage and support the department on IT systems (ex: SAP), develop applications and automated reports and are responsible for process quality, mainly supplier and customer claims.
Packaging Design and Management (BrgP/LOD)	Designs and does all the management and planning of returnable packaging.
AE/LOG–Brg	Works directly with the central headquarters of Bosch AE and develops projects for all the AE plants in the division, mainly in the fields of AI and Big Data.

The most part of the activities related to each Logistics section is reflected in physical operations in the inbound and/or outbound processes. In order to further clarify some relevant concepts to the addressed problem, additional details on the company's inventory management will be provided in the next chapter. Importantly, despite the work produced within this dissertation was conducted in a team from AE/LOG–Brg, the project essentially focuses on the "source" processes, having as its main scope the supply and inventory management of raw materials, monitored by the supplier interface BrgP/LOS.

Chapter 4

A hybrid multi-objective data-driven approach to jointly optimize inventory buffers

Previously in this research work, prior studies applying OR models and methods to address the safety stock problem were analyzed. After a comprehensive overview of the different techniques employed on this subject, some relevant findings and opportunities were uncovered from the existing literature, serving as basis and motivation towards the development of a novel data-driven approach implemented in the present business context of Bosch Car Multimedia Portugal S.A.

Throughout the following chapter, the proposed framework for optimizing safety stock and safety time values is presented and described in-depth, covering the second research question (RQ2):

> **(RQ2)** *How to design and implement a data-driven framework able to process large amounts of data towards safety stock and safety time optimization?*

As initially mentioned, each section of the present chapter follows a different phase of the CRISP-DM methodology: Business understanding (Section 4.1); Data understanding and data preparation (Section 4.2); Modeling (Section 4.3); Empirical evaluation (Section 4.4); and Deployment (Section 4.5). The aim is to structure the developed work as a DM project and to validate its implementation within the industrial context at hand while answering to RQ2.

4.1 Business understanding

According to the adopted DM methodology, the proposed framework starts with the Business understanding phase, in which it is assessed the current situation of the case company, followed by the determination of its business objectives and the corresponding DM goals. This first phase should be perceived as a pivotal step of a DM project, as the choices and outcomes derived therefrom will affect all the subsequent phases.

4.1.1 Case-study design and motivation

Bosch Car Multimedia Portugal S.A., hereinafter referred to as Bosch BrgP, is a business-to-business company in the automotive electronics industry, known for being one of the biggest production units in the division. The plant operates in a make-to-order fashion and its extensive supply chain consists on end costumers, production plants and suppliers. On the supply side, it can be considered a large costumer, with about 350 suppliers, the majority of which are from European and Asian countries. At this point, there exist different inbound supply chain dynamics for each type of supplier, according to its origin (Fig. 4.1). Apart from that, Bosch BrgP plays a prominent role in supplying companies in the automotive industry, serving about 200 customers worldwide, with a great variety of products.

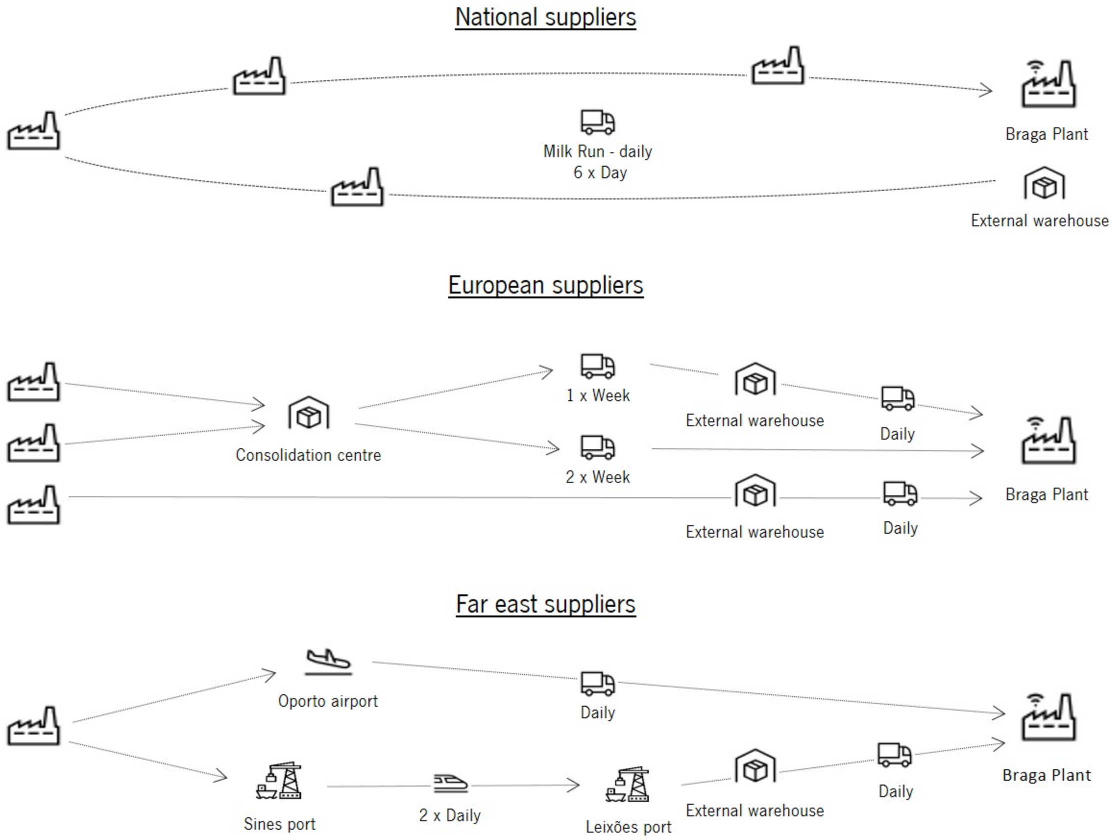

Figure 4.1: Bosch BrgP inbound supply chain flows for each type of supplier origin.

In such a complex supply chain topology, the manufacturing process is mainly affected by two sources of uncertainty: supply and demand. Supply uncertainties occur when fewer products are produced than what was planned, which may result in stockouts. The reaction time to potential inventory disruptions is mainly dependent on the frozen period (Lian et al., 2006), during which the production plan cannot suffer any alterations. On the other hand, demand uncertainties occur when ordered demand is larger than the planned needs, which may also result in a lack of stock. In order to hedge against these factors and therefore reduce its risks, Bosch BrgP establishes safety stock and safety time as inventory-buffering strategies.

To produce such a wide variety of manufactured products and therefore properly supply its customers, the plant in Braga holds a huge amount of components in stock. Safety stocks at Bosch BrgP are perceived as an additional order quantity, independent from any demand, and that should only be established according to some constraints. Indeed, the use of this inventory buffer is only considered for commodity components, being less relevant for the remaining ones. Still, even for those components, there is no formal method for setting the corresponding parameter in the enterprise resource planning (ERP) system and the adopted strategy is based on past experience for the great majority of components. Although the safety stock levels are reviewed few times per year, and may be updated if some demand changes have occurred, this process does not follow any specific guidelines either.

In detriment of safety stocks, Bosch BrgP gives priority to the application of a safety time to the overwhelming majority of its components. This inventory-buffering strategy is also set as a parameter of the employed ERP system and represents the number of workdays by which the requirements are brought forward in the planning calendar (Fig. 4.2). Hence, like safety stocks, the safety time should also follow some setting criteria, since the higher the safety time the earlier the orders will be placed in the system before the real consumption, which may lead to potential unnecessary inventories.

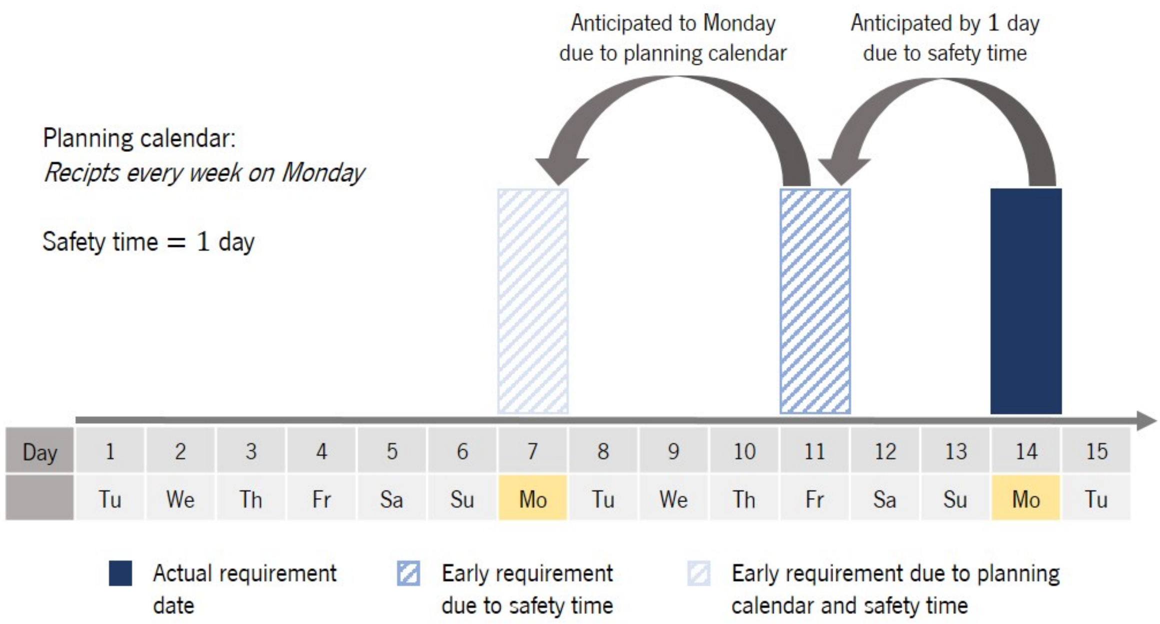

Figure 4.2: Impact of safety time in the planning calendar.

The current safety time calculation method is mainly based on two logistics criteria, such as ABC classification and supplier location. Besides, the delivery frequency and the frozen period can be also included within the considered criteria (see Fig. 4.3). Note that real values are not displayed due too confidentiality issues.

Supplier origin	ABC classification		
	A	B	C
National suppliers	x	$2x$	$2.5x$
European suppliers	$2x$	$4x$	$7.5x$
Far east suppliers	$4x$	$5x$	$7.5x$

Figure 4.3: Current reference table for safety time days determination.

Although the concepts of safety stock and safety time appear to be quite clear among the company's business experts, these two inventory-buffering strategies have been sparking some discussion within the existing literature. Some authors have been addressing the two strategies in separate, considering one as an alternative to another, depending on the uncertainty source and type (Guide Jr and Srivastava, 2000). For instance, Whybark and Williams (1976) find that, regardless the source of variability, safety stock is suitable for quantity uncertainty while safety time is preferred for timing uncertainty. Indeed, Sato and Tsai (2004) favor the use of a safety time buffer in most situations where timing uncertainty exists. Conversely, other works propose the use of safety stocks to tackle uncertain supply timing (Grasso and Taylor, 1984). In addition, a study conducted by Etienne (1987) shows that safety time should not be considered for production systems operating under quantity variability. However, concerning timing uncertainty, it proves to be useful in sparse schedules in detriment of safety stock. Molinder (1997), in turn, concludes that safety time works best whenever both supply and demand are highly variable, while safety stocks are recommended only when demand, by itself, presents high coefficients of variability. The same outcomes are further corroborated in a later study carried out by Van Kampen et al. (2010).

Besides the current lack of consensus on this matter, as far as it is known at the time of this study, scarce attention has been given to the use of both approaches simultaneously. In this particular work, it is intended to study the application of both strategies in combination, aiming to address the potential operational and financial improvements arising out of their joint optimization – which, up to now, had been neglected. Indeed, this gap was already highlighted in Section 2.5.

