D 2021

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

TACTICAL SALES AND OPERATIONS PLANNING: QUANTITATIVE DECISION-MAKING APPROACHES FOR INTEGRATED PLANNING

DANIEL FILIPE DA CONCEIÇÃO PEREIRA
TESE DE DOUTORAMENTO APRESENTADA
À FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO EM
ENGENHARIA E GESTÃO INDUSTRIAL

Daniel Filipe da Conceição Pereira

Tactical Sales and Operations Planning: quantitative decision-making approaches for integrated planning

Submitted to Faculdade de Engenharia da Universidade do Porto in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Engineering and Industrial Management, supervised by José Fernando Oliveira, Full Professor of Faculdade de Engenharia da Universidade do Porto and Maria Antónia Carravilla, Associate Professor of Faculdade de Engenharia da Universidade do Porto

Faculdade de Engenharia da Universidade do Porto

2021

Plans are only good intentions unless
they immediately degenerate into hard work.

Peter F. Drucker

Acknowledgements

This thesis has been a long and challenging journey that started three years ago. It would not have been possible without several people's support, to whom I am very grateful.

First and foremost, I would like to thank my supervisors. To José Fernando Oliveira, thank you for all your support since the beginning. Just to name a few, your contribution was essential during the initial discussions to frame the research, the guidance on where to go next, and the wise and experience counsels about the words to choose to answer to the relentless reviewers who crossed our path. To Maria Antónia Carravilla, I am very thankful for the in-depth review of my texts, the attention to the details, and the example of reliability, competence, and rigor that emanates in everything you do. I am very thankful to both of you for all the fruitful discussions and the inner motivation you gave me, which made me believe in the quality of this research. I suspect you have no idea how that was important to make me achieve this endeavor. Finally, thank you for your complementarity and example on how to work as a team. It is easy to understand why you were successful in supervising so many projects in the past.

I express my gratitude to LTPlabs for the opportunity, time, and financial support essential to accomplish this project. But people at LTPlabs are what makes the difference. First, I would like to thank Bernardo, Luís, and Pedro for the motivation you gave me to accomplish this goal, for believing that I would be capable of getting the time to do research and take part in challenging projects at the same time, and for the high standards you deliver every day. Second, I am very thankful to all the LTPeers I have been working with, that I impersonate in the ones I have known since day one: Teresa, Paulo, Queiroga, João, Campelo, Horácio. It is a privilege to share my days with such a diverse and inspiring group of people. You push me forward to become a better professional. Still, you also are the ones I can share pleasant moments with outside work.

I would like to acknowledge the importance of the various companies, teams, and projects I have came across during the past seven years. All the challenging moments, the tough problems, and business details I have learned from you were essential, on the one hand, to give me the motivation to conduct this project and, on the other hand, to help me being a more structured, hands-on, and effective researcher.

To my parents, thank you for the love and the unconditional support that allowed me to reach here. The dedication you consistently demonstrated to help Monica and me achieving our goals is something I will never forget. To Monica, my sister, I am grateful for the brotherhood moments and for being an example in the simplest things. Thank you for always remembering me about the essential values in life.

Last but never least, my final words are for Ana. I am grateful you share your time, family, and life with me. Undoubtedly, you are the one who felt the most repercussions with my rigorous and constant work/research-life balance during these years. I will try to compensate in the future. Thank you for being a steady support, for your words of encouragement, and for always believing in me. All of this effort will mean nothing without you.

Abstract

Planning a supply chain is inherently related with two key concepts: the time horizon (e.g., daily, weekly, monthly) and the scope (e.g., production, production-distribution, procurement-production) considered. Regarding the first, planning can range from strategic, where senior executives determine the future of the business for several years, to operational, where the sequence and nature of the tasks that are being taken in the next days, need to be determined. There is the tactical layer in the middle, which intends to plan resources, operations, and other related decisions in the mid-term, from a period than can span from a few weeks to several months. Regarding the second concept, planning can be detailed for a specific department or integrate decisions from different business functions. As the planning horizon increases, the more important it is to integrate decisions. This research tackles a mid-term planning layer, aiming to integrate tactical decisions from procurement, production, distribution, and sales in the same plan, entitled Sales and Operations Planning.

Research on Sales and Operations Planning is diverse. There is a soft side on the topic, related with the process, the owners, the timings, and the culture required to ensure a successful implementation. At the same time, the hard side of Sales and Operations Planning is related to the tools, systems, and models necessary to ensure data availability and plan generation to support such decision-making. This thesis focuses on the second. The main goal of this research is to study and develop quantitative (i.e., decision-making) approaches to support more advanced Sales and Operations Planning dynamics. The main motivation lies in the current lack of structured research on the models' side of Sales and Operations Planning, and the belief that advanced analytical models are essential in a world where data availability is growing, and supply chain dynamics are getting more and more complex.

The contributions of this thesis are aligned with this objective. First, we propose a conceptual framework for the decision-making approach to Sales and Operations Planning, which allows to structure the field of research and identify relevant research directions. Based on the findings of this first part of the project, we propose two quantitative S&OP models developed to close the gap between the current literature and the practitioners' needs. The first model contributes with a multi-objective S&OP approach integrating procurement, production, logistics and sales decisions for flow-shop/batch companies whose products can be Make-to-Stock or Make-to-Order. The second model, which consists of a scenario-based robust model, brings contributions to the quantitative S&OP field by deepening the integration of contractual management decisions.

Overall, this research is motivated by scientific and practical concerns, and provides breakthroughs in both domains. We provide structure to a field that has been mostly evolving erratically, in multiple directions, with no clear guidelines. We also devise innovative decision-making models, which enriches existing literature. On the practical side, these models can be the basis for effective decision-support systems, leveraging the Sales of Operations Planning of industrial companies.

Resumo

O planeamento de abastecimento está inerentemente relacionado com dois conceitos chave: o horizonte de planeamento (ex. diário, semanal, mensal) e o âmbito (ex. produção, produção-distribuição, compras-produção) considerados. Relativamente ao primeiro, o planeamento pode variar entre o planeamento estratégico, onde os executivos determinam o futuro do negócio para vários anos, e o planeamento operacional, onde a sequência e a natureza das tarefas que serão realizadas nos próximos dias devem ser determinadas. Entre estas duas camadas, existe a camada tática, que pretende planear recursos, operações e outras decisões de médio prazo, para um período que pode durar entre algumas semanas a vários meses. Relativamente ao segundo conceito, o planeamento pode ser definido para um departamento específico ou integrar decisões de diferentes funções do negócio. À medida que o horizonte de planeamento aumenta, mais relevante se torna integrar decisões. Este projeto de investigação aborda uma camada de planeamento de médio prazo, com o objetivo de integrar as decisões táticas de compras, produção, distribuição e vendas no mesmo plano. Este plano é intitulado de *Sales and Operations Planning*.

A literatura existente sobre planeamento de vendas e operações é diversa. Pode-se considerar que há uma stream que aborda mais a parte *soft* do tema, relacionado com o processo, os owners, os momentos de planeamento e a cultura necessários para garantir uma implementação bem-sucedida. Ao mesmo tempo, a parte *hard* dedica-se às ferramentas, sistemas e modelos necessários para garantir a disponibilidade de dados e a geração de planos para apoiar a tomada de decisão. Esta tese concentra-se na segunda vertente. O principal objetivo é estudar e desenvolver abordagens quantitativas (ou seja, de apoio à tomada de decisão) para apoiar dinâmicas mais avançadas de *Sales and Operations Planning*. A principal motivação reside na atual falta de literatura estruturada sobre modelos de planeamento integrado de vendas e operações e a crença de que os modelos analíticos são essenciais numa realidade onde a disponibilidade de dados é crescente e a dinâmica associadas ao planeamento da cadeia de abastecimento são cada vez mais complexas.

As contribuições desta tese estão alinhadas com este objetivo. Em primeiro lugar, propomos um modelo conceptual que descreve a temática de Sales and Operations Planning, partindo de uma perspetiva de tomada de decisão. Isto permite-nos estruturar o campo de investigação e identificar direções para investigação futuras. Com base nas conclusões desta primeira parte do projeto, propomos dois modelos quantitativos de S&OP que foram desenvolvidos com o intuito de endereçar a lacuna que atualmente existe entre a literatura e as necessidades das empresas. O

primeiro modelo contribui com uma abordagem multi-objetivo que integra as decisões de compra, produção, logística e vendas, direcionada a empresas cujo processo produtivo é organizado em *flow-shop/batch*, e cujos podem ser *Make-to-Stock* ou *Make-to-Order*. O segundo modelo, baseado numa abordagem robusta baseada em cenários, contribui para o estudo de abordagens quantitativas para S&OP através do aprofundamento da integração de decisões de gestão de contratos.

De uma forma geral, este projeto de investigação parte de uma motivação científica e prática, e resulta em avanços em ambos os domínios. Por uma lado, procuramos estruturar uma área de investigação que tem vindo a evoluir de forma errática, em múltiplas direções, e sem diretrizes claras. Por outro lado, este projeto resulta em modelos de apoio à decisão inovadores, que enriquecem a literatura da área. Na prática, acreditamos que estes modelos devem ser incorporados em sistemas de apoio à decisão, capazes de alavancar as práticas de *Sales and Operations Planning* em empresas de cariz industrial.

Contents

Chapter 1

Introduction and overview

A supply chain represents a "(...) network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer" (Stadtler & Kilger, 2008). A supply chain consists, thus, in two or more organizations (or functions within a company) which collaborate to deliver a product to the final customer. For simplicity, it is possible to assume that a supply chain is composed of four different actors: suppliers, producers, distributors, clients.

Suppliers are linked to producers through procurement. That is, producers incorporate raw materials or components in their processes. They need to acquire the materials from the market. The procurement function is responsible for managing raw materials or components stock levels and order new quantities from one or more suppliers if necessary. The production stage is composed by a set of value-added activities which transform raw materials or components into final products. Depending on the complexity of the supply chain, production may occur in multiple locations. Production processes can either be continuous or occur in batches. By definition, the former does not consider any break in time because the materials being processed are continuously in motion. The latter admits that products are produced in groups (batches) and not in a continuous stream. Distribution is then necessary to bring the products from the producer or manufacturer to customers. It can be either internal (if the company has its pool of means of transportation and its warehouses) or outsourced to third party logistics. Once the customer acquires the goods, it can be said that a sale occurs. The sales function is responsible for connecting the customers to the company. It defines, for instance, the prices of the products sold in the market or decides which orders should be accepted by the company. Depending on the business context the sales team may be closely supported by the marketing function, dedicated to the definition and implementation of pricing, promotional and communication strategies to captivate customers.

In a supply chain, decisions have to be taken and coordinated between different stakeholders. Some decisions may concern the preparation or anticipation of events which only take place in the future. However, the criticality of those events may be so high that preparation and anticipation (i.e., planning) must occur to guarantee that the supply chain is ready to take full advantage of that event once it happens. According to the importance of the decisions to be made and the length of the planning horizon, different planning levels exist (Stadtler & Kilger, 2008). At a strategic level, long-term decisions are taken to create the basis for the development of the company in the future. At the tactical level, the focus is on mid-term decisions, including preliminary plans for regular operations. Finally, in the short-term, the operational level is concerned with the detailed instructions for execution and control. Within the tactical planning level, Sales and Operations Planning (S&OP) is a key business process to match customer demand with supply capabilities in the medium term, whose output is an unified plan that can comprehend procurement, production, distribution, and sales activities.

Literature and practical work around S&OP have evolved in different directions. To achieve an effective, aligned, and consensual balance between demand and supply, companies need more than a set of instructions and robust planning tools. There are six dimensions relevant for successful S&OP implementations (Tuomikangas & Kaipia, 2014). S&OP must be, first of all, supported by a strategic alignment that links the company strategy and the operational planning. Second, a formal and standardized process for conducting S&OP must be defined. Third, such process should be supported by tools that capture, share, and treat data for decision making, and advanced planning systems capable of defining optimal plans and supporting what-if scenarios. Fourth, companies need to define the formal organization S&OP structure, involving decision making authorities, roles, and responsibilities. Fifth, all these collaborations should be supported by a leadership style which includes values such as commitment, trust, top management leading by the example, and empowerment. Sixth, performance management is important to ensure reaching the business targets. Therefore, defining a set of key performance indicators around the S&OP practice and evaluate and analyze them is critical.

This thesis focuses on the tools and data perspective in S&OP. With last years' advances in Advanced Planning Systems (APS), companies started to use available information to deploy analytical models that can support them in setting optimal plans for operations. Nevertheless, the connection between S&OP and APS has not been thoroughly explored. The APS focus on specific sets of the supply chain (e.g., production plans, distribution and routing plans), not on the necessary integration to support S&OP. Integrated business planning, as claimed by these software providers, still segregate, for instance, forecasting and demand management from response and supply planning. Despite the recent utilization of statistical forecasting processes and machine learning algorithms to improve demand forecast, these systems assume demand must be entirely met and supply plans need to be generated accordingly. What if the most profitable decision for the company is not to fulfill a set of customers, to be effective serving the remaining ones?

This thesis aims to extend the knowledge on decision-making models to support an effective match between customer demand with supply capabilities in the medium term. The first part of the thesis is focused on the motivation, resulting from an in-depth literature review on the analytical models supporting S&OP. As a result, we devised a framework composed by the decisions in the scope of this medium-term exercise, and point research directions in the field. The second part is composed of incremental quantitative approaches answering to some of the research opportunities identified.

Our research aims to provide breakthroughs in two main axes: scientific and practical grounds. First, with the systematization of S&OP topic from a decision-making perspective, this work aims to set the ground for more structured developments on the field, which have been erratic and developed to answer specific case studies. At the same time, our framework with the identification of the relevant decisions to be tackled in S&OP can be used as a guide for practitioners that are implementing a S&OP program in their companies and aim to follow a guide containing the decisions that can be potentially relevant in their case. Regarding the mathematical models developed and inherent application rationales, they are innovative and tackle challenges not addressed by the past literature on the field. Complementarily, each model is assessed using real instances, and relevant managerial insights are derived from their application, which makes this research also relevant for practitioners in the industry.

The remainder of this chapter is organized as follows. Section 1.1 presents some reflection and discussion on the origin of S&OP and its evolution and the relationship between this planning layer and the value of quantitative approaches to improve companies' planning. Afterward, the research objectives and methodological approach are discussed in Section 1.2. Finally, Section 1.3 provides an overview of the thesis, describing each chapter's main ideas and contributions.

1.1 Quantitative decision-making Sales and Operations Planning

1.1.1 The origin of Sales and Operations Planning

Finding the origin of the concept of S&OP is not straightforward. Due to its multidisciplinary nature, as the topic can be regarded from processual, cultural, strategical, or data-driven perspectives, there are multiple and sparce literature streams. Nevertheless, two roots can be traced, one from the business side and other from the production planning literature.

Regarding the former, S&OP was introduced in the late 1980's by Dick Ling, in its book 'Orchestrating Success: Improve Control of the Business with Sales & Operations Planning' (Ling & Goddard, 1988). The Manufacturing Resource Planning (MRP II) was a trend at the time, and S&OP was introduced as a driver whose main goal was to make MRPII work in a manufacturing plan. At the time, S&OP was innovative – sales planning and production planning were conducted as independent exercises. The authors proposed demand and supply to be managed as drivers for customer service and resultant inventories. Therefore, to achieve such goal, marketing and manufacturing teams should agree once a month on a set of numbers for sales, production, and inventory.

Despite the initial enthusiasm around the topic, the authors claimed years later that many implementations failed because sales, marketing, and general management were measured on financial results, whereas manufacturing and supply chain were evaluated on operational targets based on volume forecasts. In other words, the initial budgeting exercise still outweighs S&OP,

and any decisions made during the S&OP were disregarded. Therefore, reconciliation between the exercises soon started to be seen as critical. To accomplish such goal, some issues started to be pointed out. Among them, the need to build what-if scenarios in S&OP and manage uncertainty, and clarify which decisions should be escalated to senior management review.

We highlight these issues because they are important for the analysis of our work. Concerning uncertainty management, we approached it in the literature review, and one of the formulations we propose is robust to deal with the risk that is inherently expected in mid-term planning. Concerning the senior management involvement in S&OP, we could not agree more with Dick Ling and Andy Coldrick. Despite that is not the focus of our thesis, the models proposed herein potentially require mediation between divergent functions, such as operations and sales. Therefore, if the senior management, inclusively the Chief Executive Officer (CEO), is not involved in analyzing the generated plans, their implementation may be compromised.

With respect to the production planning literature, according to Singhal and Singhal (2007), early work in aggregate production planning has evolved to become sales and operations planning. In the 1950s, a team composed by Charles C. Holt, Franco Modigliani, John F. Muth, and Herbert A. Simon began a project entitled ‘Planning and Control of Industrial Operations’, culminating in a linear-quadratic model of aggregate production planning. The approach consists of selecting production and workforce levels in each period to satisfy order shipments while minimizing the sum of the costs throughout the planning horizon. An integrated approach to planning is becoming more and more frequent, facilitated by globalization and the emergence of distributed supply chains.

This traceback associating S&OP decision-making models to aggregate production planning is important to frame the research on the topic. While S&OP is an original concept, the decision-making part is closely related to other topics in operations management, such as ‘aggregate production planning’, ‘supply chain planning’, and ‘marketing-operations models’. Research on aggregate production planning has evolved to include lateral decisions from procurement, distribution, and sales. Supply chain planning models are built with a different emphasis. These models are commonly associated with complex supply chains, with multiple production and distribution locations and customers spread across multiple geographies. More strategic models deal with issues such as network design (i.e., the definition of the best locations to set the business) and are different from the models that can support S&OP. However, some models in this field of research define, for instance, the best inventory balance and tactical flows across locations. Thus, for organizations whose organization structure fits into this type of networks, such models could be a basis to support S&OP and an interdisciplinary discussion between operations teams and sales teams. Finally, marketing-operations interface models discuss how these two functions, with different objectives in mind and different issues to plan, can collaborate more fruitfully and maximize a company’s profit. With this in mind, a reader of this thesis should understand that our formulations (and related considerations) may be transposable for lateral research fields. However, our motivation is quite different.

1.1.2 Quantitative decision-making

Decision-making is becoming more and more complex. Issues such as portfolio proliferation to face the unlimited customer desires, environmental sustainability, or the growth in e-commerce relationships pose challenges never faced before. At the same time, advances in technology, the proliferation of data, and a growing computation power present an opportunity companies should take advantage of. Therefore, there is a chance to leverage advanced analytic approaches to make companies more capable of managing such complexity. Unlike human planners, such approaches can handle multiple decision variables and reflect several constraints to help manufacturers decide what to buy, what to make, what to replenish, and which customers to serve to maximize the profit in each period.

At the same time, even though companies are generating more and more data, many failed to use this mountain of potential intelligence (Dilda, Mori, Noterdaeme, & Schmitz, 2017). Techniques such machine learning models and optimization, and technologies such as visualization platforms present wondrous opportunities for companies to optimize their processes. Nevertheless, these new tools and techniques potential is only realized when properly combined with the right human skill and expertise. Analytical improvements need to be repeatedly deployed to achieve the desired results. A blend of changing mindsets, more fact-based discussions, and top leadership support is important to make such approaches result.

This work is closely related with these two axes. As quantitative decision-making is gaining more room for implementation, our findings can help leveraging such paradigm and support companies attain the next level of maturity managing S&OP. At the same time, we are not proposing new formulations and analytical approaches only. The reader will realize we make a constant effort on framing such mathematical models into companies processes and help support their implementation providing valuable analyses and insights.

1.2 Research objectives and methodological approach

As stated before, this research aims to contribute to the field of Sales & Operations Planning by approaching the topic from a decision-making perspective. To achieve such goal, we rely on quantitative approaches, namely mathematical optimization. Therefore, our research aims to bring breakthroughs to the 'hard' side of S&OP, that is, the stream of research within this tactical planning exercise related to tools, data, and advanced planning systems.

Before starting to devise new approaches to decision-making on S&OP, we begin by fully understanding the topic, grasping the decisions and interactions characterizing the problem, and the main opportunities in this field of research. To accomplish such goal, we review the literature on the topic, propose a conceptual framework for the problem, and detail the modeling approaches and solution procedures employed by past researchers. Finally, we highlight the relevant research directions, namely the need to develop general and modular formulations adaptable to the context of application, with the subsequent assessment of the models in different sectors of activity, the development of solution procedures for complex formulations, and the extensions of such models to consider uncertain parameters. Within the first direction, the review indicates an opportunity to streamline the horizontal integration between the procurement, production, distribution, and sales functions by developing models capable of integrating quantity discounts, demand shaping strategies and contract decisions. Moreover, we identify that research needs to evolve to consider multistage production processes, introduce more realistic inventory management policies, and consider objectives other than profit maximization. We further detail these opportunities in Chapter 2.

After clearly stating these research directions, we aim to develop models that can mind the gap between the current practice and the opportunities mentioned above. We tackled two different challenges, as follows:

Multi-objective S&OP model for hybrid companies with a flow shop/batch production process, fulfilling the market with a hybrid Make-to-Stock (MTS) /Make-to-Order (MTO) portfolio.

We develop a mixed-integer programming (MIP) model managing procurement, production, distribution, and sales in an integrated fashion to tackle this challenge. Products can be managed as Make-to-Stock (MTS) or Make-to-Order (MTO). The first segment comprises products sold as commodities, that need to be readily available. In contrast, the second group corresponds to customized products according to customer needs, and whose delivery lead time may be higher. When satisfying demand, the company may be requested to decide if it supplies products for the commodity market or, on the other hand, to the customized segment, if capacity reveals scarce. Therefore, this challenge begins to be multi-objective, since the profitability is not the only relevant criteria (e.g., if the company has a poor service level in one specific segment, it may be hindering is competitive position in the future).

To manage such complexity in the decision-making, we propose to solve the MIP model using multiobjective optimization. We resort to the epsilon-constraint method, given its advantages over other approaches such as the weighing method (detailed in Chapter 3). Summing up, this S&OP approach is designed to blend a mix-integer programming model with a multiobjective planning rationale.

This stream of the research is supported by the literature review, where the need to consider other objectives than profit emerges, as well as the request to adapt S&OP models to situations where the production setting is more complex (in our model, a flow shop/batch production process). But there is also a practical motivation justifying this work – this business setting is motivated by a real case faced by a cable manufacturer.

Even though there is a specific business setting behind the research, aligned with the goal of this research, we intend other companies can use this approach. To do so, we generalize as much parameters as possible (e.g., number of periods, number of production stages). Thus, we expect this model to be applied in other cases, as long as the production process is flow shop/batch oriented, and the customers' demand is fulfilled with MTS/MTO products. The type of decisions, and granularity employed in the model, makes it suitable to support S&OP meetings whose planning horizon ranges from 3-12 months.

Robust S&OP model for companies serving contract and non-contract customers, required to decide the best capacity usage for internal resources between both demand segments.

This challenge is relevant for companies whose sales-operations integrated planning implies the question on how to use existing capacity to fulfill contract and non-contract demand, particularly relevant if capacity is insufficient to fulfill potential demand. Non-contract demand may not be met in full, and sales cannot surpass the demand. Contract demand is governed by quantity-flexibility (QF) contracts, that is, there is a maximum and minimum band limiting sales. The maximum and minimum bands are defined as a percentage flexibility rate around the expected demand forecast. Moreover, the QF contract includes a portfolio decision, in which there is the possibility of including or not a specific product in an agreement with a buyer.

We develop this model as a mixed-integer nonlinear programming model. In order to ensure the model can be straightforwardly solved by commercial solvers, we linearize the formulation. It is important to approach this topic considering uncertainty. As the decisions around a contract's agreement are taken at the beginning of the planning horizon, considering uncertainty regarding future periods may impact the chosen contract parameters. So, we develop a robust counterpart of the deterministic formulation. The option for a robust optimization approach grounds on that estimating demand probability distributions in many practical applications may be very challenging. Given the limited interactions that commonly occur between a supplier and a buyer in a business-to-business context, this is an issue in our case.

This research line is motivated by the literature review, which reveals that contract management in S&OP is still a topic that has not been properly explored. Research evolved more on the characterization of contract policies considering one or a few products, and neglecting the complexity of integration with other business functions. We consider a flow shop/batch production process to make the model more general, but it is adaptable to simpler operations settings. We foresee this approach to be valuable if included in a S&OP meeting with a planning horizon ranging from 12-24 months. Although not directly motivated by a practical application, we build an instance based on the cable manufacturer case motivating the previous line of research, making use of our model and demonstrating its applicability.

Both decision-making models are developed using the same conceptual approach, as stated in Figure 1.1. We first deep dive on closely related literature to frame the value of our approach. Then, we describe the managerial challenge that arises in the mid-term integrated planning that might occur between sales and operations teams, and present the decision-making framework. Afterward, we detail the solution approach and run some computational experiments to provide researchers and practitioners with a clear description on how the models might be used. Finally, we make some managerial considerations that close the gap between the 'hard' side of S&OP and the complex and business-oriented mindset of practitioners who need to master such approaches to make them effective in decision-making.

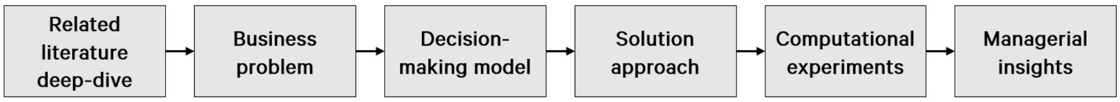


Figure 1.1: Conceptual approach used in the development of decision-making models

1.3 Thesis synopsis

Figure 1.2 presents an overview of the remaining chapters of the thesis, consisting of a collection of papers. The chapters are arranged according to the methodological approach described.

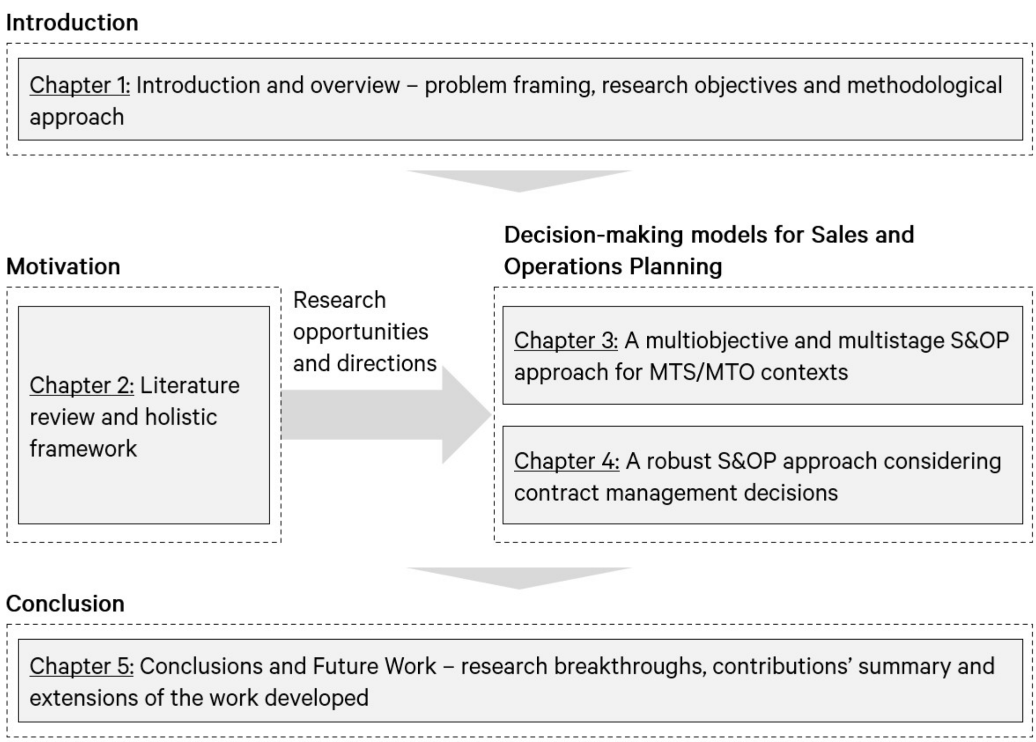


Figure 1.2: Overview of the thesis structure

Chapter 2 details the motivation for this research, while framing the problem around a conceptual framework and presenting how past researchers have approached the topic from a modeling approach perspective. Then, we tackle some of the identified research directions, which led to two additional contributions.

The first paper, included in Chapter 3, is entitled 'Merging Make-to-Stock/Make-to-Order decisions into Sales and Operations Planning: a multi-objective approach', and details a mathematical model, a decision-making framework, and its application to help companies with a complex production process organized around a flow shop/batch layout to take the best Sales and Operations decisions, in a context where some products are Make-to-Stock and others are Make-to-Order.

Then, in Chapter 4, an innovative approach to deal with a Sales and Operations challenge on how to best serve contract and non-contract customers is presented, particularly relevant if capacity is insufficient to meet potential demand. This chapter corresponds to a second paper, entitled 'Design of a sales plan in a hybrid contractual and non-contractual context in a setting of limited capacity'.

Finally, Chapter 5 summarizes the work and complements it with additional directions for further research.

Bibliography

Dilda, V., Mori, L., Noterdaeme, O., & Schmitz, C. (2017). Manufacturing: Analytics unleashes productivity and profitability. *Report, McKinsey & Company*.

Ling, R., & Goddard, W. (1988). *Orchestrating success: Improve control of the business with sales & operations planning*. Oliver Wight Limited Publications.

Singhal, J., & Singhal, K. (2007). Holt, modigliani, muth, and simon's work and its role in the renaissance and evolution of operations management. *Journal of Operations Management*, *25*(2), 300-309. doi: 10.1016/j.jom.2006.06.003

Stadtler, H., & Kilger, C. (2008). *Supply chain management and advanced planning: Concepts, models, software and case studies*. Springer Berlin Heidelberg. doi: 10.1007/978-3-540-74512-9_2

Tuomikangas, N., & Kaipia, R. (2014). A coordination framework for sales and operations planning (s&op): Synthesis from the literature. *International Journal of Production Economics*, *154*, 243-262. doi: 10.1016/j.ijpe.2014.04.026

Chapter 2

Motivation: Literature review and holistic framework

This chapter presents a literature review that approaches Sales and Operations Planning from decision-making and quantitative perspectives. It establishes the scope of the research through a thorough mapping of the relationships between business functions during mid-term planning. The paper also presents the modeling approaches employed to tackle the problem. This review is of the utmost importance for the thesis since it allowed to identify the existing gaps and relevant research directions, which motivate the remaining research carried out during the project.

Tactical Sales and Operations Planning: a holistic framework and a literature review of decision-making models

Daniel Filipe Pereira [*], José Fernando Oliveira [†], Maria Antónia Carravilla [†]

[*] Faculty of Engineering, University of Porto and LTPlabs [†] INESC TEC

Published in *International Journal of Production Economics* 228, 2020

https://doi.org/10.1016/j.ijpe.2020.107695

Abstract: Tactical Sales and Operations Planning (S&OP) has emerged as an extension of the aggregate production planning, integrating mid-term decisions from procurement, production, distribution, and sales in a single plan. Despite the growing interest in the subject, past synthesizing research has focused more on the qualitative and procedural aspects of the topic rather than on modeling approaches to the problem. This paper conducts a review of the existing decision-making, i.e., optimization, models supporting S&OP. A holistic framework comprising the decisions involved in this planning activity is presented. The reviewed literature is arranged within the framework and grouped around different streams of literature which have been extending the aggregate production planning. Afterwards, the papers are classified according to the modeling approaches employed by past researchers. Finally, based on the characterization of the level of integration of different business functions provided by existing models, the review demonstrates that there are no synthesizing models characterizing the overall S&OP problem and that, even in

the more comprehensive approaches, there is potential to include additional decisions that would be the basis for more sophisticated and proactive S&OP programs. We do expect this paper contributes to set the ground for more oriented and structured research in the field.
Keywords: Sales and operations planning, Tactical planning, Decision-making models, Modeling approaches, Supply chain integration

2.1 Introduction

A supply chain represents a network of organizations (or functions within a company) involved, through upstream and downstream linkages, in the different processes or activities that produce value in the form of products and services for the customer (Stadtler & Kilger, 2008). As some decisions need to be taken in advance to anticipate future events, planning emerges as a need. According to the importance of the decisions and the length of the planning horizon, different planning levels arise (Stadtler & Kilger, 2008):

- *Long-term (strategic) planning*: decisions that create the basis for the development of the supply chain (or company) in the future. These decisions concern the design of the supply chain for a future of several years;
- *Mid-term (tactical) planning*: determines a preliminary plan of the regular operations, usually made at an aggregate level. Rough quantities and times for the flows and resources are evaluated. The planning horizon ranges between a few months and one year;
- *Short-term (operational) planning*: this planning level is concerned with the detailed instructions for immediate execution and control. A high degree of detail is expected to be found. The planning horizon is between a few days and a few weeks.

Under the mid-term planning level, Sales and Operations Planning (S&OP) appears as a cross-functional and integrated tactical planning process within the firm, whose objective is to integrate all the plans of the business in a single plan (Y. Feng, D'Amours, & Beauregard, 2008; Pedroso, da Silva, & Tate, 2016; Thome, Scavarda, Fernandez, & Scavarda, 2012b; Tuomikangas & Kaipia, 2014). Its main goal is to be the definitive statement of the company's plans for the near to intermediate term, covering a horizon which supports the annual business planning process (Noroozi & Wikner, 2017). The planning horizon typically varies from 3 to 18 months (with a monthly granularity), performed at a product or family level (Noroozi & Wikner, 2017; Thome et al., 2012b). This plan guarantees the balance between demand and all the supply capabilities, namely production, distribution, procurement, and finance, to ensure alignment with the strategic goals (Y. Feng et al., 2008). Therefore, S&OP plays an essential role in integrating organization units as a whole, fulfilling customer demand to improve competitiveness (Tuomikangas & Kaipia, 2014).

Traditionally, the four essential functions of a supply chain (procurement, production, distribution, sales) have been managed independently and linked through stocks. This strategy reduces the managing complexity but ignores the dependencies among functional areas. In the worst case, individual plans can lead to inapplicable decisions in the moment of integration. Thus, S&OP emerged as a strategy to cope with this problem. The term originates from Manufacturing Resource Planning papers as a substitute for Aggregate Production Planning (Singhal & Singhal, 2007). The concept evolved to consist of two complementary plans: a production plan and a demand-based sales plan (Olhager, Rudberg, & Wikner, 2001). More recently, researchers started to address S&OP as a fully integrated supply-chain planning considering all the functions simultaneously (Y. Feng, D'Amours, & Beauregard, 2009).

Some authors partially position S&OP both on the tactical and strategic levels (Olhager & Rudberg, 2002; Olhager et al., 2001). These papers state that balancing supply and demand is a tactical issue but that this balancing might lead, for instance, to the expansion of the production capacity, which is a strategic issue. Nonetheless, the main perception is that S&OP is indeed a tactical level planning layer (Thome et al., 2012b). Therefore, our positioning of S&OP follows this premise.

Nowadays, globalization, market uncertainty, and growing supply chain complexity increase the need for integrated planning (Tuomikangas & Kaipia, 2014). The effort required to achieve such collaboration is justified by the existing evidence that cross-functional planning can boost the performance of an organization (Thome et al., 2012b) and maximize its global value (Y. Feng et al., 2008, 2009; Nemati, Madhoushi, & Ghadikolaei, 2017a). The value associated with the integration depends on the supply chain under consideration. For instance, in environments with constrained capacity, it is valuable to coordinate marketing (sales) and production decisions, such as integrating production planning with pricing as a strategy to shape demand (Gilbert, 2000). Another example can be found upstream in the supply chain. Efficient procurement and production may not be reached if production planning and raw materials purchasing decisions are taken independently, especially if discount quantities from suppliers are available (Cunha, Santos, Morabito, & Barbosa-Póvoa, 2018).

The relevance of S&OP for organizational performance justifies the growing interest in the subject. Publications have been increasing both from practitioners and researchers (Thome et al., 2012b; Tuomikangas & Kaipia, 2014). Accordingly, some literature reviews approaching the topic from different perspectives have already been conducted (Kristensen & Jonsson, 2018; Noroozi & Wikner, 2017; Thome, Scavarda, Fernandez, & Scavarda, 2012a; Thome et al., 2012b; Tuomikangas & Kaipia, 2014). Thome et al. (2012b) gather the literature around a framework composed by descriptors in the domains of context, inputs, structure and processes, outcomes, and results. The review from Thome et al. (2012a) summarizes the literature in an effort to identify and measure the effects of S&OP on firm performance. Tuomikangas and Kaipia (2014), in opposition to the previous reviews that approach the literature from a performance viewpoint, opt to classify the existing papers from a coordination viewpoint, defining a framework comprised of six coordination mechanisms: strategic alignment, organization, culture and leadership, tools and data, performance management, process. Noroozi and Wikner (2017) provide a systematic review focused on process industries. It is classified as an extension of the papers from Thome et al. (2012b); Tuomikangas and Kaipia (2014), combining the generic process of Thome et al. (2012b) with the integration concept addressed in Tuomikangas and Kaipia (2014). More recently, Kristensen and Jonsson (2018) approach the literature review from the perspective of how the context of application affects the design of S&OP and performance variables.

Irrespective of the viewpoint, previous authors agree that S&OP is characterized by two distinctive dimensions. The hard side of the process, defined by a set of planning rules, procedures, alignment meetings, and performance measurements, must be accompanied by soft aspects, such as collaboration, culture, and executive support. The difficulty in ensuring all these mechanisms might explain why there are some companies struggling to obtain the expected benefits from S&OP implementation (Goh & Eldridge, 2019). Accordingly, some frameworks defining maturity levels and implementation guidelines have been developed to overcome these difficulties (Danese, Molinaro, & Romano, 2018; Grimson & Pyke, 2007; Wagner, Ullrich, & Transchel, 2014).

Despite the differences between the maturity models presented, all the authors define progressive stages of implementation, that can be summarized as undeveloped, reactive, standard, advanced, and proactive. They range from a situation of a silo culture, with no meetings and a total absence of collaboration and planning tools to a totally formalized process throughout the supply chain, with event-driven meetings and a seamless planning optimized concurrently for demand and supply to maximize not just sales revenue or operational efficiency, but overall profitability (Grimson & Pyke, 2007). In the most advanced (proactive) stage, IT systems are completely aligned throughout the organization. Integrated solutions would jointly optimize sales decisions, such as pricing, with operations decisions, such as production plans (Grimson & Pyke, 2007). According to the authors, integrated S&OP optimization solutions with real-time solvers, coupled with business systems, would be required to support this transition. Wagner et al. (2014) suggest the adoption of a “single truly integrated" system capable of considering issues like promotions, price changes, risk management, new products, and life cycle optimization. Ivert and Jonsson (2014) also emphasize that tomorrow’s S&OP processes should be based on advanced planning and scheduling systems. Functionalities like integral planning, constraint-based planning, optimization, and what-if simulation are essential to support S&OP processes, mainly if they are characterized by a high planning complexity. Nonetheless, a lack of sophistication in information technology may be halting this evolution (Grimson & Pyke, 2007). In their paper analyzing different case studies, Danese et al. (2018) do not consider the transition to the more mature stage, because this last level is still considered an ideal status that companies and practitioners should strive for.

This paper presents a review of existing decision-making, i.e., optimization, models supporting S&OP. The need for such a review is twofold. First, research has focused more on S&OP definition, processes, activities, procedures, coordination mechanisms, and case studies depicting the benefits of the implementation rather than mathematical modeling (or decision-making) approaches to address the problem (Y. Feng et al., 2008; Nemati et al., 2017a). To the best of our knowledge, no previous review was conducted on this topic. Second, the future of S&OP calls for advanced planning systems supporting more proactive planning processes, given the increasingly complex contexts of modern supply chains. Therefore, according to the coordination framework from Tuomikangas and Kaipia (2014), this review aims to approach S&OP with a focus on the mechanisms of "S&OP organization" and "S&OP tools and data". Regarding the former, we propose a holistic framework characterizing S&OP from a decision-making viewpoint, analyzing and summarizing the decisions considered relevant by past researchers. We place a particular emphasis on the identification of interaction decisions between different departments of an organization. With respect to "S&OP tools and data", we present the modeling approaches (and solution methods) followed by past researchers while implementing S&OP models.

We start by explaining our literature selection procedure in Section 2.2. In Section 2.3, we present and detail the proposed framework to summarize S&OP, including the identification of the parameters more subject to uncertainty. In Section 2.4, we detail the modeling approaches applied in a context of S&OP. In Section 2.5, the goal is to find research opportunities and provide directions for future research that will contribute to the constitution of more advanced planning models in the context of S&OP. To achieve such goal we first characterize the level of integration provided by the current approaches. Finally, we draw the main conclusions of this work in Section 2.6.

2.2 Literature review methodology

The literature review conducted on this paper is based on the methodology proposed by Thome, Scavarda, and Scavarda (2016). Our procedure is a step-by-step approach composed by four main steps: planning and formulation of the problem (subsection 2.2.1); search on the literature (subsection 2.2.2); data analysis, synthesis and interpretation (subsection 2.2.3); results presentation (subsection 2.2.4).

2.2.1 Planning and formulation of the problem

The motivation for a review of existing decision-making models supporting S&OP is justified, on the one hand, by the nonexistence of such a review in the literature and, on the other hand, by the urgency of systematizing a topic recognized as an essential lever for the progression of S&OP to its next level of refinement. We propose an analysis and summary of the existing mathematical models supporting S&OP with a focus on the identification of the decisions taken in the context of integrated and coordinated mid-term planning of procurement, production, distribution, and sales. Furthermore, these models can be regarded as the basis for more sophisticated and advanced planning systems; thus, it is important to understand how far they might be from the vision of a truly integrated framework advocated by past researchers.

In order to focus the research, we defined a set of clearly framed research questions (Q), as follows:

- Q1: Which decisions concerning procurement, production, distribution, and sales are tackled at a tactical S&OP level?

- Q2: How have been procurement, distribution, and sales decisions incorporated into the aggregate production planning by past researchers?

- Q3: Which modeling options have been used to implement S&OP models?

- Q4: Which level of integration is provided by the existing models?

Our search strategy was based upon the analysis of scientific contributions (i.e., papers and conference proceedings) explicitly containing mathematical formulations.

2.2.2 Search on the literature

The body of literature was obtained using Elsevier SCOPUS and Web of Science citation databases in September 2019 (without limitation on the publication year in the search criteria), following the recommendation of Thome et al. (2016). Citation databases ensure a broader diversification of studies because they index several journals and vendors' databases in a single location. Figure 2.1 presents the query used, whose primary goal is to return S&OP models. We combined the keywords "sales and operations planning" and "S&OP" with keywords related to optimization models. As a result, we expected to filter from the literature on S&OP only the papers related to mathematical approaches to the problem. We opted not to include the word "model" because it is usually used to denominate qualitative frameworks or other approaches to the topic (e.g., simulation model). On the other hand, we chose to enumerate as many words related to optimization techniques as possible.

As S&OP emerged as an extension of aggregate production planning, our query was also adjusted to include papers related to mathematical approaches to aggregate production planning that jointly consider decisions from other functional areas (i.e., procurement, distribution, sales). There is a risk that these papers are not related to a context of S&OP program. However, studies depicting mere programs or systems used in internal supply chain planning may unveil tactical decisions that have not been considered by past research on S&OP models.

It is important to denote that, while our goal is to be comprehensive selecting the modeling problems related to a context of S&OP, we do not intend to achieve such a goal while searching for aggregate production planning models. Due to the many different combinations of features in past partially integrated models (e.g., production-distribution, production-pricing), this would be an arduous goal; thus, we aim to consider a sufficiently broad sample of papers that allows us to identify the relevant tactical decisions to address in a S&OP model.

The search returned 468 and 492 documents, respectively, in SCOPUS and Web of Science databases. Duplicate papers were removed, which led to a total of 688 studies. After abstract analysis, 141 papers were retained for a full reading by the first author of this review. Of this subset of papers, 55 were not considered relevant to the review. As a result, we retained a total of 86 papers. Throughout this process (i.e., from 688 studies to 86), the exclusion criteria for why papers were unrelated to S&OP modeling approaches are as follows:

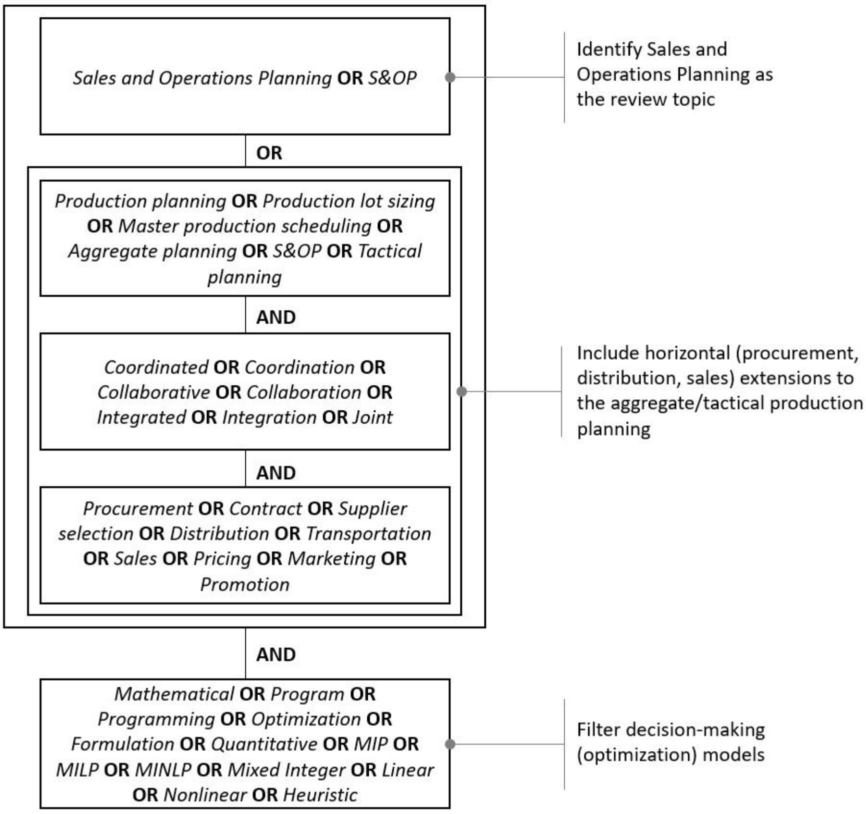


Figure 2.1: Research query

- Planning horizon: models depicting strategic issues (e.g., supply chain design, plant dimensioning) or operational issues (e.g., routing, production scheduling);
- Lack of an optimization model (e.g., qualitative approaches, such as collaboration frameworks);
- Non-inclusion of a production planning context, which we consider a central part of a S&OP model;
- Lack of representation of tactical decisions from procurement, distribution, and sales;
- Specific focus on the consideration of other functional areas (maintenance, quality, financial). While these decisions may appear in a context of S&OP, they are out of the scope of this paper;
- Specialized supply chains or specific issues (e.g., remanufacturing, disruption scenarios);
- Lack of relation with the topic of S&OP.

Finally, we added 17 papers that resulted from the process of backward search, thus resulting in a total of 103 papers. The additional papers were considered because they are cited in the articles yielded from the keyword search and revealed applicable to the topic under research.

2.2.3 Data analysis, synthesis and interpretation

The 103 papers were fully read, and the mathematical models were analyzed from four different perspectives:

- Characterization of the supply chain complexity and planning horizon. The following information was analyzed and summarized: number of planning periods, time horizon, time granularity, level of detail (product/family), number of products/families, number of production locations, number of production stages, type of industry;
- Identification of the decisions addressed (i.e., decision variables) and uncertain parameters;
- Categorization of the analytical approach (e.g., Linear Programming) and solution procedure (e.g., metaheuristic).

After an individual analysis, the models were grouped in typologies regarding their level of integration of the different business functions in a company (e.g., procurement-production-distribution-sales *versus* production-sales). The interpretation of the overall matrix containing all the typologies of models enables the identification of the main decisions included in the models as well as the main gaps.

2.2.4 Results presentation

We present the identified relationship between the decisions tackled in the current formulations using the supply chain matrix (Stadtler & Kilger, 2008). Besides the summary of the existing literature, the resulting framework is a significant contribution of this paper as it classifies S&OP from a decision-making perspective. The framework is presented in Section 2.3. In Section 2.4 we resort to an adapted framework based on the contribution from Mula, Peidro, Díaz-Madroñero, and Vicens (2010) to classify the papers according to the modeling approaches employed.

2.3 Supply chain tactical decisions

S&OP appears as a cross-functional and integrated planning process within the firm, whose objective is to gather all the plans of the business in a unified plan. The main perception is that S&OP is predominantly a tactical planning tool, deployed once business and strategic plans are set, and connecting these plans to operations (Thome et al., 2012b). We propose a holistic framework that instantiates how this is achieved from a decision-making perspective (Figure 2.2). This model results from the analysis of the literature and is applicable to any supply chain comprising procurement, production, distribution, and sales functions. Therefore, Figure 2.2 answers *Q1*, presenting the tactical decisions taken in an industrial company.

First, the board of the company defines the strategic decisions of sales and operations (procurement, production, distribution) departments (herein denominated *Sales and operations strategic planning*). It comprises a set of decisions whose goal is to guide the business in the long-term.

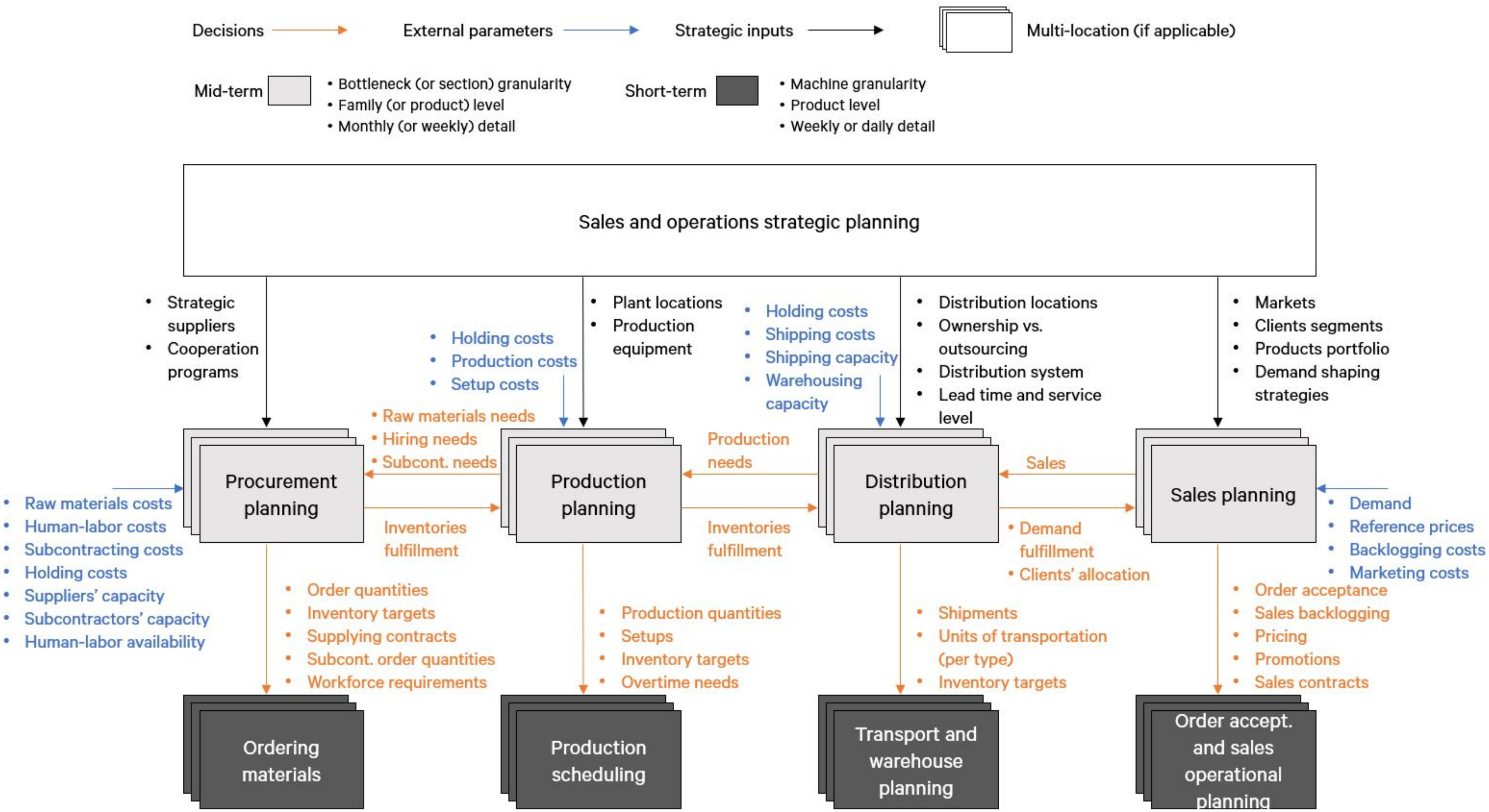


Figure 2.2: Proposed framework to represent Tactical Sales and Operations Planning

S&OP assumes these decisions as inputs. Other inputs that come directly from the market or operational context are incorporated. These inputs range from demand information to raw materials, transportation, or setup costs. An optimal planning gathers all this information and constrains it by the supply chain limitations to develop the most efficient plan for the company. This plan guides the execution (short-term) decisions, namely ordering materials, production scheduling, transport and warehouse planning and order acceptance. Kristensen and Jonsson (2018) recommend that S&OP research should put more effort in studying its design considering the interfaces with both strategic and operational planning. This framework is useful to study these relations in more detail because it makes clear which decision boundaries appear between the different planning layers.

In this section, we thoroughly describe the decisions potentially taken in the context of S&OP. We present them with a focus on how these variables have been introduced as an extension of the classical aggregate production planning (*Q2*). Therefore, we first characterize the mid-term production planning problem in terms of its temporal granularity, product structure detail, and main decisions included (subsection 2.3.1). Only then we discuss the integration of decisions from procurement, distribution, and sales (subsections 2.3.2, 2.3.3, 2.3.3). We end up the section detailing which parameters are prone to be considered uncertain in a context of sales and operations planning (subsection 2.3.5).

2.3.1 Production Planning

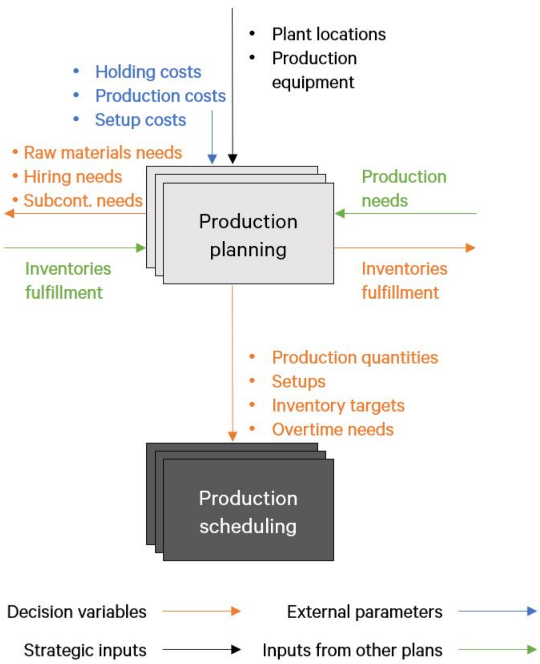


Figure 2.3: Aggregate production planning decisions

Mid-term production planning has the purpose of determining the most efficient use of the production resources in order to satisfy the demand. The main decisions interacting with mid-term production planning are depicted in Figure 2.3. *Production needs*, *inventories fulfillment* and strategic decisions such as *plant locations* or *production equipment* are inputs for the plan. The first is linked to the demand from the clients, whereas the second is related to the availability of resources guaranteed by the procurement team. Some external parameters such as *holding costs*, *production costs* and *setup costs* are also incorporated.

A set of outcomes is expected. First, the plan defines the *production quantities* of final products. Second, *setups* may be accounted for. Third, whenever seasonality is relevant, mid-term production planning should generate the best plan to deal with this demand variation. Three strategies can be used: (i) produce additional quantities to supply a future peak in demand; (ii) temporarily extend the capacity using overtime or additional workers; (iii) subcontract external suppliers to produce the additional demand. These decisions can be modeled using the variables *inventory targets*, *overtime needs*, *hiring needs*, *subcontracting needs*. Subcontracting and workforce hiring may be considered procurement activities, since they require an explicit market sourcing. Therefore, these decisions are detailed as a complement of the aggregate production planning in the next section. Finally, two more connecting decisions are generated. *Raw material needs* are communicated to the procurement department to be acquired and can be directly obtained from the planned *production quantities*. *Inventories fulfillment* translates the fulfillment rate of the production needs.

Table 2.1 presents the prevalence of the main production decisions in the literature. *Production quantities* are modeled across all papers. *Setups*, in turn, are addressed in 41% of the works. Regarding anticipated production to stock (*inventory targets*), most of the formulations (83%) model this decision, using variables to determine the optimal levels of stock to maintain in each period. Finally, considering a capacity extension strategy, 18% of the papers model *overtime needs*.

Table 2.1: Prevalence of the decisions in the literature

Decision	**Relative frequency (n=103 papers)**
Production quantities	100%
Setups	41%
Inventory targets	83%
Overtime needs	18%

In Table 2.2 we present a characterization of the aggregate production planning. Most of the papers analyzed (91%) depict a continuous production system. Nonetheless, there are some examples of batch production. We refer to the papers from Cunha et al. (2018); Fuentealba, Pradenas, Linfati, and Ferland (2019); Fumero and Vercellis (1997); Nemati and Alavidoost (2018); Nemati et al. (2017a); Susarla and Karimi (2011, 2012, 2018) as examples of this type of process.

Table 2.2: Characterization of the aggregate production planning

Characteristic	**Relative frequency**
Batch / Continuous	9% / 91%
Single period / Multiple periods	4% / 96%
Product level / Family level	81% / 19%
Single product (or family) / Multiple products (or families)	23% / 77%
Single stage / Multi stage	73% / 27%
Single plant / Multiple plants	47% / 53%

Concerning the planning horizon, aggregate production planning is a multi-period problem. 96% of the models depict a multi-period reality, which spans from a few weeks to one-two years. Weekly or monthly-time buckets are typically used. However, a few authors introduce daily intervals. Darvish, Larrain, and Coelho (2016) consider one year of planning using daily time-buckets. This option is explained by a specific constraint of the problem, which models daily time windows for the maximum lateness allowed for each order. Another example is the paper from Lin and Chen (2007), which combines daily and monthly time buckets as an attempt to integrate operational and tactical planning. In the first month of the plan, a daily time bucket is used.

From a product complexity perspective, most problems (81%) depict a product-level context. Nevertheless, some approaches consider a family-level detail. We refer to the models from Y. Feng et al. (2008, 2009); Y. Feng, Martel, D'Amours, and Beauregard (2013); Fumero and Vercellis (1997); Gansterer (2015); Ghasemy Yaghin (2018); Nemati and Alavidoost (2018); Nemati et al. (2017a); Peidro, Mula, Alemany, and Lario (2012); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005); Wei, Guimarães, Amorim, and Almada-Lobo (2017); Yuan, Low, and Yeo (2012) as examples of this approach. If the model needs to incorporate specific details of the products, the option for a product-level granularity is necessary. Otherwise, aggregation at a family-level becomes a possibility, thus reducing the complexity of the model. The paper from Fumero and Vercellis (1997) takes advantage of both levels. As the products from a specific family require the same components, absorb the same amount of a given resource, have similar transportation costs, and have negligible setup times between them, some variables are modeled at a family-level. Yet, products from the same family can have different inventory costs and different backlogging costs, so some disaggregated variables are included.

Regarding the extension of the product structure, most of the problems (77%) represent a multi-product (or family) reality. However, we cite a few papers which reproduce a single-product context (Aouam & Brahimi, 2013b; Aouam, Geryl, Kumar, & Brahimi, 2018; Askarpoor & Davoudpour, 2013; Che, 2010; J. M. Chen, Chen, & Leu, 2006; Darmawan, Wong, & Thorstenson, 2018; Darvish et al., 2016; Deng & Yano, 2006; Merzifonluoğlu & Geunes, 2006; Merzifonluoğlu, Geunes, & Romeijn, 2007; Smith, Limón Robles, & Cárdenas-Barrón, 2009). Most of these references relate to pricing-production models (i.e., formulations considering the pricing of products along with the production planning problem) (Askarpoor & Davoudpour, 2013; J. M. Chen et al., 2006; Darmawan et al., 2018; Deng & Yano, 2006; Merzifonluoğlu et al., 2007; Smith et al., 2009). As we will detail, this category of problems presents a complex problem structure and needs to be applied to simplistic production scenarios in order to be solvable. This effect is also evident in the models considering the appearance of congestion effects in function of the quantities to produce (Aouam & Brahimi, 2013b; Aouam et al., 2018).

As an aggregate planning, the usual decision is to depict the production environment considering only the bottleneck operation because it sets the pace of the system. Accordingly, 73% of the papers depict a single stage production environment. However, there are situations in which this is not the case. On one hand, it may not be possible to simplify the production stages around a single operation, because different bottlenecks may emerge depending on the production quantities per product or family. On the other hand, some authors try to add more realism to the plan, integrating operational and tactical planning. In those cases, multi-stage production environments appear.

Concerning the extension of the supply chain, if a large-scale supply chain is represented, S&OP becomes a multi-location planning exercise. In our review, roughly half of the models (47%) depict a single-location scenario, whereas the other half (53%) represents a multi-plant context. It is the complexity of the case at hand that dictates the approach to use.

2.3.2 Procurement Planning

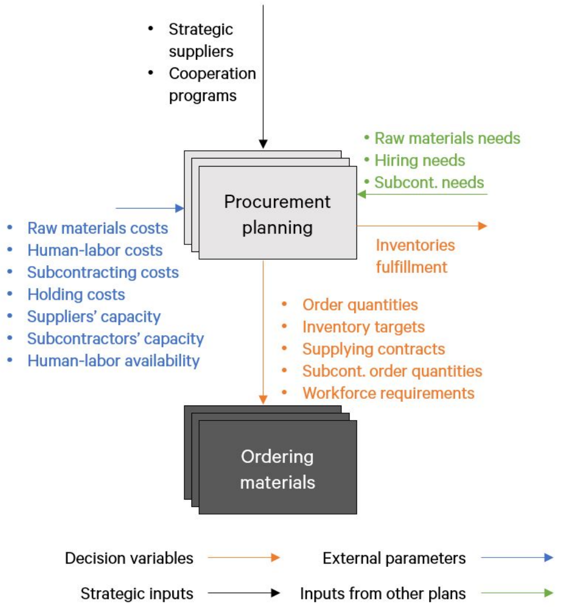


Figure 2.4: Mid-term procurement planning decisions

Mid-term procurement planning aims to determine the most efficient acquisition plan of resources from the market in order to satisfy production needs. Figure 2.4 details the involved decisions. Production needs, i.e., *raw materials needs*, *hiring needs*, and *subcontracting needs*, are the main input for procurement activities. There is a set of strategic decisions that guide the department's activity, such as *strategic suppliers* or *cooperation programs*. External costs, namely *raw materials costs*, *human-labor costs*, *subcontracting costs* and *holding costs*, and market availability, such as *suppliers capacity*, *subcontractors' capacity* and *human-labor availability*, need to be incorporated as well.

First of all, the procurement plan defines the amount of raw materials and/or final products to order from the market (decisions *order quantities* and *subcontracting order quantities*). Second, as in the production planning, it may be necessary to store raw materials between periods, given by *inventory targets*. Third, in some sectors of activity, it is possible to define *supplying contracts* with the suppliers. Finally, given human-labor needs for production activities, this plan defines the *workforce requirements*, i.e., the amount of workers to hire or dismiss.

In this section we describe how these decisions are addressed as a complement of the mid-term production planning. Papers can be grouped around four streams, according to the decisions considered: order quantities and inventory levels (subsection 2.3.2.1); order quantities and inventory levels with quantity considerations (subsection 2.3.2.2); supplying contracts (subsection 2.3.2.3); workforce dimensioning and subcontracting (subsection 2.3.2.4).

2.3.2.1 Order quantities and inventory levels

The anticipated definition of the quantities of raw materials to acquire in a specific period (*order quantities*) is relevant when suppliers have long preparation and transportation lead times. Additionally, some suppliers ask for the communication of expected needs in advance to better manage their internal capacity and guarantee a high service level. The *inventory targets* variable is used to define raw materials inventory levels per period. In many cases, companies opt to stock raw materials as a strategy to deal with a lack of capacity in the supply chain, such as raw materials availability in the market. In some contexts, there is another reason behind this decision. Safety stock may be used as a strategy to deal with unpredictable events or unexpected demand. The characterization of these variables can be seen in Table 2.3. Characteristics are classified as broad or specific, depending on whether they pose a topic of concern in a generic supply chain or are only applicable in particular contexts.

Some problems address *order quantities* regardless of the supplier or the origin of the supply. On the other hand, the consideration of suppliers or the origin of supplies becomes relevant when different costs or lead times characterize different supplying possibilities.

The business under consideration may dictate the modeling of a single material or multiple materials. For instance, the paper from Guan and Philpott (2011) depicts a problem in the dairy industry where milk is the only raw material considered. In a multi-item example, different complexities may arise, depending on whether the supply chain under study belongs, for instance, to the wood industry (Ouhimmou et al., 2008, 2009), pharmaceutical industry (Susarla & Karimi, 2018) or automobile manufacturing industry (Zhang et al., 2011).

Regarding the supply chain configuration, one matter of interest is related to the existence of a stock consolidation point between the suppliers and the production units. Most of the existing works depict a multi-location context with direct transportation of the quantities to the production units. However, some papers consider a consolidation point before the distribution to each of the locations. Finally, in all the contexts with a single unit, the quantities flow directly to the production location.

Inventory targets are commonly calculated considering the expected production needs. Safety stock inclusion is less frequent. In the papers analyzed two main limitations lead to the anticipation of the purchases: transportation capacity and sourcing availability from the suppliers, either caused by limited capacity or by shortage of raw materials in the market. However, there are not only external limitations. On the internal side, some papers report limited storage capacity, which impacts the admissible amount of stock to keep.

Table 2.3 includes other specific cases on the topic of procurement planning. For instance, Mardan et al. (2015) claim that safety stock is not the only possible measure to mitigate the effects of uncertainties. In their paper, an alternative strategy is proposed. Each item can be supplied from cheap (but unreliable) suppliers and expensive (but reliable) suppliers. The approach proposes a two-stage decision making. In the first stage, the items are bought from cheaper suppliers, and the production plan is determined. In the second stage, an emergency supplying plan can include more expensive suppliers.

Depending on the extension of the supply chain, two additional considerations are essential. First, different transportation modes can be used depending on the distance between the supplier and the production unit. Second, the lead time between the purchase and the availability for production may pose an additional constraint to be addressed if the transportation and preparation times are not negligible. Papers addressing these features are mentioned in Table 2.3.

Most of the problems are limited to meeting customer demand while minimizing the total cost or maximizing the total profit. These approaches do not include subjective criteria or opt to convert

Table 2.3: Procurement decisions characterization: order quantities and inventory levels

Scope	Decision	Description/specification	References
Broad	Order quantities	One supplier or origin	Abedi and Zhu (2017); Brahimi, Absi, Dauzère-Pérès, and Kedad-Sidhoum (2015); Chen-Ritzo, Ervolina, Harrison, and Gupta (2010); Lin and Chen (2007); Thomas, Genin, and Lamouri (2008)
		Multiple suppliers or origins	M. Chen and Wang (1997); Guan and Philpott (2011); Gunnarsson and Rönnqvist (2008); Lim, Alpan, and Penz (2017); Kanyalkar and Adil (2007); Khemiri, Elbedoui-Maktouf, Grabot, and Zouari (2017); Lidestam and Rönnqvist (2011); Mardan, Amalnik, and Rabbani (2015); Mirzapour Al-E-Hashem, Malekly, and Aryanezhad (2011); Ouhimmou, D'Amours, Beauregard, Ait-Kadi, and Chauhan (2008); Ouhimmou, D'Amours, Beauregard, Ait-Kadi, and Chauhan (2009); Paksoy, Pehlivan, and Ozceylan (2010); Pathak and S. (2012); Peidro et al. (2012); Shahi, Pulkki, Leitch, and Gaston (2017); Steinrücke and Jahr (2012); Susarla and Karimi (2012); Susarla and Karimi (2018); Van Elzakker, Zondervan, Raikar, Hoogland, and Grossmann (2014); J. Z. Wang, Hsieh, and Hsu (2012); Zhang, Shang, and Li (2011)
	Order quantities	Single material or component	Abedi and Zhu (2017); Brahimi et al. (2015); M. Chen and Wang (1997); Guan and Philpott (2011); Kanyalkar and Adil (2007); Thomas et al. (2008)
		Multiple materials or components	Chen-Ritzo et al. (2010); Lidestam and Rönnqvist (2011); Lim et al. (2017); Lin and Chen (2007); Gunnarsson and Rönnqvist (2008); Paksoy et al. (2010); Peidro et al. (2012); Khemiri et al. (2017); Mardan et al. (2015); Mirzapour Al-E-Hashem et al. (2011); Ouhimmou et al. (2008); Ouhimmou et al. (2009); Pathak and S. (2012); Shahi et al. (2017); Steinrücke and Jahr (2012); Susarla and Karimi (2012); Susarla and Karimi (2018); Van Elzakker et al. (2014); J. Z. Wang et al. (2012); Zhang et al. (2011)
	Order quantities	Directly to a single production unit	Abedi and Zhu (2017); Brahimi et al. (2015); M. Chen and Wang (1997); Chen-Ritzo et al. (2010); Lim et al. (2017); Mardan et al. (2015); Paksoy et al. (2010); Thomas et al. (2008)
		Directly to multiple production units	Guan and Philpott (2011); Gunnarsson and Rönnqvist (2008); Kanyalkar and Adil (2007); Lidestam and Rönnqvist (2011); Lin and Chen (2007); Mirzapour Al-E-Hashem et al. (2011); Ouhimmou et al. (2008); Ouhimmou et al. (2009); Pathak and S. (2012); Peidro et al. (2012); Steinrücke and Jahr (2012); Susarla and Karimi (2012); Susarla and Karimi (2018); Van Elzakker et al. (2014); J. Z. Wang et al. (2012); Zhang et al. (2011)
		With consolidation points	Khemiri et al. (2017); Shahi et al. (2017)
	Inventory targets	Demand only	Brahimi et al. (2015); Gunnarsson and Rönnqvist (2008); Kanyalkar and Adil (2007); Lidestam and Rönnqvist (2011); Lin and Chen (2007); Mardan et al. (2015); Mirzapour Al-E-Hashem et al. (2011); Ouhimmou et al. (2008); Ouhimmou et al. (2009); Shahi et al. (2017); Steinrücke and Jahr (2012); Susarla and Karimi (2018); Thomas et al. (2008); Van Elzakker et al. (2014); J. Z. Wang et al. (2012); Zhang et al. (2011)
		With safety stock	Lim et al. (2017); Peidro et al. (2012); Susarla and Karimi (2012); Susarla and Karimi (2018)
Specific	Order quantities	Limits on transportation capacity	Ouhimmou et al. (2008); Ouhimmou et al. (2009) ; Zhang et al. (2011)
	Order quantities	Limits on supplier capacity	M. Chen and Wang (1997); Guan and Philpott (2011); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Mirzapour Al-E-Hashem et al. (2011); Paksoy et al. (2010); Peidro et al. (2012); Van Elzakker et al. (2014); J. Z. Wang et al. (2012); Zhang et al. (2011)
	Inventory targets	Limits on storage capacity	Brahimi et al. (2015); Kanyalkar and Adil (2007); Steinrücke and Jahr (2012); Susarla and Karimi (2012); Thomas et al. (2008); Van Elzakker et al. (2014); J. Z. Wang et al. (2012)
	Order quantities	Emergency suppliers for the same item	Lim et al. (2017); Mardan et al. (2015)
	Order quantities	Transportation modes definition	Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Steinrücke and Jahr (2012)
	Order quantities	Lead time consideration	Kanyalkar and Adil (2007); Lim et al. (2017); Mirzapour Al-E-Hashem et al. (2011); Susarla and Karimi (2012); J. Z. Wang et al. (2012)
	Order quantities	Supplier assessment	Khemiri et al. (2017)

them into quantitative information. Even if the presence of qualitative or expert data is recognized as important, few studies include this dimension explicitly (Khemiri et al., 2017). Therefore, Khemiri et al. (2017) extend a procurement-production tactical model in order to address qualitative information about the suppliers and adopt a risk-oriented approach. A multi-criteria decision analysis methodology enriches the programming model, in which suppliers are assessed in several parameters (e.g., quality, reliability, resilience) while determining the *order quantities* simultaneously.

2.3.2.2 Order quantities and inventory levels with quantity considerations

Suppliers often define additional constraints or features in their relationship with clients. First, dynamic prices in function of the ordered quantities may be used as a strategy to stimulate volumes. Second, minimum quantities per order are introduced as a way of guaranteeing efficient orders. In this subsection, we detail how the decision *order quantities* is adapted accordingly. Further information about the models analyzed is available in Table 2.4.

Table 2.4: Procurement decisions characterization: order quantities with quantity considerations

Scope	Decision	Description/specification	References
Broad	Order quantities	Quantity discounts	Che (2010); Cunha et al. (2018); Souza, Zhao, Chen, and Ball (2004); Torabi and Hassini (2009)
		Minimum quantity orders	Ali, D' Amours, Gaudreault, and Carle (2019); Catalá, Moreno, Blanco, and Bandoni (2016); Cui (2016); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati, Madhoushi, and Ghadikolaei (2017b); Sanei Bajgiran, Kazemi Zanjani, and Nourelfath (2016); Torabi and Hassini (2009)

Che (2010) models a linear decreasing relationship between the order quantity and the unitary price, in a discrete manufacturing company. The paper from Cunha et al. (2018) presents this feature in a process manufacturing company. The paper from Souza et al. (2004) introduces the possibility of taking advantage of a one-time discount offered for any quantity purchased at the beginning of the planning period (t=0). Finally, Torabi and Hassini (2009) propose a model in which discounts are offered to the clients using a different scheme: they are different depending on the delivery date. The longer the lead time, the easier it is for the supplier to reserve more capacity to a specific client.

Minimum quantities per order are introduced by the suppliers as a strategy to guarantee efficient batches while planning their production activities. This feature is commonly introduced in the model as an additional constraint. This buying scheme decreases the number of orders, facilitating the operational work of the procurement team. On the contrary, it poses more pressure on the raw materials warehouse(s) since it requires more storage space.

All except one of the papers mentioned in Table 2.4 (Ali et al., 2019) model *inventory targets* per period. The inclusion of this decision in these contexts is essential as these buying schemes originate greater purchases whose quantities span the production needs of several periods.

2.3.2.3 Supplying contracts

Another strategy used to provide stability to the relationship between suppliers and clients is the establishment of mid-term supplying contracts. This mechanism provides more stability and visibility to suppliers but can work beneficially to producers, making it possible for them to negotiate better prices for future acquisitions. This decision is represented in Figure 2.4 as *supplying contracts*.

An example of an integrated contract definition both on supply and sales is available in the model from Y. Feng et al. (2013). The paper states that the real challenge is to design and offer the right contract policies to customers and select the right supplier contracts in order to assure customer satisfaction and raw materials supplies while optimizing allocation capacities and financial performance. Regarding supply, minimum quantity commitment contracts are used, containing different terms and prices from different suppliers. A total order quantity is then established, and, as the minimum quantity increases, the unit price decreases. A commitment to purchase at least a minimum quantity per period during the contract horizon is defined. The paper is based on a real business case from an oriented strand board manufacturing company.

2.3.2.4 Workforce dimensioning and subcontracting

Changing the size of the workforce is relevant in businesses whose production process is dependent on human labor. If the demand is stable and variations in the number of workers are not predictable, this decision may be disregarded in the mid-term planning. However, in seasonal markets or growing businesses, it is important to dimension the team in advance, especially if human labor availability may become scarce. We represent this decision using *workforce requirements* (Figure 2.4).

The most common way of addressing this problem is through the definition, period by period, of the number of workers hired and fired. A cost of hiring and firing is considered and, usually, limitations on the number of workers are imposed, as we can observe in Table 2.5. Some models consider multiple types of workers. It is the case of the paper from Torabi and Moghaddam (2012), which considers two workforce types with different parameters (productivity, hiring cost, firing cost), regular and expert workers. Another example is the paper from Yenradee and Piyamanothorn (2011), which distinguishes manual workers from machine operators.

Table 2.5: Procurement decisions characterization: workforce dimensioning and subcontracting

Scope	Decision	Description/specification	References
Broad	Workforce requirements	No limitations	Mirzapour Al-E-Hashem et al. (2011); Thomas et al. (2008); Torabi and Moghaddam (2012); Yenradee and Piyamanothorn (2011)
		Limits on hiring	Ahumada and Villalobos (2011); Darmawan et al. (2018); Ghasemy Yaghin (2018); Ghasemy Yaghin, Torabi, and Fatemi Ghomi (2012); Lusa, Martínez-Costa, and Mas-Machuca (2012); Paksoy et al. (2010); Pathak and S. (2012); R.-C. Wang and Liang (2005); Zhu (2008)
	Workforce requirements	One type of worker	Darmawan et al. (2018); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Lusa et al. (2012); Paksoy et al. (2010); Pathak and S. (2012); Thomas et al. (2008); R.-C. Wang and Liang (2005); Zhu (2008)
		Different types of workers (or productivities)	Ahumada and Villalobos (2011); Mirzapour Al-E-Hashem et al. (2011); Torabi and Moghaddam (2012); Yenradee and Piyamanothorn (2011)
	Subcontracting order quantities		M. Chen and Wang (1997); Darmawan et al. (2018); Fahimnia, Farahani, and Sarkis (2013); Fahimnia, Luong, and Marian (2012); Fumero and Vercellis (1997); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Guan and Philpott (2011); Hahn, Sens, Decouttere, and Vandaele (2016); Jolayemi and Olorunniwo (2004); Khemiri et al. (2017); Lusa et al. (2012); Merzifonluoğlu et al. (2007); Mirzapour Al-E-Hashem et al. (2011); Ouhimmou et al. (2008); Ouhimmou et al. (2009); Paksoy et al. (2010); Pathak and S. (2012); Peidro et al. (2012); Steinrücke and Jahr (2012); Susarla and Karimi (2011); R.-C. Wang and Liang (2005); Yenradee and Piyamanothorn (2011); Zhu (2008)
Specific	Workforce requirements	Training programs definition	Mirzapour Al-E-Hashem et al. (2011)
	Subcontracting order quantities	Supplier assessment	Hahn et al. (2016)

Table 2.5 refers to a particular case in which changes in the size of the workforce may be limited by union regulations (Mirzapour Al-E-Hashem et al., 2011). In those cases, workforce training may be used to increase workers productivity in order to compensate for the extra production volumes when demand peaks. The paper from Mirzapour Al-E-Hashem et al. (2011) presents a mid-term tactical model that takes into account the definition, not only, of the workers hired and fired, but also the number of workers at each level that would be subject to training. The workers can improve their level of proficiency, thus increasing their productivity.

Another possible strategy to extend the production capacity is the recourse to subcontracting the production of final products. In these situations, the plan should encompass the determination of the *subcontracting order quantities*. Table 2.5 presents the models which detail this decision in the mid-term procurement planning. A particular application is described in the paper from Hahn et al. (2016), that addresses the topic from a strategic-tactical perspective. A multi-criteria decision-making model is applied to evaluate strategic outsourcing options. Besides the consideration of service, cost, quality, and other long-term value related aspects, the model incorporates key performance indicators derived from a tactical aggregate planning model that is used to evaluate the performance of each supplying option.

2.3.3 Distribution Planning

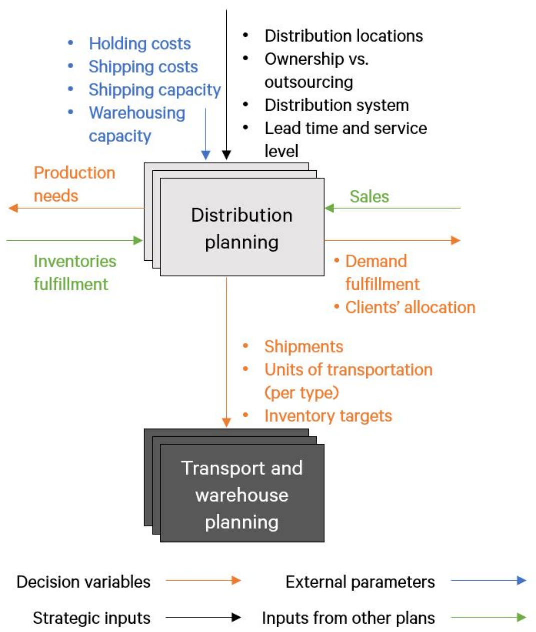


Figure 2.5: Mid-term distribution planning decisions

Mid-term distribution planning bridges the gap between production and the clients. Its primary objective lies in the fulfillment of the estimated demand considering the transportation and warehousing capacity while minimizing costs. Figure 2.5 details the mid-term distribution planning problem. The sales team provides the distribution team with the *sales* for the next periods. Given external information, i.e. *holding costs*, *shipping costs*, *shipping capacity* and *warehousing capacity*, and a set of strategic guidelines, namely *distribution locations*, *distribution system* and intended *lead time and service level*, the mid term distribution plan is generated.

The plan dictates *shipments* for each market or client, the needs in terms of *units of transportation* and the final products *inventory targets*. If applicable to the supply chain under consideration, this plan may also determine *clients' allocation* to specific distribution locations. *Shipment* quantities may be transformed into *production needs* that are passed to the production department, which, in turn, reports its capability of fulfilling future needs (*inventories fulfillment*). Finally, after this planning, the demand may not be satisfied in full (*demand fulfillment*). If so, the distribution team must align and negotiate possible measures with the sales team.

A particular comment regarding the distribution strategy (*ownership vs. outsourcing*) should be made. There are varied supply chain configurations, and their complexity may be different depending on the set of customers to serve (and their locations). Moreover, distribution is commonly outsourced, given the efficiency and economies of scale Third-Party Logistics (3PL) reach, resulting in reduced distribution costs for manufacturing companies. We relaxed this practical question when analyzing distribution planning. We are assuming that distribution is either owned by the manufacturing company or that there is perfect information between the manufacturing company and the 3PL. The 3PL company dedicates part of its capacity to this distribution activity and is interested in maximizing its efficiency.

We can group the topic of integration of mid-term distribution planning with aggregate production planning around three streams with respect to the decisions considered: shipping quantities and final products inventory levels (subsection 2.3.3.1); transportation requirements and/or distinct transportation modes (subsection 2.3.3.2); clients' allocation to distribution centers (subsection 2.3.3.3).

2.3.3.1 Shipping quantities and inventory levels

Shipping quantities (Figure 2.5) refer to the amounts of final products that need to be transported, given demand in each period. In the tactical horizon, the network design of the supply chain is already defined, as well as the distribution system (either the modes of transportation or the decision of ownership *versus* outsourcing). Therefore, the goal is to maximize the efficiency of the operations given constraints imposed by strategic decisions. The planning of the inventory levels to keep in distribution centers or retail units is another decision addressed (*inventory targets*). Table 2.6 presents a detailed characterization of these decisions.

Concerning the supply chain configuration, distribution can be made directly from the production unit(s) to the customer(s) or point(s) of sale or it can be consolidated and only then transported to the customer(s) or point(s) of sale. In some papers both possibilities are combined in the same model (Table 2.6).

Distribution centers are a natural solution when the degree of distribution possibilities is relevant, i.e., when several production units can send goods to different customers or points of sale. Distribution centers serve as consolidation points which allow more efficient logistics operations, as direct shipments to the customers would result in inefficient transportation. Naturally, the wider the supply chain, the higher the need for distribution centers to aggregate the flow. On the other hand, direct shipments to clients are associated with higher volume orders or when the distance between the production units and the clients is negligible.

Regarding *inventory targets*, logistic consolidation points can also be used to store final products, as a strategy to reach efficiency through a geographical consolidation or to reduce the lead

Table 2.6: Distribution decisions characterization: shipping quantities and inventory levels

Scope	Decision	Description/specification	References
Broad	Shipping quantities	Directly to customer(s) or point(s) of sale	Abedi and Zhu (2017); Ahumada and Villalobos (2011); Attia, Ghaithan, and Duffuaa (2019); Badhotiya, Soni, and Mittal (2019); Boutarfa, Senoussi, Mouss, and Brahimi (2016); C. F. Chen, Egbelu, and Wu (1994); M. Chen and Wang (1997); Eksioglu, Romeijn, and Pardalos (2006); Fahimnia et al. (2013); Fahimnia, Sarkis, Choudhary, and Eshragh (2015); P. Feng, Liu, Wu, and Chu (2018); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Fuentealba et al. (2019); Fumero and Vercellis (1997); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Gunnarsson and Rönnqvist (2008); Kanyalkar and Adil (2007); Lidestam and Rönnqvist (2011); Meisel, Kirschstein, and Bierwirth (2013); Mohamed (1999); Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017a); Pal, Chan, Mahanty, and Tiwari (2011); Park (2005); Sanei Bajgiran et al. (2016); Senoussi, Mouss, Penz, Brahimi, and Dauzere-Peres (2016); Souza et al. (2004); Susarla and Karimi (2012); Wei et al. (2017)
		Consolidation in distribution center(s)	Ahumada and Villalobos (2011); Ali et al. (2019); Aliev, Fazlollahi, Guirimov, and Aliev (2007) ; Darvish et al. (2016); Fahimnia et al. (2012); Fahimnia et al. (2013); Fahimnia et al. (2015); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Guajardo, Kylinger, and Rönnqvist (2013); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Meisel et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Paksoy et al. (2010); Pathak and S. (2012); Peidro et al. (2012); Raa, Dullaert, and Aghezzaf (2013); Sanei Bajgiran et al. (2016); Steinrücke and Jahr (2012); Torabi and Hassini (2009); Van Elzakker et al. (2014); Van Hoesel, Romeijn, Morales, and Wagelmans (2005); J. Z. Wang et al. (2012); Yuan et al. (2012); Zhang et al. (2011); Zhao, Huang, Dou, and Wu (2019)
	Inventory targets	Demand only	Ahumada and Villalobos (2011); Ali et al. (2019); Aliev et al. (2007); Attia et al. (2019); Badhotiya et al. (2019); Boutarfa et al. (2016); C. F. Chen et al. (1994); Darvish et al. (2016); Fahimnia et al. (2012); Fahimnia et al. (2013); Fahimnia et al. (2015); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Fuentealba et al. (2019); Guajardo et al. (2013); Gunnarsson and Rönnqvist (2008); Jolayemi and Olorunniwo (2004); Lidestam and Rönnqvist (2011); Liu, Sun, and Xu (2019); Meisel et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Park (2005); Raa et al. (2013); Sanei Bajgiran et al. (2016); Senoussi et al. (2016); Souza et al. (2004); Steinrücke and Jahr (2012); Van Hoesel et al. (2005); J. Z. Wang et al. (2012); Zhang et al. (2011); Zhao et al. (2019)
		With safety stock	Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Kanyalkar and Adil (2007); Pal et al. (2011); Peidro et al. (2012); Susarla and Karimi (2012); Torabi and Hassini (2009); Van Elzakker et al. (2014)
	Shipping quantities	Limits on transportation or expedition capacity	Abedi and Zhu (2017); Ali et al. (2019); Attia et al. (2019); Badhotiya et al. (2019); Boutarfa et al. (2016); Fahimnia et al. (2012); Fahimnia et al. (2013); Fahimnia et al. (2015); Y. Feng et al. (2008); Y. Feng et al. (2009); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Liu et al. (2019); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Paksoy et al. (2010); Raa et al. (2013); Senoussi et al. (2016); Souza et al. (2004); Steinrücke and Jahr (2012); J. Z. Wang et al. (2012); Yuan et al. (2012); Zhang et al. (2011)
	Inventory targets	Limits on storage capacity	Aliev et al. (2007); Attia et al. (2019); Badhotiya et al. (2019); Boutarfa et al. (2016); Darvish et al. (2016); Fahimnia et al. (2012); Fahimnia et al. (2013); Fahimnia et al. (2015); Fuentealba et al. (2019); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Gunnarsson and Rönnqvist (2008); Jolayemi and Olorunniwo (2004); Kanyalkar and Adil (2007); Lidestam and Rönnqvist (2011); Liu et al. (2019); Mirzapour Al-E-Hashem et al. (2011); Nemati et al. (2017b); Pal et al. (2011); Park (2005); Pathak and S. (2012); Peidro et al. (2012); Raa et al. (2013); Sanei Bajgiran et al. (2016); Senoussi et al. (2016); Steinrücke and Jahr (2012); Susarla and Karimi (2012); Torabi and Hassini (2009); Van Elzakker et al. (2014); J. Z. Wang et al. (2012); Yuan et al. (2012)
Specific	Shipping quantities	Lateral transhipment	Darvish et al. (2016); Y. Feng et al. (2008); Y. Feng et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Zhao et al. (2019)
	Shipping quantities	Reverse replenishment	Zhao et al. (2019)
	Shipping quantities	Lead time consideration	Ahumada and Villalobos (2011); Badhotiya et al. (2019); C. F. Chen et al. (1994); Pal et al. (2011); Souza et al. (2004); Susarla and Karimi (2012); J. Z. Wang et al. (2012); Zhao et al. (2019)
	Shipping quantities	Lifetime restrictions	Ahumada and Villalobos (2011); Susarla and Karimi (2012); Van Elzakker et al. (2014)

time to the client. There are cases in which the stocks are just constituted to fulfill the expected demand, whereas there are situations in which amounts of safety stock are included. In Table 2.6

it is possible to observe that safety stock inclusion in inventory targets is less common. When the supply chain under study is characterized by the existence of retail centers (e.g., consumer goods), inventory targets per period in those points can also be included (Boutarfa et al., 2016; Ghasemy Yaghin, 2018; Ghasemy Yaghin et al., 2012; Kanyalkar & Adil, 2007; Pal et al., 2011; Park, 2005; Senoussi et al., 2016; Van Elzakker et al., 2014).

Both the shipments to the clients and the storage of final products in logistic points may be subject to a limited capacity scenario. The main sources of capacity shortage are storage and transportation or shipment capacity. Some papers address both issues. It is also common, however, not to add any constraint regarding distribution capacity. When the distribution is made using a 3PL, capacity constraints are often relaxed, as these services are usually characterized by unconstrained logistic operations associated with high levels of capacity.

Regarding particular issues on distribution systems, some problems account for lateral shipments between distribution centers. Transshipment flows can work as a strategy to accommodate stock-outs in particular locations. The stock is transferred between the warehouses and is then consolidated before its expedition to the customer. Besides the consideration of lateral transshipment, the paper from Zhao et al. (2019) also includes reverse replenishment policies to deal with stock-outs.

Most problems assume transportation lead time as negligible. As aggregate mid-term planning details decisions in weekly or monthly time buckets, lead time may not need to be considered. Nonetheless, some papers model this dependency.

Some supply chains suggest the introduction of products' lifetime aspects in mid-term planning. For instance, Ahumada and Villalobos (2011) propose a model to perform tactical planning for a grower/shipper of fresh products. Transportation decisions are balanced against the decay of the quality of products that occur with time due to their perishability. The authors introduce a customized equation in the objective function that penalizes the transportation time according to the prices of the products. Susarla and Karimi (2012) consider the shelf-life of pharmaceutical products. Van Elzakker et al. (2014) also consider this effect in fast moving consumer goods industry introducing wasting costs in the objective function.

2.3.3.2 Transportation requirements and/or transportation modes

Distribution mid-term planning may need to calculate transportation requirements, i.e., the number of *units of transportation* (Figure 2.5) required to carry the final products downstream in the supply chain. This dimensioning may be used to contract transportation units to 3PL or, if the company has its fleet, it is important to make sure that there is enough capacity to fulfill demand. Additional details about this decision and how different types of vehicles and transportation routes are included in the planning are summarized in Table 2.7.

Some papers depict a supply chain in which a single transportation mode is used (e.g., truck), even though the dimensioning of *units of transportation* considers vehicles with different capacities. On the other hand, some authors model multiple transportation typologies. Finally, there

Table 2.7: Distribution decisions characterization: transportation requirements and/or transportation modes

Scope	Decision	Description/specification	References
Broad	Units of transportation	Single transportation mode	Badhotiya et al. (2019); Boutarfa et al. (2016); P. Feng et al. (2018); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Park (2005); Senoussi et al. (2016)
		Multiple transportation modes	Y. Feng et al. (2008); Y. Feng et al. (2009); Meisel et al. (2013); Sanei Bajgiran et al. (2016)
	Shipping quantities	Master routes consideration	Y. Feng et al. (2008); Y. Feng et al. (2009); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Meisel et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Sanei Bajgiran et al. (2016)
Specific	Shipping quantities	Per type of vehicle or transportation mode	Ahumada and Villalobos (2011); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Steinrücke and Jahr (2012)
	Shipping quantities	Intermodal transportation	Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Meisel et al. (2013)

are papers that, while not calculating the number of vehicles, adjust *shipping quantities* to reflect quantities per type of vehicle or transportation mode.

Table 2.7 contains some papers that consider master routes per type of vehicle used. This is a strategy to increase the realism of the tactical dimensioning, because the demand from customers distant from each other may not be placed in the same vehicles. However, these routes do not replace the operational routing that should be executed in daily operations. Tactical planning works with aggregate needs, whereas daily operations require detailed plans to guide transportation operations properly.

The extension of some supply chains may request the combination of different transportation modes (e.g., vessels and lorries). We refer to the works presented in Table 2.7 as examples which include this possibility in the formulation. The paper from Meisel et al. (2013), in particular, describes a detailed approach to intermodal transportation, including door-to-door, full-train-load, and less-than-train-load as available modes. The paper introduces a case study from an international company that produces chemical products in multiple production sites in Western Europe, and that needs to send its productions to Ukraine and Russia.

2.3.3.3 Clients' allocation to distribution centers

Most of the mentioned papers do not allocate a production unit or distribution center to a specific client or point of sale for the entire planning horizon (*clients' allocation* in Figure 2.5). The consideration of different transportation costs causes that the mid-term plan tries to avoid supplies between distant points (unless capacity is scarce to provide an efficient solution). However, there are a few papers that address this decision. The models from Steinrücke and Jahr (2012); Yuan et al. (2012) are examples of this compromise. A middle ground commitment can be found on the approach from Torabi and Moghaddam (2012). In this paper, the model includes a formal allocation of a manufacturing site to each selling region. However, this decision can change from period to period.

2.3.4 Sales Planning

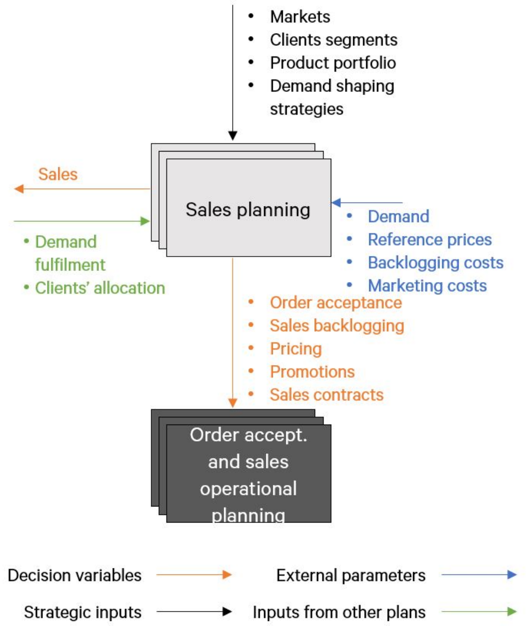


Figure 2.6: Mid-term sales planning decisions

In traditional supply chains, a commercial supremacy was observed. Operations departments received the commercial forecast and adjusted production and distribution to satisfy the expected needs, regardless of potential inefficiencies or difficulties associated with their fulfillment. Fortunately, collaboration has emerged as a major concern in modern supply chain management and, as a result, sales mid-term planning has evolved to consider additional issues.

Figure 2.6 depicts mid-term sales planning. The sales strategy defines which *markets* and *client segments* the company aims to satisfy. Moreover, the executive board of the company also approves the *product portfolio*, that is, the products that are produced and commercialized by the company. Given this scope, there is a potential *demand* from the market, that can be partially known in advance or predicted based on past sales. Moreover, demand forecasts can be complemented with information of *reference prices*, *backlogging costs* or *marketing costs*. Based on these inputs and on the operational capacity (here represented by *demand fulfillment*), the plan determines mid-term sales targets, resulting from the decisions *order acceptance* and *sales backlogging*. Depending on the strategic positioning of the company (*demand shaping strategies*) and operating sector, additional levers may be defined in the mid-term sales plan: *pricing* of the products, *promotions* for upcoming periods or *sales contracts* to establish with clients.

We can group the integration of sales planning as an extension of mid-term production planning around three streams, according to the decisions addressed: order acceptance and/ sales backlogging (subsection 2.3.4.1); pricing and other demand shaping strategies (subsection 2.3.4.2); sales contracts (subsection 2.3.4.3).

2.3.4.1 Order acceptance and/or sales backlogging

When capacity is insufficient to satisfy all the demand, demand selection decisions are necessary to determine the best orders to fulfill. The integration of these decisions with production planning allows for the determination of the most interesting orders considering the global impact in the supply chain. Otherwise, sales departments tend to use some qualitative criteria (e.g., most important clients) or, at best, to consider the revenue generated by the existent orders, regardless of the impacts their production may impose on the organization.

Demand selection decisions are classically of two types: *order acceptance*, in which there is a set of demand or placed orders that are selected not to be satisfied; *sales backlogging*, in which there is a postponement of some orders to subsequent periods. Both decisions are presented in Figure 2.6.

The less severe strategy is to use order backlogging. Nonetheless, depending on the business being modeled, backlogging may not be possible. In the primary sector, there might be unfilled demand due to unproductive harvesting seasons. Bakhrankova, Midthun, and Uggen (2014); Catalá et al. (2016) model this possibility in the fish industry and fruit industry, respectively. In these cases, order acceptance is the strategy to resort to. Moreover, clients may not be willing to wait for delayed orders and shift to other suppliers in the case their orders cannot be guaranteed in the desired period. The combination of the two strategies is also possible and is, therefore, modeled in some approaches: a company either selects to postpone part of its demand incurring in penalty costs per each period of delay or opts not to accept it, whichever is most profitable. Table 2.8 presents the existing papers in each of the streams.

Table 2.8: Sales decisions characterization: order acceptance and/or sales backlogging

Scope	Decision	Description/specification	References
Broad	Order acceptance	At customer level	Abedi and Zhu (2017); Aouam and Brahimi (2013a); Aouam and Brahimi (2013b); Aouam et al. (2018); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Fuentealba et al. (2019); Guajardo et al. (2013); Merzifonluoğlu and Geunes (2006); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Sanei Bajgiran et al. (2016); Van Elzakker et al. (2014); Wei et al. (2017); Zhao et al. (2019)
		Partial aggregation at region level	Ali et al. (2019); Attia et al. (2019); Bakhrankova et al. (2014); Catalá et al. (2016); Guan and Philpott (2011); Merzifonluoğlu and Geunes (2006); Ouazene, Yalaoui, Kelly, and Idjeraoui (2017); Park (2005); Souza et al. (2004)
		Global aggregation	Ardjmand, Weckman, Young, Bajgiran, and Aminipour (2016); Bajwa, Sox, and Ishfaq (2016); Bajwa, Fontem, and Sox (2016); Lim et al. (2017); Smith et al. (2009); Susarla and Karimi (2018)
	Sales backlogging	At customer level	Barbarosoğlu (2000); Y. Feng et al. (2008); Y. Feng et al. (2009); Y. Feng et al. (2013); Merzifonluoğlu and Geunes (2006) ; Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b); Sanei Bajgiran et al. (2016); Wei et al. (2017)
		Partial aggregation at region level	Badhotiya et al. (2019); Fahimnia et al. (2012); Fahimnia et al. (2013); Fahimnia et al. (2015); Fumero and Vercellis (1997); Merzifonluoğlu and Geunes (2006); Mirzapour Al-E-Hashem et al. (2011); Peidro et al. (2012); Torabi and Moghaddam (2012); J. Z. Wang et al. (2012)
		Global aggregation	Aouam and Brahimi (2013b); Aouam et al. (2018); Caccetta and Mardaneh (2009); Chen-Ritzo et al. (2010); Gansterer (2015); Lim et al. (2017); Lin and Chen (2007); Mardan et al. (2015); Mardaneh and Caccetta (2013); Moengin (2016); Paksoy et al. (2010); Pathak and S. (2012); Sodhi and Tang (2011); Susarla and Karimi (2011); Thomas et al. (2008); Ulusoy and Yazgaç (1995); R.-C. Wang and Liang (2005); Zhu (2008)
Specific	Order acceptance	Flexibility in the delivery date	Aouam and Brahimi (2013a); Merzifonluoğlu and Geunes (2006)
	Sales backlogging	Customer impatience	Lim et al. (2017); Wei et al. (2017)
	Order acceptance	Congestion effects	Aouam and Brahimi (2013b); Aouam et al. (2018)

The level of granularity of *order acceptance* and *sales backlogging* varies from paper to paper. Some papers model these decisions at the customer level. However, most of these works have in common that they do not generate a plan at the product level, but at the family level, reducing the complexity associated with the products (Y. Feng et al., 2008, 2009, 2013; Guajardo et al., 2013; Nemati & Alavidoost, 2018; Nemati et al., 2017a, 2017b; Sanei Bajgiran et al., 2016; Wei et al., 2017). Other papers aggregate demands and work with demand acceptance or backlogged sales at a regional level. Finally, some approaches model these decisions without differentiating the client. The level of granularity to address in these decisions depends upon the problem being modeled. For instance, the formulations from Y. Feng et al. (2008, 2009, 2013); Guajardo et al. (2013); Nemati and Alavidoost (2018); Nemati et al. (2017a, 2017b) are modeled at the customer level because they differentiate the customers in contract and non-contract customers.

Some papers address specific issues regarding *order acceptance* and *sales backlogging*. First, suppliers often have flexibility to manage customer due dates. In the model from Merzifonluoğlu and Geunes (2006) the net profit of an order depends on the time at which it is fulfilled. Somehow, their approach can be seen as equivalent to a one in which a backlogging cost is used. Aouam and Brahimi (2013a) propose a fulfilment time window for each order. Second, in some situations it is important to impose limitations on backordering, as clients may become impatient. To model the behavior of the impatient customers, Lim et al. (2017) assume that if an order is delayed by a week or more, then there is a probability to lose the order, depending on the delay length. The approach from Wei et al. (2017) is more rigid and assumes that if an order cannot be supplied within a certain time lag, a lost sale occurs. Third, Aouam and Brahimi (2013b); Aouam et al. (2018) consider the appearance of congestion effects with order acceptance in the mid-term planning. The goal is to create the option of rejecting fulfilling an order if its acceptance increases the workload causing the delay of other orders due to congestion effects.

2.3.4.2 Pricing and other demand shaping strategies

Two different levers can be used to shape demand within production planning contexts. One is the ability to select the most profitable demand, i.e., to accept the best orders in each period. The second is to use pricing. From the operations perspective, when a company can influence its demand levels through pricing strategies, these decisions may be used to optimize mid-term internal production capacity. This motivation led to the extension of production planning problems to include pricing decisions. Price targets determined at the tactical level are used as a reference in the short-term sales activities. Other levers, such as promotional activity, may also be used to shape demand. Both these decisions are depicted in Figure 2.6, as *pricing* and *promotions*. Table 2.9 contains further information about them.

Price can remain static for the entire planning horizon, or it can vary from period to period. The continuous variation of the price depends on the business being addressed. In business-to-business realities, where contractual relationships are common, it may be unacceptable to change the price of a good continuously (J. M. Chen et al., 2006). On the other hand, in business-to-consumer situations, slight but frequent changes may be easily understood by the client. Mardaneh and Caccetta (2014) add that price-adjustments are not negligible. Different studies refer that frequent changes may take up as much as 40% of a firm's profit. Therefore it is important to consider all these implications when deciding for a static or dynamic pricing strategy. Most formulations allow for price changes in each period. Examples of both practices are referred to in Table 2.9.

Pricing-production planning problems depict more elementary planning realities when compared to previously presented approaches that deal with procurement or distribution decisions —

Table 2.9: Sales decisions characterization: pricing and other demand shaping strategies

Scope	Decision	Description/specification	References
Broad	Pricing	Static	Caccetta and Mardaneh (2009); Gilbert (2000); Raza, Abdullakutty, and Rathinam (2016); Raza and Turiac (2016)
		Dynamic	Ardjmand et al. (2016); Askarpoor and Davoudpour (2013); Bajwa, Sox, and Ishfaq (2016); Bajwa, Fontem, and Sox (2016); J. M. Chen et al. (2006); Deng and Yano (2006); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); González-Ramírez, Smith, and Askin (2011); Guan and Philpott (2011); Lusa et al. (2012); Mardaneh and Caccetta (2013); Mardaneh and Caccetta (2014); Merzifonluoğlu et al. (2007); Ouazene et al. (2017); Smith et al. (2009); Ulusoy and Yazgaç (1995); Zhu (2008)
	Pricing	Single product	Askarpoor and Davoudpour (2013); J. M. Chen et al. (2006); Deng and Yano (2006); Merzifonluoğlu et al. (2007); Smith et al. (2009); Zhu (2008)
		Multiple (a few) products	Ardjmand et al. (2016); Bajwa, Sox, and Ishfaq (2016); Bajwa, Fontem, and Sox (2016); Caccetta and Mardaneh (2009); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Gilbert (2000); González-Ramírez et al. (2011); Guan and Philpott (2011); Lusa et al. (2012); Mardaneh and Caccetta (2013); Mardaneh and Caccetta (2014); Ouazene et al. (2017); Raza and Turiac (2016); Raza et al. (2016); Ulusoy and Yazgaç (1995)
	Pricing	Setups inclusion	Askarpoor and Davoudpour (2013); Bajwa, Sox, and Ishfaq (2016); J. M. Chen et al. (2006); Deng and Yano (2006); González-Ramírez et al. (2011); Ouazene et al. (2017)
		Capacity management options	Ardjmand et al. (2016); Caccetta and Mardaneh (2009); Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Lusa et al. (2012); Mardaneh and Caccetta (2013); Merzifonluoğlu et al. (2007); Ulusoy and Yazgaç (1995); Zhu (2008)
	Pricing	Price-demand function with no further effects	Ardjmand et al. (2016); Askarpoor and Davoudpour (2013); Deng and Yano (2006); Gilbert (2000); González-Ramírez et al. (2011); Guan and Philpott (2011); Mardaneh and Caccetta (2014); Merzifonluoğlu et al. (2007); Raza and Turiac (2016); Raza et al. (2016); Smith et al. (2009)
		Obsolescence of products	J. M. Chen et al. (2006); Ghasemy Yaghin et al. (2012); Zhu (2008)
		Advertisement effects	Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012); Ulusoy and Yazgaç (1995)
		Seasonality	Bajwa, Sox, and Ishfaq (2016); Bajwa, Fontem, and Sox (2016) ; Caccetta and Mardaneh (2009) ; Gilbert (2000) ; Lusa et al. (2012) ; Mardaneh and Caccetta (2013) ; Ouazene et al. (2017) ; Ulusoy and Yazgaç (1995); Zhu (2008)
	Promotions		Darmawan et al. (2018); Souza et al. (2004); Yenradee and Piyamanothorn (2011)
Specific	Pricing	Price adjustment costs	Mardaneh and Caccetta (2014)
	Pricing	Demand leakage between products	Raza et al. (2016); Raza and Turiac (2016)
	Pricing	Demand leakage between market segments	Ghasemy Yaghin (2018)
	Promotions	Promotions duration	Yenradee and Piyamanothorn (2011)

deciding price while optimizing sales makes the problem harder to solve because its structure becomes non-linear. Therefore, although the overall practice is to consider a multi-period reality, existing models either deal with single product scenarios or detail planning contexts with only two or a few products. The paper from Ardjmand et al. (2016) contains the most aspiring computational results. A modified unconscious search algorithm is applied and assessed with a real case implementation characterized by and instance of four periods and 30 products. Anyhow, the production planning context depicted is not complex (i.e., single machine - single stage process without inclusion of setups).

This category of models usually represents rather simplistic production environments, composed by a single machine or production stage in one production location. Thus, there has been an effort to continuously enrich the reality considered through the incremental consideration of other decisions. Among the extensions, we highlight the inclusion of setups and capacity management strategies, namely the possibility of extending production capacity (Ghasemy Yaghin, 2018; Ghasemy Yaghin et al., 2012; Lusa et al., 2012; Merzifonluoğlu et al., 2007), and orders backlogging (Caccetta & Mardaneh, 2009; Mardaneh & Caccetta, 2013; Ulusoy & Yazgaç, 1995).

The structure of the demand function is another relevant issue, as detailed in subsection 2.4.2. Most of the authors describe demand as a linear function of the price, whereas others consider more complex situations. From the papers addressing a price-demand function with no further effects (Table 2.9), we refer to the ones from Askarpoor and Davoudpour (2013); Gilbert (2000); González-Ramírez et al. (2011); Guan and Philpott (2011); Merzifonluoğlu et al. (2007) as examples of linear price-demand functions. However, there are situations in which other effects are taken into account, such as obsolescence of products, advertisement effects, or seasonality.

Concerning the remaining pricing specific cases mentioned in Table 2.9, a few papers introduce demand leakage between products or market segments. That is the case of the models from Raza et al. (2016); Raza and Turiac (2016), which are examples of demand leakage between products. These papers address this issue in a single-period production environment characterized by two products. Respecting demand leakage between market segments, we refer to the paper from Ghasemy Yaghin (2018). The model considers different market segments (corresponding to distinct sales channels).

The use of promotions is another possible strategy to shape demand. It is important to notice, however, that this strategy is more valuable to producers if they control the supply chain until the point(s) of sale. Intermediate business customers are less prone to react massively to promotional efforts. Darmawan et al. (2018) integrate production planning decisions with the number of promotions decision. Three discount levels are assessed for a single product scenario. Yenradee and Piyamanothorn (2011) model not only the selection of the type of promotion for each product but also its duration. Several types of promotions are modeled (e.g., temporary discounts, buy "X" get "Y" units, award gifts). Limits on the duration of promotions are included to narrow the promotional duration.

2.3.4.3 Sales contracts

In some industries, the establishment of contracts with price and quantity commitments is common. The contracts help to guarantee a fixed amount of sales at a pre-determined price but, in return, occupy a part of the capacity which could be used for more profitable non-contract sales. On the other hand, spot sales are riskier. Therefore, it is important to decide the percentages of the capacity to allocate to contract and non-contract sales (Y. Feng et al., 2008; Nemati et al., 2017a). The real challenge is to design and offer adequate contract policies to customers in order to maximize customer satisfaction while assuring operations efficiency (Y. Feng et al., 2013). Figure 2.6 refers to this decision as *sales contracts*.