4.1.2 Problem statement

Like many industrial organizations, Bosch BrgP desires to have optimal safety stock levels, but since its complex supply chain is affected by several sources of uncertainty, it becomes a challenge to accurately identify which factors to consider and which safety stock approach works best for a specific organizational process.

The current strategies adopted by Bosch BrgP to set optimal values of safety stock or safety time are typically formulated based on experience rather than technique. Hence, it is important to underline that, although these strategies consider important logistics criteria that are proven to have direct impact on inventory management, they are still vulnerable to variations on the uncertainty factors over time. Fig. 4.4 summarizes the causes and the problem that is being address, as well as the impact it may cause within the present context.

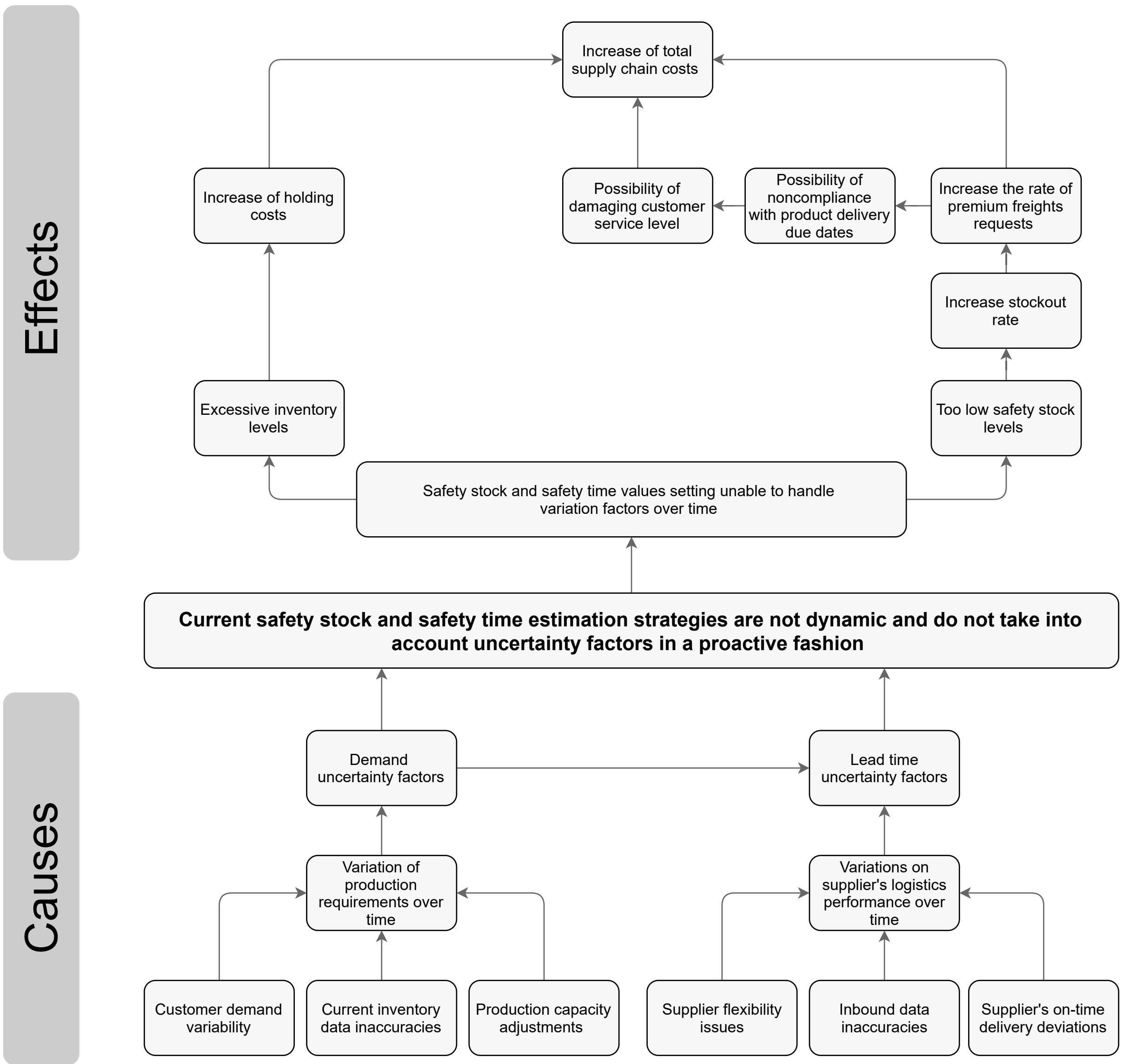

Figure 4.4: Cause-effect diagram for the problem identified.

From the presented diagram, one can note that, on the demand side, customer demand variability, inventory data inaccuracies and adjustments in production capacity justify the variations on the productions requirements over time. Moreover, demand uncertainty is known for having indirect impact on the supply variations through the so called "bullwhip effect" (Lee et al., 1997). Other factors in the supply side are in turn responsible for the variations in suppliers' logistics performance over time, such as supplier flexibility, data inaccuracies in the inbound processes and deviations on suppliers' on-time delivery. The aforementioned factors are currently being overlooked by the present approach adopted by the case-study company, which hampers an efficient management of both demand and supply variations over time. In the long term, either this may lead to excessive inventory levels or to an increase of the stockout rate, which will eventually generate additional supply chain costs.

As such, it becomes evident that the current safety stock and safety time estimation strategies are not dynamic in the sense of coping with time-varying uncertainty factors. On the other hand, the results of the SLR previously conducted have already highlighted the need to assess the potential improvements that can result from combining them in a single optimization approach.

Since no standardized quantitative strategy is being employed to this end, inventory management at Bosch BrgP becomes much more error-prone and dependent on a lot of know-how on the business process. Moreover, the process of training new human resources to acquire solid logistics knowledge to establish inventory buffers can be very time-consuming. In this context, previous inventory management studies have underlined the need to derive optimal values of MRP parameters (Louly and Dolgui, 2013), including safety stock and safety time, rather than just relying on business experience.

4.1.3 Business objectives and data mining goals

The dimensioning of safety stocks remains an outstanding problem in the inventory management literature (Ruiz-Torres and Mahmoodi, 2010; Schmidt et al., 2012; Kumar and Evers, 2015; Syntetos et al., 2016; Prak et al., 2017). Thus, considering the case study company in hand and its practical motivation, this project aims to enhance, via multi-objective optimization, the empirical safety stock and safety time estimation process (either in combination or in isolation), in an attempt to minimize current upstream holding costs while maintaining target manufacturer's levels for production. At this point, consignment parts, as well as those following a vendor-managed inventory (VMI) approach are not included within the scope of this research due to their different inventory management policies and business contract constraints.

Accordingly, the DM goal is to dynamically determine the optimal levels of safety stock and/or safety time for each component, using a data-driven multi-objective optimization approach, considering both supply and demand variability. In turn, the ultimate goal is to provide company managers with insights on how to implement safety inventory buffers under the trade-off between inventory and service level.

4.1.4 Materials and methods

To address the business goal, the project team started to discuss potential materials and methods to be employed. In this context, a panel of business experts, composed of senior logistics managers and business intelligence and analytics professionals, was involved in the initial requirements collection. Several unstructured interviews were conducted to perceive the current decision process in detail, as well as to collect expectations and needs of the logistics planners (BrgP/LOS) potentially interested in the project.

The regular meetings, which allowed ensuring the richness of detail through the clarification of questions and answers, have occurred over a period of two months, on a weekly basis, with an average time per meeting of two hours. All the interviewees have considerable knowledge in operating with the company's integrated ERP system (SAP), and are all directly involved in the procurement activities, which also enabled having easy access to the relevant data for further analysis. As a result of this process, several key issues were raised, namely:

- The lack of a standardized data storage mechanism to study the historical demand and supply behaviors of a wide range of components and suppliers. Since it is crucial to have complete knowledge on past behaviors for further improvement activities, the proposed optimization framework should be supported by advanced storage solutions, able to gather a large amount of relevant logistics inputs from multiple data sources and provide detailed information ready to be analyzed and used.

- The need to design and develop a MRP simulation system able to evaluate how a given safety stock/safety time solution impacts on upstream holding costs and manufacturer's service level for production. Importantly, such a system would serve as basis for the optimization stage.

Recalling the objective of determining optimal safety inventory-buffering mechanisms, the above-mentioned issues were perceived as the foundations of the proposed hybrid multi-objective optimization approach. Hence, the team started to develop a Big Data system in order to storage all the logistics information relevant for the computation of safety buffers. On the other hand, modeling efforts were also conducted on the development of a MRP simulation system to evaluate, in terms of the proposed objectives, the safety stock/safety time solutions generated during the optimization phase.

Overall, this first step allowed obtaining a clear picture of the underlying problem, the business objectives and the available datasets and data sources to consider in the upcoming phases of the project.

4.2 Data understanding and data preparation

Once a careful information gathering procedure has been performed in the Business understanding phase, it is now essential to profile and examine the data sources available and the information contained therein, avoiding data integrity issues and further modeling inefficiencies. Beforehand, it should be noted that the software team, which made use of the available IT resources of the company to that end, mainly carried out the activities encompassed by these phases. Therefore, since these activities do not figure in the main scope of this dissertation, the following steps will be described briefly and at a high level.

As a result of the interview process conducted in the previous phase, it became clear that the logistics department of Bosch BrgP currently operates with a MRP methodology, integrated into the ERP system, in which safety stock and safety time parameters serve as the basis for inventory replenishment decisions. Regarding this, the following step was to identify the main data attributes affecting the current MRP configuration. Note that all those involved in this procedure are aware that there exist other MRP related parameters in SAP, however, in the Bosch BrgP framework, these are not used or not considered, and therefore were initially discarded from the collection.

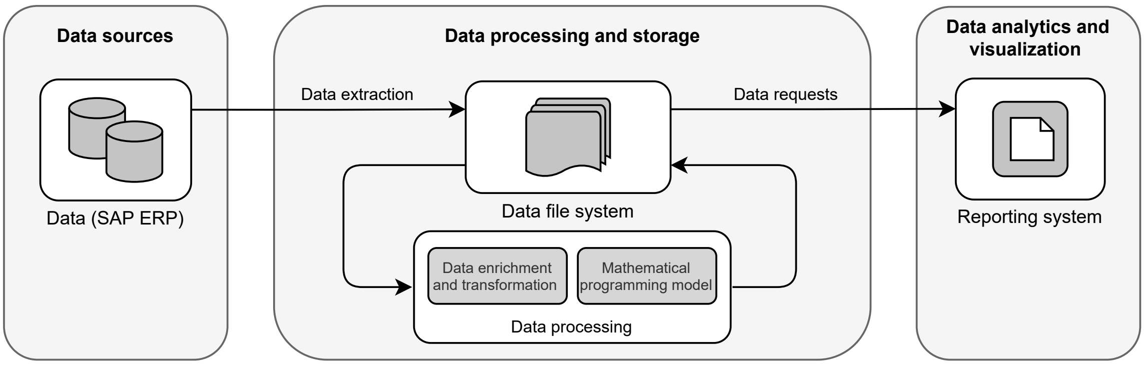

Figure 4.5: Diagram of the main components that integrate the proposed decision support system.

Following this, with the purpose of getting a better data comprehension, the selected data attributes were categorized into four different categories: functional, process, quantity, and time. Table 4.1 illustrates the list of attributes to be considered alongside its corresponding description. Each attribute was further submitted to a more detailed exploratory analysis. An extensive data quality process was executed through the elaboration of data quality reports (see, e.g., Appendix A), which allowed checking for missing values and outliers, as well as to validate data consistency and completeness. The resulting cleansed data served as an input for simulating the impact of altering safety stock and safety time parameters on both upstream inventory holding costs and service levels, which is a fundamental part of the proposed simulation-based optimization approach (see Section 4.3).