The topic of sales contracts has not been extensively addressed in the context of mid-term planning. However, a few papers address this issue (Barbarosoğlu, 2000; Y. Feng et al., 2013; Guan & Philpott, 2011; Gunnarsson & Rönnqvist, 2008; Lidestam & Rönnqvist, 2011). Y. Feng et al. (2013) presents a model which considers different types of policies to offer to customers, ranging from price-only contracts to more complex agreements with commitments both on the quantities and the prices. In the paper from Barbarosoğlu (2000), the focus is on the definition of a contract between a supplier and several buyers. The first step is concerned with determining the monthly production levels for the next year based on estimated quantities for all the buyers. The next step comprises the definition of the price and supply commitments to each buyer. Guan and Philpott (2011) includes contract offering in a mid-term programming model for the dairy industry. Each month there is the possibility to establish supplying contract for the next three months. The remaining sales are assured in the spot market.

2.3.5 Uncertainty consideration

Mid-term sales and operations decisions are inherently related to some sources of uncertainty. The moderate extent of the planning period makes some parameters difficult to foresee. Moreover, a plan that gathers decisions from procurement, production, distribution, and sales is subject to multiple parameters, such as costs or productivity metrics. The broad scope increases the probability that some degree of unpredictability emerges in the planning. As referred by Mirzapour Al-E-Hashem et al. (2011), the need for considering uncertainty in production planning arises from the fact that the mid-term planning models aim to allocate resources for the future according to current information and future circumstances. Therefore, it becomes natural that the inclusion of uncertainty has become a subject of concern to researchers and practitioners in the field.

Despite the prominence of the topic, most of the approaches are deterministic. From the 103 papers analyzed, only 28 (27%) include some sort of uncertainty. The focus of the authors has been more on extending the scope of the models, adding lateral decisions from procurement, distribution, and sales, than on the inclusion of uncertainty. Nonetheless, when considered in the optimization model, stochasticity can bring further improvements to the plans, especially in riskier contexts. For instance, Y. Feng et al. (2013) report a profit increase of 11%–15% by the utilization of a stochastic programming model in S&OP.

Table 2.10 presents which parameters have been considered uncertain in the literature. It is possible to observe that uncertain parameters have been pointed out in different business functions. Regarding procurement parameters, there has been a focus on addressing the risk associated with suppliers. Suppliers capacity (or yield uncertainty) is considered stochastic in 21% of the papers. In some papers dealing with raw materials from the primal sector, external factors such as the weather may impact the availability of the resources. For instance, the paper from Guan and Philpott (2011) contains a stochastic model in the dairy industry subject to uncertain milk supply. Not only in the supply service level uncertainty is relevant, but also on the costs of raw material. This parameter is represented in 25% of the papers. Uncertain factors associated with human-labor or subcontracting activities are also mentioned but are less frequent.

Concerning production and distribution parameters, uncertainty is essentially spread across three axes: (i) capacity to ensure production or distribution activities and keep stock; (ii) operational costs; (iii) productivity of the different resources used. In production, the most relevant topics in the literature are production costs, holding costs, and production capacity. Despite the lower number of papers dealing with uncertainty in distribution activities, the main topic of concern is the cost associated with the shipping activities.

Table 2.10: Uncertainty in Sales and Operations Planning

Business function	Type	Parameter	Incidence (%)	References
Procurement	Capacity	Human-labor availability	11	Ghasemy Yaghin et al. (2012); R.-C. Wang and Liang (2005); Zhu (2008)
		Subcontractors	11	Ghasemy Yaghin et al. (2012); Paksoy et al. (2010); Zhu (2008)
		Suppliers (or yield uncertainty)	21	Bakhrankova et al. (2014); Y. Feng et al. (2013); Guan and Philpott (2011); Mardan et al. (2015); Shahi et al. (2017); Torabi and Hassini (2009)
	Costs	Hiring and laying off	18	Ghasemy Yaghin et al. (2012); Mirzapour Al-E-Hashem et al. (2011); Paksoy et al. (2010); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005)
		Holding costs	11	Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017b)
		Human-labor	11	Mirzapour Al-E-Hashem et al. (2011); Paksoy et al. (2010); Torabi and Moghaddam (2012)
		Ordering costs	7	Nemati and Alavidoost (2018); Nemati et al. (2017b)
		Raw materials	25	Y. Feng et al. (2013); Khemiri et al. (2017); Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017b); Paksoy et al. (2010); Zhang et al. (2011)
		Subcontracting	14	Ghasemy Yaghin et al. (2012); Khemiri et al. (2017); Paksoy et al. (2010); R.-C. Wang and Liang (2005)
	Others	Suppliers or subcontractors' assessment	4	Khemiri et al. (2017)
Production	Capacity	Production	25	Aliev et al. (2007); Aouam et al. (2018); Badhotiya et al. (2019); Y. Feng et al. (2013); Paksoy et al. (2010); R.-C. Wang and Liang (2005)
		Warehouse	7	Aliev et al. (2007); Ghasemy Yaghin et al. (2012)
	Costs	Holding costs	25	Aouam et al. (2018); Ghasemy Yaghin et al. (2012); Nemati and Alavidoost (2018); Nemati et al. (2017b); Paksoy et al. (2010); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005)
		Production	32	Aliev et al. (2007); Aouam et al. (2018); Ghasemy Yaghin et al. (2012); Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017b); Paksoy et al. (2010); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005)
		Setups	11	Aouam et al. (2018); Nemati and Alavidoost (2018); Nemati et al. (2017b)
	Productivity	Human-labor	4	Ghasemy Yaghin et al. (2012)
		Machine	11	Ghasemy Yaghin et al. (2012); Hahn et al. (2016); R.-C. Wang and Liang (2005)
		Warehousing	4	Ghasemy Yaghin et al. (2012)
	Others	Inventory minimum levels	4	Ghasemy Yaghin et al. (2012)
		Plant assessment	4	Khemiri et al. (2017)
		Process quality	7	Raza and Turiac (2016); Raza et al. (2016)
Distribution	Capacity	Warehouse	7	Aliev et al. (2007); Ghasemy Yaghin et al. (2012)

Table 2.10: Uncertainty in Sales and Operations Planning

Business function	Type	Parameter	Incidence (%)	References
Distribution	Costs	Holding costs	14	Aliev et al. (2007); Ghasemy Yaghin et al. (2012); Nemati and Alavidoost (2018); Nemati et al. (2017b)
		Shipping	21	Aliev et al. (2007); Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017b); Paksoy et al. (2010); Torabi and Moghaddam (2012)
		Transhipment	11	Nemati and Alavidoost (2018); Nemati et al. (2017b); Torabi and Moghaddam (2012)
	Productivity	Transhipment	4	Torabi and Moghaddam (2012)
		Warehousing	4	Ghasemy Yaghin et al. (2012)
	Others	Inventory minimum levels	4	Ghasemy Yaghin et al. (2012)
Sales	Costs	Backlogging	21	Mirzapour Al-E-Hashem et al. (2011); Nemati and Alavidoost (2018); Nemati et al. (2017b); Paksoy et al. (2010); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005)
		Marketing	4	Ghasemy Yaghin et al. (2012)
	Revenues	Sales prices	25	Aliev et al. (2007); Aouam et al. (2018); Bakhrankova et al. (2014); Y. Feng et al. (2013); Mirzapour Al-E-Hashem et al. (2011); Nemati et al. (2017b); Torabi and Moghaddam (2012)
		Salvage value	4	Ghasemy Yaghin et al. (2012)
	Others	Demand	68	Aliev et al. (2007); Aouam and Brahimi (2013b); Aouam et al. (2018); Ardjmand et al. (2016); Badhotiya et al. (2019); Y. Feng et al. (2013); Hahn et al. (2016); Mardan et al. (2015); Mardaneh and Caccetta (2014); Mirzapour Al-E-Hashem et al. (2011); Raza and Turiac (2016); Raza et al. (2016); Shahi et al. (2017); Sodhi and Tang (2011); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005); Zhang et al. (2011); Zhao et al. (2019)
		Order configuration	4	Chen-Ritzo et al. (2010)
		Due dates	4	Aouam et al. (2018)

Finally, uncertain parameters are also found in sales activities. Some authors address unpredictability in the costs of the department, with emphasis on backlogging costs (21% of the papers). Uncertainty is also found on the side of the revenues. Risk on sales prices is included in 25% of the models. Notwithstanding, the most relevant source of uncertainty lies on demand. 68% of the papers optimize mid-term planning considering that customer orders are prone to shift from the expected amount of sales.

2.4 Modeling approaches

In the previous section, the supply chain mid-term decisions of an organization were described in detail. In this section, we aim to approach existing literature from a “S&OP tools and data" perspective (Tuomikangas & Kaipia, 2014). Therefore, our goal is to present the mathematical modeling approaches followed by past formulations as well as the main methods employed to solve the models. We classify the literature using a modified version of the classification presented in the review of Mula et al. (2010), which we present in Table 2.11. This section aims to answer *Q3*, disclosing which modeling options have been used to implement S&OP models.

Table 2.11: Classification of modeling approaches

Type	Code	Modeling approach
Linear Programming	LP	Linear Programming
	MIP	Mixed Integer Programming
Nonlinear Programming	NLP	Nonlinear Programming
	MINLP	Mixed Integer Nonlinear Programming
Multiobjective Programming	MOLP	Multiobjective Linear Programming
	MOILP	Multiobjective Integer Linear Programming
	MONLP	Multiobjective Nonlinear Programming
	MOINLP	Multiobjective Integer Nonlinear Programming
Uncertainty Approaches	FMP	Fuzzy Mathematical Programming
	SP	Stochastic Programming
	RP	Robust Programming
Solution Procedures	HEU	Model-based heuristics
	META	Metaheuristics
Other	DP	Dynamic Programming
	HYB	Hybrid Approaches

In Table 2.12 past literature is summarized around the aforementioned types. Most of the papers (i.e. 61%) are modeled utilizing either a LP or MIP approach. Some authors opt for a nonlinear relationship between the variables (i.e. 21% papers). This subset of papers is mostly composed by pricing-production algorithms. 20% of the models incorporate a multiobjective function. This category of models typically aims to obtain an extended benefit for the decision-maker, not only a maximization of profit or minimization of costs. Regarding models depicting uncertain contexts (i.e. 25%), most of the models rely on fuzzy programming or stochastic programming. In a few papers the models are solved by a robust programming approach. From a solution procedure perspective, 51% of the papers employ heuristic algorithms or metaheuristics due to the complexity involved in a real-world sized S&OP problem. Finally, there are a few examples of papers that are solved using dynamic programming techniques or employ hybrid approaches.

In the following subsections, more details of each modeling approach are provided.

2.4.1 Linear Programming and Mixed Integer Programming

Linear Programming is a specific case of mathematical optimization whose relationships between the different variables are expressed in linear terms. LP models are typically solved by commercial solvers that are able to find (near-)optimal solutions in acceptable time-frames even for large scale problems. Accordingly, all the LP problems presented in Table 2.12 are solved resorting to well-known solvers such as CPLEX or Gurobi, which in turn apply simplex or dual simplex algorithms. The only exception is the model from Aliev et al. (2007) characterized by a LP formulation that is embedded in an uncertain model. The author presents an integrated production-distribution planning model based on a fuzzy mathematical programming problem solved by a genetic algorithm.

The inclusion of binary or integer variables occurs typically due to one of the following reasons: (i) setups or activation of other resources; (ii) workforce dimensioning.

Table 2.12: Modeling approaches of the reviewed papers

References	LP	MIP	NLP	MINLP	MOLP	MOILP	MONLP	MOINLP	FMP	SP	RP	HEU	META	DP	HYB
Abedi and Zhu (2017); Ahumada and Villalobos (2011); Cunha et al. (2018); Darmawan et al. (2018); Darvish et al. (2016); Y. Feng et al. (2008, 2009); Jolayemi and Olorunniwo (2004); Lin and Chen (2007); Lusa et al. (2012); Moengin (2016); Nemati et al. (2017a); Senoussi et al. (2016); Souza et al. (2004); Steinrücke and Jahr (2012); Susarla and Karimi (2011, 2012, 2018); Ulusoy and Yazgaç (1995); Yenradee and Piyamanothorn (2011); Yuan et al. (2012)		✓													
Aouam and Brahimi (2013a); Askarpoor and Davoudpour (2013); Brahimi et al. (2015); Eksioglu et al. (2006); Fuentealba et al. (2019); Fumero and Vercellis (1997); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Liu et al. (2019); Merzifonluoğlu and Geunes (2006); Ouhimmou et al. (2008, 2009); Park (2005); Raa et al. (2013); Sanei Bajgiran et al. (2016); Van Elzakker et al. (2014); J. Z. Wang et al. (2012)		✓										✓			
Bajwa, Fontem, and Sox (2016); Caccetta and Mardaneh (2009); Ghasemy Yaghin (2018); Gilbert (2000); Mardaneh and Caccetta (2013)			✓									✓			
Bajwa, Sox, and Ishfaq (2016); C. F. Chen et al. (1994); Deng and Yano (2006); González-Ramírez et al. (2011); Ouazene et al. (2017)				✓								✓			
Badhotiya et al. (2019); Nemati and Alavidoost (2018); Peidro et al. (2012); Torabi and Hassini (2009); Torabi and Moghaddam (2012)						✓			✓						
Boutarfa et al. (2016); Cui (2016); Pal et al. (2011)		✓											✓		
Bakhrankova et al. (2014); Chen-Ritzo et al. (2010); Mardan et al. (2015)	✓									✓					
M. Chen and Wang (1997); Guajardo et al. (2013); Mohamed (1999)	✓														
Paksoy et al. (2010); Pathak and S. (2012); R.-C. Wang and Liang (2005)					✓				✓						
Ali et al. (2019); Gansterer (2015)	✓														✓
Barbarosoğlu (2000); P. Feng et al. (2018)		✓		✓								✓			
Fahimnia et al. (2013, 2012)				✓									✓		
Catalá et al. (2016); Kanyalkar and Adil (2007)						✓									
Hahn et al. (2016)	✓		✓									✓			✓
Thomas et al. (2008)	✓		✓									✓			
Van Hoesel et al. (2005)	✓		✓											✓	
Aliev et al. (2007)	✓								✓				✓		
Khemiri et al. (2017)	✓								✓						✓
Aouam and Brahimi (2013b)	✓										✓				
Nemati et al. (2017b)		✓							✓						
Y. Feng et al. (2013)		✓								✓					
Aouam et al. (2018)		✓									✓	✓			
Ardjmand et al. (2016)		✓									✓		✓		
Wei et al. (2017)		✓										✓	✓		
Merzifonluoğlu et al. (2007)		✓												✓	
Guan and Philpott (2011)			✓							✓		✓		✓	
Raza and Turiac (2016)			✓										✓		
Smith et al. (2009)			✓											✓	
Zhu (2008)				✓					✓						
Mardaneh and Caccetta (2014)				✓							✓	✓			
Zhang et al. (2011)					✓				✓	✓			✓		✓
Sodhi and Tang (2011)					✓					✓					
Lim et al. (2017)					✓								✓		✓
Attia et al. (2019)					✓										
Zhao et al. (2019)						✓				✓		✓			
Mirzapour Al-E-Hashem et al. (2011)						✓					✓				
Meisel et al. (2013)						✓						✓			
Che (2010)						✓							✓		
Ghasemy Yaghin et al. (2012)							✓		✓				✓		
Raza et al. (2016)							✓					✓			
Fahimnia et al. (2015)								✓				✓			
Shahi et al. (2017)													✓		✓
J. M. Chen et al. (2006)														✓	✓

Regarding the first, the activation variable is commonly modeled by a binary variable Y with implications both in the objective function and constraints. There is a cost c associated to the activation of the resource that is included in the objective function in the cY form. The utilization of each resource is modeled by the constraints $X \geq 0$ and $X \leq Cap \times Y$, being X the output quantity that results from the utilization of the resource and Cap the maximum capacity of the resource. This combination of constraints assures that c needs to be incurred in order to produce any quantity of X.

Despite some works presented in Table 2.5 model workforce requirements using continuous variables, others opt to introduce them using integer variables (Darmawan et al., 2018; Lusa et al., 2012; Mirzapour Al-E-Hashem et al., 2011; Torabi & Moghaddam, 2012; Yenradee & Piyamanothorn, 2011; Zhu, 2008). In those cases, two integer variables expressing the number of workers to hire and dismiss in each period are introduced in the formulation, H_t and F_t.

Given the increased solving complexity associated to large sized MIP problems, heuristic algorithms and metaheuristics are applied in some papers. The presentation of the heuristic algorithms applied is provided in subsection 2.4.5.

2.4.2 Nonlinear Programming and Mixed Integer Nonlinear Programming

Nonlinear models are characterized by a nonlinear objective function subject to constraints that can be either linear or nonlinear. Pricing-production problems comprise a special subset of nonlinear models in the reviewed literature. In these models, the revenue function is obtained by the product between the price, P, and the sold/produced quantity, X.

Table 2.13 details the demand functions behind these models. There are three main types of relationships between demand and price: linear, power and exponential. Most of the reviewed papers follow a linear relationship. From a resolution point of view, the consideration of a linear function simplifies the problem, because the structure of the constraints remains linear and the revenue function is concave. More complex demand functions make the constraints set nonlinear and may lead to non-concave revenue functions.

Among the solution procedures used to solve NLP and MINLP pricing-production problems, there has been an emphasis on Outer Approximation Algorithm, Nonlinearity Decomposition and metaheuristics (subsection 2.4.5). Some authors opt to approximate the nonlinear revenue function by a piecewise linear curve (Ardjmand et al., 2016; Askarpoor & Davoudpour, 2013; Lusa et al., 2012; Merzifonluoğlu et al., 2007; Ulusoy & Yazgaç, 1995). As a result, a MIP formulation is devised and branch-and-bound techniques (and related heuristics) can be applied.

Regarding other categories of NLP or MINLP models in the literature, C. F. Chen et al. (1994) modeled a nonlinear function calculating the total in-process inventory cost which is dependent on the length of time an order is held in inventory and the size of the order or quantity in inventory. A heuristic procedure is developed to address the problem. Fahimnia et al. (2013, 2012) present integrated aggregate production–distribution models including nonlinear relationships between the activation variables and the production and distribution decisions. Genetic and memetic metaheuristics are developed. P. Feng et al. (2018) introduce nonlinear transportation costs in the

Table 2.13: Characterization of the price-demand functions of the reviewed papers

Model type	Demand function	References
Linear	$D = a - bP$, where $a, b > 0$	Askarpoor and Davoudpour (2013); Bajwa, Sox, and Ishfaq (2016); Deng and Yano (2006); González-Ramírez et al. (2011); Guan and Philpott (2011); Mardaneh and Caccetta (2014); Merzifonluoğlu et al. (2007)
	$D = \gamma(a - bP)$, where $a, b, \gamma > 0$	Caccetta and Mardaneh (2009); Gilbert (2000); Mardaneh and Caccetta (2013); Ouazene et al. (2017)
	$D = (a - bP)e^{\lambda t}$, where $a, b > 0$	J. M. Chen et al. (2006)
	$D_1 = (1 - \delta)(a_1 - b_1 P_1)$ $D_2 = \delta(a_1 - b_1 P_1) + (a_2 - b_2 P_2)$, where $a_1, b_1, a_2, b_2 > 0$ and $0 \leq \delta \leq 1$	Raza and Turiac (2016)
	$D = \gamma(a - bP)e^{-\lambda \lvert t - t_{peak} \rvert}$, where $a, b, \gamma, \lambda, t_{peak} > 0$	Zhu (2008)
Power	$D = a\gamma P^{-b}$, where $a, b > 0$ and $\gamma \geq 0$	Bajwa, Fontem, and Sox (2016)
	$D = \beta(a - bP)A^{\rho} e^{-\lambda t}$, where $a, b, \beta, \lambda > 0$ and $0 < \rho < 1$	Ghasemy Yaghin et al. (2012)
	$D_k = (a_k - b_k P_k)A_k^{\rho_k} - \zeta_k(P_k - P_K)$, $k = 1, 2, \ldots, K-1$ $D_K = (a_K - b_K P_K)A_K^{\rho_K} + \sum_{k \in K-1} \zeta_k(P_k - P_K)$, $k = K$, where $\forall a_k, b_k > 0$, $0 \leq \rho_k \leq 1$ and $0 \leq \zeta_k \leq 1$	Ghasemy Yaghin (2018)
	$D = a - \beta P^b$, where $a, \beta > 0$ and $b \geq 0$	Lusa et al. (2012)
	$D = (-g + \beta P^{-b})(1 + E)$, where $a, b, \beta > 0$ and $E \geq 0$	Ulusoy and Yazgaç (1995)
Exponential	$D = ae^{-bP}$, where $a, b > 0$	Ardjmand et al. (2016); Smith et al. (2009)
	$D_1 = (1 - \delta)(a_1 - b_1 P_1)$ $D_2 = \delta(a_1 - b_1 P_1) + (a_2 - b_2 P_2)$, where $a_1, b_1, a_2, b_2 > 0$, $\delta = 1 - e^{-\zeta(P_1 - P_2)}$, $\zeta \geq 0$ and $P_1 \geq P_2$	Raza et al. (2016)

Notation:
D: demand, P: price, a: base or maximum demand, g: correction factor of the demand, b: price elasticity of demand,
γ: seasonal demand factor, δ: demand leakage factor, ζ: demand leakage sensitivity factor, β: scaling factor,
λ: life-cycle demand rate over time, t: number of periods ahead in the planning horizon, t_{peak}: period of maximum demand,
A: advertising cost (decision variable), ρ: advertising elasticity, E: advertising effect (decision variable)

formulation. The model is solved using Lagrangian Relaxation techniques. Hahn et al. (2016) bring forward a queuing network-based approach in the aggregate planning model to anticipate the stochastic behavior of manufacturing systems and solve the models using a gradient descent algorithm. The integrated production planning and order acceptance models from Aouam and Brahimi (2013a, 2013b); Aouam et al. (2018) are initially nonlinear but are approximated by linear functions.

2.4.3 Multiobjective Programming

The majority of the reviewed models have a single objective: minimize the total costs or maximize the overall profit. Nonetheless, there are some papers introducing complementary goals, such as delivery time or service level (Badhotiya et al., 2019; Catalá et al., 2016; Ghasemy Yaghin et al., 2012; Lim et al., 2017; Mirzapour Al-E-Hashem et al., 2011; Nemati & Alavidoost, 2018;

Peidro et al., 2012; Zhang et al., 2011; Zhao et al., 2019), inventory cover policies (Kanyalkar & Adil, 2007), operations stability or leveling (Lim et al., 2017; Peidro et al., 2012), quality issues (Raza et al., 2016; Torabi & Hassini, 2009), environmental or sustainability issues (Attia et al., 2019; Fahimnia et al., 2015; Meisel et al., 2013), suppliers evaluation (Che, 2010), storage issues (Kanyalkar & Adil, 2007), conditional value-at-risk (cVaR) metrics (Sodhi & Tang, 2011).

Table 2.14 details the multiobjective approaches applied in the reviewed literature (not including fuzzy programming approach detailed in subsection 2.4.4). Weighted-sum, lexicographic ordering and ε-constraint method are among the main methods applied. Moreover, some papers detail a *a priori* multiobjective approach in which the preferences are considered to be predefined. Other papers present a Pareto efficiency frontier aiming to support a *a posteriori* decision-making. A set of optimal solutions is generated and the decision-maker is responsible for analyzing the Pareto front approximation and decide on the preferred point(s).

Table 2.14: Characterization of multiobjective methods applied in the reviewed papers

Method	**Pareto frontier generated?**	**References**
Weighted-sum	✓	Raza et al. (2016)
		Fahimnia et al. (2015); Kanyalkar and Adil (2007); Sodhi and Tang (2011)
Lexicographic ordering		Catalá et al. (2016); Kanyalkar and Adil (2007); Zhao et al. (2019)
ε-constraint method	✓	Meisel et al. (2013)
		Lim et al. (2017)
Augmented ε-constraint method	✓	Attia et al. (2019)
LP-metrics	✓	Mirzapour Al-E-Hashem et al. (2011)
T-score transformation and Pareto Genetic Algorithm		Che (2010)

2.4.4 Uncertainty approaches

Different methodological approaches can be applied to deal with uncertainty. According to Mirzapour Al-E-Hashem et al. (2011); Sahinidis (2004), models that consider uncertainty can be categorized according to four primary approaches: (1) fuzzy programming, (2) stochastic programming, (3) stochastic dynamic programming, (4) robust optimization.

Fuzzy programming models are characterized by searching for the solution considering some parameters as fuzzy numbers. The approach is based on the fuzzy set theory (Bellman & Zadeh, 1970). In this school of thought, there is a clear distinction between randomness and imprecision. In many situations, imprecision may not be represented by probabilistic distributions. Fuzzy mathematical programming problems can be classified into two categories (Torabi & Moghaddam, 2012): (i) *Flexible programming*: flexibility in the target values of objective functions and/or elasticity of constraints; (ii) *Possibilistic programming*: ambiguous coefficients in the objective function and/or constraints.

The characterization of the FMP approaches in the literature is presented in Table 2.15. Most of the papers have both fuzzy goals and imprecise parameters (i.e., Flexible and Possibilistic FMP).

In this case, triangular and/or trapezoidal fuzzy numbers are determined for imprecise input data and linear membership functions are defined for fuzzy goals. Fuzzy constraints are converted into corresponding equivalent crisp ones and an auxiliary crisp formulation is determined. Thus the multiobjective problem associated to the several degrees of satisfaction of the objective function is converted into a single objective model. After the problem is solved, the solution is delivered to the decision maker and can be iteratively adjusted to meet his preferences.

Table 2.15: Characterization of the fuzzy mathematical programming models from the reviewed papers

Approach	Fuzzy numbers distribution	References
Flexible and Possibilistic	Triangular	Badhotiya et al. (2019); Nemati and Alavidoost (2018); Paksoy et al. (2010); Pathak and S. (2012); Torabi and Hassini (2009); Torabi and Moghaddam (2012); R.-C. Wang and Liang (2005)
	Trapezoidal	Ghasemy Yaghin et al. (2012)
Possibilistic	Triangular	Aliev et al. (2007); Nemati et al. (2017b); Zhang et al. (2011)
	Trapezoidal	Aliev et al. (2007); Khemiri et al. (2017)
Flexible	Not applicable	Peidro et al. (2012); Zhu (2008)

Stochastic programming considers that some parameters follow known probability distributions. The objective is to find a solution that is feasible for all the possible realizations of the uncertain parameters while maximizing or minimizing an objective function. In the reviewed literature, the models from Chen-Ritzo et al. (2010); Y. Feng et al. (2013); Mardan et al. (2015) are formulated as two-stage stochastic programs with recourse and are solved using the sample average approximation method. Bakhrankova et al. (2014); Sodhi and Tang (2011) translate the stochasticity of some parameters in scenario-based tree structures and evaluate all the scenarios deterministically. Zhao et al. (2019) present a multi-stage stochastic programming model and make use of the progressive hedging algorithm as the solution approach.

Stochastic dynamic programming involves the application of random parameters in dynamic programming. This approach is essentially used in the domain of multi-stage decision making. The only application of stochastic dynamic programming is found on the paper from Guan and Philpott (2011), which considers a multistage stochastic model to recreate a rolling decision horizon throughout the production year. The model is solved using a Dynamic Outer Approximation Sampling Algorithm.

Robust programming works with a deterministic, set-based description of uncertainty. The goal is to find a feasible solution irrespective of the realization of the uncertain parameters and optimal for the worst-case objective function. The papers from Mardaneh and Caccetta (2014); Mirzapour Al-E-Hashem et al. (2011) assume a framework that considers simultaneously a solution robustness term, that captures solution quality, and a model robustness term, penalizing unfeasible solutions. The objective function includes a general penalty function for both model and solution robustness. Aouam and Brahimi (2013b); Aouam et al. (2018); Ardjmand et al. (2016) consider robust formulations based on the concept of budget of uncertainty, limiting the total variation of the uncertain parameters to a pre-defined threshold.

2.4.5 Solution procedures

A significant part of the analyzed papers applies heuristic procedures to solve the proposed models, as commercial linear and nonlinear solvers were not able to reach a (near-)optimal solution in a reasonable time-frame. We are proposing a classification of the heuristic procedures into two major categories: (i) heuristic algorithms (HEU) - algorithms that take advantage of the original mathematical model and that progressively exploit parts or sub models of the original one; metaheuristics (META) - algorithmic frameworks that aims to search over a large set of solutions finding a good solution without solving the mathematical model, avoiding the associated combinatorial explosion.

Table 2.16 presents the main solution procedures adopted by past S&OP models. We adapted the classification provided by Buschkühl, Sahling, Helber, and Tempelmeier (2010) to group the solution procedures in main classes. Regarding heuristic algorithms, several approaches have been used, with an emphasis on Lagrangian Relaxation Heuristics, Decomposition Heuristics and Mathematical Programming Heuristics. In relation to metaheuristics, the most frequent option has been the application of Genetic Algorithms and other evolutionary heuristics.

2.4.6 Dynamic Programming and Hybrid Approaches

A few papers are solved using Dynamic Programming (DP) techniques. DP is based on the determination and storage of sub-problems from the original problem in a recursive manner and, thereafter, optimization running time reduces from exponential to polynomial. This technique can be effectively applied when decisions from different moments in time (or other dimension) can break apart recursively (e.g. multiperiod models). Examples of the application of DP can be found on the papers from J. M. Chen et al. (2006); Guan and Philpott (2011); Merzifonluoğlu et al. (2007); Smith et al. (2009); Van Hoesel et al. (2005)

Other approaches consider the hybridization of mathematical programming with other techniques. Hahn et al. (2016); Khemiri et al. (2017) integrate multi-criteria decision-making frameworks into linear programming models to capture qualitative information about supplying and outsourcing possibilities.

The models from Ali et al. (2019); Gansterer (2015); Lim et al. (2017); Shahi et al. (2017) adopt simulation-optimization approaches that aim to simultaneously optimize S&OP while mimicking further details of the operations. Gansterer (2015) combines a LP model with a discrete-event simulation model capable of simulating the shop floor where stochastic and nonlinear dependencies arise. Shahi et al. (2017) model the S&OP context through the application of a simulation inventory-production model with metaheuristic for optimization. Lim et al. (2017) propose a multi-objective model solved by a simulation-optimization approach that aims to control the best policies for controlling parts inventory and sales flexibility. Finally, Ali et al. (2019) introduce a rolling horizon simulation allowing to review previous order promising decisions from the S&OP model while respecting sales commitments.

Table 2.16: Solutions procedures of the reviewed papers

Approach	Class	Solution procedure	References
HEU	Mathematical Programming Heuristics	Reformulation	Deng and Yano (2006); Eksioglu et al. (2006); Gilbert (2000); Merzifonluoğlu and Geunes (2006)
		Fix-and-Relax heuristics	Aouam et al. (2018); Meisel et al. (2013); Wei et al. (2017)
		Outer approximation algorithm	Bajwa, Sox, and Ishfaq (2016); Mardaneh and Caccetta (2014); Ouazene et al. (2017)
		Dantzig-Wolfe and Column Generation	Fuentealba et al. (2019); González-Ramírez et al. (2011)
		Benders decomposition	Guan and Philpott (2011); J. Z. Wang et al. (2012)
	Decomposition and Aggregation Heuristics	Nonlinearity decomposition	Caccetta and Mardaneh (2009); C. F. Chen et al. (1994); Ghasemy Yaghin (2018); Mardaneh and Caccetta (2013)
		Time-based decomposition heuristics	Gunnarsson and Rönnqvist (2008); Ouhimmou et al. (2008, 2009); Thomas et al. (2008)
		Item-based decomposition heuristics	Raa et al. (2013); Van Elzakker et al. (2014)
		Progressive hedging algorithm	Zhao et al. (2019)
	Lagrangian Heuristics	Lagrangian relaxation or decomposition	Bajwa, Fontem, and Sox (2016); Brahimi et al. (2015); P. Feng et al. (2018); Fumero and Vercellis (1997); Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011); Liu et al. (2019); Sanei Bajgiran et al. (2016); J. Z. Wang et al. (2012)
	Monte-Carlo Heuristics	Cross-Entropy method	Fahimnia et al. (2015)
		Specific	Raza et al. (2016)
	Problem-specific Heuristics	Specific	Aouam and Brahimi (2013a); Askarpoor and Davoudpour (2013); Barbarosoğlu (2000); Hahn et al. (2016); Park (2005)
META	Metaheuristics	Genetic algorithms	Aliev et al. (2007); Che (2010); Cui (2016); Fahimnia et al. (2012); Ghasemy Yaghin et al. (2012); Zhang et al. (2011)
		Ant Colony optimization heuristics	Pal et al. (2011)
		Harmony search	Raza and Turiac (2016)
		Local Search	Lim et al. (2017)
		Memetic algorithms	Fahimnia et al. (2013)
		Simulated Annealing	Lim et al. (2017)
		Tabu Search	Boutarfa et al. (2016)
		Uncounscious search	Ardjmand et al. (2016)
		Variable Neighborhood Search	Wei et al. (2017)
		Specific	Shahi et al. (2017)

The papers from J. M. Chen et al. (2006); Zhang et al. (2011) are other examples of hybrid approaches to S&OP. The first combines a dynamic programming approach with an inventory followed by shortages policy that integrates marketing and production planning. The second proposes an integrated solution framework composed by a scatter evolutionary algorithm, fuzzy programming and stochastic chance-constrained programming.

2.5 A future agenda for decision-making approaches to S&OP

In this section, we aim to identify the main opportunities and prescribe research directions in the field of decision-making approaches to Sales and Operations Planning towards a more advanced and integrated process. We put a particular emphasis on the topic of integration, since the ultimate goal of S&OP lies in the generation of a single mid-term plan capable of coordinating the different business functions.

This integration brings several benefits, both from a procedural and economic point of view. First, an integrated model available to the company in the form of a decision support system would benefit the decision-makers since it would reduce the iterations needed to generate a consensual plan capable of guiding the activities from several teams. Past research in S&OP paid particular attention to the mechanisms of coordination and integration (Goh & Eldridge, 2019; Thome et al., 2012b; Tuomikangas & Kaipia, 2014), mainly due to the difficulties associated with the generation of a single plan coming up from the decoupled plans from the different teams.

Second, an integrated approach outperforms a decoupled one in terms of results. Y. Feng et al. (2008) report, in their case study, that profits' increase of a fully integrated supply chain model over a decoupled one ranges from 1.1% to 4.7%. Sanei Bajgiran et al. (2016), when making similar comparisons, observed that, depending on the number of decoupled models, 11%–84% profit improvement can be achieved by considering an integrated model. Bajwa, Fontem, and Sox (2016) report 0% to 34% increase in profit when they adopt a coordinated approach using a pricing-production model compared to non-coordinated planning. Similarly, Darmawan et al. (2018) present an average increase in profits in a coordinated promotion-production model versus a non-coordinated one that ranges from 1% to 43%. In a procurement-production model, Cunha et al. (2018) achieve global cost reductions ranging from 10% to 20%.

The integration results in an adaptation of the framework previously presented in Figure 2.2, as represented in Figure 2.7. Interaction variables, which were needed to communicate the fulfillment rate between the different plans, are no longer required and are decided considering the entire supply chain.

2.5.1 Current level of integration

The level of integration of the current models (*Q4*) is detailed in Table 2.17. The schema presents all the groups of decisions that we introduced as further dimensions that researchers and practitioners have been addressing as a complement to the classical models. The papers are classified around existing combinations. We can group the models in three categories: supply chain models, partially integrated models, bilateral models. Supply chain models consist of formulations that include, at least, one decision from each business function. The 28 papers included in this category represent the current state-of-the-art Sales and Operations Planning model. They treat the mid-term planning decisions as follows:

- Procurement: purchasing quantities from one or more suppliers are typically modeled, as well as inventory targets of raw materials along the planning period. Workforce requirements and subcontracting decisions are considered in a few models;
- Production: the determination of production quantities (along with inventory levels) is considered. Setups are modeled in some papers, as well as overtime as a way of extending capacity;

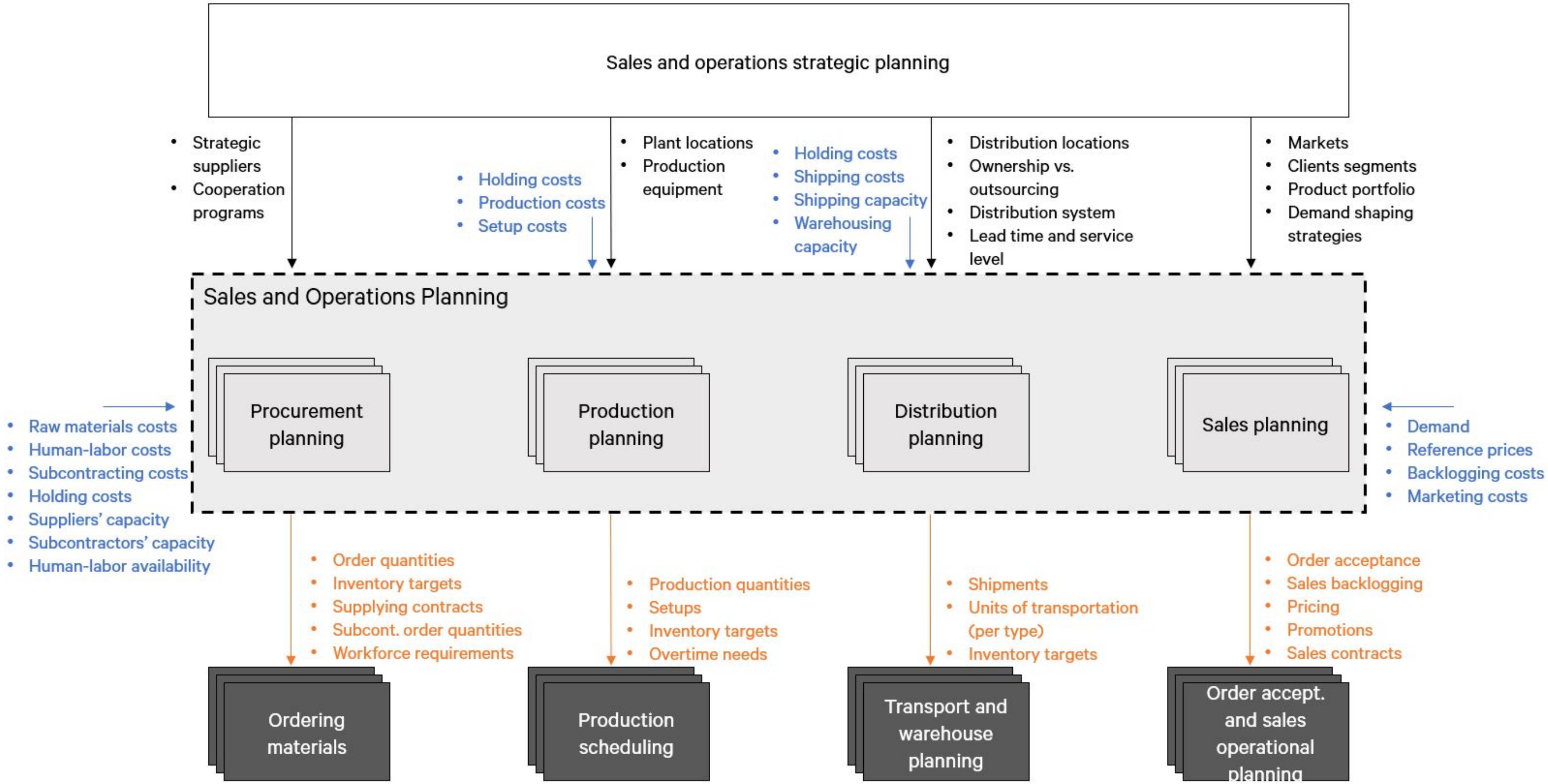


Figure 2.7: Proposed framework to represent Tactical Sales and Operations Planning: an integrated perspective

- Distribution: shipping quantities to distribution center(s) or retailer(s) and demand-only inventory levels planning are included across all the papers. Transportation requirements are introduced in a few formulations;

- Sales: order acceptance and the definition of sales backlogging are the main decisions included. Other demand shaping strategies are not addressed in these models (with a few exceptions).

Partially integrated models consist of 31 papers that model decisions from three business functions. In general terms, these models are simplified versions of the supply chain models. Some of them do not include sales variables and do not encompass decisions of commercial nature (typically assuming demand as deterministic and immutable) while others do not model distribution decisions.

Finally, the remaining papers (44) model dyadic relationships between production and another department. Either they are simplified versions of the topic under study or they model decisions that are not effectively introduced in more integrated models to this day. For instance, it is possible to observe that most problems considering pricing as a strategy to shape demand fall into this category, mainly because it is a decision that is yet difficult to introduce in complex scenarios depicting the entire supply chain.

Despite the ultimate vision of a fully integrated model (Grimson & Pyke, 2007; Ivert & Jonsson, 2014; Wagner et al., 2014), our literature review confirms that existing models do not address all the decisions described. Either some of the decisions reveal irrelevant in the moment of implementation, or they were disregarded by the authors to guarantee the solvability of the models in reasonable time-frames (due to the complexity inherent to the consideration of all the decisions in a single model). Nevertheless, this limitation caused the research on the topic to become erratic and unstructured. The development of new models has been trying to tackle specific problems of particular companies rather than to encompass a general approach to the mid-term S&OP.

2.5.2 Research opportunities and directions

From the analysis of supply chain formulations in Table 2.17, it is possible to diagnose opportunities for a broader horizontal integration in a supply chain model, that is, S&OP model. Irrespective of the relevance of each decision variable for a specific industry or company, it is important that decision-making approaches to S&OP evolve to more general models that serve as analytical frameworks that could be used as a basis for advanced planning systems. In case a specific decision is irrelevant for a specific context of application, it would be disregarded in the moment of the implementation.

Concerning procurement decisions, supply chain models addressing *order quantities (and inventory) with quantity considerations* and *supplying contracts* are not abundant. For instance, there is not a record of explicit inclusion of quantity discounts. Y. Feng et al. (2013) introduces that decision, but it is done indirectly from the activation of different supplying contracts.

Table 2.17: Integration level of existing models

		Procurement				Production			Distribution			Sales		
Type of model	**References**	Order quantities (and inventory)	Order quantities (and inventory) with quantity considerations	Supplying contracts	Workforce requirements and subcontracting	Production quantities (and inventory)	Setups	Overtime needs	Shipment quantities (and inventory levels)	Transportation requirements and/or modes	Clients' allocation	Order acceptance and/or sales backlogging	Pricing and other demand shaping strategies	Sales contracts
Supply chain model	Abedi and Zhu (2017); Shahi et al. (2017); Susarla and Karimi (2018); J. Z. Wang et al. (2012); Zhang et al. (2011)	✓				✓			✓			✓		
	Y. Feng et al. (2008); Y. Feng et al. (2009); Nemati and Alavidoost (2018); Nemati et al. (2017a); Nemati et al. (2017b)		✓			✓	✓		✓	✓		✓		
	Fahimnia et al. (2013); Fahimnia et al. (2012); Fumero and Vercellis (1997)				✓	✓	✓	✓	✓			✓		
	Mirzapour Al-E-Hashem et al. (2011); Paksoy et al. (2010); Pathak and S. (2012)	✓			✓	✓		✓	✓			✓		
	Catalá et al. (2016); Sanei Bajgiran et al. (2016)		✓			✓			✓	✓		✓		
	Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011)	✓				✓	✓		✓	✓		✓		✓
	Ali et al. (2019)		✓			✓			✓			✓		
	Y. Feng et al. (2013)		✓	✓		✓			✓			✓		✓
	Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012)				✓	✓		✓	✓				✓	
	Peidro et al. (2012)	✓			✓	✓	✓		✓			✓		
	Souza et al. (2004)		✓			✓			✓			✓	✓	
	Torabi and Moghaddam (2012)				✓	✓		✓	✓			✓		
	Van Elzakker et al. (2014)	✓				✓	✓		✓			✓		
Partially integrated model	Darmawan et al. (2018); Lusa et al. (2012); Merzifonluoğlu et al. (2007); Yenradee and Piyamanothorn (2011)				✓	✓		✓					✓	
	Attia et al. (2019); Fuentealba et al. (2019); Guajardo et al. (2013); Zhao et al. (2019)					✓			✓			✓		
	Chen-Ritzo et al. (2010); Lim et al. (2017); Mardan et al. (2015)	✓				✓						✓		
	Badhotiya et al. (2019); Park (2005)					✓	✓		✓	✓		✓		
	Kanyalkar and Adil (2007); Susarla and Karimi (2012)	✓				✓			✓					
	Ouhimmou et al. (2008); Ouhimmou et al. (2009)	✓			✓	✓	✓		✓					
	Ahumada and Villalobos (2011)				✓	✓			✓	✓				
	M. Chen and Wang (1997)	✓			✓	✓			✓					
	Fahimnia et al. (2015)					✓		✓	✓			✓		
	Guan and Philpott (2011)	✓			✓	✓						✓	✓	✓
	Jolayemi and Olorunniwo (2004)				✓	✓	✓		✓					
	Lin and Chen (2007)	✓				✓	✓					✓		
	Pal et al. (2011)	✓				✓	✓		✓					
	Steinrücke and Jahr (2012)	✓			✓	✓			✓	✓	✓			
	Susarla and Karimi (2011)				✓	✓	✓					✓		
	Thomas et al. (2008)	✓			✓	✓		✓				✓		
	Torabi and Hassini (2009)		✓			✓	✓		✓					
	R.-C. Wang and Liang (2005)				✓	✓		✓				✓		
	Wei et al. (2017)					✓	✓		✓			✓		
	Zhu (2008)				✓	✓		✓				✓	✓	
Bilateral model	Ardjmand et al. (2016); Bajwa, Fontem, and Sox (2016); Caccetta and Mardaneh (2009); Mardaneh and Caccetta (2013); Smith et al. (2009); Ulusoy and Yazgaç (1995)					✓						✓	✓	
	Aliev et al. (2007); C. F. Chen et al. (1994); Mohamed (1999); Raa et al. (2013); Van Hoesel et al. (2005)					✓			✓					
	Aouam and Brahimi (2013a); Aouam and Brahimi (2013b); Bakhrankova et al. (2014); Gansterer (2015); Sodhi and Tang (2011)					✓						✓		
	Askarpoor and Davoudpour (2013); Deng and Yano (2006); González-Ramírez et al. (2011); J. M. Chen et al. (2006)					✓	✓						✓	
	Boutarfa et al. (2016); P. Feng et al. (2018); Meisel et al. (2013); Senoussi et al. (2016)					✓	✓		✓	✓				
	Gilbert (2000); Mardaneh and Caccetta (2014); Raza et al. (2016); Raza and Turiac (2016)					✓							✓	
	Aouam et al. (2018); Merzifonluoğlu and Geunes (2006); Moengin (2016)					✓	✓					✓		
	Bajwa, Sox, and Ishfaq (2016); Ouazene et al. (2017)					✓	✓					✓	✓	
	Cui (2016); Cunha et al. (2018)		✓			✓	✓							
	Darvish et al. (2016); Liu et al. (2019)					✓	✓		✓					
	Barbarosoğlu (2000)					✓	✓					✓	✓	✓
	Brahimi et al. (2015)	✓				✓	✓							
	Che (2010)		✓			✓								
	Eksioglu et al. (2006)					✓	✓		✓		✓			
	Hahn et al. (2016)				✓	✓		✓						
	Khemiri et al. (2017)	✓			✓	✓		✓						
	Yuan et al. (2012)					✓			✓		✓			

Regarding sales decisions, there is an opportunity for the inclusion of more complex demand functions (*pricing and other demand shaping strategies*). Only the papers from Ghasemy Yaghin (2018); Ghasemy Yaghin et al. (2012) address this concept. Furthermore, only a few products examples are introduced, which discloses the methodological challenge that arises in this integration: complex demand functions increase the complexity of the models. Accordingly, research on heuristic methods capable of surpassing this challenge is another opportunity in the field.

Distribution decisions are well covered by existing models. At a tactical level, the main decision is the determination of *shipment quantities (and inventory levels)* from production unit(s) to distributions center(s), retailer(s) or client(s). It is modeled across all the supply chain models. Clients' allocation, on the other hand, is not modeled in these papers. Nonetheless, as previously explained, this decision can be indirectly modeled using shipment costs, which diminishes the relevance of its inclusion.

There are more opportunities beyond increasing horizontal integration. It might be relevant to increase the level of realism of S&OP models in some contexts of application. Most of the papers depict a single stage productive process (73%). Even though a few problems already consider a multi-stage process, to the best of our knowledge there is no model which represents complex production systems with shifting bottlenecks in function of the production quantities per product/family. Another opportunity for increased realism concerns the inclusion of state-of-the-art inventory management practices into S&OP models. Not only at the distribution center(s) or retailer(s) but also at previous stages of the supply chain, inventory levels are commonly considered to be demand-only. Safety stock inclusion is not a common practice. Even when addressed, it usually assumes a simplistic approach considering an extra coverage or amount to respect. Opportunities for a more advanced multi-echelon safety stock calculation considering, for instance, cumulative demand functions are a gap which deserves further attention. Finally, another opportunity lies in the enrichment of the objective function considered. The literature typically considers cost minimization or profit maximization as optimization goals. However, sometimes, it would be important to introduce other parameters, such as service level targets to the customers.

Figure 2.8 entails the main research directions. It is important that new formulations tackling the aforementioned opportunities are developed (RD1). The introduction of additional decisions in S&OP expands horizontal integration. Increasing the level of realism of some variables simplifies the latter implementation, which may be understood as deepening the vertical integration between different planning layers. It is important that new formulations are generic enough to be applied under different contexts of application but remain modular to be easily adaptable.

We identify three additional axes of work to ensure the implementation of new formulations. First, new models should be assessed under different contexts of application (RD2) to ensure their appropriateness for different sectors of activity. Second, the development of new solution procedures might be required to allow for the introduction of some additional decisions in the models. While we claim the need for modular formulations and generality in terms of mathematical programming approaches, the same might not be true regarding solution procedures. Different solution procedures might be used depending on the specific application (e.g., solving a MINLP

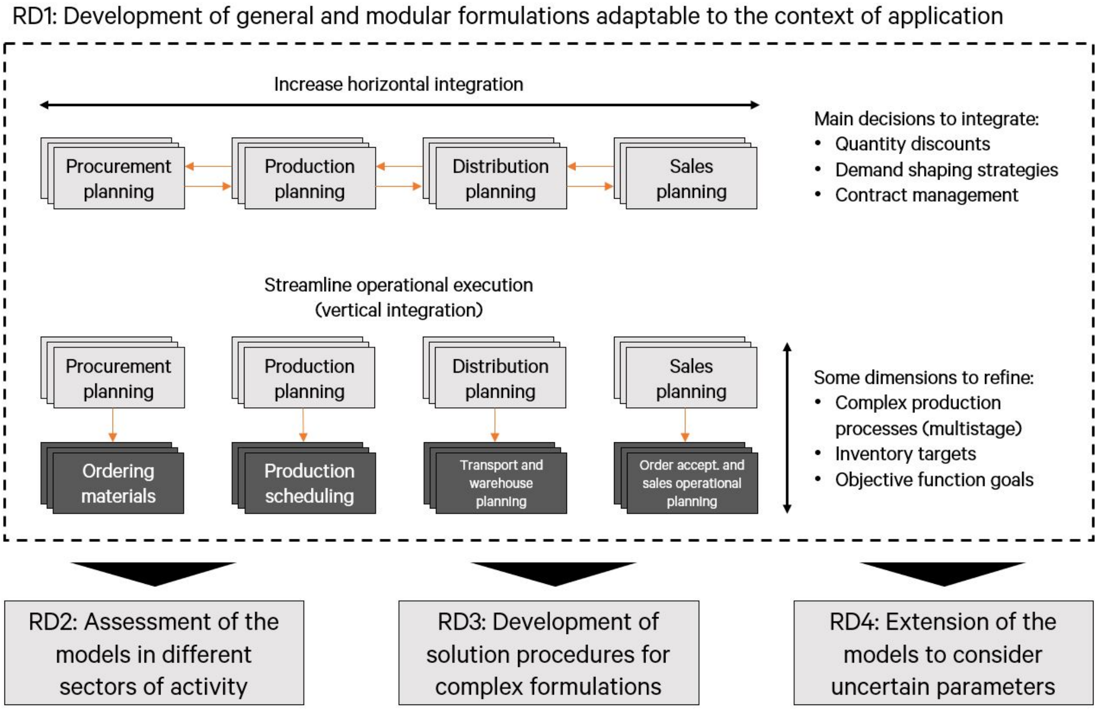


Figure 2.8: Research directions

S&OP problem with pricing considerations may require different solution procedures compared to a complex MIP problem considering contract management issues). Finally, it would be interesting if new applications could address uncertainty in some parameters, with incidence on those that revealed more relevant (e.g., demand function).

2.6 Conclusions

The main goal of this paper was to present and characterize S&OP from a modeling perspective. While past papers focused more on the process, activities and procedures around the topic, our review defines the problem from a decision-making point of view. This review leads to four main contributions.

Firstly, a holistic framework depicting the overall S&OP is introduced. This model contains all the decisions that can be potentially tackled in the mid-term supply chain planning. Moreover, the relationship between all the decisions is addressed: not only the lateral relationships between procurement, production, distribution, and sales are explained, but also the connection of these decisions with the strategic function of the company, the operational execution, and other external factors. Our review also identifies the parameters that have been modeled as uncertainty variables by researchers in the past. Secondly, the existing papers are organized according to the framework, with the identification of the streams of the literature which have been extending the tactical production planning. Thirdly, our review summarizes which modeling approaches have been used, with a focus on the mathematical modeling options and solution procedures employed.

Finally, our fourth contribution lies in the classification of the papers regarding their capability of integrating all the decisions from the supply chain and identification of research opportunities and directions towards more advanced and integrative S&OP models.

This review indicates that there is still a gap between the current practice in the field and the vision of a fully integrated model proclaimed by past researchers. The development of a generic system requires, first of all, the development of general and modular formulations that can be adaptable to the context of application. Then, it is important that these models are assessed under different sectors of activity, that they can be solved in reasonable time-frames and, ideally, that they are capable of addressing uncertain parameters.

We believe that the proposed framework and the resulting contributions will play an important role in guiding future research on models supporting S&OP for industrial companies. The absence of a review of the current state-of-the-art modeling approaches to tackle the mid-term supply chain planning complicates the development of structured approaches. Most of the past papers on the field have either been developments for specific cases or non-integrated approaches to the problem.

The adoption of an advanced S&OP decision support system can benefit the operation management practice of industrial companies in two ways. First, the number of iterations until a consensual plan is reached will be reduced since the analytical model weights the overall trade-off between the costs and the benefits associated with each decision. Second, the optimization capabilities of the model ensure the prescription of the best possible plans. This might be impossible to reach without the utilization of a system capable of simultaneously considering the decisions from the different business functions.

Nevertheless, from an implementation perspective, several managerial prerequisites need to be assured. First, it is essential to define a S&OP process capable of supporting an integrated process, including the definition of the roles, the frequency of revision, and the stages until the final validation of the plan. In end-to-end coordination between procurement, production, distribution, and sales, it may become relevant to create the role of the S&OP coordinator, responsible for the generation of the plans and alignment between the functions. Second, the definition of a clear set of supply chain metrics can enhance the consensus and interface between the business functions, avoiding functional *silos* that may arise from different objectives. Third, there must exist a digitalization of the companies aiming to implement an advanced S&OP model. The quality of the outputs, as well as the robustness of the optimization models, depend on the quality and reliability of the information. Last but not least, it is crucial that the S&OP activities are supported by the strategic function of the company. S&OP plans must support the executive meetings and be the guide for the mid-term initiatives.

As a future extension of this work, additional case studies or survey research could be interesting to unveil the importance of these decisions for each sector of activity. Finally, another interesting avenue could lie in the expansion of the framework to consider other mid-term business functions that interact with supply chain planning, such as financial planning. This would contribute to a even more integrated view of the planning function in a company.