Predominantly, the data were collected from a single data source, the company ERP system. Given that the information is mainly concentrated in a single source, the acquisition and subsequent integration of the data have been simplified. Nevertheless, it should be noted that a massive amount of data is systematically updated into the ERP system. This requires advanced data storage solutions to cope with the consequent need for faster processing of data with heterogeneous formats and related with thousands of inventory components. To attend to the above-mentioned needs, the project team took advantage of a Hadoop cluster for Big Data processing (Zhong et al., 2016). In such a setting, the data is first extracted and then ingested in a Hadoop Distributed File System (Shvachko et al., 2010). Here occurs data processing including the distributed implementation of the proposed multi-objective optimization model. Afterwards, the enriched data obtained from the processing stage is loaded and stored in the cluster, and the solutions generated from the model become available to be rapidly accessed. Hence, this data availability allowed to further design and implement data analytics and visualization tools to enhance the user experience and support decision-making. The data flow described above as well as the system components involved in it are briefly displayed in Fig. 4.5.

Table 4.1: General overview of data attributes for the MRP process.

Category	Type of attribute	Description
Functional	Base unit of measure	Unit of measure in which inventory managed.
	Lot size	Order batch quantity to control and conform both production and purchase orders.
	Material	Reference that identifies each component.
	MRP type	Specifies how and when the component is to be planned/available for the corresponding requirement.
	Plant	Reference that identifies the organizational unit of a given component.
	Plant specific material status	Defines the status of the component on each plant (e.g., available; blocked; for approval).
	Quota arrangement	Specifies the fraction of components that is to be procured from a given supplier.
	Supplier master data	Corresponds to the enterprise main source of supplier general data, including information on vendors from which the company can procure.
	Unit price	Unit cost (in m.u.) per component.
Process	Advance shipping notification	Provides details on a given delivery (order), like expected delivery date and quantity.
	Planned/real production orders	Defines which components are to be processed, at which location and time, and how much quantity is required.
	Scheduling agreements	Outline purchase agreement under which components are procured on predefined dates within a given time period.
	Scheduling lines	Provides details on the delivery process, including delivery dates and quantities, as well as on requirements transfer and inventory management.
	Records of contractual delivery dates	Contains information on delivery contracts established with customers.
	Records of component needs	Contains the records of components production requirements.
Quantity	Assembly scrap	Expected scrap rate to occur during the production of a given component.
	Component scrap	Average percentage of component malfunctions that occur before the component is put into an assembly line.
	Min lot size	Minimum order quantity for a component.
	Rounding value	Value from which the system, for a given order quantity, should round up to, once the minimum order quantity is exceeded.
	Safety stock	Extra quantity of a certain item in stock, which aims to prevent the risk of stockouts.
	Stock quantity	Available inventory quantity of a given component in the plant.
Time	Goods receipt processing time	Number of workdays required for the components quality control and storage.
	In-house production time	Number of workdays required for the component production.
	Planned delivery time	Number of workdays between the order being placed and the actual goods receipt.
	Planning calendar	Defines a flexible period for a material requirements planning at the plant.
	Planning time fence	Corresponds to the frozen period or the time period in which receipts from the planning run can no longer be changed.
	Safety time	Number of workdays added to the supply lead time that pushes a delivery order earlier than the required due date.
	Safety time indicator	Monitors whether receipts should be anticipated only for planned independent requirements and customer requirements, or for all requirements.

4.3 Modeling

This section presents the proposed hybrid multi-objective model for jointly optimize safety stock and safety time values. At first, there are provided notations and some preliminary concepts that are considered relevant from this point. Afterwards, alongside some important details on the addressed inventory management problem, the optimization stage and the simulation stage, into which the model is composed, are described.

4.3.1 Notations and preliminaries

Consider the following notation used to describe the sets, parameters, variables and functions that comprise the designed model:

Sets

$\mathcal{C}$	Set of components with c as its index
$\mathcal{T}_0$	Set of time periods before the end of the frozen period
$\mathcal{T}$	Set of time periods after the end of the frozen period
$\mathcal{P}$	Set of indexes of planning calendar days for component $c \in \mathcal{C}$

Parameters

t_c^f	Index of the day matching the end of the frozen period for component $c \in \mathcal{C}$
T_c	Maximum planning horizon ($T_c \in \mathcal{T}$) for component $c \in \mathcal{C}$ (days)
F_c	Length of frozen period for component $c \in \mathcal{C}$ (days)
$D_{c,t}$	Manufacturer's demand for component $c \in \mathcal{C}$ in period t (units)
M_c	Minimum order quantity for component $c \in \mathcal{C}$ (units)
$O_{c,t}$	Order quantity delivered for component $c \in \mathcal{C}$ in period t (units)
X	Supplier delivery risk associated with $O_{c,t}$ (days); a discrete random variable
$I_{c,t}$	Inventory level for component $c \in \mathcal{C}$ in period t (units)
h_c	Inventory holding cost of a component $c \in \mathcal{C}$ (m.u. per item per period)
γ_c	Relative change coefficient of demand for component $c \in \mathcal{C}$ ($\%$)

Decision variables

ST_c	Safety time for component $c \in \mathcal{C}$ (days); an integer decision variable
SS_c	Safety stock for component $c \in \mathcal{C}$ (units); an integer decision variable

Functions

$(\cdot)^+$	$(\cdot)^+ = \max(\cdot, 0)$
$(\cdot)^-$	$(\cdot)^- = \min(\cdot, 0)$
$\mathbb{E}[\cdot]$	Expectation operator
$1_{\{A\}}$	Indicator function (equals 1 if A is true and 0 otherwise)

The present modeling approach takes advantage of multi-objective optimization in order to obtain the set of safety stock and safety time values that minimize upstream inventory holding costs while attending the targeted manufacturer's service levels. Before elaborating on the model details, some essential background on the adopted solution technique should be provided. In this regard, the fundamental concepts hereinafter described were mainly retrieved from Deb (2005).

A general multi-objective optimization problem can be generally defined as:

$$\begin{aligned} \min \quad & f(\mathbf{x}) = (f_1(\mathbf{x}), \ldots, f_p(\mathbf{x})) \\ \text{s.t.} \quad & \mathbf{x} \in S \end{aligned} \tag{4.1}$$

where $S \subseteq \mathbb{R}^n$ is the decision (or feasible) set, $\mathbb{R}^n$ is the decision space, and $f_i : S \to \mathbb{R}$, for each $i = 1, \ldots, p$, are the objective functions to be minimized. The formulation (4.1) can be extended to cases where some or all objective functions are to be maximized. The feasible set can be characterized by nonlinear inequalities, equalities and bounded constraints, i.e., $S = \{\mathbf{x} \in \mathbb{R}^n : g_r(\mathbf{x}) \geq 0, \forall r = 1, \ldots, R,\ c_k(\mathbf{x}) = 0, \forall k = 1, \ldots, K,\ \underline{\mathbf{x}}_l \leq \mathbf{x}_l \leq \bar{\mathbf{x}}_l, \forall l = 1, \ldots, L\}$. Given $S' \subseteq S$, it is defined by $\mathbf{f}(S') = \{\mathbf{z} \in \mathbb{R}^p : \exists \mathbf{x} \in S'$ such that $\mathbf{z} = \mathbf{f}(\mathbf{x})\}$ the image set of S' in the objective (or solution) space $\mathbb{R}^p$, with $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), \ldots, f_p(\mathbf{x}))$. Likewise, $Z = \mathbf{f}(S)$ is the image set of S in the solution space $\mathbb{R}^p$, which consists of all feasible solutions (or points) derived from (4.1).

The conflicting nature of the objectives implies that it is practically impossible to optimize them simultaneously. Given two feasible points $\mathbf{z}, \mathbf{z}' \in Z$, it can be said that $\mathbf{z}$ dominates $\mathbf{z}'$ $(\mathbf{z} \prec \mathbf{z}')$ iff

$$\mathbf{z}_i \leq \mathbf{z}'_i,\ \forall i \in \{1, \ldots, p\} \wedge \exists j \in \{1, \ldots, p\} : \mathbf{z}_j < \mathbf{z}'_j \ . \tag{4.2}$$

Similarly, it can be said that $\mathbf{z}$ weakly dominates $\mathbf{z}'$ $(\mathbf{z} \preceq \mathbf{z}')$ iff $\mathbf{z}_i \leq \mathbf{z}'_i,\ \forall i \in \{1, \ldots, p\}$. It is designated by $N = \{\mathbf{z} \in Z : \nexists\, \mathbf{z}' \in Z$ with $\mathbf{z}' \prec \mathbf{z}\}$ the set of non-dominated solutions (also called *Pareto set* (Deb, 2005)). In this context, one can also define the *ideal* $(\mathbf{z}^*)$ and *nadir* $(\mathbf{z}^{nad})$ points to represent the best and worst objective values, respectively:

$$\mathbf{z}^* = \min_{\mathbf{z} \in Z} \{\mathbf{z}_i\}_{i \in \{1, \ldots, p\}} \ , \ \mathbf{z}^{nad} = \max_{\mathbf{z} \in Z} \{\mathbf{z}_i\}_{i \in \{1, \ldots, p\}} \ . \tag{4.3}$$

4.3.2 General description and assumptions

As described earlier in this chapter (Section 4.1), the supply chain topology underlying the inventory management problem at hand consists of a single manufacturer, operating with multiple suppliers and components, following a MRP methodology for inventory replenishment. Firstly, it is considered that each component follows a specific supply policy. In addition, the manufacturer's demand $D_{c,t}$ for each component is assumed to be dynamic over a finite planning horizon $\mathcal{T}_0 \cup \mathcal{T}$ of discrete time periods, resultant from BOM explosions based on finished product forecasts from downstream stages. During the order releases, it is also considered that the manufacturer's orders volume to a supplier is bounded by quantity flexibility contracts, which means that the manufacturer cannot increase or decrease order quantities to a given supplier by more than a predefined percentage from the contracted quantity. The supplied components are further assembled by the manufacturer to fulfill end-customer requirements. Moreover, each value of $D_{c,t}$ is assumed to be fulfilled entirely from the available inventory $I_{c,t}$, and the scheduled receipts and respective quantities are planned so that the inventory on-hand covers demand until the next scheduled receipt $O_{c,t}$. However, depending on the supplier delivery performance, orders may not arrive in sequence, which potentially leads to stockouts of components and damage of service levels for production jobs. In order to cope with supply-side uncertainty, supplier delivery risk is modeled by a discrete random variable $X \in \{X^-, \ldots, X^+\}$, with a finite number of outcomes and probabilities determined by previous supplier delivery performance. In other words, each scheduled receipt can suffer random deviations ranging from X^- to X^+ days. This contrasts with the common assumption that supply lead times are Gaussian-distributed. On the demand-side, the relative change of past manufacturer's demand during lead time is adopted as a correction factor to future values of demand. The above-mentioned inventory system is further described by means of a discrete simulation approach.

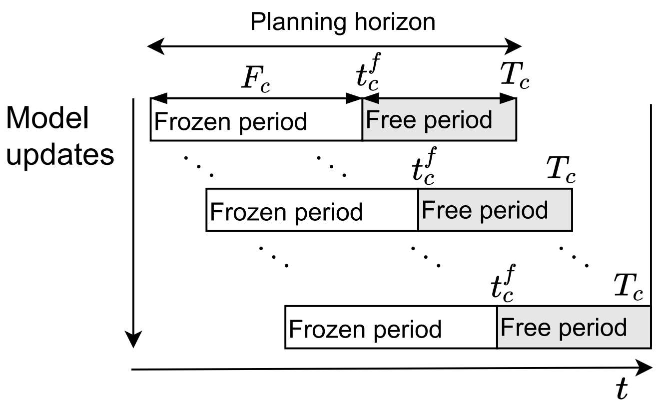

Figure 4.6: An illustrative example of the frozen and free periods for a component c.