Bibliography

Abedi, A., & Zhu, W. H. (2017). An optimisation model for purchase, production and distribution in fish supply chain - a case study. *International Journal of Production Research*, *55*(12), 3451-3464. doi: 10.1080/00207543.2016.1242800

Ahumada, O., & Villalobos, J. R. (2011). A tactical model for planning the production and distribution of fresh produce. *Annals of Operations Research*, *190*(1), 339-358. doi: 10.1007/s10479-009-0614-4

Ali, M. B., D' Amours, S., Gaudreault, J., & Carle, M. A. (2019). Integrating revenue management and sales and operations planning in a make-to-stock environment: Softwood lumber case study. *INFOR*, *57*(2), 314-341. doi: 10.1080/03155986.2018.1554420

Aliev, R. A., Fazlollahi, B., Guirimov, B. G., & Aliev, R. R. (2007). Fuzzy-genetic approach to aggregate production-distribution planning in supply chain management. *Information Sciences*, *177*(20), 4241-4255. doi: 10.1016/j.ins.2007.04.012

Aouam, T., & Brahimi, N. (2013a). An integrated production planning and order acceptance model with flexible due dates. In *Ieee international conference on industrial engineering and engineering management* (p. 1214-1218). IEEE. doi: 10.1109/IEEM.2013.6962604

Aouam, T., & Brahimi, N. (2013b). Integrated production planning and order acceptance under uncertainty: A robust optimization approach. *European Journal of Operational Research*, *228*(3), 504-515. doi: 10.1016/j.ejor.2013.02.010

Aouam, T., Geryl, K., Kumar, K., & Brahimi, N. (2018). Production planning with order acceptance and demand uncertainty. *Computers & Operations Research*, *91*, 145-159. doi: 10.1016/j.cor.2017.11.013

Ardjmand, E., Weckman, G. R., Young, W. A., Bajgiran, O. S., & Aminipour, B. (2016). A robust optimisation model for production planning and pricing under demand uncertainty. *International Journal of Production Research*, *54*(13), 3885-3905. doi: 10.1080/00207543.2016.1161251

Askarpoor, H. R., & Davoudpour, H. (2013). An effeactive approximation algorithm for joint lot-sizing and pricing problem. *International Journal of Advanced Manufacturing Technology*, *65*(9-12), 1429-1437. doi: 10.1007/s00170-012-4268-z

Attia, A. M., Ghaithan, A. M., & Duffuaa, S. O. (2019). A multi-objective optimization model for tactical planning of upstream oil & gas supply chains. *Computers & Chemical Engineering*, *128*, 216-227. doi: 10.1016/j.compchemeng.2019.06.016

Badhotiya, G. K., Soni, G., & Mittal, M. L. (2019). Fuzzy multi-objective optimization for multi-site integrated production and distribution planning in two echelon supply chain. *International Journal of Advanced Manufacturing Technology*, *102*(1-4), 635-645. doi: 10.1007/s00170-018-3204-2

Bajwa, N., Fontem, B., & Sox, C. R. (2016). Optimal product pricing and lot sizing decisions for multiple products with nonlinear demands. *Journal of Management Analytics*, *3*(1), 43-58. doi: 10.1080/23270012.2015.1121118

Bajwa, N., Sox, C. R., & Ishfaq, R. (2016). Coordinating pricing and production decisions for multiple products. *Omega (United Kingdom)*, *64*, 86-101. doi: 10.1016/j.omega.2015.11.006

Bakhrankova, K., Midthun, K. T., & Uggen, K. T. (2014). Stochastic optimization of operational production planning for fisheries. *Fisheries Research*, *157*, 147-153. doi: 10.1016/j.fishres.2014.03.018

Barbarosoğlu, G. (2000). An integrated supplier-buyer model for improving supply chain coordination. *Production Planning and Control*, *11*(8), 732-741. doi: 10.1080/095372800750038337

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science*, *17*(4), B141-B164.

Boutarfa, Y., Senoussi, A., Mouss, N. K., & Brahimi, N. (2016). A tabu search heuristic for an integrated production-distribution problem with clustered retailers. *IFAC-PapersOnLine*, *49*(12), 1514-1519. doi: 10.1016/j.ifacol.2016.07.794

Brahimi, N., Absi, N., Dauzère-Pérès, S., & Kedad-Sidhoum, S. (2015). Models and lagrangian heuristics for a two-level lot-sizing problem with bounded inventory. *OR Spectrum*, *37*(4), 983-1006. doi: 10.1007/s00291-015-0404-0

Buschkühl, L., Sahling, F., Helber, S., & Tempelmeier, H. (2010). Dynamic capacitated lot-sizing problems: a classification and review of solution approaches. *OR Spectrum*, *32*(2), 231-261. doi: 10.1007/s00291-008-0150-7

Caccetta, L., & Mardaneh, E. (2009). Joint pricing and production planning for fixed priced multiple products with backorders. *Journal of Industrial and Management Optimization*, *6*(1), 123-147. doi: 10.3934/jimo.2010.6.123

Catalá, L. P., Moreno, M. S., Blanco, A. M., & Bandoni, J. A. (2016). A bi-objective optimization model for tactical planning in the pome fruit industry supply chain. *Computers and Electronics in Agriculture*, *130*, 128-141. doi: 10.1016/j.compag.2016.10.008

Che, Z. H. (2010). A genetic algorithm-based model for solving multi-period supplier selection problem with assembly sequence. *International Journal of Production Research*, *48*(15), 4355-4377. doi: 10.1080/00207540903049399

Chen, C. F., Egbelu, P. J., & Wu, C. T. (1994). Production planning-models for a central factory with multiple satellite factories. *International Journal of Production Research*, *32*(6), 1431-1450. doi: 10.1080/00207549408957009

Chen, J. M., Chen, L. T., & Leu, J. D. (2006). Developing optimization models for cross-functional decision-making: Integrating marketing and production planning. *OR Spectrum*, *28*(2), 223-240. doi: 10.1007/s00291-005-0004-5

Chen, M., & Wang, W. (1997). A linear programming model for integrated steel production and distribution planning. *International Journal of Operations and Production Management*, *17*(6), 592-610. doi: 10.1108/01443579710167276

Chen-Ritzo, C. H., Ervolina, T., Harrison, T. P., & Gupta, B. (2010). Sales and operations planning in systems with order configuration uncertainty. *European Journal of Operational Research*, *205*(3), 604-614. doi: 10.1016/j.ejor.2010.01.029

Cui, L. X. (2016). Joint optimization of production planning and supplier selection incorporating customer flexibility: an improved genetic approach. *Journal of Intelligent Manufacturing*, *27*(5), 1017-1035. doi: 10.1007/s10845-014-0932-5

Cunha, A. L., Santos, M. O., Morabito, R., & Barbosa-Póvoa, A. (2018). An integrated approach for production lot sizing and raw material purchasing. *European Journal of Operational Research*, *269*(3), 923-938. doi: 10.1016/j.ejor.2018.02.042

Danese, P., Molinaro, M., & Romano, P. (2018). Managing evolutionary paths in sales and operations planning: key dimensions and sequences of implementation. *International Journal of Production Research*, *56*(5), 2036-2053. doi: 10.1080/00207543.2017.1355119

Darmawan, A., Wong, H., & Thorstenson, A. (2018). Integration of promotion and production decisions in sales and operations planning. *International Journal of Production Research*, *56*(12), 4186-4206. doi: 10.1080/00207543.2018.1431418

Darvish, M., Larrain, H., & Coelho, L. C. (2016). A dynamic multi-plant lot-sizing and distribution problem. *International Journal of Production Research*, *54*(22), 6707-6717. doi: 10.1080/00207543.2016.1154623

Deng, S. M., & Yano, C. A. (2006). Joint production and pricing decisions with setup costs and capacity constraints. *Management Science*, *52*(5), 741-756. doi: 10.1287/mnsc.1050.0491

Eksioglu, S. D., Romeijn, H. E., & Pardalos, P. M. (2006). Cross-facility management of production and transportation planning problem. *Computers & Operations Research*, *33*(11), 3231-3251. doi: 10.1016/j.cor.2005.02.038

Fahimnia, B., Farahani, R. Z., & Sarkis, J. (2013). Integrated aggregate supply chain planning using memetic algorithm – a performance analysis case study. *International Journal of Production Research*, *51*(18), 5354-5373. doi: 10.1080/00207543.2013.774492

Fahimnia, B., Luong, L., & Marian, R. (2012). Genetic algorithm optimisation of an integrated aggregate production–distribution plan in supply chains. *International Journal of Production Research*, *50*(1), 81-96. doi: 10.1080/00207543.2011.571447

Fahimnia, B., Sarkis, J., Choudhary, A., & Eshragh, A. (2015). Tactical supply chain planning under a carbon tax policy scheme: A case study. *International Journal of Production Economics*, *164*, 206-215. doi: 10.1016/j.ijpe.2014.12.015

Feng, P., Liu, Y., Wu, F., & Chu, C. (2018). Two heuristics for coordinating production planning and transportation planning. *International Journal of Production Research*, *56*(21), 6872-6889. doi: 10.1080/00207543.2017.1351631

Feng, Y., D'Amours, S., & Beauregard, R. (2008). The value of sales and operations planning in oriented strand board industry with make-to-order manufacturing system: Cross functional integration under deterministic demand and spot market recourse. *International Journal of Production Economics*, *115*(1), 189-209. doi: 10.1016/j.ijpe.2008.06.002

Feng, Y., D'Amours, S., & Beauregard, R. (2009). Simulation and performance evaluation of partially and fully integrated sales and operations planning. *International Journal of Production Research*, *48*(19), 5859-5883. doi: 10.1080/00207540903232789

Feng, Y., Martel, A., D'Amours, S., & Beauregard, R. (2013). Coordinated contract decisions in a make-to-order manufacturing supply chain: A stochastic programming approach. *Production and Operations Management*, *22*(3), 642-660. doi: 10.1111/j.1937-5956.2012.01385.x

Fuentealba, S., Pradenas, L., Linfati, R., & Ferland, J. A. (2019). Forest harvest and sawmills: An integrated tactical planning model. *Computers and Electronics in Agriculture*, *156*, 275-281. doi: 10.1016/j.compag.2018.11.011

Fumero, F., & Vercellis, C. (1997). Integrating distribution, machine assignment and lot-sizing via lagrangean relaxation. *International Journal of Production Economics*, *49*(1), 45-54. doi: 10.1016/s0925-5273(96)00098-9

Gansterer, M. (2015). Aggregate planning and forecasting in make-to-order production systems. *International Journal of Production Economics*, *170*, 521-528. doi: 10.1016/j.ijpe.2015.06.001

Ghasemy Yaghin, R. (2018). Integrated multi-site aggregate production-pricing planning in a two-echelon supply chain with multiple demand classes. *Applied Mathematical Modelling*, *53*, 276-295. doi: 10.1016/j.apm.2017.09.006

Ghasemy Yaghin, R., Torabi, S. A., & Fatemi Ghomi, S. M. T. (2012). Integrated markdown pricing and aggregate production planning in a two echelon supply chain: A hybrid fuzzy multiple objective approach. *Applied Mathematical Modelling*, *36*(12), 6011-6030. doi: 10.1016/j.apm.2012.01.029

Gilbert, S. M. (2000). Coordination of pricing and multiple-period production across multiple constant priced goods. *Management Science*, *46*(12), 1602-1616. doi: 10.1287/mnsc.46.12.1602.12073

Goh, S. H., & Eldridge, S. (2019). Sales and operations planning: The effect of coordination mechanisms on supply chain performance. *International Journal of Production Economics*, *214*, 80-94. doi: 10.1016/j.ijpe.2019.03.027

González-Ramírez, R. G., Smith, N. R., & Askin, R. G. (2011). A heuristic approach for a multi-product capacitated lot-sizing problem with pricing. *International Journal of Production Research*, *49*(4), 1173-1196. doi: 10.1080/00207540903524482

Grimson, J. A., & Pyke, D. F. (2007). Sales and operations planning: an exploratory study and framework. *The International Journal of Logistics Management*, *18*(3), 322-346. doi: 10.1108/09574090710835093

Guajardo, M., Kylinger, M., & Rönnqvist, M. (2013). Speciality oils supply chain optimization: From a decoupled to an integrated planning approach. *European Journal of Operational Research*, *229*(2), 540-551. doi: 10.1016/j.ejor.2013.03.007

Guan, Z., & Philpott, A. B. (2011). A multistage stochastic programming model for the new zealand dairy industry. *International Journal of Production Economics*, *134*(2), 289-299. doi: 10.1016/j.ijpe.2009.11.003

Gunnarsson, H., & Rönnqvist, M. (2008). Solving a multi-period supply chain problem for a pulp company using heuristics-an application to södra cell ab. *International Journal of Production Economics*, *116*(1), 75-94. doi: 10.1016/j.ijpe.2008.07.010

Hahn, G. J., Sens, T., Decouttere, C., & Vandaele, N. J. (2016). A multi-criteria approach to robust outsourcing decision-making in stochastic manufacturing systems. *Computers & Industrial Engineering*, *98*, 275-288. doi: 10.1016/j.cie.2016.05.032

Ivert, L. K., & Jonsson, P. (2014). When should advanced planning and scheduling systems be used in sales and operations planning? *International Journal of Operations and Production Management*, *34*(10), 1338-1362. doi: 10.1108/IJOPM-03-2011-0088

Jolayemi, J. K., & Olorunniwo, F. O. (2004). A deterministic model for planning production quantities in a multi-plant, multi-warehouse environment with extensible capacities. *International Journal of Production Economics*, *87*(2), 99-113. doi: 10.1016/S0925-5273(03) 00095-1

Kanyalkar, A. P., & Adil, G. K. (2007). Aggregate and detailed production planning integrating procurement and distribution plans in a multi-site environment. *International Journal of Production Research*, *45*(22), 5329-5353. doi: 10.1080/00207540600632174

Khemiri, R., Elbedoui-Maktouf, K., Grabot, B., & Zouari, B. (2017). A fuzzy multi-criteria decision-making approach for managing performance and risk in integrated procurement–production planning. *International Journal of Production Research*, *55*(18), 5305-5329. doi: 10.1080/00207543.2017.1308575

Kristensen, J., & Jonsson, P. (2018). Context-based sales and operations planning (s&op) research. *International Journal of Physical Distribution & Logistics Management*, *48*(1), 19-46. doi: 10.1108/ijpdlm-11-2017-0352

Lidestam, H., & Rönnqvist, M. (2011). Use of lagrangian decomposition in supply chain planning. *Mathematical and Computer Modelling*, *54*(9-10), 2428-2442. doi: 10.1016/j.mcm.2011.05 .054

Lim, L. L., Alpan, G., & Penz, B. (2017). A simulation-optimization approach for sales and operations planning in build-to-order industries with distant sourcing: Focus on the automotive industry. *Computers and Industrial Engineering*, *112*, 469-482. doi: 10.1016/ j.cie.2016.12.002

Lin, J. T., & Chen, Y. Y. (2007). A multi-site supply network planning problem considering variable time buckets- a tft-lcd industry case. *International Journal of Advanced Manufacturing Technology*, *33*(9-10), 1031-1044. doi: 10.1007/s00170-006-0537-z

Liu, W., Sun, D., & Xu, T. (2019). Integrated production and distribution planning for the iron ore concentrate. *Mathematical Problems in Engineering*, *2019*. doi: 10.1155/2019/7948349

Lusa, A., Martínez-Costa, C., & Mas-Machuca, M. (2012). An integral planning model that includes production, selling price, cash flow management and flexible capacity. *International Journal of Production Research*, *50*(6), 1568-1581. doi: 10.1080/00207543.2011.558128

Mardan, E., Amalnik, M. S., & Rabbani, M. (2015). An integrated emergency ordering and production planning optimization model with demand and yield uncertainty. *International Journal of Production Research*, *53*(20), 6023-6039. doi: 10.1080/00207543.2015.1008109

Mardaneh, E., & Caccetta, L. (2013). Optimal pricing and production planning for multi-product multi-period systems with backorders. *Journal of Optimization Theory and Applications*, *158*(3), 896-917. doi: 10.1007/s10957-013-0273-0

Mardaneh, E., & Caccetta, L. (2014). Impact of price-adjustments costs on integration of pricing and production planning of multiple-products. *Optimization Letters*, *9*(1), 119-142. doi: 10.1007/s11590-013-0718-2

Meisel, F., Kirschstein, T., & Bierwirth, C. (2013). Integrated production and intermodal transportation planning in large scale production-distribution-networks. *Transportation Research Part E: Logistics and Transportation Review*, *60*, 62-78. doi: 10.1016/j.tre.2013.10.003

Merzifonluoğlu, Y., & Geunes, J. (2006). Uncapacitated production and location planning models with demand fulfillment flexibility. *International Journal of Production Economics*, *102*(2), 199-216. doi: 10.1016/j.ijpe.2005.02.011

Merzifonluoğlu, Y., Geunes, J., & Romeijn, H. E. (2007). Integrated capacity, demand, and production planning with subcontracting and overtime options. *Naval Research Logistics*, *54*(4), 433-447. doi: 10.1002/nav.20219

Mirzapour Al-E-Hashem, S. M. J., Malekly, H., & Aryanezhad, M. B. (2011). A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. *International Journal of Production Economics*, *134*(1), 28-42. doi: 10.1016/j.ijpe.2011.01.027

Moengin, P. (2016). A mathematical model of integrated production-inventory-distribution system for billet steel manufacturing. In *Transactions on engineering technologies* (p. 317-328). Springer, Singapore. doi: 10.1007/978-981-10-1088-0_24

Mohamed, Z. M. (1999). An integrated production-distribution model for a multi-national company operating under varying exchange rates. *International Journal of Production Economics*, *58*(1), 81-92. doi: 10.1016/S0925-5273(98)00080-2

Mula, J., Peidro, D., Díaz-Madroñero, M., & Vicens, E. (2010). Mathematical programming models for supply chain production and transport planning. *European Journal of Operational Research*, *204*(3), 377-390. doi: https://doi.org/10.1016/j.ejor.2009.09.008

Nemati, Y., & Alavidoost, M. H. (2018). A fuzzy bi-objective milp approach to integrate sales, production, distribution and procurement planning in a fmcg supply chain. *Soft Computing*, 1-20. doi: 10.1007/s00500-018-3146-5

Nemati, Y., Madhoushi, M., & Ghadikolaei, A. S. (2017a). The effect of sales and operations planning (s&op) on supply chain's total performance: A case study in an iranian dairy company. *Computers & Chemical Engineering*, *104*, 323-338. doi: 10.1016/j.compchemeng.2017.05.002

Nemati, Y., Madhoushi, M., & Ghadikolaei, A. S. (2017b). Towards supply chain planning integration: Uncertainty analysis using fuzzy mathematical programming approach in a plastic forming company. *Iranian Journal of Management Studies*, *10*(2), 335-364. doi: 10.22059/ijms.2017.218842.672334

Noroozi, S., & Wikner, J. (2017). Sales and operations planning in the process industry: A literature review. *International Journal of Production Economics*, *188*, 139-155. doi: 10.1016/j.ijpe.2017.03.006

Olhager, J., & Rudberg, M. (2002). Linking manufacturing strategy decisions on process choice with manufacturing planning and control systems. *International Journal of Production Research*, *40*(10), 2335-2351. doi: 10.1080/00207540210131842

Olhager, J., Rudberg, M., & Wikner, J. (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*, *69*(2), 215-225. doi: Doi10.1016/S0925-5273(99)00098-5

Ouazene, Y., Yalaoui, F., Kelly, R., & Idjeraoui, T. (2017). Coordination and optimization of dynamic pricing and production decisions. In *2017 ieee symposium series on computational intelligence (ssci)* (p. 1-6). IEEE. doi: 10.1109/SSCI.2017.8285252

Ouhimmou, M., D'Amours, S., Beauregard, R., Ait-Kadi, D., & Chauhan, S. S. (2008). Furniture supply chain tactical planning optimization using a time decomposition approach. *European Journal of Operational Research*, *189*(3), 952-970. doi: 10.1016/j.ejor.2007.01.064

Ouhimmou, M., D'Amours, S., Beauregard, R., Ait-Kadi, D., & Chauhan, S. S. (2009). Optimization helps shermag gain competitive edge. *Interfaces*, *39*(4), 329-345. doi: 10.1287/inte.1090.0448

Paksoy, T., Pehlivan, N. Y., & Ozceylan, E. (2010). Application of fuzzy mathematical programming approach to the aggregate production/distribution planning in a supply chain network problem. *Scientific Research and Essays*, *5*(22), 3384-3397.

Pal, A., Chan, F. T. S., Mahanty, B., & Tiwari, M. K. (2011). Aggregate procurement, production, and shipment planning decision problem for a three-echelon supply chain using swarm-based heuristics. *International Journal of Production Research*, *49*(10), 2873-2905. doi: 10.1080/00207541003730847

Park, Y. B. (2005). An integrated approach for production and distribution planning in supply chain management. *International Journal of Production Research*, *43*(6), 1205-1224. doi: 10.1080/00207540412331327718

Pathak, S., & S., S. (2012). A fuzzy optimization model to the aggregate production/distribution planning decision in a multi-item supply chain network. *International Journal of Management Science and Engineering Management*, *7*(3), 163-173. doi: 10.1080/17509653.2012.10671220

Pedroso, C. B., da Silva, A. L., & Tate, W. L. (2016). Sales and operations planning (s&op): Insights from a multi-case study of brazilian organizations. *International Journal of Production Economics*, *182*, 213-229. doi: 10.1016/j.ijpe.2016.08.035

Peidro, D., Mula, J., Alemany, M. M. E., & Lario, F.-C. (2012). Fuzzy multi-objective optimisation for master planning in a ceramic supply chain. *International Journal of Production Research*, *50*(11), 3011-3020. doi: 10.1080/00207543.2011.588267

Raa, B., Dullaert, W., & Aghezzaf, E.-H. (2013). A matheuristic for aggregate production–distribution planning with mould sharing. *International Journal of Production Economics*, *145*(1), 29-37. doi: 10.1016/j.ijpe.2013.01.006

Raza, S. A., Abdullakutty, F. C., & Rathinam, S. (2016). Joint determination of process mean, price differentiation, and production decisions with demand leakage: A multi-objective approach. *Applied Mathematical Modelling*, *40*(19-20), 8446-8463. doi: 10.1016/j.apm.2016.02.043

Raza, S. A., & Turiac, M. (2016). Joint optimal determination of process mean, production quantity, pricing, and market segmentation with demand leakage. *European Journal of Operational Research*, *249*(1), 312-326. doi: 10.1016/j.ejor.2015.08.032

Sahinidis, N. V. (2004). Optimization under uncertainty: state-of-the-art and opportunities. *Computers & Chemical Engineering*, *28*(6), 971-983. doi: 10.1016/j.compchemeng.2003.09.017

Sanei Bajgiran, O., Kazemi Zanjani, M., & Nourelfath, M. (2016). The value of integrated tactical planning optimization in the lumber supply chain. *International Journal of Production Economics*, *171*, 22-33. doi: 10.1016/j.ijpe.2015.10.021

Senoussi, A., Mouss, N. K., Penz, B., Brahimi, N., & Dauzere-Peres, S. (2016). Modeling and solving a one-supplier multi-vehicle production-inventory-distribution problem with clustered retailers. *International Journal of Advanced Manufacturing Technology*, *85*(5-8), 971-989. doi: 10.1007/s00170-015-7966-5

Shahi, S., Pulkki, R., Leitch, M., & Gaston, C. (2017). Optimal production-inventory model for forest products industry supply chain under demand and supply uncertainty: Case study of a pulp mill in ontario. *Cogent Business and Management*, *4*(1). doi: 10.1080/23311975.2017.1370765

Singhal, J., & Singhal, K. (2007). Holt, modigliani, muth, and simon's work and its role in the renaissance and evolution of operations management. *Journal of Operations Management*, *25*(2), 300-309. doi: 10.1016/j.jom.2006.06.003

Smith, N. R., Limón Robles, J., & Cárdenas-Barrón, L. E. (2009). Optimal pricing and production master planning in a multi-period horizon considering capacity and inventory constraints. *Mathematical Problems in Engineering*, 15. doi: 10.1155/2009/932676

Sodhi, M. S., & Tang, C. S. (2011). Determining supply requirement in the sales-and-operations-planning (s&op) process under demand uncertainty: A stochastic programming formulation and a spreadsheet implementation. *Journal of the Operational Research Society*, *62*(3), 526-536. doi: 10.1057/jors.2010.93

Souza, G. C., Zhao, Z. Y., Chen, M. M., & Ball, M. O. (2004). Coordinating sales and raw material discounts in a global supply chain. *Production and Operations Management*, *13*(1), 34-45. doi: 10.1111/j.1937-5956.2004.tb00143.x

Stadtler, H., & Kilger, C. (2008). *Supply chain management and advanced planning: Concepts, models, software and case studies*. Springer Berlin Heidelberg. doi: 10.1007/978-3-540-74512-9_2

Steinrücke, M., & Jahr, M. (2012). Tactical planning in supply chain networks with customer oriented single sourcing. *International Journal of Logistics Management*, *23*(2), 259-279. doi: 10.1108/09574091211265387

Susarla, N., & Karimi, I. A. (2011). Integrated campaign planning and resource allocation in batch plants. *Computers & Chemical Engineering*, *35*(12), 2990-3001. doi: 10.1016/j.compchemeng.2011.03.025

Susarla, N., & Karimi, I. A. (2012). Integrated supply chain planning for multinational pharmaceutical enterprises. *Computers and Chemical Engineering*, *42*, 168-177. doi: 10.1016/j.compchemeng.2012.03.002

Susarla, N., & Karimi, I. A. (2018). Integrated production planning and inventory management in a multinational pharmaceutical supply chain. In *Computer aided chemical engineering* (Vol. 41, p. 551-567). Elsevier B.V. doi: 10.1016/B978-0-444-63963-9.00022-1

Thomas, A., Genin, P., & Lamouri, S. (2008). Mathematical programming approaches for stable tactical and operational planning in supply chain and aps context. *Journal of Decision Systems*, *17*(3), 425-455. doi: 10.3166/jds.17.425-455

Thome, A. M. T., Scavarda, L. F., Fernandez, N. S., & Scavarda, A. J. (2012a). Sales and operations planning and the firm performance. *International Journal of Productivity and Performance Management*, *61*(4), 359-381. doi: 10.1108/17410401211212643

Thome, A. M. T., Scavarda, L. F., Fernandez, N. S., & Scavarda, A. J. (2012b). Sales and operations planning: A research synthesis. *International Journal of Production Economics*, *138*(1), 1-13. doi: 10.1016/j.ijpe.2011.11.027

Thome, A. M. T., Scavarda, L. F., & Scavarda, A. J. (2016). Conducting systematic literature review in operations management. *Production Planning & Control*, *27*(5), 408-420. doi: 10.1080/09537287.2015.1129464

Torabi, S. A., & Hassini, E. (2009). Multi-site production planning integrating procurement and distribution plans in multi-echelon supply chains: An interactive fuzzy goal programming approach. *International Journal of Production Research*, *47*(19), 5475-5499. doi: 10.1080/00207540801905460

Torabi, S. A., & Moghaddam, M. (2012). Multi-site integrated production-distribution planning with trans-shipment: A fuzzy goal programming approach. *International Journal of Production Research*, *50*(6), 1726-1748. doi: 10.1080/00207543.2011.560907

Tuomikangas, N., & Kaipia, R. (2014). A coordination framework for sales and operations planning (s&op): Synthesis from the literature. *International Journal of Production Economics*, *154*, 243-262. doi: 10.1016/j.ijpe.2014.04.026

Ulusoy, G., & Yazgaç, T. (1995). Joint decision making for production and marketing. *International Journal of Production Research*, *33*(8), 2277-2293. doi: 10.1080/00207549508904815

Van Elzakker, M. A. H., Zondervan, E., Raikar, N. B., Hoogland, H., & Grossmann, I. E. (2014). Optimizing the tactical planning in the fast moving consumer goods industry considering shelf-life restrictions. *Computers & Chemical Engineering*, *66*, 98-109. doi: 10.1016/j.compchemeng.2014.01.020

Van Hoesel, S., Romeijn, H. E., Morales, D. R., & Wagelmans, A. P. M. (2005). Integrated lot sizing in serial supply chains with production capacities. *Management Science*, *51*(11), 1706-1719. doi: 10.1287/mnsc.1050.0378

Wagner, S. M., Ullrich, K. K. R., & Transchel, S. (2014). The game plan for aligning the organization. *Business Horizons*, *57*(2), 189-201. doi: 10.1016/j.bushor.2013.11.002

Wang, J. Z., Hsieh, S. T., & Hsu, P. Y. (2012). Advanced sales and operations planning framework in a company supply chain. *International Journal of Computer Integrated Manufacturing*, *25*(3), 248-262. doi: 10.1080/0951192x.2011.629683

Wang, R.-C., & Liang, T.-F. (2005). Applying possibilistic linear programming to aggregate production planning. *International Journal of Production Economics*, *98*(3), 328-341. doi: 10.1016/j.ijpe.2004.09.011

Wei, W., Guimarães, L., Amorim, P., & Almada-Lobo, B. (2017). Tactical production and distribution planning with dependency issues on the production process. *Omega*, *67*, 99-114. doi: 10.1016/j.omega.2016.04.004

Yenradee, P., & Piyamanothorn, K. (2011). Integrated aggregate production planning and marketing promotion: Model and case study. *International Journal of Management Science and Engineering Management*, *6*(2), 145-152. doi: 10.1080/17509653.2011.10671158

Yuan, X. M., Low, J. M. W., & Yeo, W. M. (2012). A network prototype for integrated production-distribution planning with non-multi-functional plants. *International Journal of Production Research*, *50*(4), 1097-1113. doi: 10.1080/00207543.2010.550640

Zhang, G., Shang, J., & Li, W. (2011). Collaborative production planning of supply chain under price and demand uncertainty. *European Journal of Operational Research*, *215*(3), 590-603. doi: 10.1016/j.ejor.2011.07.007

Zhao, H., Huang, E., Dou, R., & Wu, K. (2019). A multi-objective production planning problem with the consideration of time and cost in clinical trials. *Expert Systems with Applications*, *124*, 25-38. doi: 10.1016/j.eswa.2019.01.038

Zhu, W. Y. (2008). The application of fuzzy programming to the aggregate production planning-markdown pricing problem. In *Proceedings of the 7th international symposium on operations research and its applications* (p. 457-464).

Chapter 3

A multiobjective and multistage S&OP approach for MTS/MTO contexts

This chapter presents a multiobjective S&OP approach to industrial contexts where products may be produced to stock (MTS) or to order (MTO), comprised by a mixed integer programming model leveraged by a decision-making framework. The literature review unveiled the need to devise approaches considering other objectives than profit and able to cope with multistage production settings. This paper provides breakthroughs accordingly. This research is also motivated by a real challenge faced by a cable manufacturer.

Merging Make-to-Stock/Make-to-Order decisions into Sales and Operations Planning: a multi-objective approach

Daniel Filipe Pereira *, José Fernando Oliveira †, Maria Antónia Carravilla †
* Faculty of Engineering, University of Porto and LTPlabs † INESC TEC

Submitted and under the second round of review at *Omega*, 2021

Abstract: With the advent of mass customization and product proliferation, the appearance of hybrid Make-to-Stock(MTS)/Make-to-Order(MTO) policies arise as a strategy to cope with high product variety maintaining satisfactory lead times. In companies operating under this reality, Sales and Operations Planning (S&OP) practices must be adapted accordingly during the coordinated planning of procurement, production, logistics, and sales activities. This paper proposes a novel S&OP decision-making framework for a flow shop/batch company that produces standard products under an MTS strategy and customized products under an MTO strategy. First, a multi-objective mixed-integer programming model is formulated to characterize the problem. Then, a matrix containing the different strategies a firm in this context may adopt is proposed. This rationale provides a business-oriented approach towards the analysis of different plans and helps to frame the different Pareto-optimal solutions given the priority on MTS or MTO segments and the management positioning regarding cost minimization or service level orientation. The research is based on a real case faced by an electric cable manufacturer. The computational experiments demonstrate the applicability of the proposed methodology. Our approach brings a practical, supply chain-oriented, and mid-term perspective on the study of operations planning policies in MTS/MTO contexts.

Keywords: Sales and Operations Planning, Make-to-Stock and Make-to-Order, Multi-objective optimization, Managerial policies

3.1 Introduction

Sales and Operations Planning (S&OP) appears as a cross-functional and integrated tactical planning process within the firm, whose objective is to gather all the plans of the business in a single plan (Thome, Scavarda, Fernandez, & Scavarda, 2012; Tuomikangas & Kaipia, 2014). Its main goal is to be the definitive statement of the company's plans for the short to intermediate-term, covering a horizon that supports the annual business planning process (Noroozi & Wikner, 2017). This plan guarantees the balance between demand and all the resources, namely production, distribution, procurement, and finance, to ensure alignment with the strategic goals (Feng, D'Amours, & Beauregard, 2008). Therefore, S&OP plays an essential role in integrating organization units as a whole, fulfilling customer demand to improve competitiveness (Tuomikangas & Kaipia, 2014).

According to the framework from Olhager, Rudberg, and Wikner (2001) (Figure 3.1), there is a dependency between the production strategy, the critical success factor (order winner), and the type of industry - represented by the positioning in the production-process matrix. Thus, the S&OP rationale and guidelines need to be adapted accordingly. Companies competing in a situation of low volume and many products should focus on design, flexibility, and delivery speed and precision (Noroozi & Wikner, 2016; Olhager & Prajogo, 2012). They typically opt for a make-to-order (MTO) production strategy, which implies a chase planning strategy that keeps free capacity for accepting future orders (Olhager et al., 2001).

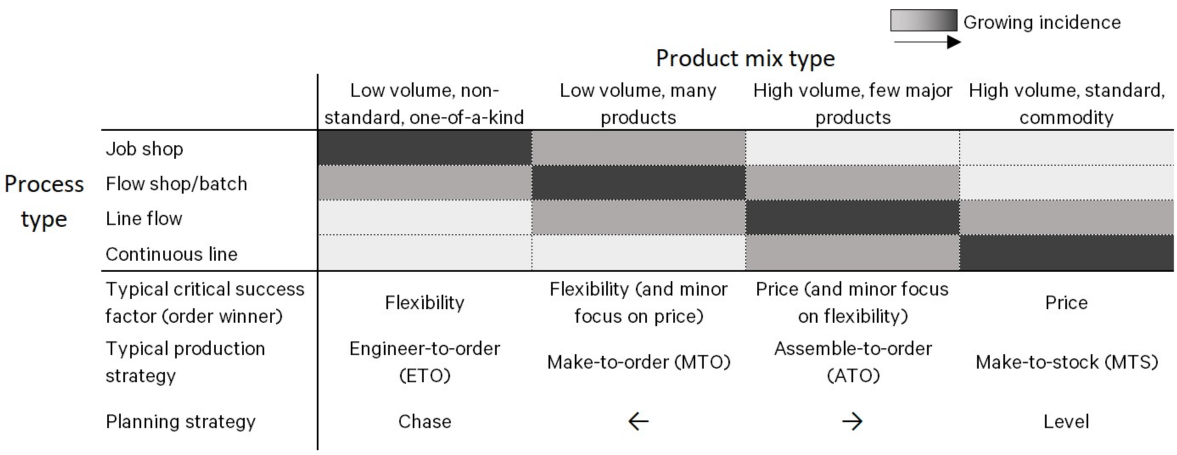


Figure 3.1: Adapted version of the production-process matrix
(Olhager et al., 2001)

On the other hand, companies producing commodity products usually compete on low prices, which means mass production, economies of scale, leanness, and high levels of utilization (Noroozi & Wikner, 2016; Olhager & Prajogo, 2012). Therefore, a level planning strategy is preferable since products can be produced using a stable production rate (Olhager et al., 2001). In this case, managers usually implement a make-to-stock (MTS) production strategy.

With the advent of mass customization and product proliferation, the capability of absorbing high product variety while maintaining acceptable delivery lead times is paramount to success (Brabazon, MacCarthy, Woodcock, & Hawkins, 2010). In this increasingly complicated context, the application of hybrid MTS/MTO policies may become an option when a firm decides its production strategy (Altendorfer & Minner, 2014). Low-valued and standard products with regular demand can be produced to stock, allowing demand to be satisfied instantly. On the other hand, stocking can be too expensive for high-valued or customized products with irregular demand (Beemsterboer, Land, & Teunter, 2016). Thus, flexibility and price (Figure 3.1) become critical success factors that need to be taken into account simultaneously.

Our work links two literature streams that have been treated as belonging to different categories: S&OP and MTS/MTO production strategy. S&OP models have been developed considering pure production strategies neglecting the issues that may arise in the MTS/MTO integration (Soman, Van Donk, & Gaalman, 2004). Nonetheless, the combination of both concepts becomes vital, since the adoption of multi-modal order fulfillment practices may benefit from the transition from a focus on meeting individual customer needs to the broader question of balancing supply and demand (Lawson, Pil, & Holweg, 2018).

Even from a conceptualization perspective, these streams are not independent. MTS/MTO production strategy is part of a hierarchical approach composed of three main stages: (i) MTS/MTO partitioning, (ii) capacity coordination, (iii) scheduling and control (Soman et al., 2004; Soman, van Donk, & Gaalman, 2007). Capacity coordination comprises the mid-term planning where managers decide on the orders to accept (and due dates), lot sizes for MTS products, and monthly production volumes. Accordingly, in companies operating in a hybrid production strategy, these decisions may be considered in holistic sales and operations planning. The coexistence of orders and forecasts, divergent priorities that emerge during the decision to produce to stock or produce to booked orders, and the balance between efficiency and speed required to implement a hybrid strategy in the same production environment are challenges that cannot be neglected.

This paper brings two main contributions. First, we present a decision-making S&OP model that provides researchers and practitioners with a planning framework that dynamically weights the trade-off between producing to stock *versus* producing to orders while optimizing sales and operations decisions of a company for the mid-term horizon. Recent literature reinforces that the future of S&OP calls for advanced planning systems capable of handling the complexity of modern supply chains (Pereira, Oliveira, & Carravilla, 2020). The integrated planning of the sales and operations decisions can be leveraged using optimization solutions with real-time solvers, coupled with business systems (Grimson & Pyke, 2007). Functionalities like integral planning, constraint-based planning, optimization, and what-if simulation are essential to support S&OP

processes (Ivert & Jonsson, 2014).

The second contribution lies in the planning rationale proposed. During S&OP meetings, different trade-offs emerge, and there are decisions to be taken that can be analyzed from distinct viewpoints. In particular, there are two main axes to consider: the production strategy priority (MTS *versus* MTO productions), and the management orientation regarding costs minimization *versus* service and availability to customers. To address such complexity in the decision-making process, we propose a multi-objective approach that can generate multiple mid-term plans representing the several positioning strategies a firm may adopt. Past decision-making models for S&OP and supply chain planning typically consider cost minimization or profit maximization as optimization goals (Liu & Papageorgiou, 2013; Pereira et al., 2020). Nevertheless, aspects such as priority customers or segments, or the decision to reinforce market share through a world-class service level to customers are examples of features that are better modeled using multi-objective optimization.

This research results from a collaboration with an electric cable manufacturer whose production is held in two factories that manufacture both custom and standard products. Standard products are sold to stockists. This market is price-regulated, several players produce equivalent products, and products are sold “off-the-shelf". Therefore, an MTS strategy fits these products perfectly. On the other hand, custom products are personalized according to each customer’s requisites. Customers in this segment are usually electrical installers in the medium-high voltage sector. Products are customized since the early product stages, which makes these products MTO.

The manufacturer has to deal with a complex sales and operations planning context. First, the production of an electric cable is composed of multiple stages, such as wire drawing, annealing, twisting and stranding, extrusion, cabling, and outer sheath extrusion (Thue, 2017). The company had no analytical framework supporting decision-making, resulting in difficulties planning a complex production process organized in a flow shop/batch layout with multiple machines producing different product types. Second, the manufacturer faces capacity limitations, and potential demand cannot be fulfilled in full. Therefore, the S&OP committee is the appropriate managerial forum to discuss how to allocate capacity to satisfy either “off-the-shelf" products or customized products to electric installers.

While our model is motivated by a specific case study and incorporates specificities from this business setting, this planning context (flow shop/batch layout with MTS/MTO products) may arise in different industrial settings. Therefore, we model the framework in generic terms to make it more applicable to other realities. However, even though the model might require adjustments in other cases, the proposed planning rationale is completely replicable - employing a multi-objective approach to generate multiple plans supporting what-if S&OP meetings, where decision-makers may evaluate the impact of privileging a specific positioning strategy.

The remainder of the paper is organized as follows. We start by detailing the business case and the challenges behind this research in Section 3.2. Afterward, we review the related literature in Section 3.3. With a clear picture of the challenge at hand and the existing knowledge from previous research, we outline the decision-making framework in Section 3.4. We detail the S&OP decisions, formulate the multi-objective S&OP model, and describe the different positioning strategies a firm may adopt. Section 3.5 is dedicated to present how our framework can be used resorting to a real instance. The technical implementation of the Augmented ε-Constraint Method is briefly described beforehand. Section 3.6 provides some discussion and managerial insights, and presents the concluding remarks of this work.

3.2 Business Case

In this section, we present the business case motivating this research. We detail the commercial setting, in which some products are MTS and others are MTO, and relate it with the production, logistic, and procurement activities (Section 3.2.1). Then, in Section 3.2.2, we state the main challenges tackled by this research.

3.2.1 Case introduction

The cable manufacturer sells two types of products. Standard products are sold to stockists that, in turn, fulfill local stores that commercialize them to end consumers. These products are typically low voltage cables used in domestic electric networks. The segment is almost regarded as a commodity since several players produce equivalent products. On the other end, the company sells customized products that comprehend cables tailored to specific customer needs. These cables are generally produced for industrial applications or electric network constructions. For standard products, price and speed are critical success factors. For customized products, flexibility and quality become the most relevant dimensions. Therefore, standard products are Make-to-Stock (MTS), and customized products are Make-to-Order (MTO).

The production is held in two factories in a flow shop/batch environment. The company operates in a three-shift (24 hours) regime for five days a week. Overtime is possible using production during the weekends, but at a premium cost. The production process comprises several stages that occur in various machines, namely: wire drawing, annealing, twisting and stranding, extrusion, cabling, steel armoring, outer sheathing, optical fiber processing. We refer to Thue (2017) for a detailed description of the production process of electric cables.

There are multiple alternatives in each production stage, and different products may require different machines. Figure 3.2 presents an illustrative example of the production possibilities of two products (A and B) along four production stages (stages #1-#4). Product A has operations throughout all stages, whereas product B has only operations in stages #1-#3. In each step, there are compatibility issues, with specific and generic machines. From the combination of machines along the process, multiple production alternatives are defined.

Each finished product is the result of the production and combination of several semi-finished products. For instance, the operations of wire drawing, annealing, twisting and stranding result in a semi-finished product. This product can then be part of a multiplicity of finished products,

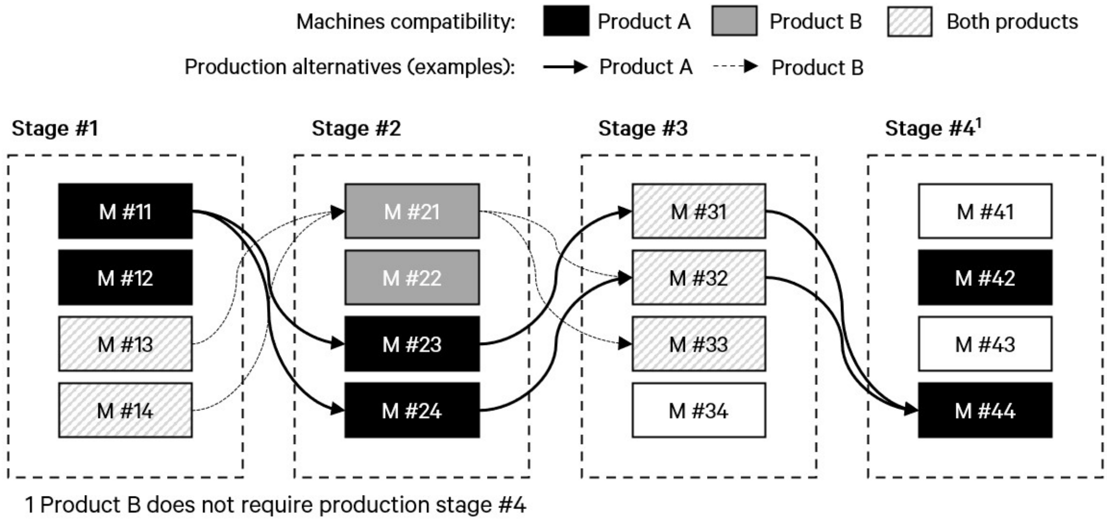


Figure 3.2: Production characterization (illustrative example with two products, four stages and four machines per stage)

depending on the downstream operations (e.g., different extrusion processes will convert this semi-finished product into specific semi-finished or finished products). Throughout this paper, we will use the generic term "product" to represent semi-finished and finished products.

MTS products planning is based on sales forecasts. MTO products planning is based on booked orders. Therefore, operations planning needs to combine orders and forecasts, to account for all the potential demand. In our case, there are some customers that, for MTS products, provide anticipated information of upcoming orders (that can be regarded as provisional orders). Such information can be used to revise original forecasts based on historical sales data only. The company also serves some customers under contractual agreements. Contractual quantities are translated into specific orders during the planning activities. As the production occurs in advance, this demand segment is also considered as Make-to-Stock.

Regarding logistic operations, all the products are packed before the expedition. This activity is performed in a single-stage operation where a set of packing machines is available. The packing operation's productivity varies by product, and capacity is finite (typically one shift five days a week) but extendable by the recourse to overtime. Even though this stage can be seen as an extension of the production, we consider it separately because the packing section is managed by a different team (i.e., the Logistics team). Shipping is ensured by third-party logistic companies with unlimited capacity, and is therefore out of the scope of this work.

On the procurement side, the company acquires raw materials (more specifically metals and polymers) from a set of suppliers. Some raw materials are subject to market availability in each period. In this case, the procurement team may purchase quantities in advance and store them internally to be used in production in the latter periods. When there is not enough capacity to fulfill the demand, the company can also acquire semi-finished products from the market at a higher cost. These semi-finished products are directly incorporated into the production.

3.2.2 Research challenges

This research proposes an approach to help the company balance the trade-off between producing to stock *versus* producing to orders while optimizing the sales and operations decisions in a coordinated way. Before the project leading to the results presented in this paper was run, there was already a S&OP committee to discuss a plan for the following months. Nevertheless, the company felt this process was inefficient, as the installed capacity is scarce to fulfill the demand. During the meeting, sales and operations teams need to discuss the trade-off between serving the stockists or the customers ordering customized products. However, there was no analytical support prescribing alternative plans, capable of evaluating the associated impacts, leading to endless meetings and low data-based discussions.

The S&OP meeting is of the utmost importance for this company. The production lead time of MTO products is long (in some cases, more than one month), and orders are placed with anticipation. Tactical planning plays a vital role in resource planning and order management. Stock levels of MTS products need to be planned to ensure enough quantities to fulfill the market, whereas MTO orders need to be fitted in the operations and procurement pipeline to guarantee customer lead time is accomplished. Raw materials shall be ordered in advance to ensure availability from the suppliers. The recourse to overtime should be anticipated for effective human resources management.

The decisions regarded in the S&OP meeting can be summarized as follows: purchasing quantities, production quantities, machines' allocation, overtime and subcontracting needs, inventory levels, packing quantities, orders acceptance, orders' delays, and forecasts and safety stocks fulfillment. These decisions are further detailed in Section 3.4. From a theoretical perspective, a S&OP meeting might include other topics, such as financial analysis, portfolio matching with potential demand, or innovations management (on the tactical-strategic range). However, we focus our research on capacity management and operations planning decisions (more on the operational-tactical range). It is into this scope that the MTS/MTO management integration becomes relevant, and it composes the decision-making range that the cable manufacturer company more poorly manages.

The common practice in S&OP is to generate aggregate plans (product family level, with a focus on the bottleneck operations), as further detailed in Section 3.3. However, to depict the process accurately, such aggregation is not possible due to the company's complex flow shop/batch process. Machine bottleneck identification is not straightforward. From the 43 machines along the multiple production stages in one of the production facilities, there are 35 that may limit the throughput depending on the processed product (Figure 3.3). We can see that there is not a bottleneck section (the most constrained section is “Shielding and steel armoring", which comprehends the bottleneck stage for 33.2% of the products). Even in each section, it is not possible to delimit one particular machine as the bottleneck. For instance, in the “Outer sheathing" stage, there are five from a total of seven machines that become bottleneck multiple times. Therefore, from period to period, changes in the forecasts or upcoming orders result in different bottleneck machines throughout the process.

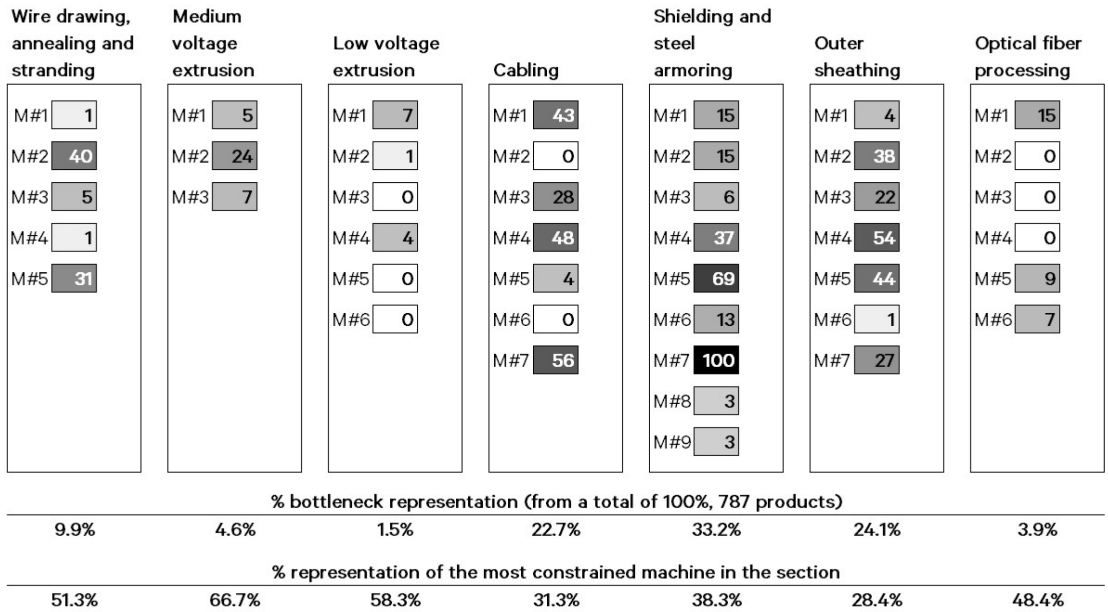


Figure 3.3: Bottleneck incidence representation in one of the facilities. For each section, the number inside each square represents the number of times the machine is bottleneck. E.g., There are 43 products whose bottleneck operation is performed at Cabling: M#1. More details on bottleneck characterization are available in Appendix 3.A

Regarding production similarity between products, it is not obvious to cluster the products according to the production alternatives. Although the 787 potential products manufactured in this production facility can be grouped around ten commercial families (more details in Appendix 3.A), they are much more diverse from a production viewpoint. Considering only the primary (preferential) production alternative for each product, there are 464 distinct production sequences enclosing all the products. Nevertheless, considering production sequences with equal production times, the number of combinations rises to 721. It is essential that the research reveals capable of generating realistic S&OP plans despite these issues. This section illustrates how aggregated approaches to S&OP are simplistic to represent a production process like ours.

3.3 Literature review

There are three streams of literature in operations research and operations management relevant to our work: the literature on S&OP models (Section 3.3.1), the literature on capacity coordination models for hybrid production contexts (Section 3.3.2), and the literature that studied managerial and production policies in MTS/MTO settings (Section 3.3.3). We also highlight some related paradigms associated to S&OP and MTS/MTO management, and position our work against those concepts (Section 3.3.4).

3.3.1 Sales and Operations Planning models

The origin of S&OP can be traced to business management and production planning domains. Regarding the former, the concept was introduced in the late 1980s by Dick Ling and Walter Goddard (Ling & Goddard, 1988). The Manufacturing Resource Planning (MRP II) was a trend, and S&OP was introduced as a driver whose main goal was to make MRPII work in a manufacturing plant. Marketing and manufacturing teams are proposed to conciliate demand and supply chain management decisions by agreeing once a month on a set of numbers for sales, production, and inventory. On the production planning side, the concept can be linked to the early work of Charles C. Holt, Franco Modigliani, John F. Muth, and Herbert A. Simon, who developed a linear-quadratic model of aggregate production planning in the 1950s (Singhal & Singhal, 2007). The concept evolved to consist of two complementary plans: a production plan and a demand-based sales plan (Olhager et al., 2001). More recently, researchers started to address S&OP as a fully integrated supply chain planning.

Research on decision support systems (and models) addressing S&OP has evolved without the definition of common ground. New models have been developed to tackle specific problems rather than to encompass generic approaches to the mid-term S&OP (Pereira et al., 2020). Therefore, several models can be seen as analytical frameworks tackling the S&OP problem. We refer to the review from Pereira et al. (2020) for an in-depth review of decision-making approaches to this category of problems. In Table 3.1, we highlight the most comprehensive models (the ones containing decisions from procurement, production, distribution/logistics, and sales, similar to our case), focusing on how they account for the particularities that arise in a situation of hybrid production strategy.

Most of the past models on S&OP consider a long planning period (12 or more months). Still, some models were designed and assessed considering a shorter planning horizon. Nonetheless, even in this latter category, there is no reference to the hybridization between orders and forecasts, except for the work from Lim et al. (2017). The demand side of the models is typically based on forecasts, and the models consider a pure production strategy (an MTS strategy for most of them). Concerning the number of production stages, most of the models consider single-stage contexts, either because the process is continuous, where the bottleneck operation is more easily found, or there is clearly a bottleneck section/machine.

Regarding the detail of this planning layer, the original definitions of S&OP call for aggregated approaches. The APICS dictionary (Cox & Blackstone, 2002) mentions an exercise that "(...) is performed at least once a month and is reviewed by management at an aggregate (product family) level." Past reviews on the topic also reinforce such characteristic. S&OP is done at the product family level (Noroozi & Wikner, 2017; Thome et al., 2012), with a monthly granularity (Noroozi & Wikner, 2017; Pereira et al., 2020; Thome et al., 2012), and considering aggregated capacities around the bottleneck operations (Noroozi & Wikner, 2017). Nevertheless, some researchers suggest that, if needed, the plan may be generated at the product level (Grimson & Pyke, 2007; Thome et al., 2012) and considering the machine level (Pereira et al., 2020).