Recalling the business objectives set at the beginning of this chapter, it is intended to determine optimal safety time (ST) and safety stock (SS) decisions for each component c, in such a way that upstream inventory holding costs are minimized and the manufacturer's service level for production is maximized. One should note that MRP systems usually consider a rolling frozen period over the planning horizon, as shown in Fig. 4.6, in which production schedule changes are generally not allowed. To be consistent with the logic behind the MRP methodology, optimal decision scenarios for safety stock and safety time are provided only for the time horizon immediately starting from the frozen period onwards, i.e., $t \in \left[t_c^f, \ldots, T_c\right] \subseteq \mathcal{T}$, hereinafter called the free period.

4.3.3 Problem modeling

In this problem, a bi-objective optimization model is considered to simultaneously optimize safety stock and safety time values for each component $c \in \mathcal{C}$, while minimizing the total upstream inventory holding costs and maximizing average service level to the manufacturer over the free period $\left[t_c^f, \ldots, T_c\right]$. As maximizing average service level to the manufacturer is logically equivalent to minimize the average fraction of unmet manufacturer's demand, the bi-objective optimization problem underlying this study can be formulated as follows:

$$\min_{ST_c, SS_c} \quad H = \sum_{c \in \mathcal{C}} \frac{h_c}{T_c - t_c^f + 1} \sum_{t=t_c^f}^{T_c} I_{c,t}(ST_c, SS_c) \tag{4.4}$$

$$\min_{ST_c, SS_c} \quad U = C^{-1} \sum_{c \in \mathcal{C}} \frac{\sum_{t=t_c^f}^{T_c} \max\left[D_{c,t} - I_{c,t}(ST_c, SS_c), 0\right]}{\sum_{t=t_c^f}^{T_c} D_{c,t}} \tag{4.5}$$

subject to:

$$0 \leq ST_c \leq \overline{ST}_c, \ \forall c \in \mathcal{C} \tag{4.6}$$

$$0 \leq SS_c \leq \overline{SS}_c, \ \forall c \in \mathcal{C} \tag{4.7}$$

$$I_{c,t}, D_{c,t} \geq 0, \ \forall c \in \mathcal{C}, \forall t \in \mathcal{T} \tag{4.8}$$

The objective (4.4) minimizes the total averaged inventory holding costs and objective (4.5) minimizes the total average fraction of unmet manufacturer's demand. It should be noted that backlogging costs are not considered in the cost function due to the difficulty to measure them in real-world contexts (Petropoulos et al., 2019). For this reason, it was preferred the use of a β-service level approach, which is implicitly considered in objective function (4.5), to estimate the expected fraction of total manufacturer's demand that can be fulfilled. In objective (4.5), for each $t \in \mathcal{T}$ of c, a shortfall of $D_{c,t} - I_{c,t}$ inventory units occurs if $D_{c,t} > I_{c,t}$. In contrast, the fraction of total manufacturer's demand that can be fulfilled is maximum whenever $D_{c,t} \leq I_{c,t}$. Note that $I_{c,t}(\cdot, \cdot)$ is a function of the decision variables, thereby playing a fundamental role in both objectives. It aims to estimate the inventory levels for component c over the free period by varying the values of safety stock and safety time. This function can be interpreted as a proxy for the expected inventory derived from a MRP simulation, in a given ERP system, using such buffering parameterizations. Section 4.3.5 provides details on the design of this function.

The present approach aims at generating the trade-off curve between the two conflicting objectives, allowing decision-makers to choose one of the Pareto optimal solutions according to their preferences. Subsequently, the optimization and simulation stages that comprise the proposed hybrid model are detailed.

4.3.4 The optimization stage

In the context of inventory management, it is known that pure analytical/optimization models are, in general, difficult to implement in real-world supply chain chains (Avci and Selim, 2018). In this particular study, a simulation-based optimization approach is adopted in order to better replicate the impact of re-parameterizing safety stock and safety time decisions in a MRP inventory replenishment system. The designed approach follows a two-stage modeling process, where the generation of the set of non-dominated Pareto-optimal solutions is obtained through an iterative process between a selected algorithm providing feasible solution pairs (ST, SS) (optimization stage), and a simulation module that evaluates each solution in terms of the proposed objectives (simulation stage). Such optimization-simulation setup is commonly adopted in multi-objective optimization applications (Avci and Selim, 2017, 2018; Altazin et al., 2020). The model comprising the two above-mentioned stages is further summarized, at the end of this chapter, in Fig. 4.7.

In the first phase of the proposed optimization-simulation approach, the non-dominated solutions for the bi-objective optimization problem are computed by employing an evolutionary algorithm. Three well-known (Nebro et al., 2009a; Durillo et al., 2010) Pareto dominance based evolutionary computation metaheuristics are considered, namely the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002), the Multi-Objective Cellular (MOCell) genetic algorithm (Nebro et al., 2009b) and the improved version of the Strength Pareto Evolutionary Algorithm (SPEA), called SPEA2 (Zitzler et al., 2001). A brief overview on each technique is provided as follows.

The NSGA-II is probably the most popular population-based metaheuristics for multi-objective optimization (Li and Zhang, 2008), and takes advantage of a fast non-dominated sorting approach to rank the different solutions according to Pareto dominance and optimality concepts (Deb et al., 2002) introduced previously. Concretely, it starts to randomly generate a parent population (of size n) comprising potential solutions. Pareto dominance relationship criteria are applied to such population and a fitness value (non-domination level) is assigned to each individual contained therein. Then, the genetic algorithm ranks the individuals according to the fitness values. If two solutions share the same ranking (i.e., are non-dominated to each other), the one with the highest crowding distance is preferred. A new population is further obtained by applying standard genetic operators like selection, crossover and mutation. These new solutions are compared to previous non-dominated ones and the best ones (in the Pareto sense) are selected (this process is referred to as *elitist selection*). The above process is repeated, for instance, for a specified maximum of function evaluations.

The MOCell is a cellular genetic algorithm that operates under the logic that each individual only interacts with individuals from its neighborhood. In particular, it stores a set of non-dominated solutions in an *external archive* during the search procedure (Nebro et al., 2009b) using the same crowding distance of NSGA-II. By selecting two neighbor parent solutions, crossover and mutation operators are then used to generate a new individual. Interestingly, MOCell employs a feedback strategy from the archive to the population so that a new individual is replaced by an archived solution if the former is worse (in the Pareto sense) than the latter. Similarly to MOCell, the SPEA2 algorithm also includes an external archive to store non-dominated solutions that result from the application of genetic operators (selection, crossover, and mutation). Yet, the latter employs an improved truncation method whenever the number of non-dominated solutions is greater than the population size so that solutions with minimum distance to any other solution are preferred to those with higher distances (Nebro et al., 2009a; Zitzler et al., 2001).

The initialization process of the specified genetic algorithm includes the definition of several features (Turan et al., 2020), ranging from the solution encoding scheme and the fitness function to the algorithm input control parameters, including the (i) the population size (n) and the bounds of the decision variables, (ii) the maximum number of iterations, (iii) the selection mechanism, and (iv) the genetic operators (mutation and crossover) with respective probabilities. For all genetic algorithms described previously, it is adopted the standard binary tournament (Deb et al., 1995) for the selection procedure, and the simulated binary crossover (SBX) and polynomial mutation (Deb, 2005) for the crossover and mutation genetic operators, respectively, with a distribution index of η_c. This index sets the spread of offspring solutions around parent solutions. The selection of suitable probability values for the genetic operators (p_m and p_c for the probability of mutation and crossover) can follow a tuning procedure (e.g., Taguchi approach (Roy, 2001)) or exhaustive manual tests.

As shown in Fig. 4.7, the simulation module is invoked at each iteration of the optimization process to evaluate and provide the objective values for each solution vector generated by the selected genetic algorithm. From this, the traditional cyclic procedure to generate the Pareto frontier is conducted when any stopping criteria is met, in this case, a predefined maximum value of function iterations, $iter^{max}$.

The hypervolume indicator (or size of space covered, in (Zitzler and Thiele, 1998, 1999)) is used in evaluating the performance of the genetic algorithms when generating the final population set across the experimental studies. In a bi-objective minimization problem, given a set $N = \{\mathbf{z}^a, \mathbf{z}^b, \ldots, \mathbf{z}^y\}$ of non-dominated solutions, the hypervolume consists of the measure of the objective space which is simultaneously dominated by N and limited above by a reference point $r \in \mathbb{R}^2$ such that $r \geq \mathbf{z}^{nad} = \max_{\mathbf{z} \in N}\{\mathbf{z}_i\}_{i \in \{1,2\}}$, with the relation $\geq$ being applied componentwisely (Fonseca et al., 2006).

4.3.5 The simulation stage

As described in the previous section, each feasible solution pair (ST_c, SS_c) generated by the genetic algorithm during the optimization stage is evaluated through a simulation procedure to estimate both the expected inventory holding cost and the fraction of unmet manufacturer's demand derived therefrom. In short, this procedure replicates the MRP logic embedded in any ERP system by simulating the inventory performance of a given safety stock and safety time parametrization.

Given the relevance of the simulation stage in the evaluation of feasible solutions for the proposed bi-objective optimization problem, the steps outlined in the right-hand part of Fig. 4.7 are explained, by narrative, for a given component c. The simulation setup, starts by setting the initial inventory at the beginning of the planning horizon ($I_{c,1}$), the day matching the end of the frozen period (t_c^f) and the maximum simulation horizon (T_c). Next, the forecasted manufacturer's demand ($D_{c,t}$) is loaded to the simulator for all time periods up until T_c and brought forward in time by ST days. This latter step forces the MRP model to plan order receipts earlier, thereby matching the definition and overall purpose of the safety time buffer. The final step of the simulation setup includes the loading of the scheduled receipts in the frozen period that, along with the shifted $D_{c,t}$ and $I_{c,1}$, allows to update the inventory levels from $t = 1$ up to t_c^f (inclusively).

The second phase of the simulation starts immediately after the end of the frozen period. From this point onwards, supply and demand uncertainty are included within the simulation scheme. Demand-side risk is included by adding a (positive/negative) change factor to each value of demand. Although not a guarantee against future demand uncertainty, this correction factor represents the relative change of past demand between homologous periods and, at a certain level, accounts for the magnitude of the demand levels. Next, for each valid delivery date in the supplier planning calendar, it is determined whether a supplier order receipt $O_{c,t}$ should be released in that period. Note that this decision is naturally affected by the shifted manufacturer's demand resultant from the ST application and the use of a certain amount of SS. A supplier order is scheduled if the available inventory on-hand does not cover the sum of manufacturer's demand until the day immediately before the next valid delivery date in the planning calendar t^*. If an order is scheduled, the respective quantity should be a multiple of the M_c while satisfying the total expected net demand $\left(\sum_{i=t}^{t*\in\mathcal{P}} D_{c,i} - I_{c,t-1}\right)$ plus SS.

To account for supply timing uncertainty, it is considered that each scheduled receipt may be delayed by approximately $\mathbb{E}\left[\mathbb{X}\right]$ days, where X is a random variable with all possible delays and respective probabilities computed based on past deliveries. This means that an order scheduled to be delivered in the current period t may be actually received at $t + \mathbb{E}\left[\mathbb{X}\right]$, potentially leading to shortfalls depending on the magnitude of the delay. The inventory records for the current period t are thus updated accordingly and serve as basis for developing the requirements plan in the following period $t + 1$.