Table 3.1: Past literature: S&OP models

Reference	Sector/ industry	Planning horizon [1]	Strategy [2,3]	Demand basis	No. stages
Abedi and Zhu (2017)	Warm fish	Medium	-	Forecast	Multi
Ali, D' Amours, Gaudreault, and Carle (2019)	Wood	Short	MTS	Forecast	Multi
Sanei Bajgiran, Kazemi Zanjani, and Nourelfath (2016)	Wood	Long	MTO	Forecast	Multi
Catalá, Moreno, Blanco, and Bandoni (2016)	Fruit	Long	-	Forecast	Multi
Chen-Ritzo, Ervolina, Harrison, and Gupta (2010)	Computers/ electronics	Medium	ATO	Forecast	Single
Darmawan, Wong, and Thorstenson (2018, 2020)	Consumer goods	Long	MTS	Forecast	Single
Fahimnia, Farahani, and Sarkis (2013); Fahimnia, Luong, and Marian (2012)	Automotive	Short	-	Forecast	Single
Feng et al. (2008); Feng, D'Amours, and Beauregard (2009); Feng, Martel, D'Amours, and Beauregard (2013)	Wood	Long	MTO	Forecast	Single
Fumero and Vercellis (1997)	Manufacturing (general)	Long	MTS	Forecast	Multi
Ghasemy Yaghin, Torabi, and Fatemi Ghomi (2012)	Short life-cycle consumer goods	Long	MTS	Forecast	Single
Ghasemy Yaghin (2018)	Textile	Short	MTS	Forecast	Single
Ghasemy Yaghin (2020)	Textile	Medium	MTS	Forecast	Single
Gunnarsson and Rönnqvist (2008)	Pulp/paper	Long	MTO	Orders	Single
Lidestam and Rönnqvist (2011)	Pulp/paper	Long	MTO	Orders	Single
Lim, Alpan, and Penz (2017)	Automotive	Long	ATO	Forecast and orders	Single
Mirzapour Al-E-Hashem, Malekly, and Aryanezhad (2011)	Pulp/paper	Long	-	Forecast	Single
Nemati and Alavidoost (2018); Nemati, Madhoushi, and Ghadikolaei (2017a)	Fast moving consumer goods	Long	MTS	Forecast	Single
Nemati, Madhoushi, and Ghadikolaei (2017b)	Plastic forming	Long	MTS	Forecast	Single
Peidro, Mula, Alemany, and Lario (2012)	Ceramics	Short	MTS	Forecast	Single
Sodhi and Tang (2011)	Computers/ electronics	Medium	-	Forecast	Single
Souza, Zhao, Chen, and Ball (2004)	Computers/ electronics	Short	-	Forecast	Multi
Susarla and Karimi (2018)	Pharmaceutical	Medium	MTS	Forecast	Multi
Torabi and Moghaddam (2012)	Minerals	Short	MTS	Forecast	Single
Van Elzakker, Zondervan, Raikar, Hoogland, and Grossmann (2014)	Fast moving consumer goods	Long	MTS	Forecast	Single
Wang, Hsieh, and Hsu (2012)	Computers/ electronics	Long	-	Forecast	Single
Wei, Guimarães, Amorim, and Almada-Lobo (2017)	Glass container	Long	MTS	Forecast	Multi
G. Zhang, Shang, and Li (2011)	Automotive	-	ATO	Forecast	Multi

1 Short - 3 months, Medium - between 3 and 12 months, Long - 12 or more months
2 Production to stock if explicitly mentioned or if the model accounts for safety stock levels
3 ATO: Assembly-to-Order

The identification and segmentation of product families should be based on the properties of the products and the markets. The products should be aggregated, so the assumed mix provides the highest consistency between marketing and production (Noroozi & Wikner, 2016). One way would be to define product families based on the production process, further sub-divided in the function of the market characteristics (Burrows, 2012). Another approach would be to perform a market segmentation by geography (Jacobs, Berry, Whybark, & Vollmann, 2011), followed by a translation into production product families (Wallace & Stahl, 2008).

3.3.2 Capacity coordination models on hybrid production contexts

On the side of the MTS/MTO literature, the paper from Soman et al. (2004) is a seminal work on the intersection of the different planning horizons (strategic, tactical, operational) and the MTS/MTO systems. The paper introduces a general framework (customized to food processing industries) to decide on the main problems in managing a combined MTS/MTO system. According to the author, the most strategic issue in an MTS/MTO system is the partitioning decision (that is, the decision whether a product should be MTS or MTO). In the mid-term horizon, MTO order acceptance policy and due date policies, and MTS lot sizes and monthly production volumes need to be determined (capacity coordination issues). Finally, the operational layer decides on the daily production volumes and production sequences. Since we focus on the mid-term issues, we do not detail the literature on order partitioning issues and operational planning and controlling.

In a subsequent work (Soman et al., 2007), the authors applied the framework to a case study and, although they recognized its importance in designing the planning and scheduling hierarchy, they also recognized the need to develop some analytical decision aids to support each of the planning layers. Hence, some subsequent contributions have built decision-making models on top of this framework. In the paper from Rafiei and Rabbani (2012), MTO product families are prioritized, so some initial capacity is allocated. Then, the production values of MTS (and MTS/MTO) product families are determined using a backward lot-sizing algorithm. Finally, a decision on order acceptance for MTO families is made. The paper from Rafiei, Rabbani, and Alimardani (2013) also considers this rationale, proposing a bi-level hierarchical production planning algorithm integrating mid-term and short-term production planning levels. Rafiei, Rabbani, and Hosseini (2014) model capacity coordination issues of a hybrid MTS/MTO production system using a system dynamics approach by which different coordination rules are evaluated in terms of delivery lead time. Although not based on the framework from Soman et al. (2004), early on, Tsubone, Ishikawa, and Yamamoto (2002) proposed a hierarchical production planning model, in which aggregated capacity decisions for MTS/MTO production are set at a higher planning level, with rules for allocating production capacity to types of products at a lower level.

More recently, a few papers have considered additional capacity coordination decisions in hybrid production contexts. Rafiei, Rabbani, and Kokabi (2014) tackle multi-site production planning of a manufacturing firm using a mixed-integer mathematical model. A network of suppliers, manufacturers, and customers is considered. T. Zhang, Zheng, Fang, and Zhang (2015) presented a nonlinear integer programming model that optimizes the multi-level inventory matching and order planning for steel plants. It weighs the cost of earliness/tardiness penalty, tardiness penalty in the delivery time window, inventory matching, order cancellation penalty, and machine capacity penalty. The paper from Khakdaman, Wong, Zohoori, Tiwari, and Merkert (2015) brings a medium-range production planning for a combined MTS–MTO business environment. The model was converted into a robust optimization framework by incorporating different sources of uncertainty. Elmehanny, Abdelmaguid, and Eltawil (2019) propose a mixed-integer linear programming capacity and financial model for production planning in the garment industry.

3.3.3 Production policies on hybrid production contexts

A different stream of literature on hybrid production contexts has been dedicated to the study of production policies. Adan and Van Der Wal (1998) model a two-stage production system as a Markov Decision Process to investigate the effect of combining MTO and MTS on the production lead time. The paper concludes that the combination of MTO and MTS orders reduces the production lead time due to stock production during idle time.

The study from Federgruen and Katalan (1999) analyzes the impact of adding an MTO item to an MTS production system considering inventory holding, stock-out, and setup costs. Different priority rules have been assessed (absolute priority *versus* postponable). The authors present cost curves for different rules under varied circumstances and calculate marginal break-even prices at different capacity utilization rates. Hadj Youssef, Van Delft, and Dallery (2004) also study the impact of distinct priority rules for MTO and MTS product classes. The authors compare a first-in-first-out (FIFO) rule with a priority rule for MTO products in a single-stage manufacturing facility producing multiple heterogeneous products.

Some papers have studied production and order acceptance policies in hybrid production systems (Beemsterboer et al., 2016; Beemsterboer, Land, & Teunter, 2017; Carr & Duenyas, 2000; Iravani, Liu, & Simchi-Levi, 2012). All use Markov Decision Process models with one MTO and one MTS product and study the problem structure to derive optimal policies. Carr and Duenyas (2000) and Iravani et al. (2012) consider manufacturers that produce on an MTS basis for contract customers and on an MTO basis for the remaining ones, where the MTS orders have a higher priority. Their studies determine decisions based on the MTS inventory level and the amount of MTO products. Beemsterboer et al. (2016), relying on the same approach, developed a more generic model regarding the type of industry. This model does not consider different levels of priority between MTS and MTO but includes lead time considerations for MTO orders. The authors conclude that relevant cost savings are obtained against planning methods that prioritize either MTO or MTS products. Beemsterboer, Land, and Teunter (2017) studied the benefits of varying MTS lot sizes in hybrid production systems. The paper finds that a flexible approach regarding lot sizes may lead to additional savings.

Early on, Gupta and Wang (2007) presented a discrete-time Markov Decision Process to analyze two scenarios. In the first one, the firm produces the demand from all the customers on an MTO basis. In the second, a hybrid MTS-MTO mode is applied, and inventory is held for contractual customers. The paper defines the structure of the optimal policies, and the models are used to study the effect of demand variability on profit.

Beemsterboer, Land, Teunter, and Bokhorst (2017) focused on integrating MTS specificities into job-shop production systems that are typically oriented to fulfill due dates, which do not apply to MTS items. The authors present four methods for considering this dynamic into the job-shop control and assess them using discrete event simulation. They conclude that advanced methods of considering MTS into job-shop outperform simple rules.

3.3.4 Related paradigms on S&OP and MTS/MTO management

In recent years, Ptak and Smith (2018) proposed a new management model that extends the traditional S&OP practices to ensure companies are more effective to sense market changes, adapt to complex and volatile environments, and incorporate market-driven innovation strategies. The model, entitled Demand Driven Adaptive Enterprise (DDAE), is composed of three main cornerstones: the Demand Driven Operating Model (DDOM), Demand Driven Sales and Operations Planning (DDS&OP), and Adaptive Sales and Operations Planning (AS&OP). Through an efficient feedback loop between these layers (respectively, operational, tactical, and strategic), the authors suggest that companies will succeed in adapting to complex and volatile circumstances.

The DDOM layer comprises a scheduling and execution model that incorporates decoupling points (*i.e.* points in the supply chain or production process where stock is kept) to create an agile system that manages the flow of information and materials within the operational range (hourly, daily and weekly). The key parameters to manage such a system are set through DDS&OP. DDS&OP is a bi-directional tactical layer connecting the strategic and operational decision-making ranges. DDS&OP is responsible for the tactical projection, that is, to understand how DDOM might perform in the upcoming tactical range and to help reconcile DDOM with the evolving business strategy. This layer also projects capacity into the future to see if it matches potential demand scenarios. Finally, AS&OP is an integrated business process that supports senior management in defining, directing, and managing the business from a strategic point of view. Market-driven innovation, go-to-market strategy, and financial strategy are incorporated to create a long-term business plan. Compared to DDS&OP, AS&OP is more flexible and suggests more changes to the current business landscape (e.g., AS&OP includes portfolio analysis, while DDS&OP considers product range as an assumption).

While framing our research within this framework, we make two considerations. First, our model can be framed in the DDS&OP stage of the DDAE framework. As further detailed, our approach comprises a framework to manage S&OP considering there are products manufactured to stock and others in function of received orders. We shape demand to existing capacity for the medium-term and define fulfillment priorities in the function of the decision-makers' preferences. The kind of decisions taken in AS&OP can be regarded as an input for our model. Second, we highlighted that DDOM incorporates the strategic definition of decoupling points which are key to ensure shorter lead times while allowing customization. This is related to Assembly-to-Order (ATO), a third production strategy, not mentioned so far, in which standard parts or components are manufactured to stock, with the final assembly occurring once a specific order is placed. An MTO company may migrate to an ATO strategy because of expanding volume and substantial similarity between some products. An MTS company may shift to an ATO strategy pressured by the market to expand its product portfolio continuously (Wemmerlov, 1984). Nevertheless, in our case, it is not interesting to define intermediate decoupling points throughout the process. Standard products (assumed MTS) are required immediately, with no customization, which positions the decoupling point at the end of the production process. On the other hand, custom products (assumed MTO) do not share significant similarities and are produced according to customers' requirements since the early stages, which positions the decoupling point at the beginning of the production process.

Another paradigm related to MTS/MTO management and strategic decoupling points definition is the concept of delayed production differentiation (DPD). DPD assumes the manufacturing process starts by making a generic intermediate product later customized according to the specific finished product. Under this management paradigm, defining where to position the stock and further customize the products is critical. Therefore, some advanced production strategies are emerging, in which final product customization is performed either by assembling or disassembling components from product platforms made to stock (Galizia, ElMaraghy, Bortolini, & Mora, 2020; Hanafy & ElMaraghy, 2015). This customization tactic is an advancement over the traditional ATO strategy.

3.4 Decision-making framework

When we connect the business case at hand with the literature review, we conclude that there is no S&OP decision-making framework capable of helping the company managing its sales and operations decisions, considering part of the portfolio is MTS, and the remainder is MTO. Past S&OP models do not address the co-existence of different production types. Simultaneously, except for the papers from Elmehanny et al. (2019); Khakdaman et al. (2015); Rafiei, Rabbani, and Kokabi (2014), MTS/MTO capacity coordination models are too narrow in the decision-making spectrum (focused on production decisions, not supply chain issues, such as raw materials acquisition, production outsourcing, or logistics activities management, important in our case).

The literature review unveiled that some papers focus on the definition of production and order acceptance policies that can minimize the total costs involved (Beemsterboer et al., 2016; Carr & Duenyas, 2000; Iravani et al., 2012). These studies explore the MTS/MTO trade-off while presenting frameworks that detail the main levers behind these policies. Nevertheless, they do not depict a holistic S&OP context, because they consider only one MTS product and one MTO product, which is insufficient for this purpose.

Concerning the complexity of the system, most of the approaches depict single-stage production environments. Even the ones referred to as multi-stage, in Table 3.1, do not consider the challenge of multiple routes and production possibilities arising in flow shop/batch environments like ours. The formulations tend to consider a bottleneck operation only, which is not the case in our problem.

As a result, we propose an innovative framework to support S&OP for hybrid flow shop/batch companies. We start by explaining the main decisions and dynamics involved in the S&OP meeting (Section 3.4.1). Afterward, in Section 3.4.2 we present the model. Finally, in Section 3.4.3 a business-oriented matrix is presented to help managers interpreting the solutions of the model in business terms. Although the approach is motivated by the cable manufacturer case presented, we model it in generic terms to make it reproducible in other similar contexts.

3.4.1 S&OP decision-making

We propose the S&OP meeting to be based in cross-functional planning with Procurement, Production, Logistics, and Sales teams, to find the most efficient plan for future periods. In this context, and to answer to the challenges raised in Section 3.2, we propose a decision-making framework capable of managing the complex operations setting while weighting the trade-off of producing to stock *versus* producing to orders in the medium term. It is a prerequisite that there is a Planning department that mediates the process - the team is responsible for gathering the information and generate the plans to be discussed in the meeting.

The proposed decision-making spectrum is detailed in Figure 3.4. The dashed arrows represent the information flows around the S&OP meeting (both inputs and outputs). The demand information triggers the process, in the form of forecasts for MTS products (based on historical demand) and booked orders for MTO products. To fulfill the market needs, during the S&OP meeting, some decisions are taken: (i) raw materials and semi-finished products volumes, (ii) production quantities for MTO and MTS products, (iii) capacity reservation for MTO products, (iv) customer orders' acceptance and realistic delivery dates, (v) packing quantities, and (vi) overtime both for production and packing. Capacity reservation is not always evaluated - depending on the amount of booked orders and MTS forecasts, plans may be generated considering all the available capacity. This lever can be seen as a strategy to minimize changes in the plans between consecutive S&OP meetings. As we advance in the planning horizon, the more likely it is that additional orders from MTO products will be placed after the current S&OP meeting. Thus, if capacity is always planned up to the maximum, the operations decisions for those periods need to be revised (mainly for MTS products).

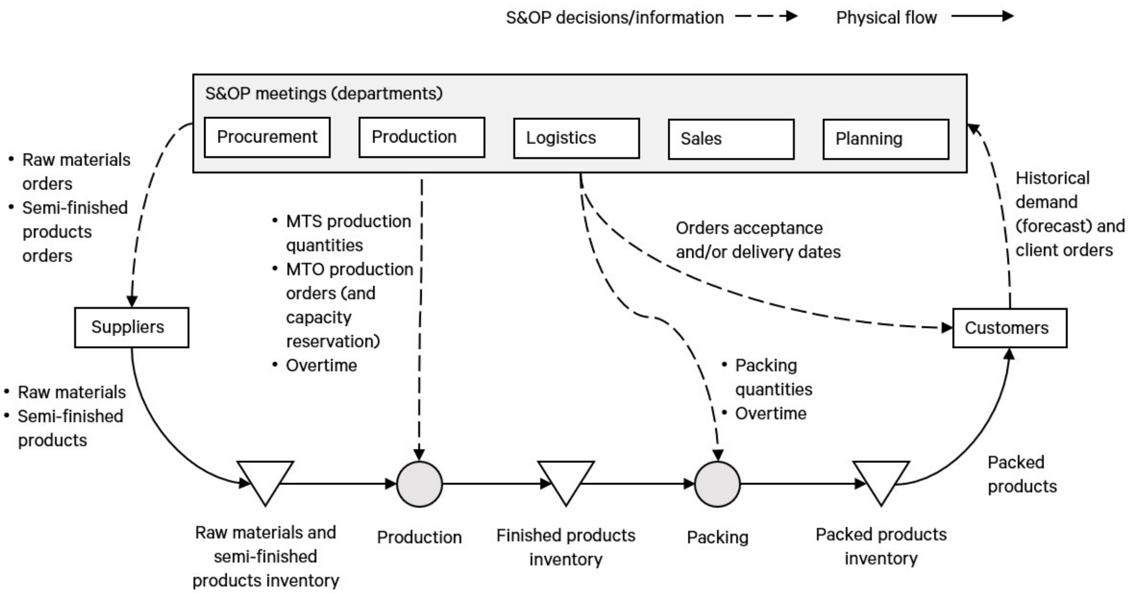


Figure 3.4: Sales and Operations decision-making spectrum

As a result, the business functions have the necessary information for short-term plans which guide the execution phase (represented by continuous arrows in Figure 3.4). The operational planning activities are not detailed as they are not part of S&OP. Some examples might be the definition of a detailed receptions plan by the Procurement team or the scheduling plan by the Production team.

To accomplish the explicit trade-off between producing to stock *versus* producing to orders, we propose a multi-objective approach during plans generation. Depending on the products and throughout the year, priority rules shift between standard and customized productions, for instance, either because stock levels of MTS products vary, or customers' portfolio with booked orders changes significantly. Thus, we provide decision-makers with various plans, so they can analyze the different options' impacts before the mid-term decisions are taken. There are three objectives to consider: the maximization of the MTO demand that is satisfied on time, the maximization of MTS forecasts' fulfillment, and the minimization of the total costs. We formulate a multi-objective Mixed-Integer Programming (MIP) model integrating sales, production, logistics, and procurement decisions. The model is described in Section 3.4.2.

Given the complexity of the production setting, we propose the plan to be generated at the product level and considering machine detail. Although this is not the most usual approach given the aggregated and tactical nature of S&OP, it can be necessary when the production setting is intricate, with multiple bottlenecks and different production alternatives. This challenge emerges in our case, but it is also evident in other flow shop/batch processes, such as twine production or textile manufacturing.

Finally, regarding the planning horizon, we propose the model to be used in a three to twelve-month horizon (adjustable to the case), with monthly time-buckets. If needed, the first periods may include a weekly detail to better account for orders' due dates. A six-month horizon is used by the cable manufacturer, with weekly detail in the first month.

3.4.2 Multi-objective S&OP MIP model

Indexes and sets:

$r \in R$	Set of raw materials
$s \in S$	Set of semi-finished products
S_{out}	Set of semi-finished products that can be outsourced from the market ($S_{out} \subset S$)
$f \in F$	Set of finished products
F_{MTO}	Set of finished products defined as make-to-order (MTO) ($F_{MTO} \subset F$)
F_{MTS}	Set of finished products defined as make-to-stock (MTS) ($F_{MTS} \subset F$)
$p \in P$	Set of products ($P = F \cup S$)
$t \in T$	Set of periods
$m \in M$	Set of machines
$a_p \in A_p$	Set of alternative sequences of machines to produce product p ($a_p = \{m(1), m(2), ..., m(n)\}, m \in M$)

$pm \in pM$	Set of packing machines
pM_f	Set of compatible packing machines for packing finished product f ($pM_f \subset pM$)
F_{pm}	Set of finished products that can be packed in packing machine pm ($F_{pm} \subset F$)
B_s	Set of direct successors of s, i.e., products containing semi-finished product s ($B_s \subset P$)
$e_f \in E_f$	Set of booked orders for finished product f
$\kappa \in K$	Degrees of satisfaction of the safety stock, that is, levels of fulfillment of the target ($K \not\ni 0$)

Parameters:

Procurement:

p^R_r	Purchasing cost of raw material r
$q^R_{r,t}$	Maximum quantity of raw material r that can be purchased in period t
$h^R_{r,t}$	Holding cost of one unit of raw material r in period t
i^R_r	Initial inventory of raw material r
p^S_s	Purchasing cost of semi-finished product s
$q^S_{s,t}$	Maximum quantity of semi-finished product s that can be purchased in period t

Production:

$\alpha_{r,s}$	Amount of raw material r used in the production of one unit of semi-finished product s
$\beta_{s,p}$	Amount of semi-finished product s used in the production of one unit of product p
i^S_s	Initial inventory of semi-finished product s
$h^S_{s,t}$	Holding cost of one unit of semi-finished product s in period t
$reg^M_{m,t}$	Amount of regular time available at machine m in period t
$over^M_{m,t}$	Amount of overtime available at machine m in period t
$\omega_{p,m}$	Production time in machine m per unit of product p
c_m	Cost per unit of time in machine m
o^M_m	Additional production cost (incremental rate) per unit of overtime in machine m
min_p	Minimum lot size of product p

Logistics:

i^F_f	Initial inventory of non-packed finished product f
$h^F_{f,t}$	Holding cost of one unit of finished product f in period t
l^F_f	Initial inventory of packed finished product f
$reg^{pM}_{pm,t}$	Amount of regular time available at packing machine pm in period t
$over^{pM}_{pm,t}$	Amount of overtime available at packing machine pm in period t
$\upsilon_{f,pm}$	Packing time in machine pm per unit of finished product f
cpa_{pm}	Cost per unit of time in packing machine pm
o^{pM}_{pm}	Additional packing cost (incremental rate) per unit of overtime in packing machine pm

Sales:

$d_{f,t}$	Total demand for finished product f in period t
pr_f	Average sales price of finished product f
prc_{e_f}	Sales price of finished product f in order e_f
z_{e_f}	Quantity of finished product f in order e_f
dt_{e_f}	Due date of order e_f (period $t \in T$)
$for_{f,t}$	Additional demand forecasted for finished product f in period t, following $d_{f,t} = for_{f,t} + \sum_{e_f \in E_f : dt_{e_f} = t} z_{e_f}$. If $f \in F_{MTO}$, $for_{f,t} = 0, \quad \forall t \in T$
pen_{e_f}	Penalty (price depreciation rate) per each day of delay of order e_f
nd	Total number of days in the planning horizon
ld_t	Last day of period t
$ss_{f,t}$	Target safety stock of finished product f in period t. If $f \in F_{MTO}$, $ss_{f,t} = 0, \quad \forall t \in T$
ϕ_κ	Percentage of attainment associated to the κ^{th} level of satisfaction ($0 \leq \phi_\kappa \leq 1$)
θ_κ	Premium coefficient within the κ^{th} level of satisfaction (i.e. multiplied by the percentage of attainment ϕ_κ)
max_p	Maximum production quantity of product p, given by $\sum_{t \in T} d_{f,t} + ss_{f,t}$. For semi-finished products, the value is obtained by the transformation of the maximum production quantity of finished products over the bill of materials

Decision variables:

Procurement:

$V^R_{r,t}$	Purchasing quantity of raw material r in period t
$V^S_{s,t}$	Purchasing quantity of semi-finished product s in period t. If $s \notin S_{out}$, $V^S_{s,t} = 0$
$I^R_{r,t}$	Inventory of raw material r at the end of period t. Assume $I^R_{r,0} = i^R_r$

Production:

$X_{a_p,t}$	Production quantity of product p using alternative a_p in period t
$Y_{a_p,t}$	Binary variable, stating if production alternative a_p is used in period t
$O^M_{m,t}$	Overtime used at machine m in period t
$I^S_{s,t}$	Inventory of semi-finished product s at the end of period t. Assume $I^S_{s,0} = i^S_s$

Logistics:

$W_{f,pm,t}$	Packed quantity of finished product f at packing machine pm in period t
$O^{pM}_{pm,t}$	Overtime used at packing machine pm in period t
$I^F_{f,t}$	Inventory of non-packed finished product f at the end of period t. Assume $I^F_{f,0} = i^F_f$
$L^F_{f,t}$	Inventory of packed finished product f at the end of period t. Assume $L^F_{f,0} = l^F_f$

Sales:

$K_{e_f,t}$	Binary variable, stating if order e_f is dispatched in period t
P_{e_f}	Binary variable, stating if order e_f will not be dispatched during the planning horizon (i.e., order acceptance)

D_{e_f}	Number of days of delay of order e_f relative to the due date
$T_{\kappa,f,t}$	Binary variable, stating if the κ^{th} level of satisfaction of the target safety stock of finished product f is attained in period t
$J_{\kappa,f,t}$	Percentage of attainment of the κ^{th} level of satisfaction of the target safety stock of finished product f in period t
$G_{f,t}$	Forecasted quantity for finished product f to be delivered in period t

Constraints:

Procurement:

$$I^R_{r,t} = I^R_{r,t-1} + V^R_{r,t} - \sum_{s\in S}\sum_{a_i\in A_i:i=s} X_{a_i,t}\alpha_{r,s}, \quad \forall r \in R, t \in T. \tag{3.1}$$

$$V^R_{r,t} \le q^R_{r,t}, \quad \forall r \in R, t \in T \tag{3.2}$$

$$V^S_{s,t} \le q^S_{s,t}, \quad \forall s \in S_{out}, t \in T \tag{3.3}$$

Production:

$$X_{a_p,t} \le max_p Y_{a_p t}, \quad \forall p \in P, a_p \in A_p, t \in T \tag{3.4}$$

$$X_{a_p,t} \ge min_p Y_{a_p,t}, \quad \forall p \in P, a_p \in A_p, t \in T \tag{3.5}$$

$$\sum_{p\in P}\sum_{a_i\in A_i:a_i\ni m\wedge i=p} X_{a_i,t}\omega_{p,m} \le reg^M_{m,t} + O^M_{m,t}, \quad \forall m \in M, t \in T \tag{3.6}$$

$$O^M_{m,t} \le over^M_{m,t}, \quad \forall m \in M, t \in T \tag{3.7}$$

$$I^S_{s,t} = I^S_{s,t-1} + \sum_{a_i\in A_i:i=s} X_{a_i,t} - \sum_{p\in B_s}\sum_{a_p\in A_p} X_{a_p,t}\beta_{s,p} + V^S_{s,t}, \quad \forall s \in S, t \in T \tag{3.8}$$

Logistics:

$$\sum_{f\in F_{pm}} W_{f,pm,t}\upsilon_{f,pm} \le reg^{pM}_{pm,t} + O^{pM}_{pm,t}, \quad \forall pm \in pM, t \in T \tag{3.9}$$

$$O^{pM}_{pm,t} \le over^{pM}_{pm,t}, \quad \forall pm \in pM, t \in T \tag{3.10}$$

$$I^F_{f,t} = I^F_{f,t-1} + \sum_{a_i\in A_i:i=f} X_{a_i,t} - \sum_{pm\in pM_f} W_{f,pm,t}, \quad \forall f \in F, t \in T \tag{3.11}$$

$$L^F_{f,t} = L^F_{f,t-1} + \sum_{pm\in pM_f} W_{f,pm,t} - \sum_{e_f\in E_f} z_{e_f} K_{e_f,t} - G_{f,t}, \quad \forall f \in F, t \in T \tag{3.12}$$

Sales:

$$P_{e_j} + \sum_{t\in T:t\ge dt_{e_j}} K_{e_j,t} = 1, \quad \forall e_j \in E_j : j = f, f \in F \tag{3.13}$$

$$D_{e_j} = \sum_{t \in T: t \geq dt_{e_j}} ld_t K_{e_j,t} - dt_{e_j}(1 - P_{e_j}), \quad \forall e_j \in E_j : j = f, f \in F \tag{3.14}$$

$$G_{f,t} \leq for_{f,t}, \quad \forall f \in F, t \in T \tag{3.15}$$

$$L^F_{f,t} \geq ss_{f,t} \phi_\kappa T_{\kappa,f,t}, \quad \forall f \in F_{MTS}, \kappa \in K, t \in T \tag{3.16}$$

$$L^F_{f,t} \geq ss_{f,t} \phi_1 J_{1,f,t} + \sum_{\kappa \in K: \kappa > 1} ss_{f,t}(\phi_\kappa - \phi_{\kappa-1}) J_{\kappa,f,t}, \quad \forall f \in F_{MTS}, t \in T \tag{3.17}$$

$$J_{\kappa,f,t} \leq T_{\kappa-1,f,t}, \quad \forall f \in F_{MTS}, \kappa \in K : k > 1, t \in T \tag{3.18}$$

$$J_{1,f,t} \leq 1, \quad \forall f \in F_{MTS}, t \in T \tag{3.19}$$

Domain constraints:

$$\begin{aligned} V^R_{r,t}, V^S_{s,t}, I^R_{r,t}, X_{a_p,t}, O^M_{m,t}, I^S_{s,t}, W_{f,pm,t}, I^F_{f,t}, L^F_{f,t}, O^{pM}_{pm,t}, D_{e_f}, G_{f,t}, J_{\kappa,f,t} \geq 0, \quad \forall r \in R, \\ s \in S, f \in F, p \in P, a_p \in A_p, e_f \in E_f, m \in M, pm \in pM, t \in T, \kappa \in K \end{aligned} \tag{3.20}$$

$$Y_{a_p,t}, K_{e_f,t}, P_{e_f}, T_{\kappa,f,t} \in \{0,1\}, \quad \forall p \in P, a_p \in A_p, f \in F, e_f \in E_f, t \in T, \kappa \in K \tag{3.21}$$

Regarding procurement constraints, constraints (3.1) are necessary to ensure the inventory balance of raw materials between periods. Constraints (3.2) and (3.3) guarantee that the purchases in each period respect the raw materials and semi-finished products availability.

Constraints (3.4) and (3.5) impose limitations on production quantities. Equations (3.4) are activation constraints, ensuring that production quantities of a product in a given alternative must be preceded by the activation of that alternative. Constraints (3.5) impose that the minimum lot size is respected in the case of production. Constraints (3.6) and (3.7) limit production quantities. The first set limits the production on each machine to the available time. The second set states that overtime can not surpass a specified value. Inventory balance equations of semi-finished products are given by constraints (3.8), defining that the amount of inventory of semi-finished product s at the end of period t is given by the amount from the previous period plus the production of the period and eventual quantities acquired from the market subtracted by the quantity of s used in the production of B_s.

Concerning logistics, constraints (3.9) and (3.10) are equivalent to constraints (3.6) and (3.7), limiting quantities for each packing machine pm in each period t. Equations (3.11) ensure the inventory balance for non-packed finished products. The inventory of any product f at the end of t is given by the inventory at the end of $t-1$ plus the production of p in t minus the amount sent for packing in the same period. Constraints (3.12) concern the inventory balance for packed products. The inventory balance of f in t is given by the amount of packed inventory at the end of $t-1$ adjusted by inflow and outflow variables. The outflow variables are expressed by the quantities dispatched to customers, both from orders and forecasts. These constraints define the linkage between internal operations and customers.

With respect to sales, constraints (3.13) define that each order can be either fulfilled in any of the planning periods t in the due date or after ($\sum_{t\in T:t\geq dt_{e_f}} K_{e_j,t} = 1$) or not satisfied at all ($P_{e_j} = 1$). Constraints (3.14) determine the potential delivery delay of order e_f. Recall that we model the possibility that provisional/anticipated orders might be placed for MTS products, even though we assume that most of the demand is placed in the short-term, and, therefore, matched directly with existing stock. On the side of the additional forecasted quantities, constraints (3.15) establish that delivered quantities of any MTS product f in period t must not surpass the forecast (for MTO products, $for_{f,t} = 0, \quad \forall t \in T$). Equations (3.16)-(3.19) are used to model safety stocks. Equations (3.16) define if the k^{th} level of satisfaction of the target safety stock of every MTS product is attained in each period given inventory at the end of t. Constraints (3.17) define the percentage of attainment for the several levels of satisfaction of the target safety stock of finished product f, given the packed inventory $L^F_{f,t}$. Constraints (3.18) and (3.19) define the relationship between the binary and the linear variables. The percentage of attainment of the k^{th} level of satisfaction of the target safety stock of f can only be positive if $T_{\kappa-1,f,t}$ is accomplished. With this approach we are defining safety stock levels as an objective to reach rather than a constraint. The premium coefficient associated to the percentage of attainment of the k^{th} level is lower than the shortage cost (to ensure the preference for demand satisfaction) but greater than the holding cost. For the ones interested in detailing this approach, we refer to the paper from Absi and Kedad-Sidhoum (2009).

Finally, constraints (3.20) and (3.21) define the domains of the variables.

Objective functions:

$$max\ \Upsilon_{MTO} = \sum_{f\in F_{MTO}} \sum_{e_j\in E_j:j=f} z_{e_j} prc_{e_j} \left(1 - P_{e_j} - pen_{e_j} D_{e_j}\right) \tag{3.22}$$

$$\begin{aligned} max\ \Upsilon_{MTS} = &\sum_{f\in F_{MTS}} \sum_{e_j\in E_j:j=f} z_{e_j} prc_{e_j} \left(1 - P_{e_j} - pen_{e_j} D_{e_j}\right) + \\ &\sum_{f\in F_{MTS}} \sum_{t\in T} pr_f \left(G_{f,t} + \sum_{\kappa\in K} ss_{f,t} \left(\phi_\kappa - \phi_{\kappa-1}\right) \theta_\kappa J_{\kappa,f,t} \right) \end{aligned} \tag{3.23}$$

$$min\ \Upsilon_{Cost} = Purchasing + Holding + Production + Packing + Overtime,$$

$$Purchasing = \sum_{t\in T} \left(\sum_{r\in R} p^R_r V^R_{r,t} + \sum_{s\in S} p^S_s V^S_{s,t} \right)$$

$$
\begin{aligned}
Holding &= \sum_{t\in T}\left(\sum_{r\in R} h^R_{r,t} I^R_{r,t} + \sum_{s\in S} h^S_{s,t} I^S_{s,t} + \sum_{f\in F} h^F_{f,t}\left(I^F_{f,t} + L^F_{f,t}\right)\right)\\
Production &= \sum_{m\in M}\sum_{p\in P}\sum_{a_i\in A_i : a_i \ni m \wedge i = p}\sum_{t\in T} c_m X_{a_i,t}\,\omega_{p,m}\\
Packing &= \sum_{pm\in pM}\sum_{f\in F_{pm}}\sum_{t\in T} cpa_{pm} W_{f,pm,t}\,\upsilon_{f,pm}\\
Overtime &= \sum_{t\in T}\left(\sum_{m\in M} c_m o^M_m O^M_{m,t} + \sum_{pm\in pM} cpa_{pm} o^{pM}_{pm} O^{pM}_{pm,t}\right)
\end{aligned}
\tag{3.24}
$$

We model the problem around three main axes: (i) MTO production, (ii) MTS production, (iii) Fulfillment costs. The first component (3.22) expresses the amount of MTO sales made during the planning horizon. Penalties due to late deliveries are deduced from the total amount of sales. The second dimension (3.23) represents the sales of MTS products and includes the attainment of the safety stocks in each period. Finally, (3.24) includes fulfillment costs (purchasing, holding, production, packing, and overtime costs).

As a methodological note, the premium coefficients of safety stocks (θ_κ) need to be carefully calibrated. In the case-study detailed in Section 3.5 we defined three levels of attainment of the target safety stock (0.25, 0.5, and 1). In each level, the decision variable $G_{f,t}$ can range from 0 to 1. The premium coefficient associated with each of the levels' achievement was dimensioned to model the decreasing marginal utility associated with greater attainment of the target safety stock (increasing stock reduces the likelihood of sufficient demand to consume it). The premium coefficients are, respectively, 80%, 40%, and 20%. As the holding cost of finished products corresponds to approximately 10% of the good price and lost sales are valued at 100%, we adjust the safety stock's importance in this interval.

Given the importance decision-makers assign to each dimension, different mid-term plans can be generated. The relative importance of Υ_{MTO} and Υ_{MTS} dictate whether the company will prioritize the satisfaction of the standard products' market or the customized products' one. The component Υ_{Cost} may be leveraged to define up to which degree the company will be more efficient or service-oriented. These positioning options are detailed next.

3.4.3 Positioning strategies

The multi-objective MIP framework can be leveraged to investigate how different policies and managerial decisions impact S&OP solutions and the profit and service metrics. Figure 3.5 presents the positioning options a firm operating in this context may adopt.

If the company's focus is on the commodity market with a great effort on guaranteeing product availability and service level (quadrant I), decision-makers need to head S&OP positioning towards MTS production (in response to forecasts and target stock levels). At the same time, cost impacts become secondary, and the plan may explore overtime and acquisition of semi-finished

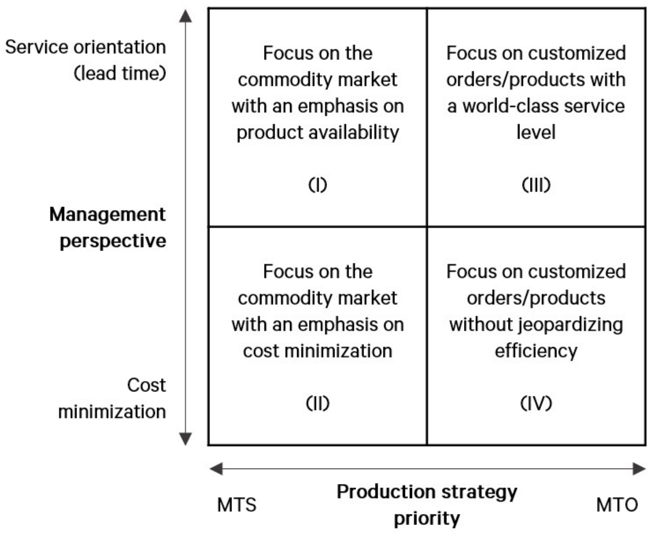


Figure 3.5: Strategic positioning options on S&OP

products from the market if capacity becomes scarce. In fact, many firms rely on overtime and subcontracting to reduce lead times in settings of limited capacity (Aouam & Kumar, 2019). While these options result in an improved response to the market's needs, they deteriorate the products' margin.

Even though an emphasis on product availability is attractive from a commercial perspective, concerns whether a specific plan ensures the desired profitability emerge during S&OP meetings. The definition and monitoring of financial targets is a relevant part of performance management in the context of S&OP (Tuomikangas & Kaipia, 2014). Past literature has developed mid-term planning frameworks for the simultaneous planning of investments, operations, and financial decisions (Hahn & Kuhn, 2012). Therefore, when managers focus on the commodity market, emphasizing cost minimization (quadrant II), they are still concentrating on supplying the MTS segment, but with increased concern about all the costs required to satisfy demand.

When the production strategy priority shifts towards customized orders/products, the importance is no longer directed to satisfying MTS needs but on ensuring customized deliveries. A customer on this segment expects its orders to be fulfilled not only on the right quantity but also on the agreed date. Again, the notion of service level is essential. If the company intends to accept all the orders and meet due dates at any cost (quadrant III), profits can be harmed. First, if the company accepts orders without analyzing the potential operating margin, it may be accepting non-profitable orders. Then, as mentioned for quadrant I, capacity extension options can become expensive.

On the other end, if the company decides to be more discerning while accepting and managing their customized orders, the fulfillment costs may become smaller. There is still an emphasis on customized orders/products but without jeopardizing efficiency (quadrant IV). Profitability-oriented thresholds can be employed to accept only lucrative orders. Simultaneously, the sales team may need to negotiate due dates with customers if operations capacity is limited or there is potential for a more efficient production plan through the consolidation of different orders (to ensure, for instance, minimum lot sizes).

To achieve such viewpoints, we propose the determination of the Pareto-optimal front. Then, decision-makers can analyze the different alternatives and their impacts, discuss them in S&OP meetings, and reach a more informed consensus on the plan to follow.

3.5 Computational experiments

To prove our model's usefulness and the importance of incorporating the trade-off between an MTS and MTO strategy in a Sales and Operations Planning framework, we assess our model using a real instance provided by the cable manufacturer motivating this research (available at http://dx.doi.org/10.17632/kg63y3j7pd.1). The case scope is outlined in Table 3.2, which entails products from the industrial aluminum low voltage family. This instance represents the real problem and depicts all its idiosyncrasies, both in complexity (multiple product stages and different production routes) and comprehensiveness. We are considering the costs and operations from raw materials acquisition and processing up to final product packaging.

Table 3.2: Details of the instance

Indexes	**Size**
Finished products	67
MTO products	26
MTS products	41
Semi-finished products	225
Products (considering semi-finished products)	292
Relationships between successive products	415
Semi-finished products that can be acquired from the market	40
Raw materials	4
Orders	61
Production alternatives	592
Machines	39
Packing machines	7

Sixty-seven finished products are being considered (26 MTO and 41 MTS). Semi-finished products included, the problem is composed of a total of 292 products. Some semi-finished products can be acquired from the market but at a higher cost. Although the case only considers aluminum low voltage products, production complexity is notable, with 415 connections along the bill of materials, which results in 592 production alternatives using 39 machines.

The demand values are as follows: MTO products' demand equals €1,983,892. MTS products' forecasts amount to €6,627,989. The fulfillment of the target safety stocks of all the products in all the periods would result in €2,038,834 ($\sum_{f\in F_{MTS}}\sum_{t\in T}\sum_{\kappa\in K} pr_f ss_{f,t}\,(\phi_\kappa - \phi_{\kappa-1})\,\theta_\kappa$).

We use three metrics to evaluate the fulfillment of the demand: the expected service level on the MTO segment (OTIF - *On Time In Full*), given by the ratio of the demand considered in equation 3.22 that is satisfied on time (orders with $D_{e_f} = 0$) to the total MTO demand in the planning horizon; the amount of MTS demand that is satisfied (MTS forecasts satisfaction), given by the ratio between the forecasts delivered (represented in equation 3.23 by $\sum_{f\in F_{MTS}}\sum_{t\in T} pr_f G_{f,t}$) and the total MTS demand for the planning horizon ($\sum_{f\in F_{MTS}}\sum_{t\in T} pr_f for_{f,t}$); and the safety stock levels compliance (SS attainment), calculated by the ratio of the accomplishment of the k^{th} levels of satisfaction of the target safety stock ($\sum_{f\in F_{MTS}}\sum_{t\in T} pr_f \sum_{\kappa\in K} ss_{f,t}\,(\phi_\kappa-\phi_{\kappa-1})\,\theta_\kappa J_{\kappa,f,t}$ in equation 3.23) to the complete satisfaction of the target safety stock for all the products in all the periods ($\sum_{f\in F_{MTS}}\sum_{t\in T} pr_f \sum_{\kappa\in K} ss_{f,t}\,(\phi_\kappa-\phi_{\kappa-1})\,\theta_\kappa$). All these metrics are weighted by monetary value, not number of orders or other metrics. Finally, for each plan, we determine the expected operating margin, given by the value from sales, including the average safety stock level, minus fulfillment costs (equation 3.24).

The instance reports to mid-November 2019 and comprises eight planning periods (six weeks and two months – the level of detail is higher in the first month to ensure the proper management of orders' dates). As stated in Section 3.2, the company operates in a three-shift (24 hours) regime five days a week in production. The packing machines, in Logistics, operate in a one-shift (8 hours) regime five days a week. Overtime is possible in order to extend the existing capacity. We do not assume any capacity reservation for upcoming orders (MTO products) - capacity may be used up to 100%.

As real data is being used, the model takes all the operational information into account. There are nine orders already delayed at the beginning of the period, resulting in a maximum OTIF value of 97%. Existing inventory levels are also considered - some portion of the MTS forecasts and safety stock levels can be satisfied using resources already acquired or produced at the beginning of the period.

The main cost drivers impacting the case are aluminum acquisition cost (the primary raw material in this family): €1.5 per kilogram; average production cost: €61 per hour; average packing cost: €36 per hour. The overtime factor is 25% (i.e., an overtime hour costs 25% more than a regular working hour), and the acquisition of semi-finished products from the market is, on average, 50% more expensive than internal production. As mentioned before, we are considering a holding cost of 10% of the cost of the products or raw materials, and safety stock attainment is valued at 20%, 40%, and 80% of the average sales price of the product. Finally, the penalty cost associated with orders backlogging is valued such that an order runs out of its value 90 days after the due date.

3.5.1 Solution approach

Multiple objectives or multiple criteria arise in most practical decision-making problems. Multi-objective optimization appeared as a strategy to cope with this challenge. Instead of finding one optimal solution, multi-objective optimization gives rise to a set of trade-off optimal solutions, represented by the Pareto-optimal front (Burke & Kendall, 2005).

The Weighted-Sum Approach and the ε-Constraint Method are two commonly used classical multi-objective optimization methods (Burke & Kendall, 2005). The ε-Constraint presents well-known advantages over the Weighted-Sum Approach, namely the capacity of finding solutions without the need of defining and scaling weights, greater control over the number of efficient solutions to generate, and the potential of finding solutions that lie on the non-convex portion of the Pareto-optimal front (Mavrotas, 2009; Mavrotas & Florios, 2013). Moreover, the ε-Constraint is regarded as simple since it transforms the multi-objective problem into a single-objective optimization problem (Sabri & Beamon, 2000).

Assume the following multi-objective problem:

$$max\ (f_1(X), f_2(X), ..., f_p(X)),\ s.t.\ X \in S, \tag{3.25}$$

where X is a vector of decision variables, $f_1(X), f_2(X), ..., f_p(X)$ are the p objective functions and S the feasible region. The ε-Constraint Method determines the optimal solution of the problem considering one of the objective functions, while all the others are added as constraints:

$$\begin{aligned} & max\ f_1(X),\ s.t. \\ & f_2(X) \geq e_2, f_3(X) \geq e_3, ..., f_p(X) \geq e_p, \\ & X \in S. \end{aligned} \tag{3.26}$$

where the variation of the right-hand side of the constrained objective functions (e_i) dictates that the efficient solutions are obtained.

In our case, we used a more efficient and adapted version of the ε-Constraint proposed by Mavrotas and Florios (2013) to generate the Pareto-optimal front. This method addresses some weak points of the conventional ε-Contraint, resulting in a more efficient approach, namely for problems with several (more than two) objective functions. We refer to Mavrotas (2009) and Mavrotas and Florios (2013) for the ones interested in a thorough explanation of the approach.

First, we determined the range of every objective function. The best value is easily attainable, as it is the optimal value of each objective's individual optimization. On the other hand, the nadir values' estimation (the worst objective values over the entire Pareto-optimal set) is not trivial. Therefore, we applied lexicographic optimization for every objective function, obtaining the solution that maximizes (or minimizes, in the case of Υ_{Cost}) not only the first objective but also the objectives of lower order. These points are Pareto-optimal (non-dominated) solutions. The resulting payoff matrix is represented in Table 3.3.

Table 3.3: Payoff matrix applying lexicographic optimization

Maximization objective	Υ_{MTO}	Υ_{MTS}	Υ_{Cost}
Υ_{MTO}	**€1,973,769**	€7,850,552	€7,547,782
Υ_{MTS}	€7,223	**€8,470,268**	€6,399,691
Υ_{Cost} [1]	€184,766	€1,131,056	**€17,487**

1 Minimization, in this case

Afterward, we divided the ranges of objective functions (Υ_{MTS} and Υ_{Cost}) in 10 equal intervals, resulting in a grid of 11x11 combinations to be explored. The Pareto-optimal front (Figure 3.6) is obtained from the points that correspond to the maximization of Υ_{MTO} for each combination of the grid points as the right-hand sides of the constraints $f_{MTS}(X) \geq e_{MTS}$ and $-f_{Cost}(X) \geq e_{Cost}$.

Given the efficiency shortcuts proposed by the Augmented ε-Constraint algorithm, we run 42 optimization problems from 121 potential runs (results in Appendix 3.B).

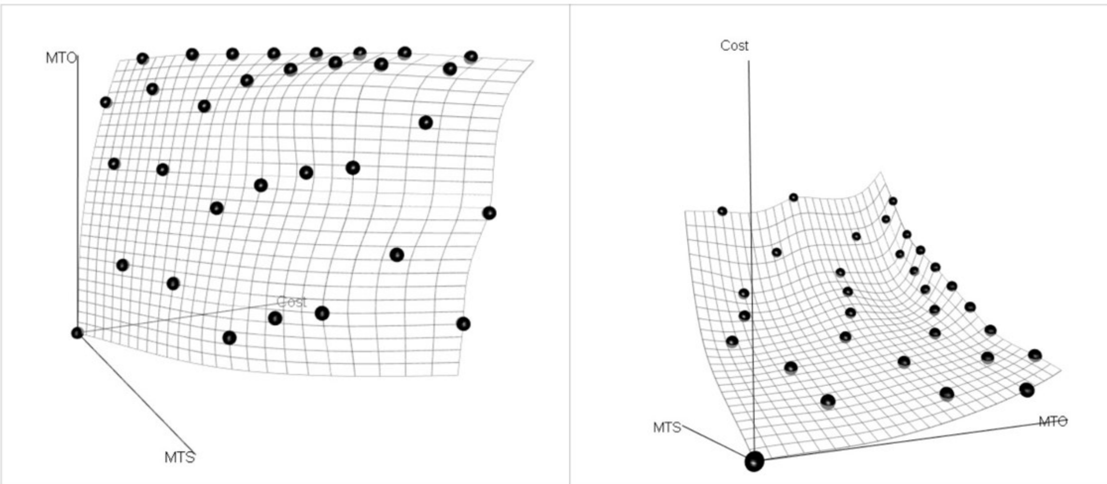


Figure 3.6: Representations of the Pareto-optimal front

3.5.2 Numerical results

The numerical results corresponding to the Pareto front depicted in Figure 3.6 are detailed in Figure 3.7. The values of Υ_{MTO} vary in function of the other two objective functions. In this case, the resources required to deliver all the demand of MTO products is smaller than the corresponding amount to achieve the full satisfaction of the forecasts of MTS products (as well as the attainment of safety stock levels) - recall from Table 3.3 that the maximum value of Υ_{MTO} is €1,973,769, against a total of €8,470,268 for MTS products. Therefore, we can observe that the absolute variation of Υ_{MTS} is steeper along the range of Υ_{Costs} when compared to the variation of Υ_{MTS}. This effect is also visible in the Pareto-optimal front depicted in Figure 3.6.

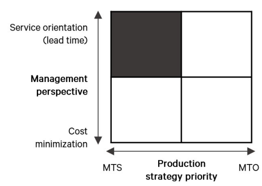
Υ_{MTO}		Υ_{Cost}										
		€ 7,547,782	**€ 6,794,752**	**€ 6,041,723**	**€ 5,288,693**	**€ 4,535,664**	**€ 3,782,634**	**€ 3,029,605**	**€ 2,276,576**	**€ 1,523,546**	**€ 770,517**	**€ 17,487**
Υ_{MTS}	**€ 1,131,056**	*Dominated solutions*									€ 1,693,884	€ 184,766
	€ 1,864,977									€ 1,973,769	€ 1,297,007	
	€ 2,598,898									€ 1,764,572	€ 679,200	
	€ 3,332,819								€ 1,973,769	€ 1,272,165		
	€ 4,066,740							€ 1,973,769	€ 1,650,091	€ 616,409		
	€ 4,800,662						€ 1,973,769	€ 1,797,700	€ 1,065,918			
	€ 5,534,583					€ 1,973,769	€ 1,860,956	€ 1,204,891	€ 366,229			
	€ 6,268,504				€ 1,973,769	€ 1,897,636	€ 1,283,367	€ 495,336				
	€ 7,002,425			€ 1,973,769	€ 1,888,314	€ 1,317,223	€ 541,570					
	€ 7,736,347	€ 1,973,769	€ 1,884,930	€ 1,574,853	€ 857,034							
	€ 8,470,268	€ 1,084,170	€ 473,037									*Infeasible region*

Figure 3.7: Pareto-optimal solutions

A multi-objective approach to this problem empowers the decision-making process. The managers can study in advance the impacts and expected results that derive from different options. In the next subsections, we illustrate, using this numerical example, how different scenarios for the company's positioning could be analyzed before deciding on the plan to follow in the following months. To frame the multiple plans in the matrix depicting the positioning strategies, we set two types of limits: service thresholds, both for MTS and MTO segments, and a cost threshold. For the first set, we assume that a great emphasis on service level is ensured for OTIF and forecast satisfaction values greater than 75-80%, respectively, for MTO and MTS segments. The strategic management sets these target values. For the second, we assume that a plan is cost-oriented if neither overtime nor semi-finished products' acquisition from the market is necessary (plans whose total cost is inferior to €3 million, as further detailed). The definition of the cost limit may be set by historical comparison or by a preliminary analysis of the plans.

3.5.2.1 Focus on commodity market with an emphasis on product availability

Following this strategy, a company might explore different capacity extension possibilities to ensure MTS products' availability. Recall that in our case, overtime costs are 25% greater than regular production and logistic costs, and the acquisition of semi-finished products from the market is 50% more expensive than internal production.



We can see the results of this strategy in Table 3.4. We evaluate the amount of MTS production used to ensure MTS forecasts satisfaction and safety stock levels attainment, the expected service level on the MTO segment, and the margin derived from each plan. For instance, with a Υ_{Cost} of €4,535,664, the company may expect an MTS forecasts satisfaction of 82% from a maximum (upper bound) value of €6,627,989, a safety stock attainment of 66% (from a maximum of €2,038,834), and an OTIF of 66%. This plan would result in an expected margin of 53%.

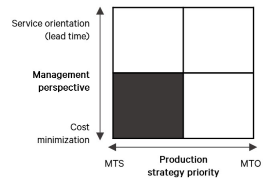
Table 3.4: Results from a focus on commodity market with an emphasis on product availability

Υ_{Cost}	MTS forecasts satisfaction (Upper bound (UB): €6,627,989)	Safety stock (SS) attainment (UB: €2,038,834)	OTIF (UB: 97%)	Margin
€4,535,664	82%	66%	66%	53%
€5,288,693	88%	77%	43%	30%
€6,041,723	88%	77%	79%	26%
€6,794,752	94%	86%	23%	2%
€7,547,782	94%	86%	51%	0%

The first conclusion is that, even if the managers decide to jeopardize fulfillment cost, it is impossible to meet all the forecasted demand for MTS products (and reach safety stock levels). The maximum values are respectively 94% and 86% for a situation in which the total amount of costs exceed €7.5 million, with a null operating margin. In this case, about 50% of the MTO requests would be delivered on time (OTIF of 51%).

As the value of costs decreases, the same happens to MTS production, with a minimum of 82% and 66% respectively for delivered forecasts and stock levels attainment. This plan's prosecution would return a total cost of nearly €4.5 million with an operating margin of 53%.

3.5.2.2 Focus on commodity market with an emphasis on cost minimization



When examining an efficiency positioning, it is relevant to grasp which factors may be impacting the margin. Figure 3.8 depicts the decomposition of the fulfillment costs throughout Υ_{Cost}. The most impactful cost rubrics of this problem correspond to raw materials acquisition, semi-finished products' acquisition from the market, and production (regular and overtime). As we can observe, the lower the costs, the less relevant the rubrics of semi-finished products' acquisition and overtime become. Thus, we imply that plans with a total cost inferior to €3 million can be regarded as margin-oriented.

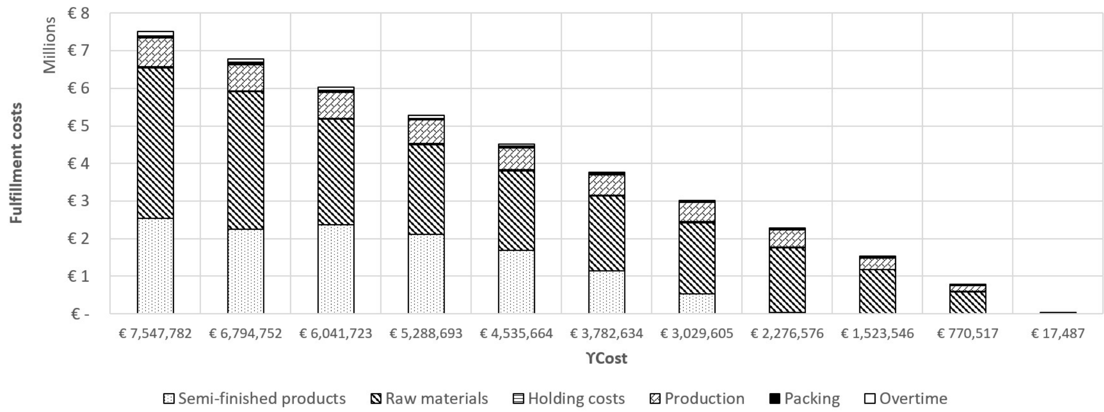


Figure 3.8: Decomposition of the fulfillment costs along Υ_{Cost} range

Figure 3.9 complements the analysis with an outlook on occupation values. Machines' occupation decreases with the reduction of Υ_{Cost}. While the global occupation is 52% for plans with a total cost of €7,547,782, this value is 34% when the total cost reduces to €3,029,605, for instance. However, the global machine occupation is not representative of all the shop floor idiosyncrasies. As we can observe, bottleneck machines have an average occupation superior to 100% for plans with a total cost greater than €5,288,693. Overtime is considerable in these situations - overtime utilization is calculated considering the ratio between the overtime and the maximum amount of available overtime.

Table 3.5 outlines the impacts of margin oriented plans. As the company decides not to resort to capacity extension decisions, the delivered forecasts and stock levels are affected. With a total cost of €3,029,605, the company satisfies 73% of the MTS forecasts and ensures 61% of stock levels attainment. While these values are inferior to the ones presented for a focus on product availability, the operating margin is superior (81%). As the willingness to spend decreases, the operating margin increases significantly. Recall that it is possible to satisfy some portion of the commercial needs using only resources already acquired or produced at the beginning of the period (e.g., existing stocks of finished products, semi-finished products, or raw materials).

Notwithstanding, with this strategy, the company would deliver only a small portion of the demand, which probably impacts its results in the medium term. Values such as 20-50% of MTS

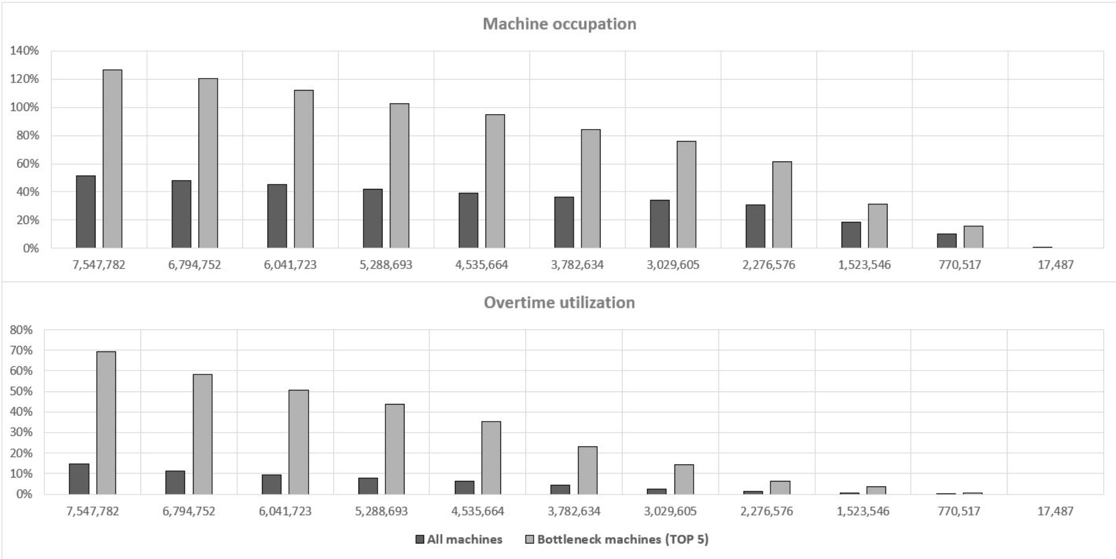


Figure 3.9: Machine occupation details along Υ_{Cost} range

Table 3.5: Results from a focus on commodity market with an emphasis on cost minimization

Υ_{Cost}	MTS forecasts satisfaction (UB: €6,627,989)	SS attainment (UB: €2,038,834)	OTIF (UB: 97%)	Margin
€17,487	13%	13%	9%	6132%
€770,517	28%	35%	18%	237%
€1,523,546	46%	46%	25%	147%
€2,276,576	63%	58%	27%	106%
€3,029,605	73%	61%	31%	81%

forecasts satisfaction may hinder the company's competitive positioning since it would probably lose this demand to other competitors. In the medium term, this could impact the company's market share in this segment.

3.5.2.3 Focus on customized orders/products with a world-class service level

In our study, as the required production quantity to satisfy all the orders is smaller than the quantity to fulfill MTS needs, if decision-makers aim to head towards customized orders, that could be achieved for different cost values (depending on the amount of MTS products' forecasts not satisfied). These values are outlined in Table 3.6.

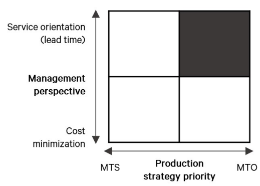
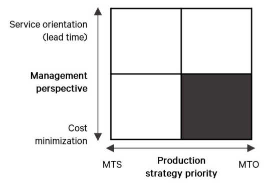


Table 3.6: Results from a focus on customized orders/products with a world-class service level

Υ_{Cost}	Orders acceptance (UB: 100% - 61 orders)	OTIF (UB: 97%)	MTS forecasts satisfaction (UB: €6,627,989)	SS attainment (UB: €2,038,834)	Margin
€1,523,546	100%	97%	23%	25%	132%
€3,029,605	100%	97%	51%	46%	81%
€4,535,664	100%	97%	71%	57%	50%
€6,041,723	100%	97%	83%	69%	27%
€7,547,782	100%	97%	90%	74%	8%

The company can ensure the production and delivery of 100% of the orders with cost values greater than €1.5 million. Regarding the delivery on time in full, the expected OTIF is 97% - recall that nine orders are already delayed at the beginning of the planning horizon. Therefore, even if the company opts to prioritize the customizable segment, the decision on which plan to follow could not be isolated from the planning of the commodity market. Plans with lower cost values do not ensure the MTS needs' reasonable satisfaction.

3.5.2.4 Focus on customized orders/products without jeopardizing efficiency



As stated before, if the company decides not to extend internal production capacity, the unitary fulfillment costs become smaller, positively impacting the operating margin. In the Pareto-optimal surface, this strategy is evident for plans with a total cost less or equal than €3 million. When the decision-makers prioritize the customized orders segment, it is possible to satisfy all the demand if the cost is equal or greater to €1.5 million. If the value drops below this threshold, decision-makers will not accept all the orders in the period, and priority will be given to the most profitable ones. This trade-off can be viewed in Table 3.7.

Table 3.7: Results from a focus on customized orders/products without jeopardizing efficiency

Υ_{Cost}	Orders acceptance (UB: 100% - 61 orders)	OTIF (UB: 97%)	MTS forecasts satisfaction (UB: €6,627,989)	SS attainment (UB: €2,038,834)	Margin
€17,487	25%	9%	13%	13%	6132%
€770,517	74%	83%	12%	16%	229%
€1,523,546	100%	97%	23%	25%	132%
€2,276,576	100%	97%	39%	38%	105%
€3,029,605	100%	97%	51%	46%	81%

3.5.2.5 A perspective on past studies addressing production and admission policies in hybrid production contexts

Recall from Section 3.3 that some past papers have already investigated the benefits of a hybrid planning method for MTS/MTO systems. In particular, the studies from Beemsterboer et al. (2016); Carr and Duenyas (2000); Iravani et al. (2012) focused on the definition of production and order acceptance policies that minimize the total costs. Despite our claim that MTS/MTO prioritization may not be defined using profitability measures solely, it is interesting to compare our study's metrics with some past results. Beemsterboer et al. (2016) present costs savings up to 65% when a hybrid production system is compared with planning methods that prioritize either MTO or MTS products. Carr and Duenyas (2000) describe a potential decrease of 38% in profits whenever the aftermarket (MTO) and OEM (MTS) sales are not coordinated. Iravani et al. (2012) found, on average, that the profit improvement obtained by using the proposed policy is 8.1% (and can range up to 40%).

In our study, profits can be regarded from different perspectives. The value differs significantly in function of the cost (capacity) that the firm is willing to resort to (Figure 3.10). On the one hand, if the company focuses on service level (Υ_{Cost} greater than €5 million), profit values range from €9 thousand to about €2 million. At the other end, if managers aim to reduce fulfillment costs (and therefore, the required cash flow) and satisfy the market from existing stocks, profit ranges from €1-2 million. The most profitable option for the company under study is to spend €2-4 million in fulfillment costs, which can bring up to €2.5 million of profit.

Profit (operational margin)		Υ_{Cost}										
		€ 7,547,782	€ 6,794,752	€ 6,041,723	€ 5,288,693	€ 4,535,664	€ 3,782,634	€ 3,029,605	€ 2,276,576	€ 1,523,546	€ 770,517	€ 17,487
Υ_{MTS}	€ 1,131,056	*Dominated solutions*									€ 1,766,520	€ 1,072,344
	€ 1,864,977									€ 2,011,562	€ 1,868,903	
	€ 2,598,898									€ 2,140,738	€ 1,828,730	
	€ 3,332,819								€ 2,389,796	€ 2,268,946		
	€ 4,066,740							€ 2,442,827	€ 2,499,421	€ 2,242,032		
	€ 4,800,662						€ 2,419,373	€ 2,501,778	€ 2,516,623			
	€ 5,534,583					€ 2,284,570	€ 2,451,528	€ 2,507,506	€ 2,414,086			
	€ 6,268,504				€ 2,145,462	€ 2,393,441	€ 2,471,583	€ 2,451,209				
	€ 7,002,425			€ 1,628,962	€ 2,197,348	€ 2,391,523	€ 2,378,846					
	€ 7,736,347	€ 611,568	€ 1,196,251	€ 1,546,393	€ 1,579,747							
	€ 8,470,268	€ 9,128	€ 137,555									*Infeasible region*

Figure 3.10: Profit (operating margin) of the different solutions

Regarding the trade-off between the focus on the commodity market and customized orders, the profit is maximized considering a hybrid planning prioritization, which corroborates past studies. When the company spends €2.3 million in fulfillment costs, profits can range from €2.389 million up to €2.516 million (an increase of 5.3%). A greater emphasis on the customized orders segment results in an expected profit of €2.389 million with an OTIF of 97%, a satisfaction of 39% of the expected demand from the commodity market, and the attainment of 38% of the safety stock levels. An emphasis on the MTS segment has an expected profit of €2.414 million, an OTIF of 18%, but a satisfaction of 63% of the expected demand, and an attainment of 58% of the safety stock targets. The strategy that reaps the most benefit for the company results in €2.516 million of profit with a hybrid prioritization: 54% of OTIF in the customized orders segment, 54% of satisfaction of the expected demand from the commodity market, and 51% in stock levels' attainment.

Nevertheless, the profit maximization only relates to the plan's horizon. With such reduced values of OTIF and expected demand satisfaction, decision-makers should evaluate the impact that a low service level might have on the business's future. This example perfectly illustrates how profit-orientation S&OP may be misleading and not the best option in the long run because reduced service level may compromise the ability to retain the customers over the planning horizon. In this case, opting for a profit of €2.393 million results in an OTIF of 93% in the customized orders segment and a 74% of satisfaction of the expected demand from the commodity market, which is much more acceptable from a customer's perspective.

A second iteration of the model considering a compromising area on the service level to both product segments counteracts this issue. Thereby the model would return solutions that, regardless of the objective followed, do not result in unacceptable service levels in any of the segments. In

Appendix 3.C, we present the new Pareto-optimal set detailing the objectives ranges to achieve a minimum service level (OTIF and MTS forecast satisfaction) of 75% for both MTS and MTO products.

3.6 Final remarks

This article proposes a S&OP decision-making framework for a flow shop/batch company that produces both MTS and MTO products. Because other factors than profitability impact sales and operations decisions, we address the challenge considering a multi-objective approach. We propose that the S&OP meetings should be based on a set of solutions belonging to the Pareto-optimal front representing the possible strategies to follow. Our contributions are twofold.

First, our paper proposes a new S&OP rationale that allows the managers to position themselves on the Pareto-optimal front, instead of assuming a predefined optimization goal. In general, optimization models are not easily understood by managers. We make more transparent the impact that different managerial options have on the solutions of the model. In Section 3.6.1 we detail how our approach can be used in a S&OP meeting.

Second, the multi-objective MIP model offers the analytical support for a manufacturer to optimize its medium-term sales and operations decisions in a context of hybrid flow shop/batch production. In comparison with past S&OP models, our model provides advancements as follows: (i) inclusion of different production strategies (MTS/MTO), (ii) utilization of a multi-objective approach, capable of measuring other impacts rather than profit, (iii) development of a granular formulation, more flexible and adjustable to complex production settings of some flow shop/batch contexts. In Section 3.6.2 we discuss some modeling considerations of our approach.

In Section 3.6.3 we point out some directions for future research.

3.6.1 Implications for S&OP practice

In this section, we present how the proposed framework can be used during the S&OP meeting. To do so, we resort to the cable manufacturer case motivating this research. Compared with the previous meetings, this research led to a more effective and efficient approach, as presented in Figure 3.11.

The process starts with generating the Pareto-optimal solutions. Afterward, the Planning team prepares the S&OP meeting. First, the solution evaluation metrics are analyzed, and a few solutions are selected from the Pareto set. The planners usually choose four solutions: (i) and (ii) with emphasis on (i) MTO products or (ii) MTS products, both avoiding overtime and the acquisition of semi-finished products from the market; (iii) and (iv) with a focus on either (i) MTO or (ii) MTS segments but with a focus on service metrics fulfillment. This set of solutions is aligned with the matrix depicted in Figure 3.1. Even though the solutions are selected to ensure different plans, compromising OTIF and MTS forecasts satisfaction values are ensured, so neither market segment is hugely penalized. Second, the Planning team translates the solutions into actionable information to be analyzed in the S&OP meeting.

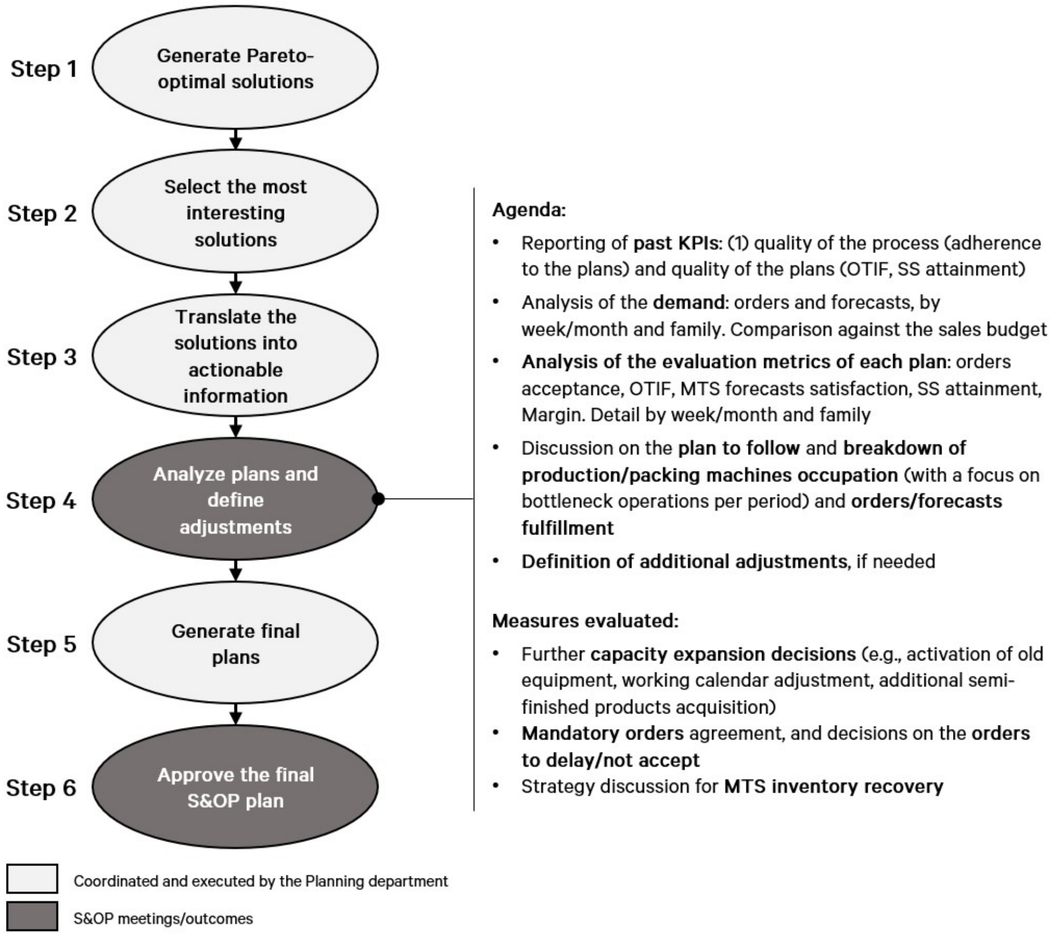


Figure 3.11: Translation of the analytical methodology into practice

The meeting starts by analyzing past metrics to monitor the quality of both the process and the planning outputs. Then, the cross-functional teams analyze the potential demand. Differences between the sales budget and the most recent forecasts are discussed. The Planning team subsequently presents the analysis of each plan's evaluation metrics. Sales and operations teams discuss each of the strategies' impacts and agree on the direction to follow. The company's CEO participates in the meetings and ensures the agreement around a common objective.

Once the direction is defined, a breakdown of the plan is presented, emphasizing machines' occupation and analysis of the most critical orders, customers, or product families. Additional adjustments to the plan are discussed, and the Planning team consolidates the action plan. Among the multiple issues, the need for a refined plan emerges if capacity is particularly short to fulfill the demand satisfactorily. In this case, further capacity adjustments measures are defined (impacting the right-hand side of constraints 3.3, 3.6 and 3.7, or 3.9 and 3.10), or mandatory orders need to be ensured for a next iteration of the plan (imposing specific values on the variables P_{e_f} or $K_{e_f,t}$). Another countermeasure comprises the sales team's agreement on orders or products whose demand will be fulfilled with delay or not satisfied at all. When inventory levels are too low (which, in our case, happened a few times after various months privileging the MTO segment), a prioritization on the products whose inventory levels are more important to replenish may be defined. The model is then run with adjusted target safety stocks $ss_{f,t}$. The Planning team is responsible for running the model with the refined parameters and sharing the results with the S&OP committee. If changes are significant, a final meeting must be required to discuss the final plan and get it approved.

With this case, we aim to demonstrate some managerial implications for companies aiming to sophisticate their S&OP practices following these recommendations. First, there must exist the necessary digitalization to embrace an advanced multi-objective S&OP model to ensure that there are the required resources to run the decision-support system and guarantee the quality and reliability of the information. Second, the role of the S&OP coordinator is relevant (in our case, the Planning team). This element is responsible for the generation and pre-validation of the different plans. Third, the agenda of S&OP meetings must be rearranged to support the discussion proposed in this paper.

3.6.2 Modeling considerations

The proposed model is more granular than the usual approach on S&OP. While we use aggregated time buckets, our model considers detail on product and machine levels. This approach is justified by the production setting of the cable manufacturer motivating this research, where (1) the definition of the bottleneck operation is not straightforward, and (2) there is a limited similarity between the production sequences of the multiple products. Our model is suitable for any flow shop/batch company where aggregating production data is impossible without failing to depict the actual production process accurately. Nevertheless, we would like to stress that, regardless of the aggregation level used in the mathematical model, the analyses and indicators obtained from the plan can be aggregated to ensure communication with the senior management is effective.

In the company motivating this research, the production lead time is long, especially in customized products for industrial applications. It implies that there is information on specific orders in advance. Therefore, even though the monthly S&OP meeting accounts for several months, the first month is modeled at a weekly level and is discussed with a level of detail that is not common in every sector. This conjecture results in a planning rationale where there is no intermediate level of planning between the S&OP and the operational planning. The weekly detail of the first month is directly incorporated into the scheduling activities.

However, in situations where the S&OP does not need to account for a weekly detail, our model can cohabit with other tactical lower planning levels. It is a fact that the detail that our model possesses in terms of products and machines results in an intersection with the Master Production Scheduling (MPS). As our model's output is at the product level, this level of detail can be directly incorporated into the MPS (with target stock levels at the product level). The major contribution of that later planning stage is on the plan's disaggregation into a more detailed time bucket (e.g., weekly). Nevertheless, even though our S&OP model predefines machine allocation, planners could relax this constraint when performing MPS because differences in time granularity may lead to machine allocation changes between periods.

Establishing the connection with the Demand Driven Adaptive Enterprise model from Ptak and Smith (2018), our approach falls under this recent S&OP paradigm, as it fits in a business management paradigm where the traditional MRP concept is replaced by a demand-driven MRP (DDMRP). Instead of dealing with all the products as MTS, with a finished inventory stock amount coordinating the planning and execution of upstream activities, we differentiate MTS and MTO products. For the latter group, the tactical planning layer employs demand-driven planning, triggering order acceptance and capacity allocation guidelines in function of existing demand.

We make some additional considerations directed to the ones aiming to implement this approach. The proposed framework is suited for companies whose production is flow shop/batch-oriented. Even though the multi-objective rationale and positioning strategies matrix can be directly translated to other types of processes, the same does not hold for the MIP model. In continuous process types (*i.e.,* line flow or continuous line), it is likely that finding the bottleneck operation is straightforward. The model might be simplified in those situations, representing the critical machines only and information aggregated at the product family level. Even for discrete process types like the one we are resembling, if aggregation could be made preserving an accurate process representation, we encourage simplification to be made.

Nevertheless, we expect researchers and practitioners dedicated to the study of other process types apart from the flow shop/batch to find this overall approach less applicable. As stated from Olhager et al. (2001), pure job shop processes are typically used with Engineer-to-Order or Make-to-Order products, whereas continuous line processes are associated with Make-to-Stock portfolios. In those cases, the trade-off between producing to order *versus* to stock becomes less relevant, and conducting the S&OP processes to maximize the overall profit might be enough.

Finally, regarding the decisions and teams included in our approach, researchers and practitioners employing our model are encouraged to analyze its context and adapt the model accordingly. For instance, we considered raw materials' acquisition as a relevant decision to analyze in the S&OP practice. On the other hand, distribution decisions were not regarded because they are outsourced. We do not intend our model to be comprehensive regarding all the decisions to tackle in S&OP. Thus, we recommend for researchers and practitioners using our model in their case to start by conducting a thorough mapping of the decisions and constraints to include in the S&OP dynamic.

3.6.3 Future research

As future research avenues, innovative matheuristic and metaheuristic procedures can be combined with the proposed multi-objective optimization loop, ensuring the models' solvability in an acceptable time frame even for larger instances. Second, case studies of implementation of this framework in other business realities could be interesting to grasp the potential benefits in the S&OP practices and identify possible limitations that may arise. For instance, we foresee that our model requires adjustments to be used by companies applying ATO or other DPD strategies. This is undoubtedly an interesting opportunity for future study. Third, a thorough analysis of the impacts on the S&OP plans of different aggregation levels on products and resources deserves further attention. Although the literature recommends an aggregated approach irrespective of the operational setting, our research reveals that the effort required for accurately aggregating resources may exceed the analytical effort of computing the model using detailed data.

3.7 Acknowledgements

This work is partially financed by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia, within project UIDB/50014/2020.

Bibliography

Abedi, A., & Zhu, W. H. (2017). An optimisation model for purchase, production and distribution in fish supply chain - a case study. *International Journal of Production Research*, *55*(12), 3451-3464. doi: 10.1080/00207543.2016.1242800

Absi, N., & Kedad-Sidhoum, S. (2009). The multi-item capacitated lot-sizing problem with safety stocks and demand shortage costs. *Computers & Operations Research*, *36*(11), 2926-2936. doi: https://doi.org/10.1016/j.cor.2009.01.007

Adan, I. J. B. F., & Van Der Wal, J. (1998). Combining make to order and make to stock. *OR Spectrum*, *20*(2), 73-81. doi: 10.1007/BF01539854

Ali, M. B., D' Amours, S., Gaudreault, J., & Carle, M. A. (2019). Integrating revenue management and sales and operations planning in a make-to-stock environment: Softwood lumber case study. *INFOR*, *57*(2), 314-341. doi: 10.1080/03155986.2018.1554420

Altendorfer, K., & Minner, S. (2014). A comparison of make-to-stock and make-to-order in multi-product manufacturing systems with variable due dates. *IIE Transactions*, *46*(3), 197-212. doi: 10.1080/0740817X.2013.803638

Aouam, T., & Kumar, K. (2019). On the effect of overtime and subcontracting on supply chain safety stocks. *Omega (United Kingdom)*, *89*, 1-20. doi: 10.1016/j.omega.2018.09.010

Beemsterboer, B., Land, M., & Teunter, R. (2016). Hybrid mto-mts production planning: An explorative study. *European Journal of Operational Research*, *248*(2), 453-461. doi: 10 .1016/j.ejor.2015.07.037

Beemsterboer, B., Land, M., & Teunter, R. (2017). Flexible lot sizing in hybrid make-to-order/make-to-stock production planning. *European Journal of Operational Research*, *260*(3), 1014-1023. doi: https://doi.org/10.1016/j.ejor.2017.01.015

Beemsterboer, B., Land, M., Teunter, R., & Bokhorst, J. (2017). Integrating make-to-order and make-to-stock in job shop control. *International Journal of Production Economics*, *185*, 1-10. doi: https://doi.org/10.1016/j.ijpe.2016.12.015

Brabazon, P. G., MacCarthy, B., Woodcock, A., & Hawkins, R. W. (2010). Mass customization in the automotive industry: Comparing interdealer trading and reconfiguration flexibilities in order fulfillment. *Production and Operations Management*, *19*(5), 489-502. doi: 10.1111/ j.1937-5956.2010.01132.x

Burke, E., & Kendall, G. (2005). *Search methodologies—introductory tutorials in optimization and decision support techniques*. Springer Science+ Business Media, Incorporated. doi: 10.1007/0-387-28356-0

Burrows, R. (2012). *The market-driven supply chain: a revolutionary model for sales and operations planning in the new on-demand economy*. Amacom.

Carr, S., & Duenyas, I. (2000). Optimal admission control and sequencing in a make-to-stock/make-to-order production system. *Operations Research*, *48*(5), 709-720. doi: 10.1287/opre.48.5.709.12401

Catalá, L. P., Moreno, M. S., Blanco, A. M., & Bandoni, J. A. (2016). A bi-objective optimization model for tactical planning in the pome fruit industry supply chain. *Computers and Electronics in Agriculture*, *130*, 128-141. doi: 10.1016/j.compag.2016.10.008

Chen-Ritzo, C. H., Ervolina, T., Harrison, T. P., & Gupta, B. (2010). Sales and operations planning in systems with order configuration uncertainty. *European Journal of Operational Research*, *205*(3), 604-614. doi: 10.1016/j.ejor.2010.01.029

Cox, J. F., & Blackstone, J. H. (2002). *Apics dictionary*. APICS Educational Society for Resource Management.

Darmawan, A., Wong, H., & Thorstenson, A. (2018). Integration of promotion and production decisions in sales and operations planning. *International Journal of Production Research*, *56*(12), 4186-4206. doi: 10.1080/00207543.2018.1431418

Darmawan, A., Wong, H., & Thorstenson, A. (2020). Integrated sales and operations planning with multiple products: Jointly optimizing the number and timing of promotions and production decisions. *Applied Mathematical Modelling*, *80*, 792-814. doi: 10.1016/j.apm.2019.12.001

Elmehanny, A. M., Abdelmaguid, T. F., & Eltawil, A. B. (2019). Optimizing production and inventory decisions for mixed make-to-order/make-to-stock ready-made garment industry. In *Ieee international conference on industrial engineering and engineering management* (Vol. 2019-December, p. 1913-1917). doi: 10.1109/IEEM.2018.8607516

Fahimnia, B., Farahani, R. Z., & Sarkis, J. (2013). Integrated aggregate supply chain planning using memetic algorithm – a performance analysis case study. *International Journal of Production Research*, *51*(18), 5354-5373. doi: 10.1080/00207543.2013.774492

Fahimnia, B., Luong, L., & Marian, R. (2012). Genetic algorithm optimisation of an integrated aggregate production–distribution plan in supply chains. *International Journal of Production Research*, *50*(1), 81-96. doi: 10.1080/00207543.2011.571447

Federgruen, A., & Katalan, Z. (1999). The impact of adding a make-to-order item to a make-to-stock production system. *Management Science*, *45*(7), 980-994. doi: 10.1287/mnsc.45.7.980

Feng, Y., D'Amours, S., & Beauregard, R. (2008). The value of sales and operations planning in oriented strand board industry with make-to-order manufacturing system: Cross functional integration under deterministic demand and spot market recourse. *International Journal of Production Economics*, *115*(1), 189-209. doi: 10.1016/j.ijpe.2008.06.002

Feng, Y., D'Amours, S., & Beauregard, R. (2009). Simulation and performance evaluation of partially and fully integrated sales and operations planning. *International Journal of Production Research*, *48*(19), 5859-5883. doi: 10.1080/00207540903232789

Feng, Y., Martel, A., D'Amours, S., & Beauregard, R. (2013). Coordinated contract decisions in a make-to-order manufacturing supply chain: A stochastic programming approach. *Production and Operations Management*, *22*(3), 642-660. doi: 10.1111/j.1937-5956.2012.01385.x

Fumero, F., & Vercellis, C. (1997). Integrating distribution, machine assignment and lot-sizing via lagrangean relaxation. *International Journal of Production Economics*, *49*(1), 45-54. doi: 10.1016/s0925-5273(96)00098-9

Galizia, F. G., ElMaraghy, H., Bortolini, M., & Mora, C. (2020). Product platforms design, selection and customisation in high-variety manufacturing. *International Journal of Production Research*, *58*(3), 893-911. doi: 10.1080/00207543.2019.1602745

Ghasemy Yaghin, R. (2018). Integrated multi-site aggregate production-pricing planning in a two-echelon supply chain with multiple demand classes. *Applied Mathematical Modelling*, *53*, 276-295. doi: 10.1016/j.apm.2017.09.006

Ghasemy Yaghin, R. (2020). Enhancing supply chain production-marketing planning with geometric multivariate demand function (a case study of textile industry). *Computers and Industrial Engineering*, *140*. doi: 10.1016/j.cie.2019.106220

Ghasemy Yaghin, R., Torabi, S. A., & Fatemi Ghomi, S. M. T. (2012). Integrated markdown pricing and aggregate production planning in a two echelon supply chain: A hybrid fuzzy multiple objective approach. *Applied Mathematical Modelling*, *36*(12), 6011-6030. doi: 10.1016/j.apm.2012.01.029

Grimson, J. A., & Pyke, D. F. (2007). Sales and operations planning: an exploratory study and framework. *The International Journal of Logistics Management*, *18*(3), 322-346. doi: 10.1108/09574090710835093

Gunnarsson, H., & Rönnqvist, M. (2008). Solving a multi-period supply chain problem for a pulp company using heuristics-an application to södra cell ab. *International Journal of Production Economics*, *116*(1), 75-94. doi: 10.1016/j.ijpe.2008.07.010

Gupta, D., & Wang, L. (2007). Capacity management for contract manufacturing. *Operations*

Research, *55*(2), 367-377. doi: 10.1287/opre.1060.0359

Hadj Youssef, K., Van Delft, C., & Dallery, Y. (2004). Efficient scheduling rules in a combined make-to-stock and make-to-order manufacturing system. *Annals of Operations Research*, *126*(1), 103-134. doi: 10.1023/B:ANOR.0000012277.97069.a6

Hahn, G. J., & Kuhn, H. (2012). Simultaneous investment, operations, and financial planning in supply chains: A value-based optimization approach. *International Journal of Production Economics*, *140*(2), 559-569. doi: https://doi.org/10.1016/j.ijpe.2012.02.018

Hanafy, M., & ElMaraghy, H. (2015). Developing assembly line layout for delayed product differentiation using phylogenetic networks. *International Journal of Production Research*, *53*(9), 2633-2651. doi: 10.1080/00207543.2014.974839

Iravani, S. M. R., Liu, T., & Simchi-Levi, D. (2012). Optimal production and admission policies in make-to-stock/make-to-order manufacturing systems. *Production and Operations Management*, *21*(2), 224-235. doi: 10.1111/j.1937-5956.2011.01260.x

Ivert, L. K., & Jonsson, P. (2014). When should advanced planning and scheduling systems be used in sales and operations planning? *International Journal of Operations and Production Management*, *34*(10), 1338-1362. doi: 10.1108/IJOPM-03-2011-0088

Jacobs, F. R., Berry, W. L., Whybark, D. C., & Vollmann, T. E. (2011). *Manufacturing planning and control for supply chain management: Apics/cpim certification edition*. McGraw-Hill Education.

Khakdaman, M., Wong, K. Y., Zohoori, B., Tiwari, M. K., & Merkert, R. (2015). Tactical production planning in a hybrid make-to-stock-make-to-order environment under supply, process and demand uncertainties: A robust optimisation model. *International Journal of Production Research*, *53*(5), 1358-1386. doi: 10.1080/00207543.2014.935828

Lawson, B., Pil, F. K., & Holweg, M. (2018). Multi-modal order fulfillment: Concept and application. *Production and Operations Management*, *27*(2), 269-284. doi: 10.1111/poms.12801

Lidestam, H., & Rönnqvist, M. (2011). Use of lagrangian decomposition in supply chain planning. *Mathematical and Computer Modelling*, *54*(9-10), 2428-2442. doi: 10.1016/j.mcm.2011.05.054

Lim, L. L., Alpan, G., & Penz, B. (2017). A simulation-optimization approach for sales and operations planning in build-to-order industries with distant sourcing: Focus on the automotive industry. *Computers and Industrial Engineering*, *112*, 469-482. doi: 10.1016/j.cie.2016.12.002

Ling, R., & Goddard, W. (1988). *Orchestrating success: Improve control of the business with sales & operations planning*. Oliver Wight Limited Publications.

Liu, S., & Papageorgiou, L. G. (2013). Multiobjective optimisation of production, distribution and capacity planning of global supply chains in the process industry. *Omega (United Kingdom)*, *41*(2), 369-382. doi: 10.1016/j.omega.2012.03.007

Mavrotas, G. (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. *Applied Mathematics and Computation*, *213*(2), 455-465. doi: https://doi.org/10.1016/j.amc.2009.03.037

Mavrotas, G., & Florios, K. (2013). An improved version of the augmented ε-constraint method (augmecon2) for finding the exact pareto set in multi-objective integer programming problems. *Applied Mathematics and Computation*, *219*(18), 9652-9669. doi: https://doi.org/10.1016/j.amc.2013.03.002

Mirzapour Al-E-Hashem, S. M. J., Malekly, H., & Aryanezhad, M. B. (2011). A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. *International Journal of Production Economics*, *134*(1), 28-42. doi: 10.1016/j.ijpe.2011.01.027

Nemati, Y., & Alavidoost, M. H. (2018). A fuzzy bi-objective milp approach to integrate sales, production, distribution and procurement planning in a fmcg supply chain. *Soft Computing*, 1-20. doi: 10.1007/s00500-018-3146-5

Nemati, Y., Madhoushi, M., & Ghadikolaei, A. S. (2017a). The effect of sales and operations planning (s&op) on supply chain's total performance: A case study in an iranian dairy company. *Computers & Chemical Engineering*, *104*, 323-338. doi: 10.1016/j.compchemeng.2017.05.002

Nemati, Y., Madhoushi, M., & Ghadikolaei, A. S. (2017b). Towards supply chain planning integration: Uncertainty analysis using fuzzy mathematical programming approach in a plastic forming company. *Iranian Journal of Management Studies*, *10*(2), 335-364. doi: 10.22059/ijms.2017.218842.672334

Noroozi, S., & Wikner, J. (2016). A modularized framework for sales and operations planning with focus on process industries. *Production & Manufacturing Research*, *4*(1), 65-89. doi: 10.1080/21693277.2016.1200502

Noroozi, S., & Wikner, J. (2017). Sales and operations planning in the process industry: A literature review. *International Journal of Production Economics*, *188*, 139-155. doi: 10.1016/j.ijpe.2017.03.006

Olhager, J., & Prajogo, D. I. (2012). The impact of manufacturing and supply chain improvement initiatives: A survey comparing make-to-order and make-to-stock firms. *Omega*, *40*(2), 159-165. doi: https://doi.org/10.1016/j.omega.2011.05.001

Olhager, J., Rudberg, M., & Wikner, J. (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*, *69*(2), 215-225. doi: Doi10.1016/S0925-5273(99)00098-5

Peidro, D., Mula, J., Alemany, M. M. E., & Lario, F.-C. (2012). Fuzzy multi-objective optimisation for master planning in a ceramic supply chain. *International Journal of Production Research*, *50*(11), 3011-3020. doi: 10.1080/00207543.2011.588267

Pereira, D. F., Oliveira, J. F., & Carravilla, M. A. (2020). Tactical sales and operations planning: A holistic framework and a literature review of decision-making models. *International Journal of Production Economics*, *228*, 107695. doi: https://doi.org/10.1016/j.ijpe.2020.107695

Ptak, C., & Smith, C. (2018). *The demand driven adaptive enterprise: Surviving, adapting, and thriving in a vuca world*. Industrial Press.

Rafiei, H., & Rabbani, M. (2012). Capacity coordination in hybrid make-to-stock/make-to-order production environments. *International Journal of Production Research*, *50*(3), 773-789. doi: 10.1080/00207543.2010.543174

Rafiei, H., Rabbani, M., & Alimardani, M. (2013). Novel bi-level hierarchical production planning in hybrid mts/mto production contexts. *International Journal of Production Research*, *51*(5), 1331-1346. doi: 10.1080/00207543.2012.661089

Rafiei, H., Rabbani, M., & Hosseini, S. H. (2014). Capacity coordination under demand uncertainty in a hybrid make-to-stock/make-to-order environment: A system dynamics approach. *Scientia Iranica*, *21*(6), 2315-2325.

Rafiei, H., Rabbani, M., & Kokabi, R. (2014). Multi-site production planning in hybrid make-to-stock/make-to-order production environment. *Journal of Industrial Engineering International*, *10*(3). doi: 10.1007/s40092-014-0060-z

Sabri, E. H., & Beamon, B. M. (2000). A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega*, *28*(5), 581-598. doi: 10.1016/S0305-0483(99)00080-8

Sanei Bajgiran, O., Kazemi Zanjani, M., & Nourelfath, M. (2016). The value of integrated tactical planning optimization in the lumber supply chain. *International Journal of Production Economics*, *171*, 22-33. doi: 10.1016/j.ijpe.2015.10.021

Singhal, J., & Singhal, K. (2007). Holt, modigliani, muth, and simon's work and its role in the renaissance and evolution of operations management. *Journal of Operations Management*, *25*(2), 300-309. doi: 10.1016/j.jom.2006.06.003

Sodhi, M. S., & Tang, C. S. (2011). Determining supply requirement in the sales-and-operations-planning (s&op) process under demand uncertainty: A stochastic programming formulation and a spreadsheet implementation. *Journal of the Operational Research Society*, *62*(3), 526-536. doi: 10.1057/jors.2010.93

Soman, C. A., Van Donk, D. P., & Gaalman, G. (2004). Combined make-to-order and make-to-stock in a food production system. *International Journal of Production Economics*, *90*(2), 223-235. doi: 10.1016/S0925-5273(02)00376-6

Soman, C. A., van Donk, D. P., & Gaalman, G. J. C. (2007). Capacitated planning and scheduling for combined make-to-order and make-to-stock production in the food industry: An illustrative case study. *International Journal of Production Economics*, *108*(1-2), 191-199. doi: 10.1016/j.ijpe.2006.12.042

Souza, G. C., Zhao, Z. Y., Chen, M. M., & Ball, M. O. (2004). Coordinating sales and raw material discounts in a global supply chain. *Production and Operations Management*, *13*(1), 34-45. doi: 10.1111/j.1937-5956.2004.tb00143.x

Susarla, N., & Karimi, I. A. (2018). Integrated production planning and inventory management in a multinational pharmaceutical supply chain. In *Computer aided chemical engineering* (Vol. 41, p. 551-567). Elsevier B.V. doi: 10.1016/B978-0-444-63963-9.00022-1

Thome, A. M. T., Scavarda, L. F., Fernandez, N. S., & Scavarda, A. J. (2012). Sales and operations planning: A research synthesis. *International Journal of Production Economics*, *138*(1), 1-13. doi: 10.1016/j.ijpe.2011.11.027

Thue, W. A. (2017). *Electrical power cable engineering*. Crc Press.

Torabi, S. A., & Moghaddam, M. (2012). Multi-site integrated production-distribution planning with trans-shipment: A fuzzy goal programming approach. *International Journal of Production Research*, *50*(6), 1726-1748. doi: 10.1080/00207543.2011.560907

Tsubone, H., Ishikawa, Y., & Yamamoto, H. (2002). Production planning system for a combination of make-to-stock and make-to-order products. *International Journal of Production Research*, *40*(18), 4835-4851. doi: 10.1080/00207540210158834

Tuomikangas, N., & Kaipia, R. (2014). A coordination framework for sales and operations planning (s&op): Synthesis from the literature. *International Journal of Production Economics*, *154*, 243-262. doi: 10.1016/j.ijpe.2014.04.026

Van Elzakker, M. A. H., Zondervan, E., Raikar, N. B., Hoogland, H., & Grossmann, I. E. (2014).

Optimizing the tactical planning in the fast moving consumer goods industry considering shelf-life restrictions. *Computers & Chemical Engineering*, *66*, 98-109. doi: 10.1016/j.compchemeng.2014.01.020

Wallace, T., & Stahl, R. (2008). *Sales and operations planning: the how-to handbook*. TF Wallace & Co.

Wang, J. Z., Hsieh, S. T., & Hsu, P. Y. (2012). Advanced sales and operations planning framework in a company supply chain. *International Journal of Computer Integrated Manufacturing*, *25*(3), 248-262. doi: 10.1080/0951192x.2011.629683

Wei, W., Guimarães, L., Amorim, P., & Almada-Lobo, B. (2017). Tactical production and distribution planning with dependency issues on the production process. *Omega*, *67*, 99-114. doi: 10.1016/j.omega.2016.04.004

Wemmerlov, U. (1984). Assemble-to-order manufacturing: Implications for materials management. *Journal of Operations Management*, *4*(4), 347-368. doi: https://doi.org/10.1016/0272-6963(84)90021-4

Zhang, G., Shang, J., & Li, W. (2011). Collaborative production planning of supply chain under price and demand uncertainty. *European Journal of Operational Research*, *215*(3), 590-603. doi: 10.1016/j.ejor.2011.07.007

Zhang, T., Zheng, Q. P., Fang, Y., & Zhang, Y. (2015). Multi-level inventory matching and order planning under the hybrid make-to-order/make-to-stock production environment for steel plants via particle swarm optimization. *Computers and Industrial Engineering*, *87*, 238-249. doi: 10.1016/j.cie.2015.05.001

3.A Machine and products production details

Table 3.A.1 depicts the machines available at one of the production facilities. Bottleneck aggregation is not straightforward because 35 machines may limit the throughput depending on the processed product. The information on the number of products and processing needs per machine reinforces the high diversity between machines belonging to the same production stage and the difficulty in defining the production stage that limits the throughput. Different forecasts/orders may result in a different bottleneck in the process.

Table 3.A.1: Details of machines utilization

Production stage	Machine	No. products as bottleneck	No. products	Processing needs (sec/m)[1]
Wire drawing, annealing and stranding	1	1	129	18.3
	2	40	116	799.3
	3	5	22	27.6
	4	1	448	55.3
	5	31	201	278.4
Medium voltage extrusion	6	5	11	221.6
	7	24	45	461
	8	7	18	207.6
Low voltage extrusion	9	7	229	953.9
	10	1	188	484.8
	11	0	79	138.5
	12	4	55	219.5
	13	0	23	12.5
	14	0	98	356.1
Cabling	15	43	130	995
	16	0	20	147.8
	17	28	43	571.4
	18	48	69	821.9
	19	4	32	312.5
	20	0	17	140.4
	21	56	134	804.4
Shielding and steel armoring	22	15	21	342.7
	23	15	34	566.1
	24	6	9	89.6
	25	37	57	861.3
	26	69	94	1276.6
	27	13	14	243.3
	28	100	113	1450.4
	29	3	3	123.5
	30	3	136	475
Outer sheathing	31	4	32	452
	32	38	150	948.9
	33	22	153	564.9
	34	54	202	691.3
	35	44	106	1207.5
	36	1	9	10.5
	37	27	97	795.3
Optical fiber processing	38	15	27	99.4
	39	0	7	16.6
	40	0	26	108.6
	41	0	29	23
	42	9	27	97.5
	43	7	16	95

1 Sum of the processing time required per meter of demand of the products processed in the machine

Table 3.A.2 illustrates the simplification benefits when we aggregate product information. Considering the same production facility, 787 products may be grouped in 10 families. If we determine the number of distinct sequences at the family level, there are 464 combinations (a reduction of 41%). However, if we consider production sequences with equal production times, this reduction is less significant - 721 combinations (i.e., reduction of 8%).

Table 3.A.2: Impacts of aggregation using the primary (or preferential) sequence per product

Family	**No. products**	**No. sequences**	**No. sequences with equal production times**
Domestic cables	88	43	78
Industrial aluminium low voltage	177	88	157
Industrial copper low voltage	336	219	309
Industrial aluminium medium voltage	44	20	44
Industrial copper medium voltage	17	16	17
Industrial aluminium high voltage	3	3	3
Industrial copper high voltage	1	1	1
Bare conductors	26	9	23
Telecom	65	46	60
Optical fiber	30	19	29
	787	**464(-41%)**	**721(-8%)**

3.B Computational results

The proposed model was solved with the commercial solver CPLEX 12.9.0 in a machine with a processor Intel(R)Xeon(R)CPU E5-2640 V2 @ 2.60GHz and 78GB of RAM.

To force the solver to minimize the surplus variables, *eps* (parameter determining the weight of the lexicographic optimization on the rest of the objective functions) was chosen to be 10^{-5} (Mavrotas & Florios, 2013).

The computational results from the application of the Augmented ε-Constraint Method are as follows:

Υ_{MTS}	Υ_{Cost}	Υ_{MTO}	Running time (sec.)[1]	Bypass coefficient[2]	Gap
€1,131,056	€7,547,782	€1,973,769	57	9	0.00%
€8,470,268	€7,547,782	€1,084,170	977	0	0.00%
€1,131,056	€6,794,752	€1,973,769	13	8	0.00%
€7,736,347	€6,794,752	€1,884,930	628	0	0.00%
€8,470,268	€6,794,752	€473,037	7,206	0	0.30%
€1,131,056	€6,041,723	€1,973,769	42	8	0.00%
€7,736,347	€6,041,723	€1,574,853	7,214	0	0.02%
€8,470,268	€6,041,723	Infeasible	0		
€1,131,056	€5,288,693	€1,973,769	23	7	0.00%
€7,002,425	€5,288,693	€1,888,314	7,205	0	0.02%
€7,736,347	€5,288,693	€857,034	7,202	0	0.08%
€8,470,268	€5,288,693	Infeasible	0		
€1,131,056	€4,535,664	€1,973,769	139	6	0.00%
€6,268,504	€4,535,664	€1,897,636	939	0	0.00%
€7,002,425	€4,535,664	€1,317,223	7,220	0	0.05%
€7,736,347	€4,535,664	Infeasible	0		
€1,131,056	€3,782,634	€1,973,769	41	5	0.00%
€5,534,583	€3,782,634	€1,860,956	7,238	0	0.18%
€6,268,504	€3,782,634	€1,283,367	7,204	0	0.02%
€7,002,425	€3,782,634	€541,570	7,202	0	0.03%
€7,736,347	€3,782,634	Infeasible	0		
€1,131,056	€3,029,605	€1,973,769	35	4	0.00%
€4,800,662	€3,029,605	€1,797,700	7,225	0	0.20%
€5,534,583	€3,029,605	€1,204,891	7,226	0	0.03%
€6,268,504	€3,029,605	€495,336	7,212	0	0.22%
€7,002,425	€3,029,605	Infeasible	0		
€1,131,056	€2,276,576	€1,973,769	49	3	0.00%
€4,066,740	€2,276,576	€1,650,091	7,223	0	0.36%
€4,800,662	€2,276,576	€1,065,918	7,229	0	0.70%
€5,534,583	€2,276,576	€366,229	7,223	0	0.31%
€6,268,504	€2,276,576	Infeasible	0		
€1,131,056	€1,523,546	€1,973,769	14	1	0.00%
€2,598,898	€1,523,546	€1,764,572	7,225	0	0.33%
€3,332,819	€1,523,546	€1,272,165	7,202	0	0.63%
€4,066,740	€1,523,546	€616,409	7,221	0	1.49%
€4,800,662	€1,523,546	Infeasible	0		
€1,131,056	€770,517	€1,693,884	7,208	0	0.06%
€1,864,977	€770,517	€1,297,007	7,228	0	0.71%
€2,598,898	€770,517	€679,200	7,247	0	1.95%
€3,332,819	€770,517	Infeasible	0		
€1,131,056	€17,487	€184,766	9	0	0.00%
€1,864,977	€17,487	Infeasible	0		

1 Time limit of 7200 seconds

2 Number of iterations bypassed given the surplus variable of the innermost objective function (Mavrotas & Florios, 2013)

3.C Computational results for a compromising area

From the analysis of the OTIF and MTS forecasts satisfaction metrics from the first-iteration solutions, Υ_{MTS} and Υ_{Cost} were narrowed to yield solutions belonging to a compromising area (with OTIF and MTS forecasts satisfaction greater than 75%). The new ranges are as follows: €5,534,583 $\leq \Upsilon_{MTS} \leq$ €8,470,268; €4,535,664 $\leq \Upsilon_{Cost} \leq$ €7,547,782. Again, we divided the ranges of objective functions in 10 equal intervals.

The new Pareto-optimal solutions are as follows:

Υ_{MTS}	Υ_{Cost}	Υ_{MTO}	Gap	Orders accept.	OTIF	MTS forecasts satisf.	SS attainment	Margin
€7,883,131	€7,547,782	€1,960,254	0.01%	97%	94%	91%	75%	€619,612
€8,176,699	€7,547,782	€1,804,469	0.01%	87%	87%	94%	79%	€673,685
€7,883,131	€7,246,570	€1,902,396	0.02%	97%	91%	91%	76%	€857,985
€8,176,699	€7,246,570	€1,684,163	0.05%	67%	83%	93%	80%	€815,972
€7,589,562	€6,945,358	€1,973,769	0.00%	100%	97%	88%	72%	€1,044,610
€7,883,131	€6,945,358	€1,836,814	0.01%	89%	89%	91%	76%	€1,111,553
€7,589,562	€6,644,146	€1,920,520	0.01%	97%	94%	88%	73%	€1,275,706
€7,883,131	€6,644,146	€1,741,727	0.02%	82%	84%	90%	77%	€1,268,355
€7,295,994	€6,342,935	€1,973,769	0.00%	100%	97%	84%	69%	€1,381,387
€7,589,562	€6,342,935	€1,863,372	0.01%	92%	92%	87%	74%	€1,475,022
€7,883,131	€6,342,935	€1,519,123	0.03%	62%	76%	90%	78%	€1,325,640
€7,295,994	€6,041,723	€1,946,183	0.00%	93%	96%	84%	71%	€1,637,543
€7,589,562	€6,041,723	€1,786,671	0.03%	90%	86%	87%	75%	€1,677,341
€7,002,425	€5,740,511	€1,973,769	0.00%	100%	97%	81%	67%	€1,805,295
€7,295,994	€5,740,511	€1,876,222	0.01%	93%	92%	84%	71%	€1,858,375
€7,589,562	€5,740,511	€1,590,214	0.01%	67%	80%	86%	76%	€1,756,948
€7,002,425	€5,439,299	€1,939,714	0.01%	98%	95%	81%	67%	€2,032,377
€7,295,994	€5,439,299	€1,777,488	0.01%	84%	87%	84%	71%	€2,088,095
€6,708,857	€5,138,088	€1,973,769	0.00%	100%	97%	79%	61%	€2,248,270
€7,002,425	€5,138,088	€1,821,462	0.01%	92%	89%	82%	65%	€2,304,837
€7,295,994	€5,138,088	€1,548,935	0.01%	66%	78%	84%	71%	€2,160,865
€6,415,288	€4,836,876	€1,973,769	0.00%	100%	97%	76%	59%	€2,309,550
€6,708,857	€4,836,876	€1,820,721	0.05%	87%	89%	79%	64%	€2,356,191
€7,002,425	€4,836,876	€1,596,538	0.02%	64%	80%	82%	66%	€2,370,510
€6,415,288	€4,535,664	€1,816,232	0.02%	89%	89%	75%	61%	€2,412,037
€6,708,857	€4,535,664	€1,588,866	0.01%	69%	80%	78%	64%	€2,417,626

Solutions whose OTIF and MTS forecasts metrics are below 75% not shown

Chapter 4

A robust S&OP approach considering contract management decisions

This chapter presents a robust S&OP model to support the sales and marketing teams to define the sales plan in a setting of limited capacity to serve multiple customers that can be either non-contractual or operate under quantity-flexibility arrangements. This approach answers to the need of developing new models incorporating contract management into Sales and Operations Planning. We illustrate the benefit of our model resorting to extensive computational experiments, which allowed us to derive some key managerial insights.

Design of a sales plan in a hybrid contractual and non-contractual context in a setting of limited capacity

Daniel Filipe Pereira [*], José Fernando Oliveira [†], Maria Antónia Carravilla [†]

[*] Faculty of Engineering, University of Porto and LTPlabs [†] INESC TEC

Submitted to *Production and Operations Management*, 2021

Abstract: Many companies face capacity limitations that impair them to satisfy potential demand. In this context, sales/marketing teams have to decide which demand segments the company should prioritize. In business-to-business contexts, it is common that this selection includes customers with and without a contract. On the operations side, the production teams are interested in finding the most efficient usage for the available capacity. However, decision-making approaches to face such challenge are scarce. In this paper, we propose a scenario-based robust optimization model to support the sales and marketing teams to define the most profitable sales plan in a setting of limited capacity, to serve multiple customers that can be either non-contractual or operate under quantity-flexibility contracts. The proposed model integrates contract design, portfolio selection, and tactical production planning decisions. The computational results demonstrate the model's capacity to select resource utilization and define the contract parameters that maximize the expected profitability. We expect this approach supports industrial companies defining the mid-term sales plan and deciding on the conditions to offer to contract customers.

Keywords: Marketing-Operations interface, Sales and Operations Planning, Contract design, Portfolio management, Demand management, Robust optimization

4.1 Introduction

In companies where capacity is insufficient to satisfy potential demand and capacity is difficult to adjust, the decision on how to optimally use the installed capacity is paramount for success (Carr & Lovejoy, 2000). In this context, sales and marketing teams decide how to best invest the existing capacity by choosing the best customers to serve and the more interesting products to promote (Esper, Ellinger, Stank, Flint, & Moon, 2010). Simultaneously, in some business-to-business (B2B) contexts, contractual agreements are used as a countermeasure to deal with demand uncertainty and achieve supply chain coordination (Araneda-Fuentes, Lustosa, & Minner, 2015). Therefore, marketing and sales teams must decide how to allocate capacity to those agreements and which contractual clauses are reasonable to practice to ensure an adequate service level. Our paper focuses on this challenge, which is tactical. It consists of defining the sales plan for a company that serves both contract and non-contract customers but cannot fulfill the potential demand in full.