Note that the simulation process does not make any distributional assumption, neither regarding demand nor supply lead time. For this reason, the simulation process is deterministic and does not require several runs in order to soften random variabilities. In contrast, the optimization process is naturally stochastic due to the nature of the evolutionary algorithms employed. Nevertheless, for the sake of computational time and given the high dimensional dataset available, each evolutionary algorithm runs once per component. In this sense, it is expected that random variations are reduced by considering thousands of components. When the simulation horizon is reached, the second phase of the simulation scheme ends and the objective values for the solution vector (ST_c, SS_c) is returned to the optimization process.

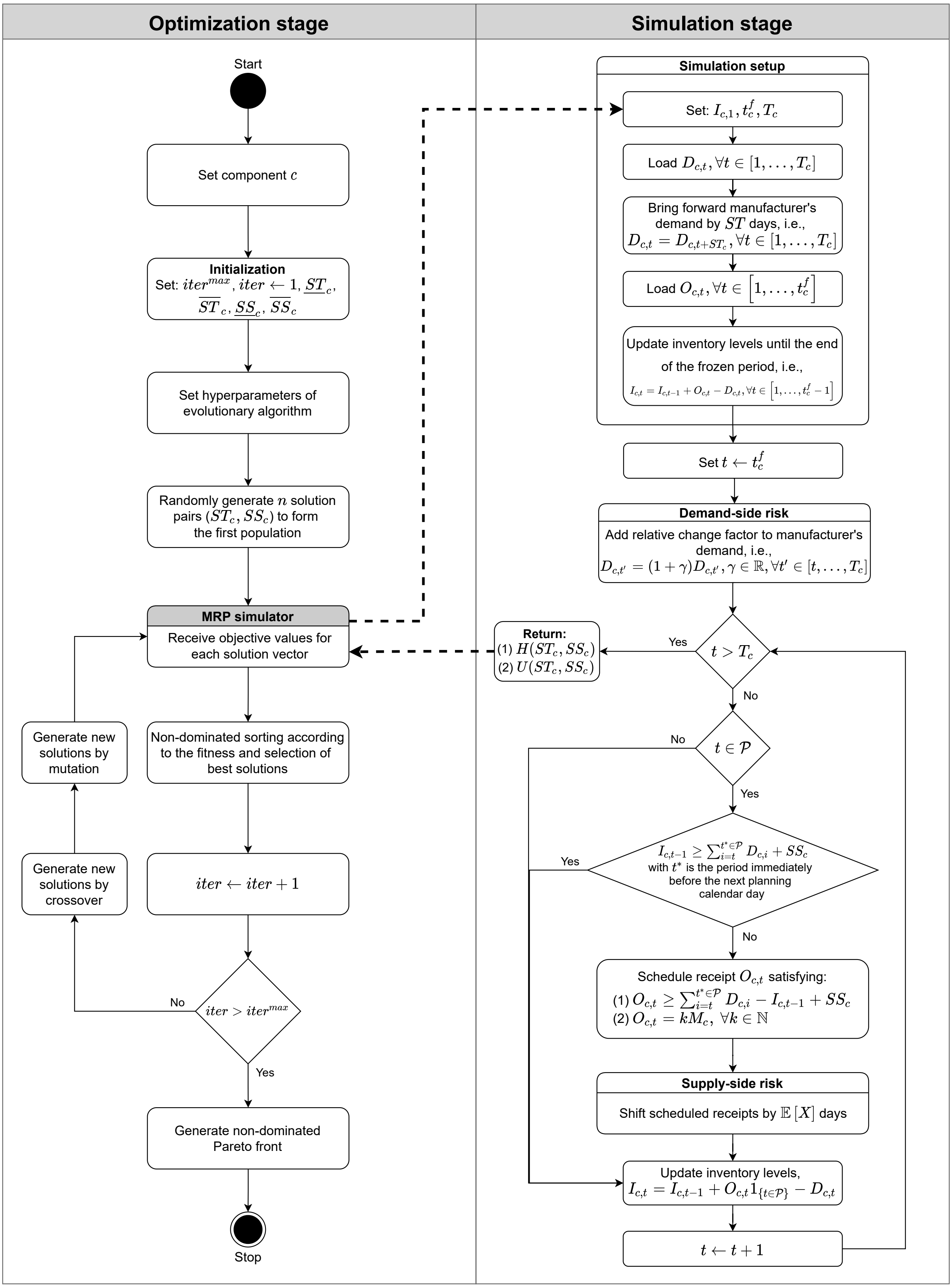

Figure 4.7: The proposed optimization-simulation model for the joint optimization of safety time and safety stock buffers.

4.4 Empirical evaluation

Throughout this section, it is intended to validate the results of applying the proposed bi-objective optimization model within the industrial environment at hand. Computational experiments are performed with a view on extracting knowledge from the obtained optimal solutions. Moreover, the potential benefits derived from the joint optimization of safety stock and safety time are also discussed.

4.4.1 Experimental setting

The computational experiments were conducted in a Big Data cluster with 9 nodes (2 with 4 cores each, 2 with 12 cores each, and 5 with 24 cores each) and a total of 1603 GiB of memory capacity. For the full implementation of NSGA-II, MOCell and SPEA2, the jMetalPy (Benitez-Hidalgo et al., 2019) library, implemented in Python, has been used. Regarding the hyperparameters of the evolutionary algorithms, a crossover probability of $p_c = 0.8$, a mutation probability of $p_m = 1/\#var$ (where $\#var$ represents the number of decision variables considered), and a population size of 150 individuals were initially set. In addition, recalling the arguments referred in Section 4.3, the crossover and mutation genetic operators are the SBX and the polynomial mutation, respectively, with distribution indices of $\eta_c = \eta_m = 20$. The above parameters were selected through exhaustive manual testing and agree with those selected in previous studies (Durillo et al., 2006; Nebro et al., 2009a; Redondo et al., 2015). Note that grid search procedures were not conducted to enable a better computational efficiency.

Due to the high dimension of the dataset considered, a set of controlled experimental studies were performed to select the best evolutionary algorithm for the addressed problem. For that, the hypervolume and computational time (in seconds) were analyzed by taking advantage of a random set of 15 components. Each of the three metaheuristics was applied to each component over 5 runs, with 1500 function evaluations. The expected value over the 5 runs is considered for each component. Then, the final estimated median for the hypervolume and computational time for the whole set of components were obtained via non-parametric Wilcoxon signed-rank test (Hollander et al., 2013). The results appear summarized in Table 4.2. For the computation of the hypervolume metric, the objective space of each component was normalized so that the nadir point and the ideal point are $(1, 1)$ and $(0, 0)$, respectively. While no statistical significant differences (5% significance level) were found for the hypervolume metric among the different algorithms used, it is clear that the computational time is excessively higher for the MOCell and SPEA2 when compared to NSGA-II. For this reason, the NSGA-II was selected as the most suitable genetic algorithm for the data under study.

Table 4.2: Average hypervolume and computational time (in seconds) values, over 15 components, for the different evolutionary algorithms after 5 model runs with 1500 functional evaluations.

	NSGA-II		MOCell		SPEA2	
#	Avg (hyper)	Avg (time)	Avg (hyper)	Avg (time)	Avg (hyper)	Avg (time)
1	0.840	37.767	0.806	291.453	0.803	41.899
2	0.810	9.608	0.810	176.851	0.812	336.725
3	0.841	15.111	0.841	194.560	0.841	374.953
4	0.889	11.849	0.891	176.912	0.888	224.606
5	0.681	12.243	0.686	182.971	0.686	363.954
6	0.830	15.302	0.829	195.548	0.827	189.625
7	0.815	42.956	0.812	352.513	0.813	372.771
8	0.717	10.840	0.717	176.513	0.717	297.884
9	0.793	11.322	0.791	179.126	0.781	276.083
10	0.789	11.672	0.792	182.727	0.789	192.143
11	0.655	8.842	0.653	170.193	0.653	255.239
12	0.654	14.868	0.657	200.057	0.652	234.208
13	0.727	14.908	0.729	206.861	0.729	301.663
14	0.641	15.715	0.669	203.560	0.693	86.232
15	0.792	14.700	0.790	194.346	0.811	248.638
EMH*	0.765	13.483	0.764	191.367	0.766	262.748

* EMH: Estimated Median Hypervolume computed via the non-parametric Wilcoxon signed-rank test.

A final study was carried out to assess a suitable number of function evaluations to be configured in the NSGA-II setting. Fig. 4.8 shows the Pareto fronts of a given component varying the number of iterations from 100 to 5000. To provide a better comprehension of the following plot, the service level was considered over the unfulfillment rate, which is specified in the second objective function of the proposed bi-objective optimization problem.

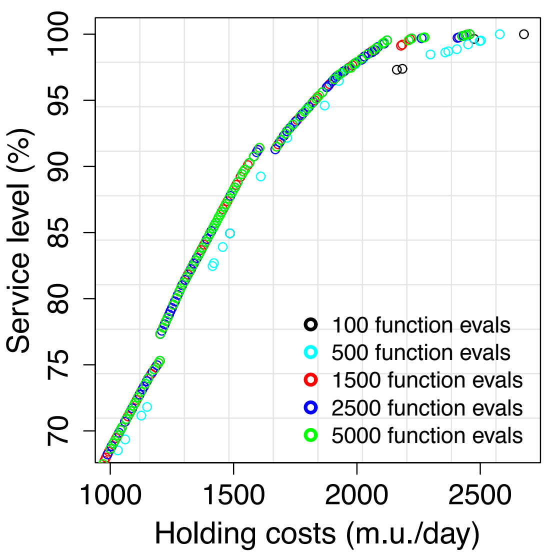

Figure 4.8: Illustrative example of a Pareto front generated by NSGA-II using different function evaluations.

By observing the plot displayed in the figure, it becomes clear that the Pareto fronts appear to converge, in terms of shape, from 1500 function evaluations onwards. These dynamics hold for the remaining components tested. However, it is also evident that the number of Pareto-optimal solutions using 5000 functional evaluations is higher than that obtained using 1500 functional evaluations. For these reason, in order to create a diverse set of solutions, all the results hereinafter presented are derived from the application of NSGA-II, with the above-mentioned hyperparameters and 5000 function evaluations. A set of exhaustive tests (not presented) were conducted to evaluate the suitability of using more than 5000 functional evaluations. Yet, the results allowed to conclude that increasing the number of evaluations does not improve the algorithm's performance in terms of hypervolume.

4.4.2 Extracting knowledge from the bi-objective optimization

A set of 3024 components from the plant were included in this evaluation process. Commodities, as well as other parts considered with low relevance for this testing phase, were excluded from the sample. The selected components were first grouped according to their ABC class. Since, in general, components A, B, and C have considerably different inventory management dynamics among them, it was decided to adopt such a strategy to simplify the following analysis and make fair comparisons. Furthermore, three different analyses were performed, one considering the planning calendar density (Section 4.4.2.1), and two others concerning demand and supply uncertainty (Section 4.4.2.2). In what follows, all the analyses only considered Pareto-optimal solutions generated for service levels between 90% and 99%, and a simulated planning period of 8 calendar weeks. The threshold for the service level was established taking into account the minimum manufacturer's service level for production, which the company is willing to comply with.

4.4.2.1 Impact of planning calendar density on Pareto-optimal solutions

At first, it is intended to study the behavior of the solutions (SS, ST) obtained from the application of NSGA-II to the sampled components, considering the density of the planning calendar. The concept of density should be perceived as the ratio between the number of scheduled receipts for a given component, and the planning period (also referred as free period) of the simulation horizon. In other words, a component with a dense planning calendar is characterized by frequent scheduled delivers over the simulation horizon, while another with a sparse calendar has scheduled delivers in wider timeframes. For each group of components (A, B and C), a 3-dimensional plot (see Fig. 4.9) was created, integrating the variables of the planning calendar density (z-axis), the number of stock coverage (in days) provided by the amount of safety stock suggested (x-axis) and the proposed number safety time days (y-axis). The goal was to draw conclusions, for each component class, based on the location of the generated non-dominated Pareto optimal solutions within the matching plot. A color scale was included to enable a better perception of the solutions positioning over the three considered dimensions.

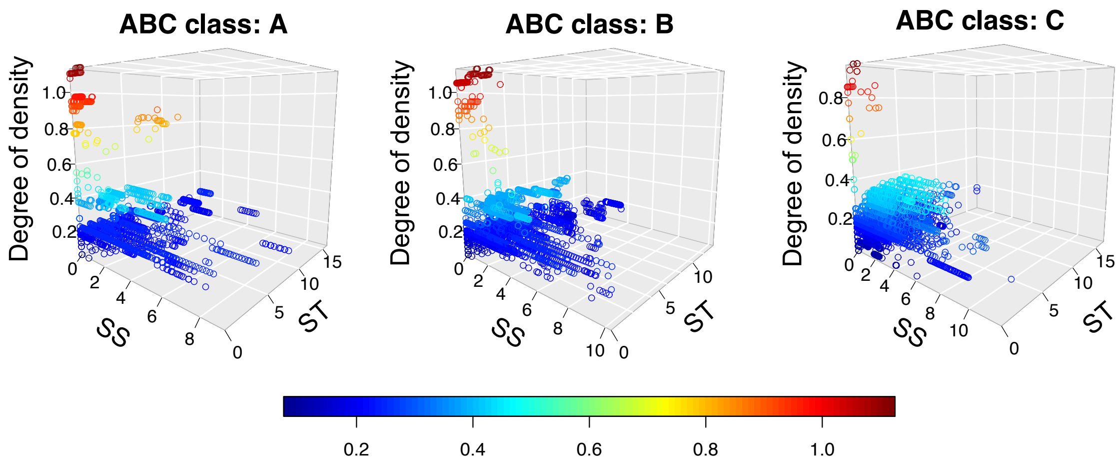

Figure 4.9: Decision space dynamics in terms of planning calendar density for components A, B and C.

From the left side of Fig. 4.9, it is possible to note that, for A-components, the overwhelming majority of the solutions including both safety stock and safety time are mainly aligned with low-density values. Moreover, there exists also evidence that the lower the density of the considered period, the higher are the magnitude of these inventory buffers. On the other hand, the figure suggests that optimal solution pairs for dense planning calendars are apparently associated to lower values of each one of the considered inventory buffers. Besides, it also shows that the magnitude of safety stock is higher when compared to safety time, which indicates that safety stock is preferable compared to safety time for components with more frequent scheduled receipts.

Fig. 4.9 as a whole shows that the pattern displayed by the plot corresponding to the optimal solutions generated for class A components is also shared by the plots related to class B components (middle of Fig. 4.9) and C components (right side of Fig. 4.9). This somehow emphasizes the potential relation between the calendar density and the magnitude assumed by the safety inventory values. Thus, for all the three classes of components, the most part of the solutions combining higher levels of safety stock and safety time are mainly attached to sparse calendars. Conversely, the figure exhibits, for the three same groups, few solutions aligned with higher values of planning calendar density, with most preferring safety stock in detriment of safety time.

In practical terms, the results observed in this analysis suggest that, regardless of the ABC class in which a certain component is inserted, when dealing with a more sparse delivery schedule, it is often recommended that the company should take advantage of a hybrid solution that involves setting both a safety stock quantity and a number of safety time days. In contrast, it also indicates that, for components with more frequent deliveries, the optimal solutions to be adopted should mostly involve lower values in each of the inventory buffers, and that preference should be given to the choice of safety stocks.

Despite the evidences presented by Fig. 4.9, it should be noted that only the number of scheduled receipts over the simulation horizon is being considered in the previous analysis. The results depicted by the three plots might be suffering from influence of the uncertainty levels assign to each component, thus a more detailed analysis, considering such factors, have to be conducted in order to draw more solid conclusions on this matter.

4.4.2.2 Impact of uncertainty sources on Pareto-optimal solutions

Following the previous analyses, which accounted the planning calendar density of the sampled components, the goal is now to explore the potential links existing between the proposed optimal solutions and the different levels of uncertainty either in demand or in supply side.

Consider Fig. 4.10, in which there are displayed three plots according to the ABC class of each component.

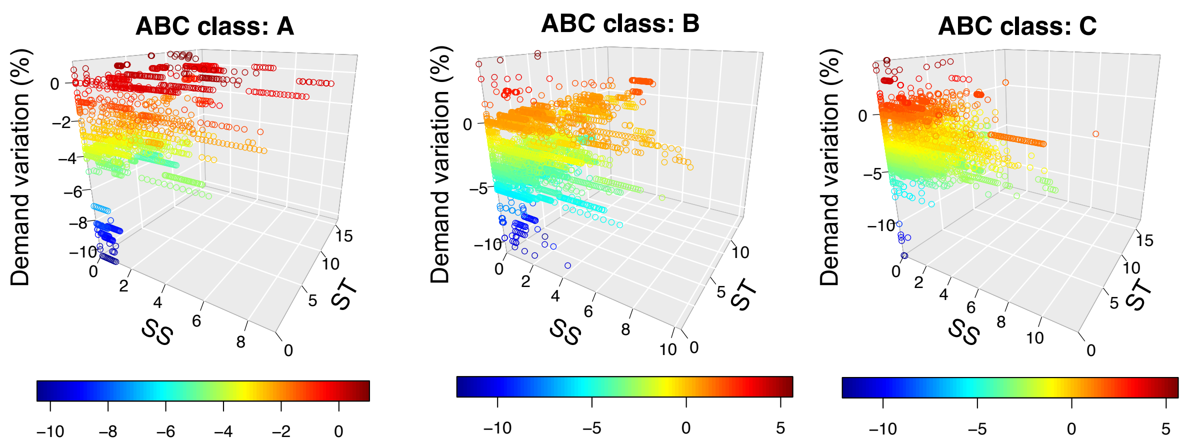

Figure 4.10: Decision space dynamics in terms of demand variation for components A, B and C.

Along the z-axis, it is shown the percentage of demand variation associated to each component. Note that a negative variation values mean that the expected production requirements are lower than the real ones, while the positive variation values correspond to a scenario of potential stockout, in which the real requirements may be higher than the expected ones. In addition, and equally as in the previous illustration, the x-axis represents the expected coverage days corresponding to a safety stock quantity, while the y-axis contains the days of safety time.

By analyzing the left side of Fig. 4.10, it can be noted that the highest concentration of points containing Pareto-optimal solutions, for components A, is located close to positive demand variations. In contrast, one can observe that as the demand variation becomes more negative across the z-axis, the number of optimal solutions containing both safety stock and safety time values decreases. Additionally, it can also be observed that most of the solutions aligned with these negative values of demand variation contain low magnitudes of safety stock and only a few of them are complemented with safety time. In fact, as demand varies negatively, where the production requirements are apparently lower than expected, the need to introduce an inventory buffer is also reduced. On the other hand, as the demand variation approaches positive values, the magnitude of safety stock and safety time solutions increases. For positive variations in demand, which correspond to possible shortage scenarios, there is a high concentration of optimal solution pairs with higher values of both safety stock and safety time. This outline allows understanding that the higher the chance of a stockout, the higher is the number of optimal solutions suggesting the combination of these two safety buffers.

For the plots corresponding to class B and class C components, it can be verified the same scenario as the one described for components A. In general, regarding demand variability, the results in Fig. 4.10 show evidence that, for any component class, the highest number of optimal solutions combining both buffers are likely to be associated with positive variations in production requirements. Importantly, in these plots only demand variation is being accounted, so that, supply variations as well as the planning calendar density might also affect the displayed solutions.

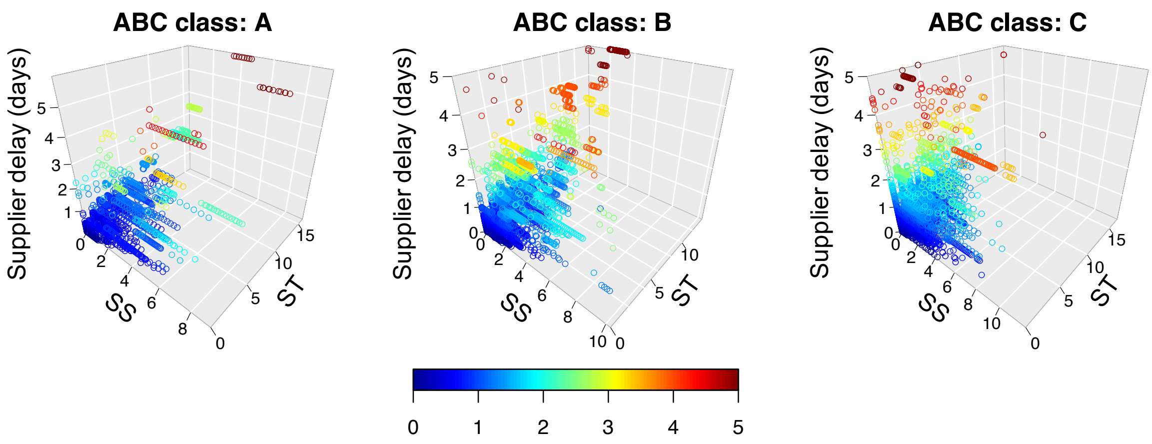

Figure 4.11: Decision space dynamics in terms of supplier delays for components A, B and C.

Analogously to the analysis performed for the demand variation, another set of 3-dimensional plots, one for each component class, was generated to attend supply variations (see Fig. 4.11). In this case, the z-axis shows the supplier delays (in days) for a given component, being the x-axis and the y-axis for safety stock coverage days and safety time days, respectively. It is important to recall that, the supplier delay is a variable that assumes an average value for each component and depends exclusively on the historical records of the component's supplier deliver performance. In other words, each component is associated to a given supplier delay and this value can change over time according to changes in its respective deliver performance.

Starting to observe the left side of Fig. 4.11, related to the safety time and safety stock solutions for components A, it is shown that lower delays are associated with solution pairs containing low magnitudes of safety time compared to safety stock. It also becomes clear, as the number of delays increase, the solution pairs aligned with these values of delays are increasing the magnitude of their safety time values. In turn, safety stock does not show evidence of increasing in the same proportion, except in some particular cases. Turning to the B components (middle of Fig. 4.11), it is also possible to note that for higher of supplier delays, more solutions are displayed with higher values of safety time. Similarly to the case of A-components, safety stock does not appear to suffer considerable changes in its magnitude. The same arguments also hold for C components (on the right of Fig.4.11).

The main conclusion to draw from the observation of the three plots of Fig. 4.11 is that, the magnitude of safety time values in the optimal solutions increases as the supplier delay increases. Safety stock, in turn, do not suffer such variations regarding its magnitude. Practically speaking, for components with higher values of supplier delays (whether it is from A, B or C class), the model generally suggests the company to select solutions with higher values of safety time. This, in fact, highlights the relevance of the safety time buffer to hedge against supply variability. Moreover, it might also underline the importance of always keeping units of safety stock at the plant, to prevent supplier disruptions.

However, it is noteworthy that, as in the preceding analyzes, the results presented only consider one variable (supplier delays). Hence, it is acknowledged that other factors, namely the two previously considered (demand uncertainty and planning calendar density) might affect the observed solution pattern.

4.4.3 On the benefits of the joint optimization of safety inventory buffers

Following the same strategy of grouping the sample components according to their ABC class, a more quantitative analysis of the results derived from the application of the NSGA-II was performed, aiming to assess the potential financial impact of employing the proposed multi-objective optimization model. For a range of service levels comprised between 90% and 99%, the average holding costs resulting from the optimal safety stock and safety time solutions with the average ones generated by the current methodology adopted by the company were compared. Of note, one should recall that the overwhelming majority of the plant components were only following a safety time strategy. The results obtained for each class of components are provided in Table 4.3.