Different literature streams prescribe strategies for a seamless mid-term relationship between the marketing and sales teams and the operations teams. Sales and operations planning (S&OP) emerged as an extension of the aggregate production planning (Singhal & Singhal, 2007), integrating mid-term decisions from procurement, production, distribution, and sales in a single plan (Pereira, Oliveira, & Carravilla, 2020; Thome, Scavarda, Fernandez, & Scavarda, 2012; Tuomikangas & Kaipia, 2014). Research on the marketing-operations interface has been trying to encourage marketing and operations groups to work on a joint marketing and operations plan (Tang, 2010). The study on demand and supply integration advocates that a strategic alignment on these functions brings significant and long-term top and bottom line impacts (Esper et al., 2010). All these scholars and practitioners advocate that an organization should balance and follow the market needs regarding operational constraints and the costs of fulfilling such needs. In the end, bringing both manufacturing and marketing to the same table is smart business (Hausman, Montgomery, & Roth, 2002).

Despite the advances made in the past, no study exists to support the sales and marketing teams to define the sales plan in a setting of limited capacity to serve multiple customers that can be either non-contractual or operate under quantity-flexibility arrangements. This paper aims to fill such a gap contributing to the enrichment of the marketing-operations interface literature. If we draw attention to past literature, our work can be seen as a response to requests for further research on the topic. According to Tang (2010), there is an opportunity to develop models to study the trade-offs between customer acquisition plans, marketing plans, and operations plans. On the marketing side, Esper et al. (2010) suggest work capable of better describing how demand and supply can be integrated and which managerial perspectives are necessary to ensure such integration. Jüttner, Christopher, and Baker (2007) stress the importance of research that considers the effect of marketing activities from an integrated process perspective as a lever for collaboration between marketing and supply chain. More recently, on the S&OP stream, Goh and Eldridge (2019) claims that there is a lack of literature that demonstrates how managers can leverage marketing-operations models to achieve better outcomes in cross-functional settings. Pereira et al. (2020) highlight that future research on decision-making models for S&OP should foster a more effective relationship with the sales function. The integration of contract management plays a vital role.

We tackle this challenge using optimization techniques. It is a mathematically-oriented approach that is easily adaptable, broadly understood, and capable of dealing with detailed and real-world-sized problems. We strive for a generic model by considering a multi-stage production process where multiple production alternatives are available, commonly observed in flow shop/-batch industries. The approach can be simplified and employed in single-stage production settings.

As mentioned, our approach focus on the tactical spectrum. On this level, the benefits of integration are more impactful and more easily implemented (Esper et al., 2010; O'Leary-Kelly & Flores, 2002). If the integration occurs only at a manufacturing planning stage, it may be too late for implementing suggested improvements (O'Leary-Kelly & Flores, 2002). We propose a yearly model, with a monthly detail, that can be leveraged during budgeting or strategic committees and provide the marketing and sales and the operational teams with an integrated plan that maximizes business profitability. In more detail, our model prescribes the sales quantities for contract and non-contract customers in each period, which contract parameters to offer, which products deserve to be included in the contracts, and the tactical production plan to achieve such sales (that is, aggregated production quantities and inventory levels). As uncertainty arises given the moderate extent of our planning horizon, we acknowledge demand uncertainty for risk management. Our optimization model is a robust counterpart comprising a scenario-based approach (Mulvey, Vanderbei, & Zenios, 1995) that considers different demand estimates for contract and non-contract customers. In comparison with stochastic optimization, we propose a robust optimization approach since estimating demand probability distributions in many practical applications is challenging. In our case, given the limited interactions that commonly occur between a supplier and a buyer in a B2B context, this is undoubtedly an issue.

Afterward, we employ our model in a set of computational experiments using an instance based on real data provided by a cable manufacturer. We analyze the optimal plan prescribed by the model, detail the rationale behind the decisions proposed, and perform sensitivity analysis on some parameters to evaluate the related impacts. We use these experiments to derive managerial insights regarding the importance of factors such as available capacity, volume, and discount rates on the decisions proposed. In the end, our research unveils that the implementation of this decision-making approach brings benefits for managers.

The remainder of the paper is organized as follows. We start by reviewing related literature in Section 4.2. In Section 4.3, we detail the problem, the decision-making model, and the robust approach employed. Section 4.4 is dedicated to computational experiments and performing sensitivity analysis. Finally, Section 4.5 provides the concluding remarks of this work.

4.2 Related Literature

There are two sets of literature in analytical models that are related to our work: the literature on models on the marketing-operations interface and S&OP (Section 4.2.1), and the literature on contract management (Section 4.2.2). Due to the vast body of literature in each field, we do not intend to be exhaustive. On the contrary, we expect to highlight the current state of knowledge in each domain and frame the need for our approach. In Section 4.2.3, we point out the main contributions provided by this research.

4.2.1 Integrated planning models

Tang (2010) defines six types of marketing-operations interface models: customer portfolio selection models, guaranteed customer service models, new product development and sales channel models, product assortment models, production and pricing models, and channel coordination models. According to the author, research on product assortment planning and production and pricing models was getting saturated. On the other hand, additional developments were suggested in customer portfolio selection, channel coordination, and the identification of mechanisms to reduce waste.

Developments on customer portfolio selection, related to this paper's topic, have been occurring considering the inverse newsvendor model proposed by Carr and Lovejoy (2000). The traditional newsvendor problem sets capacity to demand, whereas demand is fitted to capacity in the inverse newsvendor problem. Taaffe, Geunes, and Romeijn (2008) propose a model to analyze market entry decisions for products with a single selling season under uncertain demand. In the context of the problem, there is a limited marketing budget to optimize. Taaffe, Romeijn, and Tirumalasetty (2008) apply a selective newsvendor problem to choose the orders to pursue and the total quantity to procure before the beginning of the selling season. The goal is to maximize the profits, and demand is random and given by the set of pursued orders. Choi and Ketzenberg (2018) determine the number of customers that could be served using the available capacity. Contrary to previous research, this paper studies the number of customers and not the demand distribution to fulfill. The approach may be leveraged to determine the optimal service level in the context of aggregate planning. The papers from Bavafa, Leys, Örmeci, and Savin (2019); Choi and Wilhelm (2014) consist of applications of the inverse newsvendor problem to allocate surgical specialties given hospital resources capacity (e.g., operating rooms).

On the side of S&OP, Pereira et al. (2020) conducted a literature review on analytical models supporting S&OP with a focus on identifying the decisions that are considered in this planning layer and the level of integration provided by existing models. The authors conclude that further efforts should be made to strengthen the sales business function's integration with the remaining supply chain functions (i.e., procurement, production, distribution). More specifically, the enrichment of existing models is suggested to tackle more complex demand functions - including pricing and promotional considerations - and to integrate contract management.

Regarding the latter, only a handful of papers exist considering contract management while planning sales and operations. Barbarosoglu (2000) focuses on the definition of a contract between a supplier and several buyers. Monthly production levels are defined for the following year. Price and supply commitments to each buyer are determined. In the model from Guan and Philpott (2011), every month, there is a possibility of defining a supplying contract for the next three months, with the remaining sales being assured in the spot market. The model is focused on the dairy industry. Gunnarsson and Rönnqvist (2008); Lidestam and Rönnqvist (2011) include the possibility of accepting contractual agreements in supply chain models for a pulp company. The most comprehensive approach to contract management in a context of S&OP belongs to Feng, Martel, D'Amours, and Beauregard (2013). The model considers the coordinated contract selection and capacity allocation problem. Using stochastic programming with recourse, the authors study how these decisions are taken considering economic, market, supply, and system uncertainties using a real business case from the Oriented Strand Board industry. The model considers different types of policies to offer to customers, ranging from price-only contracts to various forms of quantity-flexibility contracts.

4.2.2 Contract management

Several types of contractual arrangements have been studied in the literature and supply chain management practice. This research considers quantity commitment contracts under a multi-product setting. The classification from Anupindi and Bassok (1999) brings forward three types of agreements: (i) total minimum quantity (TMQ) commitment, (ii) total minimum dollar volume (TMDV) commitment, and (iii) periodical commitment with flexibility. In (i), the sum of the quantities Q that a customer consents to buy of the product p over the length of the planning period $t \in T$ needs to be greater or equal than a minimum quantity $Q_{min,p}$, that is, $\sum_{t \in T} : Q_{p,t} \geq Q_{min,p}$. The supply relationship is parameterized by (s_p, $Q_{min,p}$), where s_p is the sales price of p. Variant (ii) consists of a multi-product equivalent of (i), where the commitment is established on the total business volume for all products.

Periodical commitment with flexibility comprises a more complex agreement with minimum and maximum quantities in each period. In the classification from Cachon (2003), the variant (iii) is framed into the quantity-flexibility (QF) contracts category, defined by a scheme of commitment with order band. Typically, minimum and maximum quantities are imposed by the contract, and the price can range depending on the level of the commitment. In mathematical terms, the supply relationship is defined by (s_p, $Q_{f,p}$, α_p, ω_p) (Tsay, 1999). In each period t, the customer consents to purchase at least $Q_{f,p}(1-\omega_p)$ and the seller guarantees product availability up to $Q_{f,p}(1+\alpha_p)$.

Past research focuses more on the characterization of optimal policies between a supplier and a buyer rather than on the inclusion of contract management on the joint mid-term planning between marketing and sales teams and operations teams. Research has stressed the optimal definition of policies and replenishment strategies between a supplier and a buyer and in contexts where only a single product exists. Hardly this is the setting faced by an industrial company when deciding on its sales plan and contracts to subscribe to. Even the papers dealing with multiple segments (contractual and spot markets) commonly deal with the topic from the buyer's perspective, not the supplier's perspective, which we do. Past literature on quantity commitment contracts is detailed in Appendix 4.A.

From the reviewed papers, two deserve particular comments. The first is the paper from Feng et al. (2013) that, as referred, embeds contracts selection on a broader S&OP problematic. In terms of decisions addressed and approach framing, this paper comprises the most similar approach to ours. The second is the work from J. Li, Luo, Wang, and Zhou (2020) that studies QF and capacity reservation contracts in a context where the capacity cost is high, similar to ours. Such characteristic has a profound impact on the managerial decisions, and infrequent are the studies addressing this issue.

4.2.3 Contribution of this study

We propose a decision-making model to support the sales and marketing teams in defining the sales plan in a setting of limited capacity to serve multiple customers that can be either non-contractual or operate under QF arrangements. We extend the contract management literature by considering a sales ecosystem where contract and non-contract customers compete for the same capacity, considering a multi-period and multi-product context (as detailed in Section 3.4.2). Our literature review demonstrated that this topic has not been adequately explored and it is a relevant problem in a real-world setting.

Even though the paper from Feng et al. (2013) already approaches this issue, our research is distinctive in several ways. First, our model performs portfolio selection along with contract design. If a supplier foresees difficulties in providing a specific product to a customer given limited capacity, or if the inclusion of that product is not profitable, the supplier will be better off not offering the product to the buyer. Second, we propose a more flexible production structure, given by a multi-stage production process. Third, we derive different insights from our study, namely thorough analyses of the inter-dependencies between contract and non-contract demand and the impacts caused by a limited production capacity.

Although the focus of this research is not on the development of new modeling approaches, the approach followed (robust optimization) has not been extensively applied in marketing-operations interface and S&OP models (Pereira et al., 2020). We are contributing to the assessment of the applicability of this approach in this type of problem.

4.3 Decision-making model

In this section, we first detail the problem and present the decision-making model proposed (Section 4.3.1). Later on, we present the scenario-based robust optimization approach employed and adapt the formulation of the mathematical model accordingly (Section 4.3.2).

4.3.1 Problem description and formulation

At the beginning of the horizon composed of $t \in T$ periods, the company defines the sales targets for each product $p \in P$, and for each market $k \in K$. Simultaneously, the company has the chance of defining sales contracts with contract customers ($c \in C$). Therefore, the integrated sales/marketing (from now on referred to as *sales*) and operations plan considers both market segments the company operates into (contract and non-contract customers). The goal is to determine the best usage of production resources, the most favorable product-market allocation, and which contracts should be established to maximize overall profitability. From the company's products portfolio, P_k ($P_k \subset P$) comprises the products potentially sold in market k, and P_c ($P_c \subset P$) gathers the products that can be included in the contract with customer c.

The products are produced along $s \in S$ production stages, and there is a set of $m_s \in M_s$ machines belonging to the production stage s. Due to technological and compatibility issues, products may not be processed in every machine in a specific stage, with $M_{s,p}$ ($M_{s,p} \subset M_s$) representing the set of machines belonging to the production stage s where product p can be produced. The operations parameters considered in the model are presented in Table 4.3.1. Each machine m is characterized by a unitary production time and an amount of regular time available per period. Production in regular time can be complemented by recourse to overtime in each machine, but with incremental cost over the cost per unit of time. Finally, besides production and holding costs, a cost per unit of product is regarded to account for the cost of goods sold (e.g., raw material costs).

Table 4.3.1: Operations parameters

Parameter	Description
$\beta_{p,m}$	Production time in machine m per unit of product p
$r_{m,t}$	Amount of regular time available at machine m in period t
$o_{m,t}$	Amount of overtime available at machine m in period t
ρ_m	Cost per unit of time in machine m
γ_m	Additional production cost (incremental rate) per unit of overtime in machine m
$h_{p,t}$	Holding cost of one unit of product p in period t
c_p	Cost per unit of product p (other than production costs: raw materials, administrative variable costs...)

There are three relevant decisions for the operations team, detailed in Table 4.3.2: production quantities of the different products in each machine across the $t \in T$ periods, the necessary overtime to fulfill such quantities, and the end-of-period inventory levels of the several products.

Table 4.3.2: Operations decision variables

Variable	Description
$X_{p,m,t}$	Production quantity of product p in machine m in period t
$E_{m,t}$	Overtime used at machine m in period t
$I_{p,t}$	Inventory of product p at the end of period t.

The main parameters on the sales side are given in Table 4.3.3. We assume a primary uncertain non-contract demand, with given sales prices. In each of the $k \in K$ markets, contract customers may exist. Multi-period agreements between a buyer and a supplier in B2B contexts are frequent in commerce, manufacturing, and service industries (Araneda-Fuentes et al., 2015). Due to his high practical relevance and applicability, we model QF contracts. There is an expectancy of sales for each product, which is also uncertain. The contract is established considering the expected quantity obtained by the best forecast available at the beginning of the period. We assume that QF limits are imposed over the total quantity, which means that there is flexibility for the buyer regarding the purchasing quantity of each product included in the agreement - similar to what is proposed by Karakaya and Bakal (2013) - as long as the aggregated limits are respected. From the supplier's side (our perspective), the contract is beneficial to ensure overall capacity reservation. Thus, we consider more value is globally ensured for both parties if an aggregated capacity control is imposed rather than individual limits for each product.

Table 4.3.3: Sales parameters

Parameter	Description
$\widetilde{d}_{p,k,t}$	Demand of product p in period t for non-contract customers from market k
$\phi_{p,k,t}$	Sales price of product p in period t in non-contract sales in market k
$\widetilde{d}_{p,c,t}$	Demand of product p in period t for contract customer c
$\overline{d}_{p,c,t}$	Expected demand (forecast) of product p in period t for contract customer c
$\psi_{c,\alpha}$	Level of discount offered to customer c over the sales price $\phi_{p,k_c,t}$ under a QF contract with flexibility α_c (assuming the same flexibility upwards and downwards, measured as a percentage deviation over the expected demand). k_c is the market the contract c belongs to. α_c is a decision variable

A buyer only accepts signing a contract if prospective benefits exist. The buyer expects service level, given by the mandatory on-time fulfillment of a minimum quantity, expressed by the α_c parameter. Furthermore, we also assume that sales under a contract agreement are made with a discount over the sales price of product p practiced in the market k_c the customer c operates in. The flexibility-dependent discount is defined by customer, with the discount factor $\psi_{c,\alpha}$ varying in function of α_c. For greater values of α_c, the degree of flexibility is so high that the discount will tend to zero (i.e., a price equivalent to non-contract sales). This research assumes perfect information about each customer's flexibility-dependent curves (or that at least they can be reasonably approximated). Another significant assumption is that our model does not aim to study the conditions under which such arrangements result in supply chain efficiency. We consider that any discount below the discount curve, for any flexibility level, represents conditions in which the customer c is unwilling to sign the contract.

We assume lost sales are possible and backlogs are not allowed. Such assumptions are particularly relevant because of our premise that capacity is scarce to fulfill all the demand. In the case of QF contracts, demand over the maximum agreed quantity $\sum_{p\in P_c} \widetilde{d}_{p,c,t}, \forall c \in C, t \in T$ is not fulfilled, with no additional penalty. For non-contract sales, we assume that no additional penalties are imposed either, with the company operating in a perfectly competitive market. The market is large and homogeneous enough that if the company cannot fulfill all the potential demand, other competitors can.

As a result of this tactical planning exercise, the sales team will have a prescriptive plan with the optimal strategy for non-contract demand satisfaction, expressed by the quantity sold of product p to non-contract customers from market k in period t, $Q_{p,k,t}$. This allocation is determined in parallel with the decision on the contractual plan to negotiate with the contract customers. Table 4.3.4 summarizes the sales decision variables. Besides the definition on which type of contract is preferable for each customer, we also include the portfolio decision on which products deserve to be included in the contract, $Z_{p,c}$. The supplier is rational not to include a product in a contract if its fulfillment is not profitable or if it foresees that capacity limitations may arise. The flexibility level of the QF arrangement is given by the product of α_c and the total quantity associated with the products included in the contract.

Table 4.3.4: Sales decision variables

Variable	Description
$Q_{p,k,t}$	Quantity sold of product p to market k in period t
W_c	Binary variable, 1 if a QF contract is offered to contract customer c, 0 otherwise
α_c	Flexibility of the QF contract offered to customer c, valid if $W_c = 1$
$Z_{p,c}$	Binary variable, 1 if product p is sold to contract customer c, 0 otherwise
$Q_{p,c,t}$	Quantity sold of product p to contract customer c in period t
$A^{min}_{c,t}/A^{max}_{c,t}$	Auxiliary binary variable, 1 if the sum of the demand of the products included in the contract ($\sum_{p\in P_c:Z_{p,c}=1}\widetilde{d}_{p,c,t}$) reaches the minimum/maximum agreed quantity in the QF contract established with the customer c in period t, 0 otherwise

The decisions described are summarized in Figure 4.3.1. The contract decisions are taken at the beginning of the horizon and influence the subsequent sales and operations decisions. At the same time, as we model the entire planning horizon while designing the contract terms, we consider the impacts in later periods to make the best decision. The same figure also introduces that the plan is determined to maximize the overall profitability and is subject to some constraints, as we further detail.

The objective function is given by the sum of the contract sales (equation 4.1) and the non-contract sales (equation 4.2), subtracted by the production and other costs (equations 4.3-4.4).

$$SalesQF = \sum_{c\in C}\sum_{p\in P_c:Z_{p,c}=1}\sum_{t\in T} Q_{p,c,t}\phi_{p,k_c,t}(1-\psi_{c,\alpha}) \tag{4.1}$$

$$NonContractSales = \sum_{k\in K}\sum_{p\in P_k}\sum_{t\in T} Q_{p,k,t}\phi_{p,k,t} \tag{4.2}$$

$$ProductionCost = \sum_{p\in P}\sum_{s\in S}\sum_{m\in M_{s,p}}\sum_{t\in T} X_{p,m,t}\beta_{p,m}\rho_m + \sum_{m\in M}\sum_{t\in T} E_{m,t}\gamma_m \tag{4.3}$$

$$OtherCosts = \sum_{p\in P}\sum_{t\in T} I_{p,t}h_{p,t} + \sum_{p\in P}\sum_{s\in S:s=S}\sum_{m\in M_{s,p}}\sum_{t\in T} X_{p,m,t}c_p \tag{4.4}$$

$$Max\ Profit = SalesQF + NonContractSales - ProductionCost - OtherCosts \tag{4.5}$$

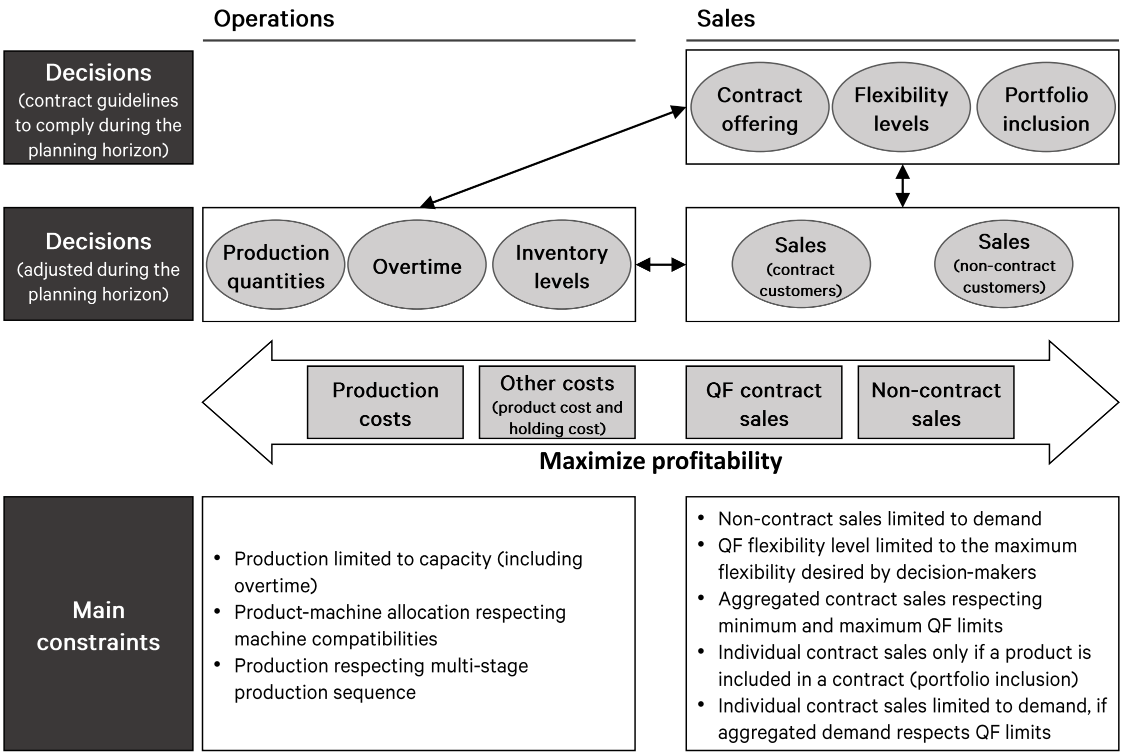


Figure 4.3.1: Integrated marketing/sales-operations planning model

The plan is limited by constraints on the operations side (constraints 4.6-4.9). Equations (4.6) define that the production time in each machine must not surpass the amount of regular and overtime available in each period. Constraints (4.7) limit the overtime used. The production process along the multiple stages is guaranteed by constraints (4.8), which define that production in stage s can only exist if production in stage $s-1$ is also done. Our model does not consider carryovers between periods because we model production in aggregated terms, which is the practice in mid-term planning practices such S&OP (Pereira et al., 2020; Thome et al., 2012). Finally, constraints (4.9) comprise the inventory balance constraints. The amount of inventory of p at the end of period t is given by the inventory available at the end of the previous period $t-1$ plus the production of the period (modeled by the quantity processed in the last production stage) minus the quantity sold for contract and non-contract customers.

$$\sum_{p \in P} X_{p,m,t} \beta_{p,m} \leq r_{m,t} + E_{m,t}, \quad \forall m \in M, t \in T \tag{4.6}$$

$$E_{m,t} \leq o_{m,t}, \quad \forall m \in M, t \in T \tag{4.7}$$

$$\sum_{m \in M_{s,p}} X_{p,m,t} \leq \sum_{m \in M_{s-1,p}} X_{p,m,t}, \quad \forall p \in P, s \in S : s > 1, t \in T \tag{4.8}$$

$$I_{p,t} = I_{p,t-1} + \sum_{m \in M_{s,p}: s=S} X_{p,m,t} - \sum_{c \in C} Q_{p,c,t} - \sum_{k \in K} Q_{p,k,t}, \quad \forall p \in P, t \in T \tag{4.9}$$

Equations (4.10)-(4.22) state the boundaries on the sales side. Constraints (4.10) define that the amount of each product p sold to non-contract customers must not surpass the expected demand for each market k in each period t. There is no obligation to propose a QF contract to a customer. Therefore, only if a contract is offered to a customer, a specific product p can make part of that menu, which is represented by constraints (4.11). Equations (4.12) define that the amount of product p sold to each contract customer c in period t can not be greater to the demand of the product if the minimum commitment agreed with the customer is achieved by the sum of the demand of all the products included in the contract (given by the binary variable $A_{c,t}$, equal to one in that case). On the other hand, if the minimum threshold is not achieved, $Q_{p,c,t}$ must not surpass a big M (in this case, defined as the sum of the demand of all the products in all periods). Irrespective of the case, $Q_{p,c,t}$ is only greater than zero if the product is part of the contractual arrangement offered to the customer. Constraints (4.13) define that the demand of each product in each period must be respected if the product p is included in the contract, and the maximum quantity defined by the QF contract is not surpassed by the sum of the demand of all the products. Constraints (4.14)-(4.17) define, for each customer in each period, the value of the binary variables $A^{min}_{c,t}$ and $A^{max}_{c,t}$.

$$Q_{p,k,t} \leq \widetilde{d}_{p,k,t}, \quad \forall k \in K, p \in P_k, t \in T \tag{4.10}$$

$$Z_{p,c} \leq W_c \quad \forall c \in C, p \in P_c \tag{4.11}$$

$$Q_{p,c,t} \leq \widetilde{d}_{p,c,t} Z_{p,c} A^{min}_{c,t} + \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} Z_{p,c} (1 - A^{min}_{c,t}), \quad \forall c \in C, p \in P_c, t \in T \tag{4.12}$$

$$Q_{p,c,t} \geq \widetilde{d}_{p,c,t} Z_{p,c} (1 - A^{max}_{c,t}), \quad \forall c \in C, p \in P_c, t \in T \tag{4.13}$$

$$\sum_{p \in P_c} \widetilde{d}_{p,c,t} Z_{p,c} - \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 - \alpha_c) \leq \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} A^{min}_{c,t}, \quad \forall c \in C, t \in T \tag{4.14}$$

$$\sum_{p \in P_c} \widetilde{d}_{p,c,t} Z_{p,c} - \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 - \alpha_c) \geq - \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} (1 - A^{min}_{c,t}), \quad \forall c \in C, t \in T \tag{4.15}$$

$$\sum_{p \in P_c} \widetilde{d}_{p,c,t} Z_{p,c} - \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 + \alpha_c) \leq \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} A^{max}_{c,t}, \quad \forall c \in C, t \in T \tag{4.16}$$

$$\sum_{p \in P_c} \widetilde{d}_{p,c,t} Z_{p,c} - \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 + \alpha_c) \geq - \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} (1 - A^{max}_{c,t}), \quad \forall c \in C, t \in T \tag{4.17}$$

$$\alpha_c \leq max_{\alpha} W_c, \quad \forall c \in C \tag{4.18}$$

$$\sum_{p \in P_c} Q_{p,c,t} \geq \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 - \alpha_c), \quad \forall c \in C, t \in T \tag{4.19}$$

$$\sum_{p \in P_c} Q_{p,c,t} \leq \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 + \alpha_c), \quad \forall c \in C, t \in T \tag{4.20}$$

$$\sum_{p \in P_c} Q_{p,c,t} \leq \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 - \alpha_c) + \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} A^{min}_{c,t}, \quad \forall c \in C, t \in T \tag{4.21}$$

$$\sum_{p \in P_c} Q_{p,c,t} \geq \sum_{p \in P_c} \overline{d}_{p,c,t} Z_{p,c} (1 + \alpha_c) - \sum_{c \in C} \sum_{p \in P_c} \sum_{t \in T} \widetilde{d}_{p,c,t} (1 - A^{max}_{c,t}), \quad \forall c \in C, t \in T \tag{4.22}$$

The remaining constraints specify the contract terms. Equations (4.18) define that for each customer c covered by this type of agreement, it must be defined a flexibility level α_c limited by an upper bound max_α, that represents the maximum degree of flexibility the company aims to provide. Constraints (4.19) and (4.20) ensure that in each period t, the sum of the quantity sold of all the products included in the contract lies between the band defined, an interval of $\pm\ \alpha_c$ of the aggregated forecast. As stated, the limit is imposed over the total quantity, which means that there is flexibility regarding the quantity of each product composing the menu, as long as the aggregated volume is respected. Finally, constraints (4.21) and (4.22) impose limitations on the quantities sold to contract customers if the minimum and maximum bands of the QF contract are, respectively, not achieved or surpassed once the demand of the products included in the contract is realized. The first set states that the total quantity sold to a customer c in period t must be equal to the minimum threshold if the sum of the realized demands is below that value. The second set ensures that the total quantity sold equals the maximum threshold if the sum of the realized demands is above the limit.

To complete the problem formulation, we add the domain constraints, represented by the equations (4.23)-(4.25). Note that the non-linearities arising from the product of variables $Z_{p,c}$ and $A_{c,t}^{min}$, $Z_{p,c}$ and $A_{c,t}^{max}$, and $Z_{p,c}$ and α_c in equations (4.12)-(4.17) and (4.19)-(4.22) can be surpassed with the addition of auxiliary binary variables and related constraints. However, the model is still non-linear due to the product of the quantity sold to contract customers $Q_{p,c,t}$ by the discount factor $\psi_{c,\alpha}$ (function of α_c) in the objective function. To maintain the problem linear and solvable using methods for mixed integer linear programs, one possible solution is to consider discrete flexibility levels, with the inclusion of additional binary variables in the formulation. We use that strategy in the computational experiments carried out in this paper.

$$X_{p,m,t}, E_{m,t}, I_{p,t} \geq 0, \quad \forall p \in P, m \in M, t \in T \tag{4.23}$$

$$\alpha_c, Q_{p,c,t}, Q_{p,k,t} \geq 0, \quad \forall c \in C, p \in P, k \in K, t \in T \tag{4.24}$$

$$W_c, Z_{p,c}, A_{c,t}^{min}, A_{c,t}^{max} \in \{0,1\}, \quad \forall p \in P, c \in C, t \in T \tag{4.25}$$

4.3.2 Approach to uncertainty

There are two main approaches to deal with data uncertainty in optimization, namely robust and stochastic optimization. Stochastic programming considers that the probability distribution of uncertain data is known. Robust optimization does not assume probability distributions are known (Gorissen, Yanıkoglu, & den Hertog, 2015). On the other hand, it works with a deterministic, set-based description of uncertainty. The goal is to find a feasible solution irrespective of the realization of the uncertain parameters and optimal for the worst-case objective function. The degree of conservatism of robust optimization has been pointed out as a disadvantage of the approach because the robust solution has an objective function value much worse than the one obtained in the nominal (deterministic equivalent) linear optimization problem (Bertsimas & Sim, 2004). Therefore, approaches such as the ones proposed by Ben-Tal and Nemirovski (2000); Bertsimas and Sim (2004) attempt to make the optimality/feasibility trade-off more attractive. We propose our model to be tackled using robust optimization. In many real-world applications, estimating the demand probability distributions is difficult, as in B2B contexts, where the limited interactions between a supplier and a buyer narrow the available data.

In robust optimization, uncertainties can be classified into continuous and discrete. In continuous uncertainty, data lie within upper and lower bounds representing the uncertainty set that can assume multiple shapes (e.g., box, ellipsoidal, polyhedral). In discrete uncertainty, a scenario-based approach is applied to deal with uncertain data (Peykani, Mohammadi, Saen, Sadjadi, & Rostamy-Malkhalifeh, 2020). Given the more practical and business-oriented rationale of the latter, we opt for a discrete uncertainty set.

Mulvey et al. (1995) introduce a framework for robust optimization considering two types of robustness: (i) solution robustness, *i.e.* the solution is robust concerning optimality if it remains "close" to optimal irrespective of the scenario; (ii) model robustness, that is, the solution is robust from a feasibility perspective if it is "almost" feasible for any scenario. The definition of "close" and "almost" is left up to the modeler by choosing parameters that weigh the importance of both model robustness and solution robustness in the objective function. This framework has been used in several applications, such as Bakhtavar and Mahmoudi (2020); Leung, Tsang, Ng, and Wu (2007); Mirzapour Al-e hashem, Malekly, and Aryanezhad (2011).

The optimization structure proposed by Mulvey et al. (1995) is as follows:

$$
\begin{aligned}
&Min \quad c^T x + d^T y, \quad subject\ to\\
&Ax = b\\
&Bx + Cy = e\\
&x, y \geq 0
\end{aligned}
$$

The vector x represents the design variables, whose optimal value is not conditioned by the realization of the uncertain data. Vector y denotes the control variables, which are adjusted once the uncertain parameters are realized. $Ax = b$ represents structural constraints with deterministic coefficients. $Bx + Cy = e$ denotes the constraints whose coefficients are subject to uncertainty. The robust problem is composed by a set of scenarios. Each scenario $\xi \in \Xi$ is characterized by the subset $d_\xi, B_\xi, C_\xi, e_\xi$, and has a probability of occurrence p_ξ $(\sum_{\xi \in \Xi} p_\xi = 1)$.

Introducing a set of control variables $y_1, y_2, y_3, ..., y_\Xi$ for each scenario and a set of error vectors $z_1, z_2, z_3, ..., z_\Xi$ measuring the infeasibility of the control constraints under scenario $\xi \in \Xi$, the formulation can be adapted as follows:

$$
\begin{aligned}
&Min \quad \sigma(x, y_1, y_2, y_3, ..., y_\Xi) + \omega\rho(z_1, z_2, z_3, ..., z_\Xi), \quad subject\ to\\
&Ax = b\\
&B_\xi x + C_\xi y_\xi = e_\xi, \quad \forall \xi \in \Xi\\
&x, y_\xi \geq 0, \quad \forall \xi \in \Xi
\end{aligned}
$$

The first term represents solution robustness, measuring the degree of risk aversion. The second term denotes model robustness, penalizing infeasible solutions. If we assume that $\Gamma_\xi = f(x, y_\xi)$ represents a cost or benefit function for scenario ξ, a high variance for $\Gamma_\xi = f(x, y_\xi)$ means the solution is a high-risk decision. In that case, the objective function changes significantly for a small change in the value of the uncertain parameters. Thus, the first term can be expressed as $\sigma(x, y_1, y_2, y_3, ..., y_\Xi) = \sum_{\xi \in \Xi} p_\xi \Gamma_\xi + \lambda \sum_{\xi \in \Xi} p_\xi (\Gamma_\xi - \sum_{\xi' \in \Xi} p_{\xi'} \Gamma_{\xi'})^2$. The term λ is used to denote the weight attributed to the solution variance. A higher value of λ makes the solution value less sensitive to changes on uncertain parameters. Applying the absolute deviation instead of the quadratic term as proposed by Yu and Li (2000), the solution robustness term can be expressed as represented below. We refer to the original paper, where the reformulation is deduced, for those interested in the details behind this adapted approach.

$$
\begin{aligned}
& Min \sum_{\xi \in \Xi} p_\xi \Gamma_\xi + \lambda \sum_{\xi \in \Xi} p_\xi \left[\left(\Gamma_\xi - \sum_{\xi' \in \Xi} p_{\xi'} \Gamma_{\xi'} \right) + 2\theta_\xi \right], \quad subject\ to \\
& \Gamma_\xi - \sum_{\xi \in \Xi} p_\xi \Gamma_\xi + \theta_\xi \geq 0, \quad \forall \xi \in \Xi \\
& \theta_\xi \geq 0, \quad \forall \xi \in \Xi
\end{aligned}
$$

If we consider the feasibility penalty function $\rho(z_1, z_2, z_3, ..., z_\Xi)$, whose weight in the problem is set by ω, the objective becomes:

$$
Min \sum_{\xi \in \Xi} p_\xi \Gamma_\xi + \lambda \sum_{\xi \in \Xi} p_\xi \left[\left(\Gamma_\xi - \sum_{\xi' \in \Xi} p_{\xi'} \Gamma_{\xi'} \right) + 2\theta_\xi \right] + \omega \sum_{\xi \in \Xi} p_\xi z_\xi
$$

Adapting this approach to our model, consider that Γ_ξ represents the value of profit expressed by equation 4.5 for a given scenario $\xi \in \Xi$. The objective function can be easily converted into a maximization problem as follows:

$$
Max \sum_{\xi \in \Xi} p_\xi \Gamma_\xi - \lambda \sum_{\xi \in \Xi} p_\xi \left[\left(\Gamma_\xi - \sum_{\xi' \in \Xi} p_{\xi'} \Gamma_{\xi'} \right) + 2\theta_\xi \right] - \omega \sum_{\xi \in \Xi} p_\xi z_\xi
$$

Table 4.3.5 presents how the variables of the problem are classified between design and control variables. Contract variables W_c, α_c, and $Z_{p,c}$ are defined in the beginning of the planning horizon, and, therefore, not adjusted once the demand is realized. All the other variables are adjustable in function of the value of $\widetilde{d}_{p,k,t}$ and $\widetilde{d}_{p,c,t}$ in scenario $\xi \in \Xi$ (an additional subscript ξ shall be added in the notation of each of these variables). Constraints (4.6)-(4.9), (4.10), (4.12)-(4.17), and (4.19)-(4.22) are also made scenario-dependent.

Table 4.3.5: Classification of variables in robust formulation

Type	Variables
Design	W_c, α_c, $Z_{p,c}$
Control	$X_{p,m,t}$, $E_{m,t}$, $I_{p,t}$, $Q_{p,k,t}$, $Q_{p,c,t}$, $A^{min}_{c,t}$, $A^{max}_{c,t}$

To account for possible demand infeasibilities, an additional variable $U_{\xi,p,c,t}$ is included, representing the unsatisfied demand of product p ordered by the contract customer c in period t in scenario ξ, even though this means a contract violation. The term $\sum_{\xi\in\Xi} p_\xi z_\xi$ in the objective function is expressed as $\sum_{\xi\in\Xi}\sum_{c\in C}\sum_{p\in P_c:Z_{p,c}=1}\sum_{t\in T} p_\xi U_{\xi,p,c,t}$. Constraints (4.13), (4.19) and (4.22) are replaced, respectively, by (4.26), (4.27), and (4.28). Note that we are only including the possibility for demand not to be satisfied in full. Our model does not allow quantities to be delivered above the demand, as it is highly unlikely the customer would accept such case. The complete formulation of the robust model is available in Appendix 4.B.

$$Q_{\xi,p,c,t} + U_{\xi,p,c,t} \geq d_{\xi,p,c,t} Z_{p,c}(1 - A^{max}_{\xi,c,t}), \quad \forall \xi \in \Xi, c \in C, p \in P_c, t \in T \tag{4.26}$$

$$\sum_{p\in P_c} (Q_{\xi,p,c,t} + U_{\xi,p,c,t}) \geq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1-\alpha_c), \quad \forall \xi \in \Xi, c \in C, t \in T \tag{4.27}$$

$$\sum_{p\in P_c} (Q_{\xi,p,c,t} + U_{\xi,p,c,t}) \geq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1+\alpha_c) - \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t}(1 - A^{max}_{\xi,c,t}), \quad \forall \xi \in \Xi, c \in C, t \in T \tag{4.28}$$

4.4 Model application

In this section, we present how the model can be used to support decision-making. In Section 4.4.1, we detail the instance used. To generate a plan, we must define the robust optimization parameters (ω and λ), which is done in Section 4.4.2. In Section 4.4.3, we present the results of the model's application[1]. Finally, Section 4.4.4 includes a sensitivity analysis to some parameters.

4.4.1 Instance description

We use a real instance provided by a cable manufacturer[2]. The company produces different electric cables - low voltage products (domestic cables) and medium to high voltage products (industrial cables). The cables are processed throughout different stages: wire drawing, annealing, twisting and stranding, extrusion, cabling, steel armoring, outer sheathing. The factory is organized in a flow shop/batch process, composed of several machines. For the ones interested in studying the production of an electric cable, we refer to Thue (2017).

The instance scope is outlined in Table 4.4.1, which entails products from the industrial aluminum low voltage family. Forty-seven products are considered. The production is ensured by 37 machines, with products being, on average, produced in 5.98 machines. The instance comprehends 12 months. Table 4.4.2 details expected potential demand by segment and market. Contract demand amounts to 6,910,815 monetary units (m.u.) and non-contract demand amounts to

[1]Model solved with CPLEX 12.9.0 in a machine with a processor Intel(R)Xeon(R)CPU E5-2640 V2 @ 2.60GHz (limited to 12 threads) and 78GB of RAM. All the runs solved up to optimality.
[2]Available at https://dx.doi.org/10.17632/88k7y6t2mv.1

5,979,409 m.u.. A significant share of the contract demand belongs to three customers from market #1. Overall, there are seven contract customers from four different markets. The potential demand associated to each customer is presented in Table 4.4.3. Regarding non-contract demand, it is originated from four markets, with a clear concentration from market #6.

Table 4.4.1: Details of the instance

Indexes	**Size**
Products (P)	47
Markets (K)	6
Contract customers (C)	7
Products with potential sales to non-contract customers ($P_k, \forall k$)	30
Products with potential sales to contract customers ($P_c, \forall c$)	30
Machines (M)	34
Average no. stages (S)	5.98
Periods (T)	12

Table 4.4.2: Demand drill-down by segment and market

Segment	**Market**	**Products**	**Customers**	**Demand (m.u.)**	**Demand (meters)**
Contract	#1	12	3	4,726,539	1,961,300
	#2	8	1	1,080,934	488,954
	#3	12	2	647,719	192,134
	#4	4	1	455,623	58,414
	Total	**30**	**7**	**6,910,815**	**2,700,803**
Non-contract	#5	8	-	57,904	31,302
	#6	24	-	5,153,880	2,288,799
	#1	2	-	241,342	62,612
	#3	21	-	526,283	184,761
	Total	**30**	**-**	**5,979,409**	**2,567,474**

Values on contract demand (m.u.) not including QF contract discount

Table 4.4.3: Demand per contract customer

Market	**Customer**	**Demand (m.u.)**	**Demand (meters)**
#1	3622	1,668,278	728,415
	3971	2,076,237	848,010
	4012	982,023	384,876
#2	3291	1,080,934	488,954
#3	1358	587,167	177,660
	1571	60,552	16,162
#4	2750	455,623	58,414

Contract customers are subject to discount on the reference price in function of the flexibility issued in the contract. In our experiments we assume the customers may be offered one of the following five flexibility levels {10%,20%,30%,40%,50%}, with associated discount factors of {30.0%,20.0%,15.0%,10.0%,7.5%}.

Although an expected demand can be estimated for contract and non-contract segments, as presented in Tables 4.4.2 and 4.4.3, effective demand is subject to uncertainty. We consider three demand scenarios: around expectations (AE), over expectations (OE), under expectations (UE). To come up with the values, we generated random numbers between 0 and 1 and applied a linear progression over the initial expectation (IE), at the detailed level (in case of contract demand, at the product/customer/period level; in case of non-contract demand, at the product/market/period level). The lower and upper limits for the linear progression are as follows: AE [-25%;+25%], OE [0%;100%], UE [-100%;0%]. Demand in each scenario, as well its comparison against the initial expectation (IE) is detailed in Table 4.4.4. In aggregate terms, total demand in scenario AE remains close to the IE. On the opposite, in scenario OE total demand turns out to be around 50% greater than the IE; in scenario UE total demand is roughly half (-50%) of the IE.

Table 4.4.4: Demand in the several scenarios

Segment	**Market**	**Demand (m.u.)**			
		IE	AE	OE	UE
Contract	#1	4,726,539	4,611,943 (-2.4%)	7,138,918 (+51.0%)	2,144,026 (-54.6%)
	#2	1,080,934	999,762 (-7.5%)	1,691,354 (+56.5%)	637,844 (-41.0%)
	#3	647,719	637,719 (-1.5%)	999,705 (+54.3%)	292,816 (-54.8%)
	#4	455,623	481,655 (+5.7%)	713,890 (+56.7%)	255,335 (-44.6%)
	Total	**6,910,815**	**6,731,080** (-2.6%)	**10,543,867** (+52.6%)	**3,330,022** (-51.8%)
Non-contract	#5	57,904	58,914 (+1.7%)	90,188 (+55.8%)	33,431 (-42.3%)
	#6	5,153,880	5,085,539 (-1.3%)	7,679,211 (+49.0%)	2,730,940 (-47.0%)
	#1	241,342	263,832 (+9.3%)	356,921 (+47.9%)	100,171 (-58.5%)
	#3	526,283	560,687 (+6.5%)	780,016 (+48.2%)	229,639 (-56.4%)
	Total	**5,979,409**	**5,968,971** (-0.2%)	**8,906,335** (+49.0%)	**3,094,182** (-48.3%)

Values on contract demand (m.u.) not including QF contract discount

The company does not have sufficient installed capacity to meet demand, as described in Table 4.4.5. Overall regular utilization given initial demand expectancy is 47%. Nevertheless, we can see that machine utilization is not uniform across the machines. Machines 543, 590, 324, 316, 338, 612, and 530 present a machine utilization above 100%. Even resorting to the maximum available overtime, it would be not possible to produce all the demand since machines 543 and 590 would require an utilization, respectively, of 167% and 111%. The setting would be even more demanding if scenario OE is realized. In this case, even with a full utilization of the available overtime, machines 543, 590, 324, 316, 338, 612, and 530 do not have enough capacity. A detailed perspective on utilization by product is available in Appendix 4.C.

Each product has its own cost. In this instance, the average cost, weighted by the expected demand, is 1.65 m.u. per meter. The average sales price is 2.44 m.u. per meter, resulting in a gross margin of 0.80 m.u. per meter (32.7% of the sales price). The average production cost, considering full satisfaction of the demand, is 0.33 m.u. per meter in regular time. Each product has its own production cost, depending on the necessary machines and the processing time in each machine. Thus, the resulting average margin is 0.47 m.u. per meter (19.3% of the sales price). Production using overtime is 25% more expensive than production in regular time. Finally, we consider a yearly holding cost of 10%. Individual details of the products considered in the instance are available in Appendix 4.D.

Table 4.4.5: Machine utilization to meet demand (IE, OE)

	Machines													Total
	543	590	324	316	338	612	530	527	375	327	325	555	Others	
Regular time (h)[1]	1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687	37,114	57,358
Maximum overtime (h)[2]	723	723	723	723	723	723	723	723	723	723	723	723	15,906	24,582
Capacity (h)	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	53,020	81,940
Required production time IE (h)	4,018	2,683	2,278	2,079	2,019	1,859	1,688	1,437	1,218	975	690	647	5,189	26,780
Regular utilization IE	238%	159%	135%	123%	120%	110%	100%	85%	72%	58%	41%	38%	14%	47%
Utilization with overtime IE	167%	111%	95%	86%	84%	77%	70%	60%	51%	40%	29%	27%	10%	33%
Required production time OE (h)	6,202	3,967	3,487	3,094	2,990	2,840	2,562	2,123	1,797	1,452	1,045	1,002	7,761	40,322
Regular utilization OE	368%	235%	207%	183%	177%	168%	152%	126%	107%	86%	62%	59%	21%	70%
Utilization with overtime OE	257%	165%	145%	128%	124%	118%	106%	88%	75%	60%	43%	42%	15%	49%

Machines detailed comprehend 80% of the total production time. The remaining ones are grouped in the category 'Others'

1 Considering each machine has seven working hours per day; 2 Maximum overtime: three hours per day for each machine

4.4.2 Robust optimization parameters definition

In this section, we explain how the robust optimization parameters were set. To define the parameters value proposed by the framework of Mulvey et al. (1995), we specified a grid search and ran a set of problems changing the weight of feasibility penalty function and the weight of solution variance parameters (ω and λ), analyzing the impacts on model robustness and solution robustness. We considered two metrics of evaluation: to check model robustness, we compared the sum of infeasibilities against the sum of the contract demand across all the scenarios[3]. To account for solution robustness, we calculated the coefficient of variation of the objective function[4]. These metrics are presented in Figure 4.4.1.

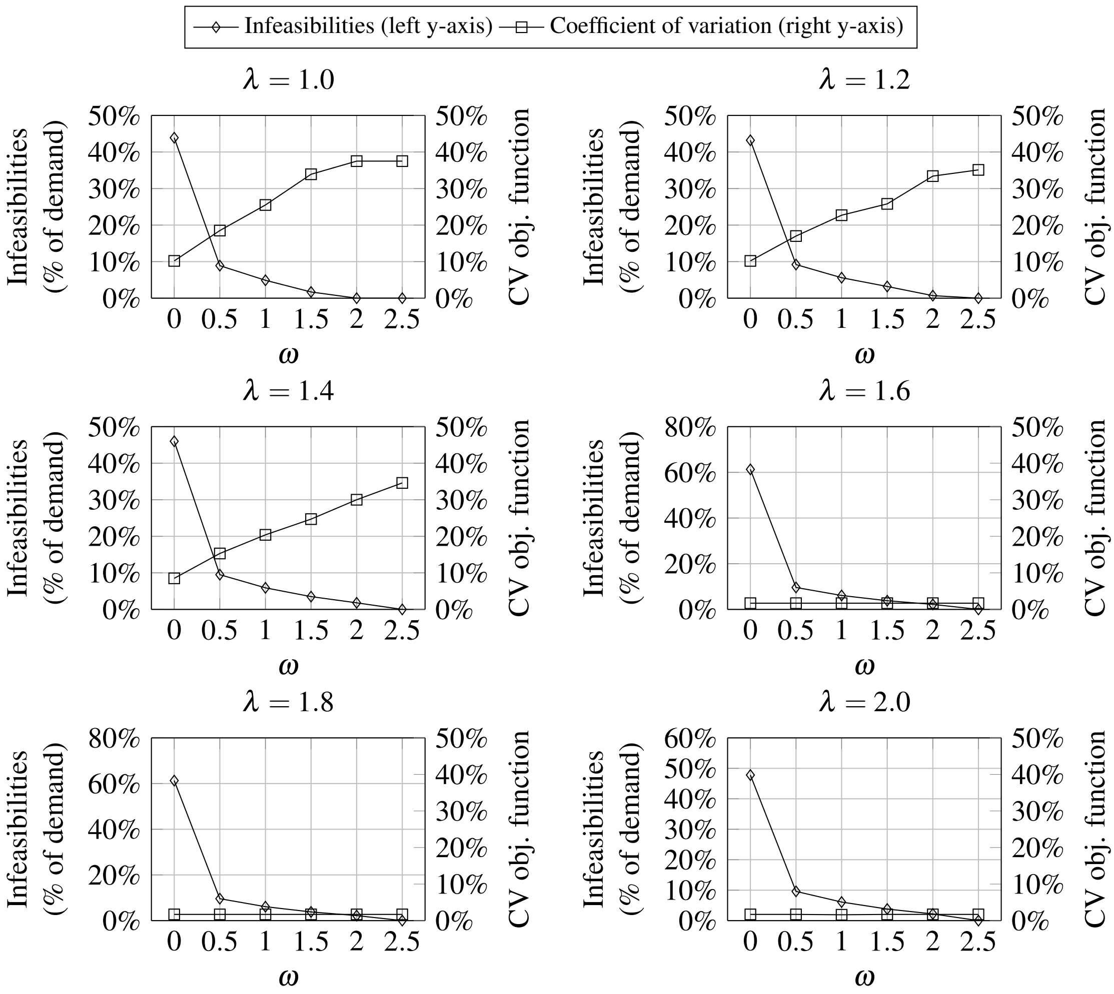


Figure 4.4.1: λ and ω calibration: runs results

As expected, the greater the value of ω, the lower the infeasibilities in the solutions (the percentage of realized demand not satisfied). Irrespective of the value of the λ parameter, this percentage ranges from 40-60% if the ω is 0 and converges to 0 for values of ω of 2-2.5. We

[3] $\sum_{\Xi}\sum_{P}\sum_{C}\sum_{T} U_{\xi,p,c,t} / \sum_{\Xi}\sum_{P}\sum_{C}\sum_{T} d_{\xi,p,c,t}$

[4] $\sqrt{\sum_{\Xi}|Profit_{\xi} - \overline{Profit}|^2/|\Xi|}/\overline{Profit}$

assume the decision-makers are not prone to accept a recommendation that leads to high values of unsatisfied demand in the contract segment. Having predictability in fulfillment is one reason why a buyer signs a QF contract with a supplier. Nevertheless, we consider that the decision-makers do not need to have 0% of risk of having unsatisfied demand since small deviations might be managed operationally. Therefore, a percentage of unsatisfied demand between 0-5% is interesting since it may allow for exploring a more interesting contract and product portfolio strategy without harming the relationship with the customers.

Concerning solution robustness, the analysis of Figure 4.4.1 unveils that for each value of λ, an increase in ω leads to an increase in the coefficient of variation (CV) of the objective function value. That would be likely since the focus is on model robustness rather than solution robustness. However, as the CV varies between 8.5% and 37.5% if λ is calibrated for 1.0, 1.2, and 1.4, it is noticeable that the CV stabilizes in 1.7% for greater values of λ (that is, for 1.6, 1.8, 2.0). A more detailed search of solutions for λ between 1.4 and 1.5 revealed an abrupt reduction of the CV when the value of λ is tuned for 1.49-1.50. In any case, we assume decision-makers are mid-risk-oriented and, therefore, willing to accept a CV between 20% and 25%. Given the combination of solution and model robustness parameters, we set the λ and ω to 1.4 and 1.5, respectively. These parameters are used in the solutions detailed in the remainder of the paper.

4.4.3 Analysis of the plan

In this section, we detail the results from the application of our model to the instance described. We start by presenting and analyzing the plan (Section 4.4.3.1). Afterward, a thorough explanation of the rationale behind the contract parameters chosen is carried out in Section 4.4.3.2.

4.4.3.1 Proposed plan

Tables 4.4.6 and 4.4.7 present demand satisfaction and sales amounts proposed by the model, detailed by scenario. The average demand satisfaction values of the non-contract and contract segments are, respectively, 88.0% and 73.5%, resulting in sales of 5,126,424 m.u. and 5,263,894 m.u.. In the non-contract segment, the sales team should direct its effort towards satisfying the demand of markets #6 and #1, in contrast with markets #5 and #3. Naturally, the sales strategy depends on the realized scenario. Market #1 should be satisfied in full irrespective of the demand level. On the other hand, even though the proposal is to satisfy 97.1% and 100.0% of the demand of the market #6 for scenarios AE and UE, this strategy does not hold if demand is higher (scenario OE). Given the high volume associated to this market, there is not enough capacity to keep the pace in scenario OE. Market #3 deserves to be satisfied almost in full if demand unveils low (scenario UE). Finally, irrespective of the scenario, market #5 remains with a reduced demand satisfaction proposal (around 13%).

We can group the contract sales strategy into two groups: the customers recommended to be fulfilled in full (or almost in full) - 3622, 4012, 1358, and 2750 - and the ones with lower fulfillment rates - 3971, 3291, 1571. Demand satisfaction is lower if demand becomes higher (scenario OE),

Table 4.4.6: Non-contract demand satisfaction and sales, by market and scenario

Market	Demand satisfaction				Sales (m.u.)			
	AE	OE	UE	Average(Avg)	AE	OE	UE	Avg
#5	13.4%	13.4%	12.7%	13.1%	4,521	5,958	2,059	4,179
#6	97.1%	74.3%	100.0%	90.5%	5,019,660	5,814,715	2,730,940	4,521,772
#1	100.0%	99.1%	100.0%	99.7%	263,832	352,553	100,171	238,852
#3	59.1%	44.1%	98.3%	67.2%	493,589	364,638	226,635	361,620
Total	93.3%	71.9%	98.7%	88.0%	5,781,602	6,537,864	3,059,805	5,126,424

and higher in the opposite situation (scenario UE). In the latter, demand satisfaction is over 100% for some customers due to minimum quantities imposed by the contract.