Table 4.3: Expected holding cost reduction (in %) derived from the application of the proposed bi-objective optimization approach for different ABC criteria.

	Average daily holding costs		Improvement (%)
β-service level	NSGA-II	Company benchmark	
ABC Class: A $]90\%, 99\%]$	**8459.44 m.u.**	9978.39 m.u.	-15.22%
ABC Class: B $]90\%, 99\%]$	**766.22 m.u**	1048.51 m.u.	-26.92%
ABC Class: C $]90\%, 99\%]$	**102.85 m.u.**	151.81 m.u	-32.26%

The results suggest that the average daily holding costs generated by the optimal solutions provided by the NSGA-II are, in general, lower than the ones obtained from the current approach. These results are verified for all the three components class, being the biggest reduction for components C (32.26%). At this point, as the unit price of components from this class are lower compared with the other two classes, the company usually decides for setting higher values of inventory buffers to them since keeping stock of these components does not represent such high holding costs. Thus, it is expected that the holding costs provided by the proposed optimal solutions are also reduced.

Within the same industrial context, and considering the same range of service levels (between 90% and 99%) it was also intended to study the cost efficiency provided by the joint optimization of safety stock and safety time buffers compared to using these two buffers independently.

For this purpose, the model has run under the same conditions set initially (see Section 4.4.1), to generate solutions for three different scenarios: one including solutions with both safety stock and safety time ("SS & ST"), and two other involving solutions with one of the safety buffers in isolation ("Only SS" and "Only ST"). Due to the high computational effort associated with running the model 3 times for 3014 units, a smaller sample, randomly generated from the initial one, was selected consisting of 150 components. To keep the sample balanced in terms of components from different classes, the considered amount was composed of 50 components from each one of classes A, B, and C.

The average holding costs generated by each scenario were displayed in Fig. 4.12 assuming the form of boxplots. The goal was to show the median value of the holding costs for each solution scenario, since the high variability of costs existing among components of different classes makes it difficult to obtain a complete understanding of the results, just by observing the average values of holding costs generated for each one of them.

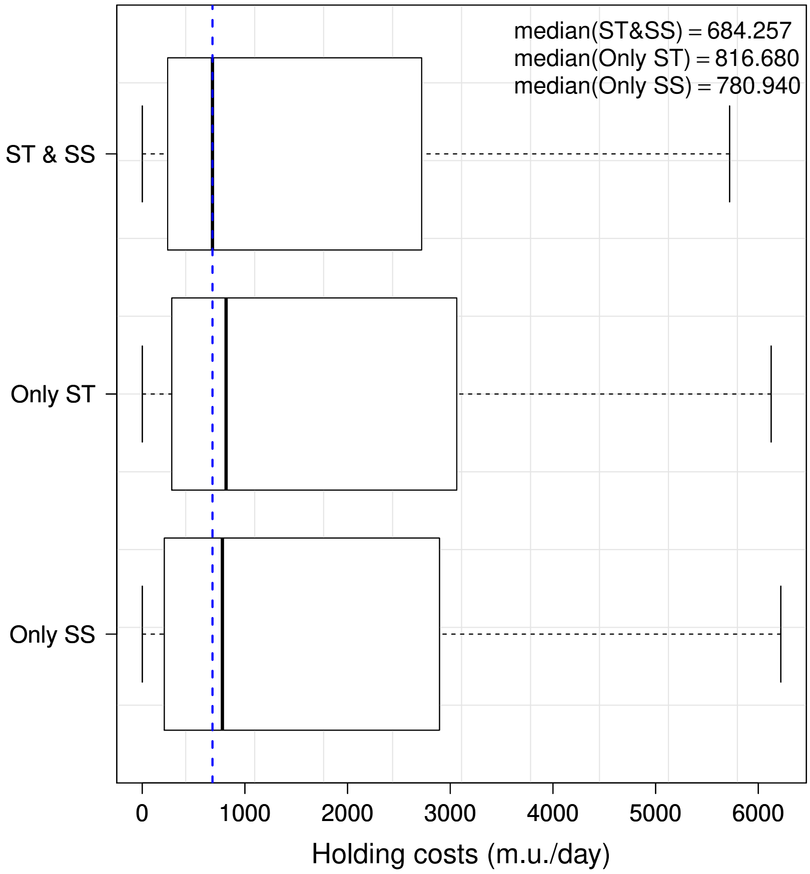

Figure 4.12: Performance of the bi-objective optimization model using different scenarios for the decision variables.

Note that, the median value of the daily holding costs obtained for the scenario of the joint optimization of both safety inventory buffers (684.26 m.u./day) is lower when compared to the ones from the independent use of safety stock (780.94 m.u./day) and the independent use of safety time (816.68 m.u./day). Regarding these two alternatives, it appears that the solutions resulting from use of safety stock in isolation is less costly than the ones obtained by using just safety time. This might be due to the fact that a smaller increase in safety time may imply ordering well in advance than necessary according to the planning calendar. In other words, the holding costs derived from the application of a safety time value are highly dependent on the schedule receipts density.

In general, for the considered range of service levels, the results show evidence that the company might benefit in terms of cost reductions by choosing optimal solutions including values of safety stock and safety time, relatively to considering these two inventory buffers in a separate fashion.

4.5 Deployment

As stated before, the construction of the model, followed by an empirical validation of its results, does not determine the end of a DM project. Throughout the previous sections, the process steps involved in the development of the proposed data-driven approach were described, resulting in a first pilot system, which should be currently available for testing before it goes operational. Since important decisions concerning inventory management might be strongly influenced by the results of this data-driven approach, special emphasis should be given to its deployment process at the company.

Once set in productive mode, the system should provide up-to-date information to enhance, in an efficient way, the decision-making process carried out by its final users: the logistics planners. The raw data from the data source should be extracted on a weekly basis, and then converted into inputs for the mathematical programming model incorporated in the cluster (recall the data flow presented in Fig. 4.5). Note that, to maintain the relevance of the MRP simulator, the data records regarding production requirements, suppliers' deliveries, and inventory quantities need to be updated permanently from the data source. In addition to the processing executed by the model, other data enrichment and transformation activities can occur if needed. The results displayed as dots in the Pareto front, as well as other relevant data that sustain the generated solutions, become easily accessed through the reporting system (see Fig. 4.13), providing support on the safety stock and safety time decisions.

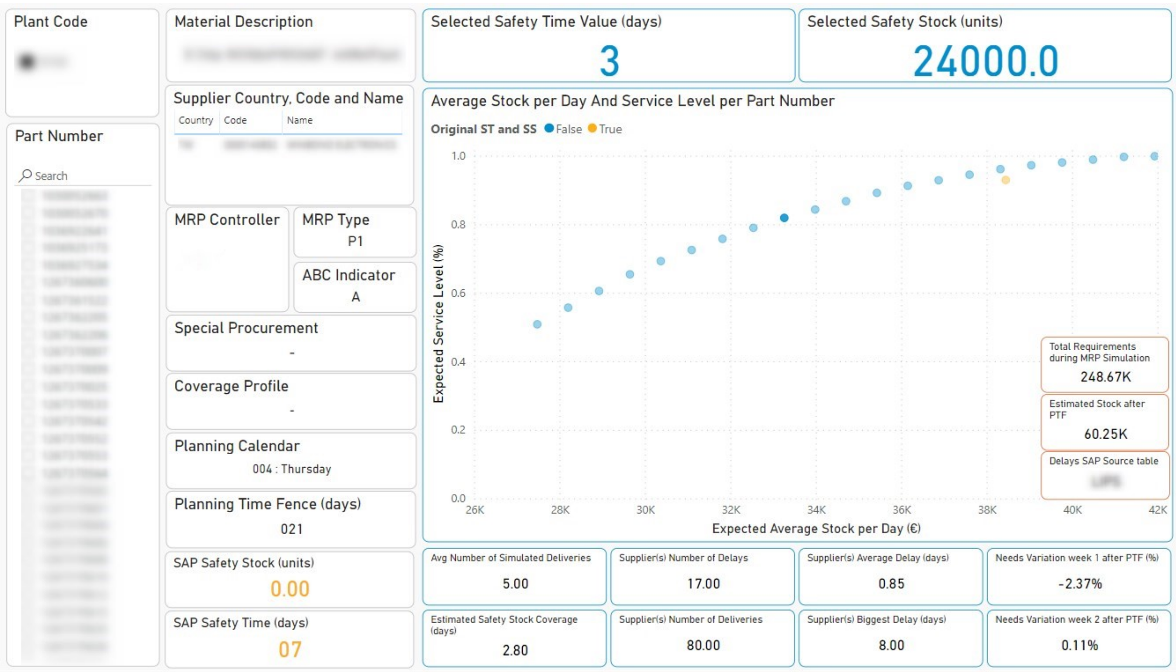

Figure 4.13: An outline for the end user interface of the proposed decision support system.

To become fully operational within the enterprise, the system consisting of the designed simulation-based optimization model and the entire IT infrastructure involved should be submitted to a stabilization phase. During this period, the model might still experience some minor adjustments as a result of eventual technical issues that may arise. On the other hand, software monitoring tools (Jayathilake, 2012) can be also adopted with the purpose of ensuring the system's performance while detecting potential malfunctions on its applications. Moreover, is noteworthy that such a complex system, involving several data-flows, data processing and storage operations, requires not only a careful monitoring process but also the elaboration of a maintenance plan, containing a strategy to avoid unnecessary long periods of misuse of the DM results.

So far, in this project, few activities have been initiated in this stage, so that the content described over this section represents only a brief discussion on several issues regarding the system's integration within the company's existing services and systems.

Chapter 5

Discussion and conclusions

This last chapter analyzes the obtained results and discusses their theoretical and managerial implications. Furthermore, it outlines the limitations of the present work while uncovering opportunities for future research.

5.1 Critical analysis of the results

The work produced throughout this dissertation aimed to develop a data-driven framework for optimizing safety stock and safety time decisions in general supply chain contexts with assembly operations, being the inbound logistics of Bosch Car Multimedia Portugal, S.A. the business environment in which it was conducted.

As initial steps of this project, two research questions **(RQ1, RQ2)** were raised to support achieving the expected goals.

> **(RQ1)** *What operations research models and methods have been explored concerning the problem of setting safety stocks?*
>
> **(RQ2)** *How to design and implement a data-driven framework able to process large amounts of data towards safety stock and safety time optimization?*

To answer these questions, a comprehensive literature review on the OR models and methods that have been explored to address the safety stock problem was first elaborated (see Chapter 2). A set of 81 papers were selected from an initial sample and then analyzed in detail, allowing to categorize the different strategies found according to the adopted modeling approach and the type of supply chain structure into which they were applied. Afterwards, each publication was further grouped into five distinct categories to obtain a closer overview of the produced techniques. The findings of this broad investigation allowed answering the first research question **(RQ1)**.

This preliminary research generated outcomes and uncovered gaps that allowed structuring a DM project that envisioned developing a decision-support tool able to provide optimal values of safety stock and safety time through a hybrid multi-objective evolutionary model (Chapter 4). Following a brief introduction to the corporate background of Bosch Group and Bosch Car Multimedia Portugal S.A. (Chapter 3), the design process of the proposed data-driven framework has been presented by taking advantage of the well-grounded CRISP-DM methodology.

The Business understanding phase (Section 4.1) corresponded to the initial requirements collection, in which the project objectives and the DM goals were set from the business perspective. The inventory management problem, as well as the preliminary strategies to achieve the pretended goals, were also defined. This initial stage allowed to understand the drawbacks underlying the current experience-based strategy for setting inventory buffers and to outline potential solution techniques to adopt.

In the following phases of Data understanding and data preparation (Section 4.2), it was possible to obtain a closer overview of the collected data attributes through the execution of data quality and data exploration processes. Additionally, the different activities and technologies that encompassed the construction of the used dataset were also presented.

Next, in the Modeling phase (Section 4.3), the proposed hybrid multi-objective optimization model, used to jointly optimize safety time and safety stock buffers, was described in-depth alongside with other relevant details on the addressed inventory management problem.

In order to test the model and consequently gather insights from the obtained results, an Evaluation phase (Section 4.4) was performed. Here, the proposed approach is shown to work well across a wide range of components with dynamic demands and stochastic lead times, and characterized by requirements plans with different degrees of sparsity. Besides, the results provided evidences that previous studies tend to underestimate the potential benefits of combining different safety-buffering decisions. Being the ultimate goal to achieve high service levels while minimizing inventory-related costs, the findings observed in this phase suggest that, in certain cases, it appears to be more cost-effective to combine safety stock with safety time compared to considering safety stock and safety time independently.

Lastly, in the Deployment phase (Section 4.5), some relevant issues, concerning the integration of the designed decision support tool within the considered business environment, were further discussed.

In short, the development of such a framework, as well as the results from testing a pilot version in an industrial context, provided the answer to the second research question **(RQ2)**.

5.1.1 Theoretical implications

The research scope of this dissertation allowed adding substantial contributes to the existing literature on OR models and methods for optimizing safety stocks. Recalling the literature gaps raised at the end of Chapter 2, several interesting theoretical inputs derived from the conducted work, can be summarized as follows.

From the analyzed studies on OR-based safety stock configuration techniques, it could be noted that few data-driven approaches were applied in the context of Big Data. Against this background, the developed framework built upon the well-grounded DM methodology of CRISP-DM, takes advantage of Big Data technologies to improve supply chain operations decisions, particularly the ones concerning inventory management. The adoption of such materials and methods was prompted by the designed hybrid model, which requires access to massive amounts of data to obtain complete knowledge on supply and demand behaviors over time, for a large number of component parts in the plant. Accordingly, the data-driven nature of the proposed approach emphasizes the relevance of introducing such technologies to seek more sustained inventory management decisions.

Besides the technological environment into which this research project was carried out, some interesting findings can also arise from its corporate background. This particular work underlines the logistics procurement processes attached to the inventory management of a multinational automotive electronics company. Although most of the existing work on the safety stock problem has been developed over a wide range of empirical contexts, only a few have been using this industry branch to produce new solution techniques. Thus, recalling the automotive electronics market growth and the potential benefits of applying data analytics in such a setting (see Section 2.5), the outcomes arising from this dissertation bring new perspectives to future research on this domain.

Another implication for the underlying theory that this dissertation may generate is reflected in the adoption of a non-parametric approach to address the inherent dynamics of supply chain demand and lead time. It is noteworthy that the common statistical distributional assumptions about these two sources of uncertainty do not truly represent the reality of multi-item supply chain contexts since these are typically characterized by volatile and non-stationary demands. Instead of assuming a Gaussian-distributed demand or lead time, the designed model bases the configuration of these issues on inputs from historical data. Hence, by adopting such a strategy to model these factors, the field of safety stock optimization might benefit from the results of this work, as it potentiates future developments of more reliable and suitable ways to tackle this problem.

Finally, by jointly optimizing safety stock and safety time, the designed hybrid multi-objective model brings together the two main inventory-buffering strategies considered in the classical existing literature. In fact, several authors have produced studies including both strategies while concerning the inherent trade-off between inventory related-costs and customer service levels. Yet, it is also clear that these have been only investigated separately and as an alternative to each other, depending on the variability source and/or type. In sharp contrast, the results of this project have shown evidence that, in certain cases, it appears to be more cost-effective to combine safety stock with safety time compared to considering these two inventory buffers independently. Accordingly, this work ultimately provides insights into the inventory management body of knowledge, as it tests the simultaneous use of safety stock and safety time combined in a bi-optimization approach, whilst studying the potential financial and operational benefits derived therefrom.

Apart from that, conclusions on the suitability of each one of the considered safety inventory buffers can be drawn. On one hand, the results derived from this project agree with some seminal studies (Whybark and Williams, 1976; Van Kampen et al., 2010) in the sense of using safety stock to cope with demand quantity uncertainty, as well as safety time to soften supply timing uncertainty. Yet, in this context, the results presented in this dissertation suggest that safety time might be combined, in some circumstances, with safety stock. On the other hand, with exception of Etienne (1987) and Alves et al. (2004), this work is, as far as it is known, the only one assessing the dynamics of safety stock and safety time according to planning calendar. Concretely, the results suggest that for sparse calendars the best approach appears to be the combination of the two inventory buffers. Regarding dense schedules, the results comply with those found by Etienne (1987) and Alves et al. (2004) concerning the role of safety stock for components with a high density degree.

5.1.2 Managerial implications

The results of this work also have considerable practical significance for the case study company, since it generates a number of useful managerial implications.

For logistics planners from BrgP/LOS, it becomes evident that adopting such a novel approach enhances the process of determining safety stock and safety time values for each component at the plant compared to the current experience-based strategy. Indeed, the developed framework not only provides guidance for the parameterization of inventory buffers but also sustains these decisions with data insights on several logistics variables related to them. For instance, on displaying records about demand variation and supplier delivery performance over time, the proposed approach can act as a decision support system that proactively helps to clarify the reasons underlying each suggested pair of solutions. With further improvements, the reporting system could even include triggers or alert generation mechanisms, reinforcing its role as a SCRM tool. Importantly, this approach also enables assessing the expected financial impact of every decision for multiple service levels, which so far has been impossible to estimate by the current method.

Concerning company managers and other decision-makers, the findings suggest that, due to the inherent dynamics of supply chain demand and lead-time, the overdependence on intuition and experience in inventory management decisions might be very risky.

As a key message, this work also emphasizes the effects of supply and demand variability and highlights their relevance when determining inventory buffers by introducing them in the modeling process. Moreover, while considering the magnitude of the uncertainty source, it allows choosing the optimal solution that minimizes inventory-holding costs for a targeted service level, and further stresses the need of employing safety stock units at the plant as a complementary strategy to the already used safety time.

5.2 Limitations and future research directions

Naturally, this dissertation suffers from some limitations, and further research opportunities can be identified to extend the developed work.

Including shortage-related costs. Enhanced estimations of the total costs, associated with choosing a given pair of safety stock and safety time, are likely to consider every type of supply chain costs related to inventory management activities. In other words, both inventory holding costs and backlogging costs should be taken into account when selecting an optimal buffering strategy. However, since businesses find it hard to assess such values in practice (Petropoulos et al., 2019), the preferred method to measure the stockout probability is by adopting the variable of service level, or in this particular case, the average percentage of unmet demand during a considered period. Hence, the need to include further shortage cost variables can be seen as an opportunity to strengthen the efficiency of the developed bi-objective optimization model, as it would provide a more realistic perspective of the costs arising from the choice of each solution.

Extending the current approach to finished goods. From the performed literature review, it was observed that, in general, research works on safety stock decisions cover the problems of dimensioning, positioning, management and placement. This particular work focused on the development of a safety stock dimensioning strategy, which consisted not only in determining the safety stock level for each component (Caridi and Cigolini, 2002) in the plant, but also in deciding the number of safety time days to assign to each supplier order. One should note that, the designed approach can be further extended to other safety stock problems, such as determining the optimal location and quantities of safety stocks that minimizes costs for the desired service level (typically known as safety stock placement (Graves and Willems, 2000)). Yet, before heading into more complex safety stock problems, it was decided to develop a more targeted approach that allows testing and consolidating its results for one single dimension first.

Using data analytics to predict supplier disruptions. As discussed before, the present research work brings by itself relevant theoretical contributions concerning modeling supplier disruptions. Nevertheless, along with the existing literature, scarce attention has been given to the role of predictive data analytics (Brintrup et al., 2020) in anticipating and managing future disruptions on the primary sources of variability in a supply chain. Considering lead time as a critical factor when optimizing safety stocks, future studies could be conducted towards the development and further integration of machine learning models, aiming to enhance the measurement of supplier's delivery performance. Importantly, such research direction could add both substantial inputs for the current body of knowledge of safety stock optimization models, and significant practical relevance, as it would allow setting dynamic safety stock and safety time values against supplier-related delays in a proactive fashion rather than a reactive one.

Considering ordering and storage capacity constraints. The solutions generated by the hybrid bi-objective optimization model only includes constraints linked to the limit values of quantity and time that safety stock and safety time can assume, respectively. However, it is acknowledged that other factors can also affect these same solutions (Graves and Schoenmeyr, 2016), such as the warehouse capacity and quantity limits to order from a supplier. The former (which is not being considered due to lack of historical data) is expected to bound the safety stock levels that the plant can hold. In its turn, the latter is also being overlooked for similar reasons, assuming that the plant can order as much quantity as it desires. This can also impact the values of inventory buffers suggested by the current decision support system. Since the developed model does not integrate such threshold factors, additional studies can be done on this matter to assess its impact on the generated solutions.

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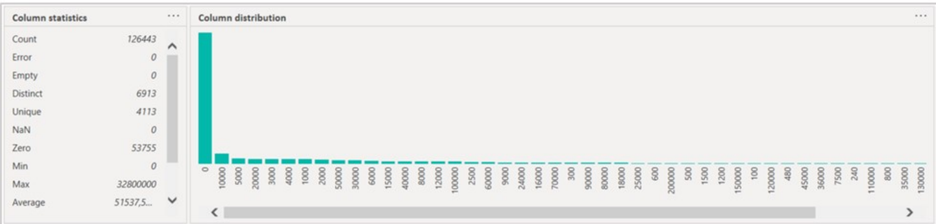
Appendix A

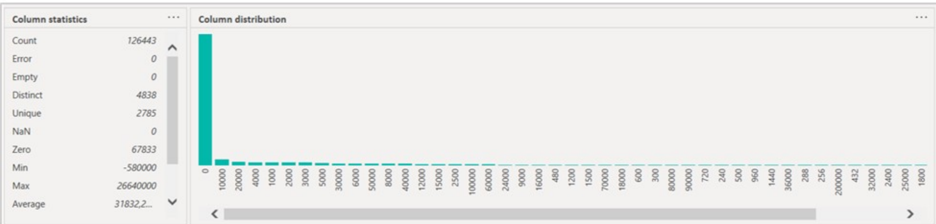
Data quality reports

A.1 Data quality report on Microsoft Power BI

Attribute	WEMNG
Data Type	NUMBER
Description	Fulfillment Quantity
Example	“32800000”



Attribute	OBMNG
Data Type	NUMBER
Description	Open Quantity
Example	“26640000”



Attribute	MEINS
Data Type	VARCHAR2
Description	Base Unit of Measure
Example	“ST”

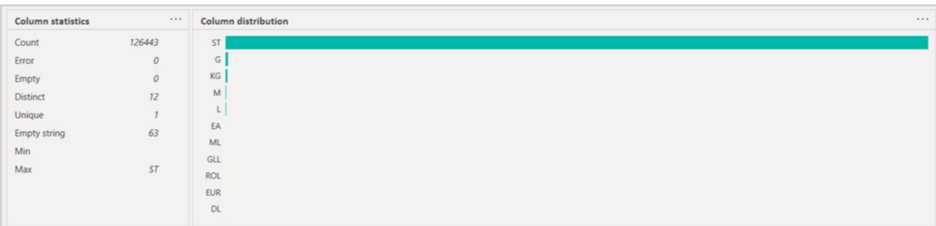


Figure A.1: Reports on data quality using Power BI tool.

A.2 Data quality report on Talend Open Studio for Data Quality

Attribute	BDTER
Data Type	VARCHAR2
Description	Requirement Date for the Component
Example	"20200709"

Figure A.2: Reports on data quality using Talend Open Studio tool.