Table 4.4.7: Contract demand satisfaction and sales, by customer and scenario

Market	Cust.	Demand satisfaction				Sales (m.u.)			
		AE	OE	UE	Avg	AE	OE	UE	Avg
#1	3622	100.0%	88.3%	145.7%	111.3%	1,505,292	2,080,258	1,431,733	1,672,428
	3971	35.2%	34.0%	53.7%	41.0%	1,000,259	1,489,207	762,555	1,084,007
	4012	100.0%	91.5%	137.7%	109.7%	840,424	1,221,396	715,723	925,848
#2	3291	41.5%	37.5%	37.0%	38.7%	535,879	802,244	350,672	562,932
#3	1358	98.7%	91.4%	120.0%	103.4%	534,366	733,296	303,347	523,670
	1571	83.8%	77.2%	99.8%	87.0%	51,368	80,511	28,201	53,360
#4	2750	100.0%	94.0%	108.2%	100.7%	445,531	624,000	255,419	441,650
Total		69.2%	62.9%	88.3%	73.5%	4,913,121	7,030,913	3,847,650	5,263,894

In Table 4.4.8, we present the contract proposal and the corresponding demand satisfaction. For customers 3622, 4012, and 2750, the proposal includes all the potential products in the portfolio; for the remaining, a partial inclusion is suggested. In particular, for customer 3971, the best option is to include only three out of the six potential products. Regarding flexibility levels, customers 3622 and 4012 should be offered 40%, whereas, for the remaining, the proposal keeps the maximum flexibility level of 50%. Recall that flexibility levels of 40% and 50% mean a discount over the market price of 10.0% and 7.5%, respectively.

Table 4.4.8: Contract proposal details, by customer and scenario

Market	Customer	Demand satisf. (contract only[1])				Products included	Flexibility
		AE	OE	UE	Avg		
#1	3622	100.0%	88.3%	145.7%	111.3%	6 out of 6	40%
	3971	100.0%	92.5%	121.6%	104.7%	3 out of 6	50%
	4012	100.0%	91.5%	137.7%	109.7%	6 out of 6	40%
#2	3291	100.0%	95.8%	114.8%	103.5%	6 out of 8	50%
#3	1358	100.0%	92.8%	122.8%	105.2%	4 out of 5	50%
	1571	100.0%	88.4%	124.9%	104.4%	8 out of 9	50%
#4	2750	100.0%	94.0%	108.2%	100.7%	4 out of 4	50%
Total		100.0%	91.0%	132.2%	107.7%	-	-

1 Demand satisfaction considering the products in the contract only

To satisfy this sales plan, the operations team must ensure the production of several products throughout the year. The production time plan is presented in Figure 4.4.2. The charts present the production time in each scenario. Horizontal black lines represent the regular time and the available time. Machines 590, 324, 316, 338, and 543 have a regular utilization above 100% in scenario AE. Machine 590 is particularly overloaded since it has a regular utilization of 142.9%, which means overtime is used in full in all the periods. The overall regular utilization is 37.5%. In scenario OE, there are eight machines with a regular utilization above 100% (the five machines referred for scenario AE plus machines 527, 530, and 375). In this case, the overall regular utilization goes up to 45.3%. Finally, in scenario UE, the overall regular utilization is 20.9%. Even in this situation, machine 590 has a regular utilization of 105.6%. The required production time proposed for machines 543 and 612 drops below the intuition - the model chooses not to meet demand of products 7222001, 7222002, and 7222005, incurring in infeasibilities allowed by constraints (4.26) and (4.27) for customer 3622. On the contrary, an additional fulfillment of product 7207111 is proposed, which justifies that machine 618 maintains the utilization.

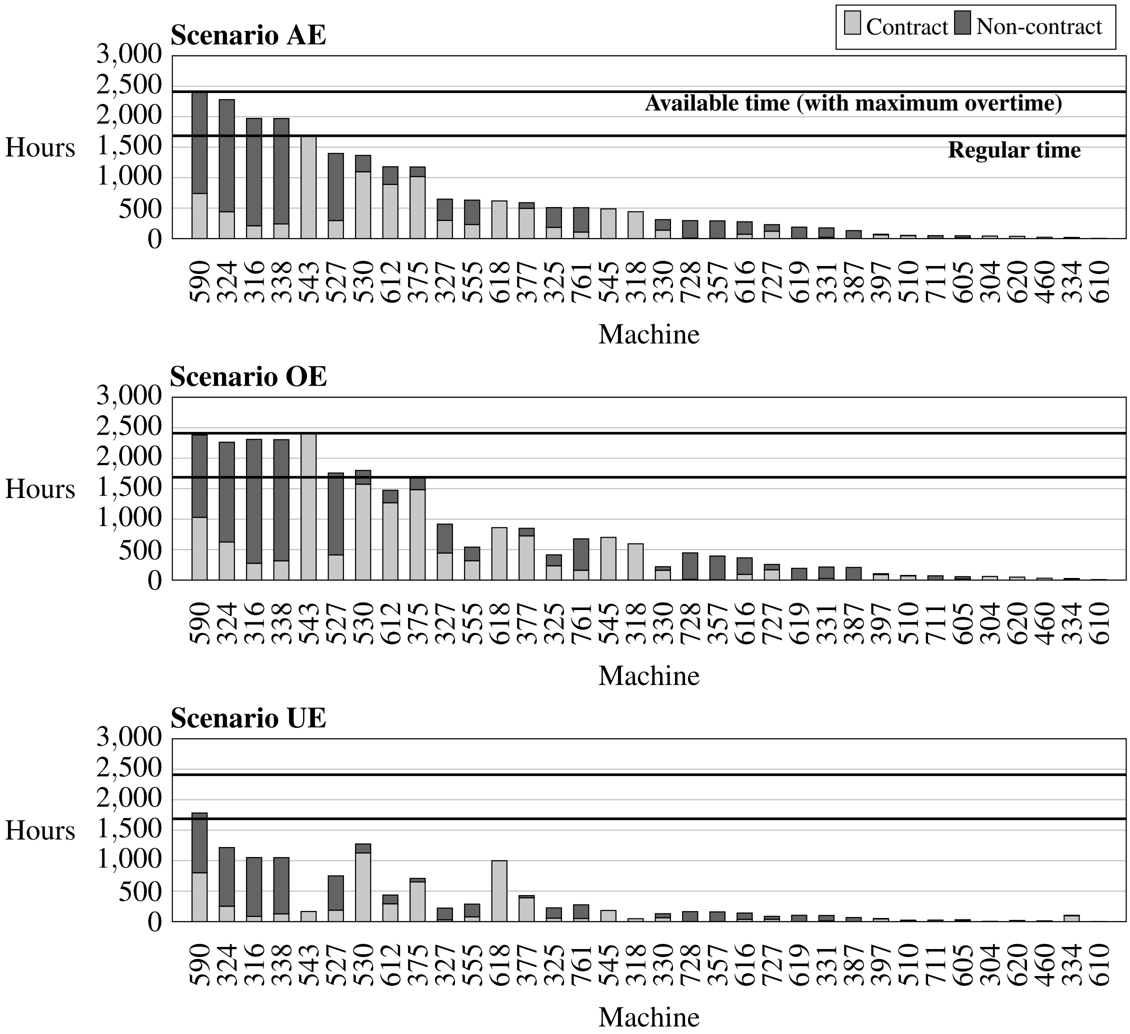


Figure 4.4.2: Required production hours, by machine and scenario

The primary motivation behind this research is to propose a decision-making model to support a profitability-oriented integration between the sales and operations teams on how to utilize the existing productive resources to fulfill contract and non-contract demand. Nevertheless, utilization across the different machines is not uniform, as presented in Figure 4.4.2. This characteristic is not specific to our case - companies with several production resources, with the diversification and expansion of their product portfolios, might be subject to a high discrepancy on occupation across the different machines/lines. Therefore, our model can also support marketing/sales teams on how existing capacity shall be promoted externally. Products whose production occurs in non-bottleneck machines may be announced more aggressively in the market to find commercial opportunities to "sell" existing capacity.

Table 4.4.9 displays the products whose production is held in non-bottleneck machines, considering scenario AE. These products should deserve special attention from the sales team since incremental demand in each of them does not mean that other products sales need to be cannibalized. If the sales team is able, during the year, to increase non-contract demand, that will result in additional sales. Assuming additional sales can still be made with a positive margin (that is currently the case of each product), that would mean additional profit. We are not considering products produced in non-bottleneck machines only in scenario UE since it may be risky to get additional sales in those products. Machines involved in the production of products 7222008, 7222012, and 72220081 become a bottleneck in scenario OE (Table 4.4.9), which also indicates that these products are not so interesting as the remaining ones to be promoted, at least from a capacity perspective.

Table 4.4.9: Products whose production does not occur in bottleneck machines (scenario AE)

Product	Machines	Bottleneck?		Demand satisfaction AE		OE	
		AE	OE	NC[1]	C[1]	NC	C
7182506	327;357;605;761	No	No	100%	0%	100%	0%
7182757	327;357;605;761	No	No	100%	100%	100%	100%
7207074	605;711;728;761	No	No	100%	-	100%	-
7207075	387;605;728;761	No	No	100%	-	100%	-
7207076	387;605;728;761	No	No	100%	-	100%	-
7222008	375;377;397;510;527;530;612	No	Yes	100%	100%	100%	95%
7222012	325;375;397;460;510;530;612	No	Yes	-	100%	-	92%
7225201	327;357;605;761	No	No	100%	100%	99%	34%
7225248	327;357;605;761	No	No	100%	-	100%	-
72220081	375;377;397;510;527;530;612	No	Yes	-	100%	-	80%

1 NC: Non-contract; C: Contract

As expected, demand from these products is satisfied in full in scenario AE, both in Non-contract (NC) and Contract (C) segments (exception of product 7182506 that is not included in the contract for customer 1358 and will be further analyzed in the following section). In scenario OE, products 7222008, 7222012, 72220081, and 7225201 are not satisfied in full. For the first three, as discussed, there is not enough available capacity (machines involved become bottleneck). The latter is not sold in full because the demand of customer 1571 in scenario OE surpasses the maximum threshold defined in the QF contract.

4.4.3.2 Rationale behind contract offering

The rationale on the basis of our model is to select the best demand satisfaction composition to maximize overall profitability. Therefore, when analyzing the portfolio selection for a specific QF contract, there are two main reasons why a product is not selected. First, the product offering may not be profitable for the company. If the sales price of a product (considering QF discount) does not compensate the cost of the product, including the production cost, the margin is negative and it is expected the product not to be included in the proposal. There might be exceptional situations where this rule does not hold, since demand variability associated with the forecast of a non-profitable product may be used to sell more of the other products included in the contract than if the product was not included, since upper and lower limits are defined based on the expected demand of all products composing the contract. The second reason, even if a product is profitable, production capacity may reveal short of fulfilling the associated demand. In this case, a product shall not be included in the contract if there are more interesting capacity usage alternatives, either on the contract or non-contract segments.

Tables 4.4.10 and 4.4.11 corroborate such business insights in our case. In the first table, it is noticeable that, except for product 7182506 for customer 1358, all the other products, if added to the contract offering portfolio, could not be fully satisfied, everything else remains the same. In all the cases, the average utilization of the bottleneck machine would be superior to 100% - in the case of scenario OE utilization would be greater than 142.9%, which corresponds to the maximum utilization if available overtime is used in full. Products 7207030 for customer 1571, and 7222001 and 7222005 for customer 3971 are non-profitable given the QF discount offered to these customers, which explains why they are not included. For the other products, this is not true. In these cases, Table 4.4.11 supports the rationale behind their non-inclusion. Analyzing the average hourly gross margin of the machines involved in the production of each of the products (7222001 and 722002 for customer 3291, and 7222002 for customer 3971), we denote that the current product offering is more profitable since the monetary value derived for each hour of work in these machines is higher than the value obtained with the products not included.

Table 4.4.10: Analysis of products not included in the contracts: margin and potential utilization

Cust.	Product	Price[1] m.u./m	Cost m.u./m	Prod. cost m.u./m	Margin m.u./m	Utilization if added[2] AE	OE	UE	Bottle.[3]
1358	7182506	1.00	0.68	0.17	0.15	38.5%	54.7%	16.4%	327
1571	7207030	0.73	0.65	0.09	-0.01	143.1%	141.3%	105.7%	590
3291	7222001	1.23	0.93	0.27	0.03	120.2%	169.2%	76.7%	543
3291	7222002	1.67	1.32	0.26	0.08	125.5%	193.7%	77.8%	543
3971	7222001	0.94	0.93	0.27	-0.26	126.7%	181.8%	76.6%	543
3971	7222002	1.79	1.32	0.26	0.21	161.7%	232.8%	77.7%	543
3971	7222005	2.37	2.00	0.57	-0.20	145.3%	145.6%	107.8%	590

1 Including QF discount; 2 Utilization of the most occupied machine if product is added and satisfied in full; 3 Bottleneck machine with maximum utilization, considering scenarios AE/OE

Finally, the analysis of this instance unveiled a third reason for a product not to be included in the contract portfolio. The product 7182506 for customer 1358 has a positive margin (0.15

Table 4.4.11: Analysis of products not included in the contracts: productive value

Customer	Product	Machines	Gross margin (m.u./h)	
			Product	Current
1358	7182506	327;357;605;761	6,464	12,088
1571	7207030	530;590;605;728;761	1,379	9,894
3291	7222001	304;325;510;530;543;612	3,044	5,164
3291	7222002	304;327;510;530;543;612	3,252	5,095
3971	7222001	325;510;530;543;612	78	4,138
3971	7222002	304;327;510;530;543;612	4,488	5,095
3971	7222005	304;318;510;527;530;555;590;612	2,940	4,100

m.u./m) and is produced in a set of non-bottleneck machines (327;357;605;761). Machine 327 is the most occupied, with an average utilization of 54.7% in scenario OE. However, the fact that this product's demand is not high (4,033 meters in a total of 275,156 meters for scenario OE split across five products) and the sales margin is low (0.15 m.u. per meter compared to an average of 0.38 m.u. per meter considering all the customer's products), sustains the low interest in its inclusion. Its demand pattern is erratic (with forecasted demand in months 6, 10, 11, and 12 only). In scenario UE, demand is not enough to achieve the minimum QF threshold in these months. Therefore, customer 1358 would need to acquire additional quantities of the products in the contract to comply with the contract rules. In our case, if product 7182506 was included, the additional quantity of the other products the customer would need to acquire would be lower. As the other products have a higher margin (particularly 7207088 with a margin of 0.55 m.u. per meter), the model suggests not to include 7182506 to explore such effect.

As detailed in Table 4.4.8, the model prescribes the maximum flexibility level (50%) for all the customers except 3622 and 4012, whose proposal is 40%. Figure 4.4.3 compares the demand quantity in each scenario, for each customer and period, against the minimum and maximum QF limits, represented by the blacked dashed lines. As we can see, particularly for customers 3622 and 4012, there are expressive demand peaks in some periods for scenario OE. Intuitively, we would consider to be risky to propose a contract to a customer whose flexibility level allows him to achieve this level of sales, impacting the occupation of the productive resources. Our model corroborates such expectation and, even though it still proposes high flexibility to these customers, it is not so high as the flexibility level offered to the other customers. As customers 1358, 1571, 2750, 3291, and 3971 present more moderate demand, the model proposes the maximum flexibility level to take advantage of the minimum discount associated.

4.4.4 Sensitivity analysis

In this section, we run a sensitivity analysis on some key parameters to investigate how the change of some conditions affects the plan proposed by the model. In Section 4.4.4.1, we analyze the impacts associated to capacity variations. In Section 4.4.4.2, there is some reflection regarding the impact of discounts levels on the contracts offered to customers.

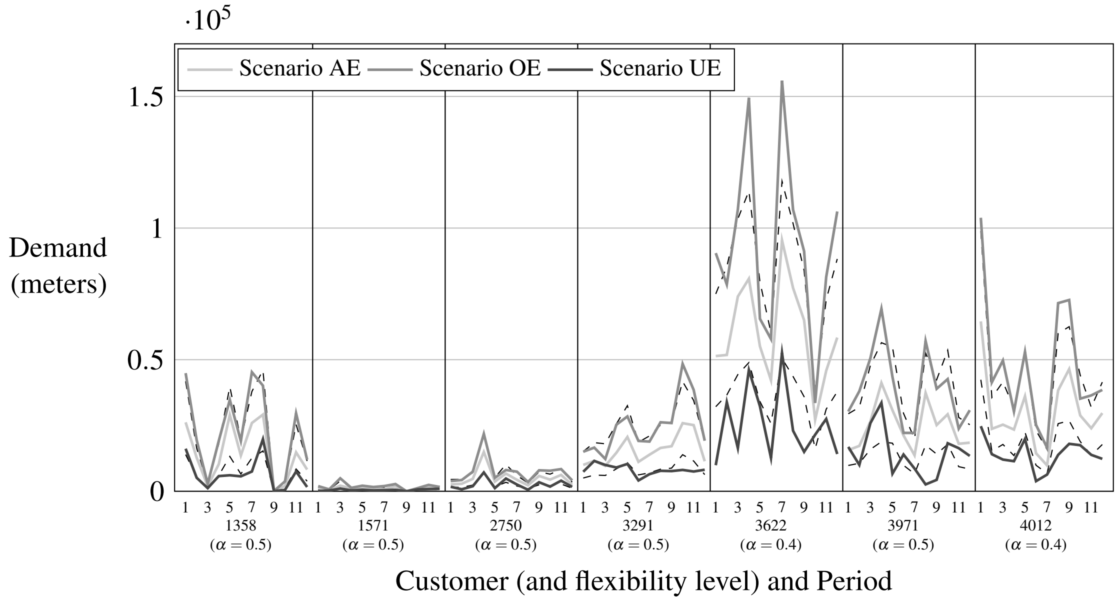


Figure 4.4.3: Demand comparison and QF limits for each customer and period

4.4.4.1 Capacity variation

Our results consider a capacity per machine of 1,687 hours in regular time, plus an additional overtime option that can be extended up to 723 hours (Table 4.4.5). This capacity is given by the total number of working days during a year considering that there are seven available hours per working day in regular time plus the possibility of using overtime up to three hours per day. A decision-maker analyzing the model results might be interested in evaluating how capacity changes impact the plan and the business's profitability. We introduce three additional configurations: (1) no overtime, (2) two additional working hours in overtime, (3) one additional shift. The available capacity per day in configurations (1), (2), and (3) is as follows: seven hours, seven hours plus five available hours in overtime, 14 hours plus three available hours in overtime.

Figure 4.4.4 details the expected profit for each configuration. The 'basis' configuration (the one we have been analyzing so far) is expected to generate a profit of 1,764,083 m.u.. If overtime is not possible, the profit is expected to decrease by 7.0% to 1,641,047 m.u.. This reduction is explained by a decline in the contract sales, but more expressively by a reduction in the non-contract sales, especially in scenarios AE and OE. Capacity expansion by giving operations the possibility of using two additional hours in overtime permits a profit increase of 2.4% to 1,805,871 m.u., supported by an expressive increase in contract sales. Regarding the option of setting up an additional shift, it also allows for the increase in profit compared to the 'basis' configuration by 2.9%, to 1,814,780 m.u.. There is a considerable increase in contract sales in this configuration compared to the 'basis' scenario (around 1.1 million monetary units). Nevertheless, the associated costs also increase significantly. Even though the company can sell more, it will end up marketing products with lower margins. Thus, if one might conclude that more flexibility in overtime is interesting to potentiate sales, extending the capacity permanently by one shift hardly pays off -

even more if we consider that there are some structure / fixed costs that the company might have to support if it decides to extend the capacity to 14 hours, which is not reflected in the unitary values used.

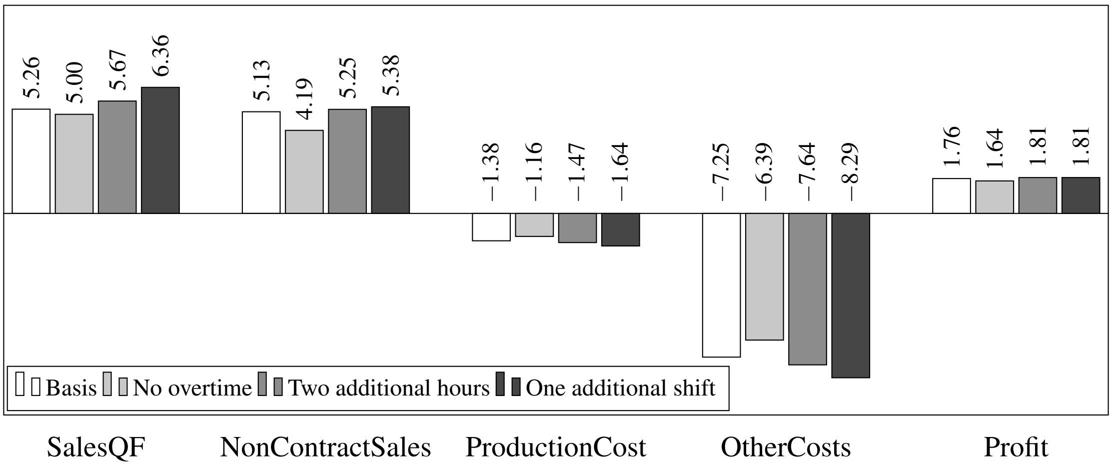


Figure 4.4.4: Profit comparison and drill-down for each configuration, in monetary units (millions). Values resulting from the average of the three scenarios: AE, OE, UE

From a utilization perspective, the 'basis' configuration's plan results in an average regular utilization of 34.5%. Disregarding the production done in overtime, regular utilization equals 30.5%. In the configuration with no overtime, regular utilization is 29.8%. If two additional hours are permitted in overtime, the regular utilization increases to 31.4%, not considering production in overtime. This means that the possibility of using two additional hours introduces additional flexibility that makes a better use of the existing resources even during regular time. On the opposite, opening an additional shift (which doubles the regular time) leads to an average regular utilization of 16.9% if overtime is not considered, and 20.8% if we account for production made in overtime, still relevant in scenario OE.

Regarding contract offering, there are some key changes among the configurations. Table 4.4.12 summarizes the contract offering for each customer given available capacity. In the 'basis' configuration, contracts offered to customers include 37 out of 44 possibilities available in the portfolio, with an estimated demand (IE) of 5,514,618 m.u.. Unexpectedly, the number of products remains the same for configurations (1) and (2). However, there are changes in the products proposed, with the associated demand shifting to 5,234,302 m.u. and 5,890,531 m.u., which aligns, respectively, with less and more available capacity. In configuration (3), given the significant capacity increment, the contract offer is reviewed to 41 products, with an estimated demand of 6,436,837 m.u.. Concerning the flexibility levels, more capacity does not mean additional flexibility offered to customers. The model proposes a reduction of the flexibility for customers 1571 and 3971. Summing up, the model takes advantage of more capacity to enlarge the product offering in terms of sales volume, not giving customers more flexibility.

Table 4.4.12: Contract offering for each customer in each configuration

	Conf.	1358	1571	2750	3291	3622	3971	4012	Total
Products	Basis	4/5	8/9	4/4	6/8	6/6	3/6	6/6	37/44
included	(1)	4/5	9/9	4/4	6/8	5/6	4/6	5/6	37/44
(out of: '/')	(2)	4/5	9/9	4/4	6/8	5/6	4/6	5/6	37/44
	(3)	4/5	9/9	4/4	6/8	6/6	6/6	6/6	41/44
Estimated	Basis	584,636	58,678	455,623	609,487	1,668,278	1,155,892	982,023	5,514,618
demand	(1)	584,636	60,552	455,623	609,487	888,630	1,852,014	783,360	5,234,302
(m.u.)	(2)	584,636	60,552	455,623	609,487	1,544,859	1,852,014	783,360	5,890,531
	(3)	584,636	60,552	455,623	609,487	1,668,278	2,076,237	982,023	6,436,837
Flexibility	Basis	0.5	0.5	0.5	0.5	0.4	0.5	0.4	
level	(1)	0.5	0.4	0.5	0.5	0.4	0.5	0.4	
	(2)	0.5	0.4	0.5	0.5	0.4	0.4	0.4	
	(3)	0.5	0.4	0.5	0.5	0.4	0.4	0.4	

Configurations: (1) No overtime, (2) Two additional hours in overtime, (3) One additional shift
Estimated demand (m.u.) not including the QF discount

4.4.4.2 Discount factors variation

The computational experiments demonstrate that, in the instance being analyzed, the model tends to propose high levels of flexibility (40-50%) to ensure a profitable outcome by offering low discount values to customers. In this section, we analyze the changes on the plan proposed if the customers would accept lower discounts for reduced levels of flexibility. Recall that we assumed that the original QF discount curve represents the indifference barrier below which customers will not be willing to sign a contract. Thus, the results presented in this section only denote hypothetical cases in which the commercial bargain of a customer reduces. Figure 4.4.5 presents two new QF discount curves, besides the original one (identified as 'basis'). The original discount pattern, for the levels of flexibility {10%,20%,30%,40%,50%} is {30.0%,20.0%,15.0%,10.0%,7.5%}. The new ones are {25.0%,17.5%,12.5%,10.0%,7.5%} and {20.0%,15.0%,11.0%,9.0%,7.5%}, named 'reduced slope #1' and 'reduced slope #2'.

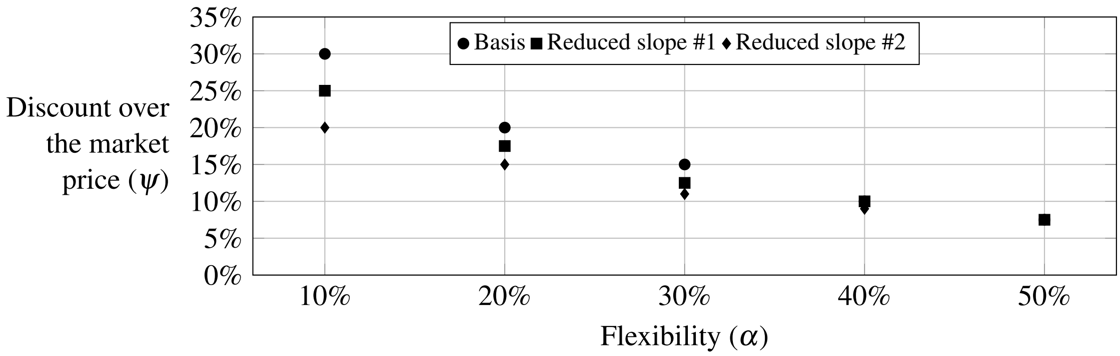


Figure 4.4.5: QF discount curve options

Table 4.4.13 details the contract offering strategy proposed for each discount curve. The flexibility strategy is clearly influenced by the discount pattern - based on these experiments, as the discount curve's slope reduces, the lower are the flexibility levels proposed to customers. In particular, reducing the discount assumed for 30% of flexibility from 15.0% ('basis') to 11.0% ('reduce slope #2') makes this flexibility level more interesting to offer.

Table 4.4.13: Contract offering for each customer for each discount curve

	Disc.	1358	1571	2750	3291	3622	3971	4012	Total
Products	Basis	4/5	8/9	4/4	6/8	6/6	3/6	6/6	37/44
included	(1)	4/5	8/9	4/4	6/8	5/6	5/6	5/6	37/44
(out of: '/')	(2)	4/5	9/9	4/4	6/8	5/6	5/6	5/6	38/44
Estimated	Basis	584,636	58,678	455,623	609,487	1,668,278	1,155,892	982,023	5,514,618
demand	(1)	584,636	58,678	455,623	609,487	1,544,859	1,928,491	783,360	5,965,134
(m.u.)	(2)	374,015	60,552	455,623	609,487	1,544,859	1,928,491	783,360	5,756,388
Flexibility	Basis	0.5	0.5	0.5	0.5	0.4	0.5	0.4	
	(1)	0.5	0.5	0.5	0.5	0.3	0.3	0.3	
	(2)	0.3	0.4	0.5	0.3	0.3	0.3	0.3	

Discount curve: (1) Reduced slope #1, (2) Reduced slope #2
Estimated demand (m.u.) not including the QF discount

Associated with reducing the flexibility level proposed, an increase in the demand included in the contract is noticeable. In the 'basis' setting, demand amounts to 5,514,618 m.u., whereas for 'reduced slope #1' and 'reduced slope #2', the estimated demand included in the contract is superior, 5,965,134 m.u. and 5,756,388 m.u., respectively. Such optimal behavior is understandable since the supplier, bound to a contract whose upper limit is lower, acquires flexibility in fulfillment and can reject orders for very positive demand variations. In this case, a reduction in the level of flexibility of customer 3971 from 50% to 30% allows for the inclusion of the product 7222002, whose estimated demand is significant. Another interesting note when analyzing the values in Table 4.4.13 relates with the fact that, although demand included increases in the transition 'basis'-'reduced slope #1', that does not occur when shifting from 'reduced slope #1' to 'reduced slope #2', although our intuition would suppose so. The reason behind such behavior relates to the reduction of the flexibility offered to customer 1358, with an impact on the discount level that changes from 7.5% to 11.0%. The product 7202031 is left out of the contract since its margin becomes negative (from 0.06 m.u. per meter to -0.19 m.u. per meter).

Concerning sales value, albeit the values are not directly comparable (the discount policy is not equivalent), there is a relevant change when the flexibility proposed to the customers reduces. On the 'basis' situation, the average weight of the contract sales on the total sales is 50.7%. For curves 'reduced slope #1' and 'reduced slope #2', the weight of the contract sales is, on average, 54.1% and 53.7%. Although this effect is visible across the demand scenarios, it is quite expressive in scenario UE (Figure 4.4.6). The lower limit of a QF contract is higher for lower levels of flexibility, which explains that contract sales are higher when demand is below this threshold. On the opposite, we do not observe a higher weight of the contract sales for higher levels of flexibility because capacity is limited. As there is the risk of not fulfilling all the demand if it reveals pretty high, the plan suggests including a more reduced demand value.

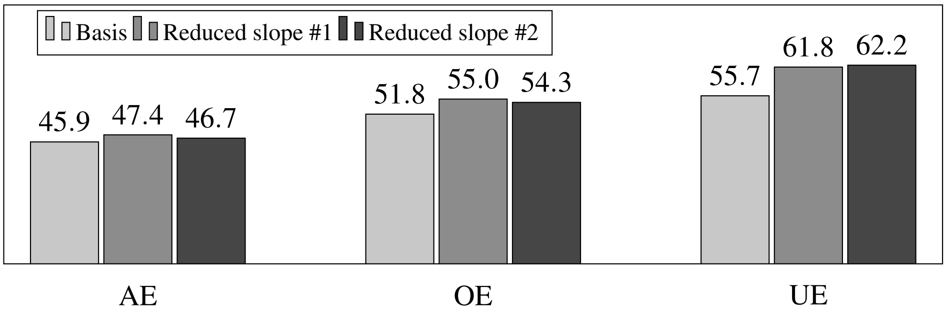


Figure 4.4.6: Weight of contract sales on total sales (%)

4.5 Final remaks

This research proposes a novel model to support the sales and marketing teams to define the sales plan in a context of limited capacity. Demand can be either non-contractual or derive from quantity-flexibility contracts. We demonstrated the usefulness of this approach by resorting to a real instance from an industrial manufacturer. The application of the model to this case allowed us to derive some managerial insights that we point out in Section 4.5.1.

In this section, we also summarize the distinguishing points of our model and evidence that its application can be beneficial for a company that needs to define its tactical sales and operations plan during budget planning or a strategic committee (Section 4.5.2). Finally, we end up this work by marking some directions for further research (Section 4.5.3).

4.5.1 Managerial insights

The application of our model unveils that the decision-making rationale behind each plan proposed is profitability-oriented. This is natural since we define the objective function to maximize the expected profit while complying with operational, contractual, and commercial constraints. Therefore, all the conclusions presented during the presentation of the computational experiments are conditioned to this mindset. If we assumed managers have other objectives (e.g., increasing sales for a specific customer, maximizing the portfolio width), the conclusions might have differed. This assumption is the cornerstone for the insights presented in this section.

Our computational experiments evidence that the definition of an optimal sales plan consists of finding the best resource utilization, or equivalently, maximizing the value derived, that is, the gross margin per hour of work. This rationale is behind the optimal mix between contract and non-contract demand. Non-contract demand is managed more straightforwardly from a sales perspective since there are no minimum and maximum quantities to respect. Managing a contract portfolio is more complex. In more detail, we concluded that there are three main reasons why managers should not include a product in a contract. First, it is not individually profitable, given that sales price affected by the quantity-flexibility discount minus the production and other associated costs results in a negative margin. Second, even if a product is profitable, if an alternative production mix maximizes the hourly value derived from the necessary machines, the product should be kept out of the plan. Third, even if a product is individually profitable and there is available capacity to produce it, if it is less profitable than the other products included in the contract with a customer, it might be the case that global sales will be lower if demand turns out to be below the minimum quantity-flexibility threshold. If the product is not included, and the customer is contractually obligated to buy a certain quantity, the quantity sold over the demand would be more significant for the remaining products.

Regarding the flexibility included in a contract, our computational tests and sensitivity analyses demonstrate that volume and discount rates are the two main reasons explaining the flexibility offered. For customers whose estimated demand for the products included in the portfolio reveals high and unattainable from a capacity perspective, offering the maximum flexibility level might be risky. On the other hand, for customers whose demand satisfaction is ensured by the existing capacity, it may be a thoughtful option to offer a higher level of flexibility to take advantage of a reduced discount factor. Nevertheless, this strategy is highly sensitive to the quantity-flexibility discount curve. As the slope associated with the discount rate in function of the flexibility decreases, the more profitable it might be to offer more reduced flexibility in the contract. This leaves sales managers with the need to determine the curve that accurately depicts a customer's preference between flexibility and discount factor.

For the same capacity level, lower levels of flexibility mean that more demand might be included in a contract. As the supplier reserves the right not to fulfill demand peaks above the maximum quantity-flexibility limit, it means managers may assume the risk of including more products/quantities in the agreement to instigate sales if actual demand remains close to the initial forecast. The model also recommended offering a lower level of flexibility because if demand is lower than the minimum quantity-flexibility contract, the customer must order above the demand. All in all, it is the triad between volume-discount rate-demand expectation (regarding deviations from the forecast) that defines which flexibility level is optimal to offer. The proposed model is capable of blending and weighing all these dimensions.

With respect to the available capacity, two main takeaways for managers deserve our attention. First, increasing the available capacity (if possible) is not always the best strategy. The break-even point above which offering more capacity does not mean more profit needs to be determined. It might be the case that further sales would be possible only for products whose profitability is smaller. Moreover, enlarging capacity significantly (again, if possible) through the opening of an additional shift might require some structure or fixed costs to be taken into account, which erases margin from incremental sales. To sum up, it is important that managers ensure that the marginal cost of increasing the capacity is smaller than the gross margin of the products/quantities that can be added to the plan. The second takeaway, more available capacity means more demand included in the contract. The additional demand does not need to take the form of new products. It might be obtained through portfolio changes in which existing products are replaced by products whose estimated demand is higher.

4.5.2 The value of an optimal and robust sales/marketing-operations planning

This research extends the current literature on tactical planning, marketing-operations interface, and contract management. As detailed in Section 4.2.3, the proposed model extends contract management literature by considering a sales ecosystem where contract and non-contract customers are competing for the same capacity. We propose a flexible, multi-product, and multi-stage production setting. Our model bridges a clear gap between theoretical modeling research and practical work reflecting the complexity of tactical planning between operations and sales teams. Finally, our formulation merges portfolio selection and quantity-flexibility contract design in the same model, which has not been addressed in the past literature.

From a managerial perspective, our model is flexible in the product, machine, and customer structures, which can be used in various cases. The question that remains to be answered is: should managers adapt their decision-making processes to use this approach? We ran an additional computational experiment to demonstrate that the answer should be positive. Imagine a sales team designing a contract offering without using this model. Even if some alignment is ensured with the operations team, imagine that it is in the form of flexibility offered to each customer given its potential volume (and, therefore, impact on machine utilization). The sales and operations team agreed that high-volume customers (3622 and 4012) should be proposed a contract with the flexibility of 30%. Medium-volume customers (in our case, 3971) should be issued a flexibility level of 40%, and, finally, low-volume customers (1358, 1571, 2750, 3291) should be offered a flexibility of 50%, in order to take advantage of reduced discount rates. Afterward, the sales team decides to include in the contracts all the products with a positive margin. Imposing this strategy in our model returns an expected profitability of 1,696,694 m.u., 3.8% under the profit anticipated with the optimal plan (1,764,083 m.u.). However, more harmful is the expected infeasibility rate of the alternative plan. The optimal plan, as presented in Figure 4.4.1, is expected to generate a percentage of unsatisfied demand of 3.5%. In this alternative plan, the rate is 12.1%, which is unjustifiable in a quantity-flexibility arrangement. More details about this business rules-based plan are available in Appendix 4.E.

Another key aspect of our model is the robust optimization approach proposed. Through the computational experiments conducted, it is noticeable that uncertainty is important since the contract design and portfolio selection decisions considered as design variables (that is, decided at the beginning of the period) are influenced by the demand scenarios considered. To quantify such importance, we ran a deterministic version of the model and compared the results with the ones from the robust counterpart. In the deterministic version, the model returns an expected profit of 1,918,188 m.u.. The optimal strategy, in this case, would be to offer a flexibility level of 50% to all the customers and a different product mix. Fixing this contract strategy in the robust model, we obtain an average expected profit of 1,900,318 m.u., which is 7.7% higher than the profit of the plan analyzed so far (more details in Appendix 4.F). Nevertheless, such plan would result in a higher percentage of unsatisfied demand (4.1% *versus* 3.5%) and a higher coefficient of variation of the objective function (27.9% *versus* 24.7%). Therefore, despite the higher profit, the deterministic strategy would not comply with defined decision-makers' preferences assumed for both model robustness and solution robustness. From an objective function perspective, fixing the deterministic plan results in a suboptimal plan with a gap of 7.7% with respect to the optimal plan. From this analysis, we infer that implementing a robust optimization approach is valuable since it permits the explicit consideration of the risk-orientation profile of decision-makers, beyond the explicit analysis of the plan towards different demand scenarios.

4.5.3 Further research

As future research opportunities, we propose implementing this model in different business realities to grasp and quantify the associated benefits and enlarge the managerial insights on the complex interaction between contract and non-contract demand. Second, in some situations, it may not be possible to synchronize the contract negotiation moment and contract duration for different customers. The adaptation of the model to face such a situation deserves attention. Third, from an operations research perspective, we propose applying matheuristic or metaheuristic procedures to this model to ensure the model's solvability in acceptable time frames for larger instances in terms of products, machines, or demand scenarios considered.

4.6 Acknowledgements

This work is partially financed by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia, within project UIDB/50014/2020.

Bibliography

Anupindi, R., & Bassok, Y. (1998). Approximations for multiproduct contracts with stochastic demands and business volume discounts: single supplier case. *IIE Transactions*, *30*(8), 723-734. doi: 10.1023/A:1007595807964

Anupindi, R., & Bassok, Y. (1999). Supply contracts with quantity commitments and stochastic demand. In S. Tayur, R. Ganeshan, & M. Magazine (Eds.), *Quantitative models for supply chain management* (p. 197-232). Boston, MA: Springer US. doi: 10.1007/978-1-4615-4949-9_7

Araneda-Fuentes, C., Lustosa, L. J., & Minner, S. (2015). A contract for coordinating capacity decisions in a business-to-business (b2b) supply chain. *International Journal of Production Economics*, *165*, 158-171. doi: https://doi.org/10.1016/j.ijpe.2015.03.016

Bakhtavar, E., & Mahmoudi, H. (2020). Development of a scenario-based robust model for the optimal truck-shovel allocation in open-pit mining. *Computers & Operations Research*, *115*, 104539. doi: https://doi.org/10.1016/j.cor.2018.08.003

Barbarosoglu, G. (2000). An integrated supplier-buyer model for improving supply chain coordination. *Production Planning & Control*, *11*(8), 732-741. doi: 10.1080/095372800750038337

Bassok, Y., & Anupindi, R. (1997). Analysis of supply contracts with total minimum commitment. *IIE Transactions*, *29*(5), 373-381. doi: 10.1023/A:1018547918494

Bassok, Y., & Anupindi, R. (2008). Analysis of supply contracts with commitments and flexibility. *Naval Research Logistics (NRL)*, *55*(5), 459-477. doi: https://doi.org/10.1002/nav.20300

Bavafa, H., Leys, C. M., Örmeci, L., & Savin, S. (2019). Managing portfolio of elective surgical procedures: A multidimensional inverse newsvendor problem. *Operations Research*, *67*(6), 1543-1563. doi: 10.1287/opre.2019.1848

Ben-Tal, A., Golany, B., Nemirovski, A., & Vial, J.-P. (2005). Retailer-supplier flexible commitments contracts: A robust optimization approach. *Manufacturing & Service Operations Management*, *7*(3), 248-271. doi: 10.1287/msom.1050.0081

Ben-Tal, A., & Nemirovski, A. (2000). Robust solutions of linear programming problems contaminated with uncertain data. *Mathematical Programming*, *88*(3), 411-424. doi: 10.1007/PL00011380

Bertsimas, D., & Sim, M. (2004). The price of robustness. *Operations Research*, *52*(1), 35-53. doi: 10.1287/opre.1030.0065

Cachon, G. P. (2003). Supply chain coordination with contracts. In *Handbooks in operations* *research and management science* (Vol. 11, p. 227-339). Elsevier. doi: https://doi.org/10.1016/S0927-0507(03)11006-7

Cai, W., Abdel-Malek, L., Hoseini, B., & Rajaei Dehkordi, S. (2015). Impact of flexible contracts on the performance of both retailer and supplier. *International Journal of Production Economics*, *170*, 429-444. doi: https://doi.org/10.1016/j.ijpe.2015.06.030

Carr, S., & Lovejoy, W. (2000). The inverse newsvendor problem: Choosing an optimal demand portfolio for capacitated resources. *Management Science*, *46*(7), 912-927. doi: 10.1287/mnsc.46.7.912.12036

Chen, F. Y., & Krass, D. (2001). Analysis of supply contracts with minimum total order quantity commitments and non-stationary demands. *European Journal of Operational Research*, *131*(2), 309-323. doi: https://doi.org/10.1016/S0377-2217(99)00445-2

Choi, S., & Ketzenberg, M. (2018). An inverse newsvendor model to set the optimal number of customers in a capacitated environment. *International Journal of Production Economics*, *196*, 188-197. doi: https://doi.org/10.1016/j.ijpe.2017.11.017

Choi, S., & Wilhelm, W. E. (2014). On capacity allocation for operating rooms. *Computers & Operations Research*, *44*, 174-184. doi: https://doi.org/10.1016/j.cor.2013.11.007

Chung, W., Talluri, S., & Narasimhan, R. (2014). Quantity flexibility contract in the presence of discount incentive. *Decision Sciences*, *45*(1), 49-79. doi: https://doi.org/10.1111/deci.12058

Durango-Cohen, E. J., & Yano, C. A. (2006). Supplier commitment and production decisions under a forecast-commitment contract. *Management Science*, *52*(1), 54-67. doi: 10.1287/mnsc.1050.0471

Erhan Kesen, S., Kanchanapiboon, A., & Das, S. K. (2010). Evaluating supply chain flexibility with order quantity constraints and lost sales. *International Journal of Production Economics*, *126*(2), 181-188. doi: https://doi.org/10.1016/j.ijpe.2010.03.006

Esper, T. L., Ellinger, A. E., Stank, T. P., Flint, D. J., & Moon, M. (2010). Demand and supply integration: a conceptual framework of value creation through knowledge management. *Journal of the Academy of Marketing Science*, *38*(1), 5-18. doi: 10.1007/s11747-009-0135-3

Feng, Y., Martel, A., D'Amours, S., & Beauregard, R. (2013). Coordinated contract decisions in a make-to-order manufacturing supply chain: A stochastic programming approach. *Production and Operations Management*, *22*(3), 642-660. doi: 10.1111/j.1937-5956.2012.01385.x

Goh, S. H., & Eldridge, S. (2019). Sales and operations planning: The effect of coordination mechanisms on supply chain performance. *International Journal of Production Economics*, *214*, 80-94. doi: 10.1016/j.ijpe.2019.03.027

Gorissen, B. L., Yanıkoglu, I., & den Hertog, D. (2015). A practical guide to robust optimization. *Omega*, *53*, 124-137. doi: https://doi.org/10.1016/j.omega.2014.12.006

Govindan, K., Diabat, A., & Popiuc, M. N. (2012). Contract analysis: A performance measures and profit evaluation within two-echelon supply chains. *Computers & Industrial Engineering*, *63*(1), 58-74. doi: https://doi.org/10.1016/j.cie.2012.01.010

Guan, Z., & Philpott, A. B. (2011). A multistage stochastic programming model for the new zealand dairy industry. *International Journal of Production Economics*, *134*(2), 289-299. doi: https://doi.org/10.1016/j.ijpe.2009.11.003

Gunnarsson, H., & Rönnqvist, M. (2008). Solving a multi-period supply chain problem for a pulp company using heuristics—an application to södra cell ab. *International Journal of Production Economics*, *116*(1), 75-94. doi: https://doi.org/10.1016/j.ijpe.2008.07.010

Hausman, W. H., Montgomery, D. B., & Roth, A. V. (2002). Why should marketing and manufacturing work together?: Some exploratory empirical results. *Journal of Operations Management*, *20*(3), 241-257. doi: https://doi.org/10.1016/S0272-6963(02)00010-4

He, B., & Yang, Y. (2018). Mitigating supply risk: an approach with quantity flexibility procurement. *Annals of Operations Research*, *271*(2), 599-617. doi: 10.1007/s10479-018-2840-0

Heydari, J., Govindan, K., Ebrahimi Nasab, H. R., & Taleizadeh, A. A. (2020). Coordination by quantity flexibility contract in a two-echelon supply chain system: Effect of outsourcing decisions. *International Journal of Production Economics*, *225*, 107586. doi: https://doi.org/10.1016/j.ijpe.2019.107586

Jüttner, U., Christopher, M., & Baker, S. (2007). Demand chain management-integrating marketing and supply chain management. *Industrial Marketing Management*, *36*(3), 377-392. doi: https://doi.org/10.1016/j.indmarman.2005.10.003

Karakaya, S., & Bakal, I. S. (2013). Joint quantity flexibility for multiple products in a decentralized supply chain. *Computers & Industrial Engineering*, *64*(2), 696-707. doi: https://doi.org/10.1016/j.cie.2012.12.004

Leung, S. C. H., Tsang, S. O. S., Ng, W. L., & Wu, Y. (2007). A robust optimization model for multi-site production planning problem in an uncertain environment. *European Journal of Operational Research*, *181*(1), 224-238. doi: https://doi.org/10.1016/j.ejor.2006.06.011

Li, J., Luo, X., Wang, Q., & Zhou, W. (2020). Supply chain coordination through capacity reservation contract and quantity flexibility contract. *Omega*, 102195. doi: https://doi.org/10.1016/j.omega.2020.102195

Li, X., Lian, Z., Choong, K. K., & Liu, X. (2016). A quantity-flexibility contract with coordination. *International Journal of Production Economics*, *179*, 273-284. doi: https://doi.org/10.1016/j.ijpe.2016.06.016

Lian, Z., & Deshmukh, A. (2009). Analysis of supply contracts with quantity flexibility. *European Journal of Operational Research*, *196*(2), 526-533. doi: https://doi.org/10.1016/j.ejor.2008.02.043

Lidestam, H., & Rönnqvist, M. (2011). Use of lagrangian decomposition in supply chain planning. *Mathematical and Computer Modelling*, *54*(9), 2428-2442. doi: https://doi.org/10.1016/j.mcm.2011.05.054

Mirzapour Al-e hashem, S. M. J., Malekly, H., & Aryanezhad, M. B. (2011). A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. *International Journal of Production Economics*, *134*(1), 28-42. doi: https://doi.org/10.1016/j.ijpe.2011.01.027

Moinzadeh, K., & Nahmias, S. (2000). Adjustment strategies for a fixed delivery contract. *Operations Research*, *48*(3), 408-423.

Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations Research*, *43*(2), 264-281. doi: 10.1287/opre.43.2.264

O'Leary-Kelly, S. W., & Flores, B. E. (2002). The integration of manufacturing and marketing/sales decisions: impact on organizational performance. *Journal of Operations Management*, *20*(3), 221-240. doi: https://doi.org/10.1016/S0272-6963(02)00005-0

Pereira, D. F., Oliveira, J. F., & Carravilla, M. A. (2020). Tactical sales and operations planning: A holistic framework and a literature review of decision-making models. *International Journal of Production Economics*, *228*, 107695. doi: https://doi.org/10.1016/j.ijpe.2020.107695

Peykani, P., Mohammadi, E., Saen, R. F., Sadjadi, S. J., & Rostamy-Malkhalifeh, M. (2020). Data envelopment analysis and robust optimization: A review. *Expert Systems*, *37*(4), e12534. doi: https://doi.org/10.1111/exsy.12534

Sethi, S. P., Yan, H., & Zhang, H. (2004). Quantity flexibility contracts: Optimal decisions with information updates. *Decision Sciences*, *35*(4), 691-712. doi: 10.1111/j.1540-5915.2004.02873.x

Singhal, J., & Singhal, K. (2007). Holt, modigliani, muth, and simon's work and its role in the renaissance and evolution of operations management. *Journal of Operations Management*, *25*(2), 300-309. doi: 10.1016/j.jom.2006.06.003

Soo Kim, J., Il Park, S., & Young Shin, K. (2014). A quantity flexibility contract model for a system with heterogeneous suppliers. *Computers & Operations Research*, *41*, 98-108. doi: https://doi.org/10.1016/j.cor.2013.08.012

Taaffe, K., Geunes, J., & Romeijn, H. E. (2008). Target market selection and marketing effort under uncertainty: The selective newsvendor. *European Journal of Operational Research*, *189*(3), 987-1003. doi: https://doi.org/10.1016/j.ejor.2006.11.049

Taaffe, K., Romeijn, E., & Tirumalasetty, D. (2008). A selective newsvendor approach to order management. *Naval Research Logistics (NRL)*, *55*(8), 769-784. doi: https://doi.org/10.1002/nav.20320

Tang, C. S. (2010). A review of marketing–operations interface models: From co-existence to coordination and collaboration. *International Journal of Production Economics*, *125*(1), 22-40. doi: https://doi.org/10.1016/j.ijpe.2010.01.014

Thome, A. M. T., Scavarda, L. F., Fernandez, N. S., & Scavarda, A. J. (2012). Sales and operations planning: A research synthesis. *International Journal of Production Economics*, *138*(1), 1-13. doi: 10.1016/j.ijpe.2011.11.027

Thue, W. A. (2017). *Electrical power cable engineering*. Crc Press.

Tsay, A. A. (1999). The quantity flexibility contract and supplier-customer incentives. *Management Science*, *45*(10), 1339-1358. doi: 10.1287/mnsc.45.10.1339

Tsay, A. A., & Lovejoy, W. S. (1999). Quantity flexibility contracts and supply chain performance. *Manufacturing & Service Operations Management*, *1*(2), 89-111. doi: 10.1287/msom.1.2.89

Tuomikangas, N., & Kaipia, R. (2014). A coordination framework for sales and operations planning (s&op): Synthesis from the literature. *International Journal of Production Economics*, *154*, 243-262. doi: 10.1016/j.ijpe.2014.04.026

Urban, T. L. (2000). Supply contracts with periodic, stationary commitment. *Production and Operations Management*, *9*(4), 400-413. doi: https://doi.org/10.1111/j.1937-5956.2000.tb00466.x

van Delft, C., & Vial, J.-P. (2001). Quantitative analysis of multi-periodic supply chain contracts with options via stochastic programming.

Wu, J. (2005). Quantity flexibility contracts under bayesian updating. *Computers & Operations Research*, *32*(5), 1267-1288. doi: https://doi.org/10.1016/j.cor.2003.11.004

Yu, C.-S., & Li, H.-L. (2000). A robust optimization model for stochastic logistic problems. *International Journal of Production Economics*, *64*(1), 385-397. doi: https://doi.org/10.1016/S0925-5273(99)00074-2

Yuan, Q., Chua, G. A., Liu, X., & Chen, Y. (2015). Unsold versus unbought commitment: Minimum total commitment contracts with nonzero setup costs. *Production and Operations Management*, *24*(11), 1750-1767. doi: https://doi.org/10.1111/poms.12364

4.A Past literature on quantity commitment contracts

Reference	Contract	Topic	Products	Periods	Participants [1]	Segments [2]
Bassok and Anupindi (1997)	TMQ	Characterization of the optimal policy for a buyer when he agrees to commit to a total minimum quantity commitment	Single	Multiple	1-1	Single
Anupindi and Bassok (1998)	TMDV	Study of a contract offering price discounts for total minimum dollar volume commitments over the horizon, with flexibility above the commitment, and stochastic demands	Multiple	Multiple	1-1	Single
Tsay (1999)	QF	Characterization of the structure of a QF contract and study of the implications of the use of such arrangements for the behaviour of a supplier and a customer, and the supply chain as a whole	Single	Single	1-1	Single
Tsay and Lovejoy (1999)	QF	Presentation of a model for performance and design of QF supply chains, relating flexibility in supply with inventory levels. The supply chain operates under a rolling horizon planning (RHP)	Single	Multiple	1-1	Single
Moinzadeh and Nahmias (2000)	QF	Study of policies for a contractual arrangement that determines fixed delivery quantities per period that can be increased by the buyer, if willing to pay a premium to do so	Single	Multiple	1-1	Single
Urban (2000)	QF	Modeling and analysis of a periodical commitment supply contract. Quantities are stationary, but there is flexibility for the order to be changed, at an extra cost	Single (and multiple)	Multiple	1-1	Single
Chen and Krass (2001)	TMQ	Characterization of a contract policy in which the buyer may combine different strategies: a commitment basis, at a lower cost, and an as-ordered basis, at a higher cost and after the commitment quantity is achieved	Single	Multiple	1-1	Single
van Delft and Vial (2001)	QF (and buyback)	Study of a contract characterized by a periodical commitment with options, in presence of correlated demands. In the beginning of the horizon, the buyer agrees to buy specific quantities in each period, with possibility of future adjustments	Single	Multiple	1-1	Single
Sethi, Yan, and Zhang (2004)	QF	Analysis of single and multiple quantity flexibility contracts in which an initial order is placed at the beginning of the period. Additional purchases are possible in the middle of the period either on contract (with a higher price and subject to a flexibility threshold) or on spot market	Single	Single and multiple	1-1	Multiple [3]
Ben-Tal, Golany, Nemirovski, and Vial (2005)	QF	Approach to a QF contract - named retailer-supplier flexible commitment - using robust optimization. The focus of the paper lies on the study of the benefits of the solution method	Single (and multiple)	Multiple	1-1	Single

Wu (2005)	QF	Study of a QF contract in which the retailer uses a Bayesian procedure to update demand information and adjust the initial order, which is constrained by the negotiated flexibility and the manufacturer's production	Single	Multiple	1-1	Single
Durango-Cohen and Yano (2006)	QF	Characterization of a forecast-commitment contract in which the customer agrees to provide a forecast and purchase a fraction of the forecast and a supplier commits to production quantities	Single (and multiple)	Single	1-1	Single
Bassok and Anupindi (2008)	QF	Study of a RHP contract between a buyer and a supplier. At the beginning of the horizon the buyer makes commitments for each period, and receives some degree of flexibility from the supplier to adjust quantities in the future	Single	Multiple	1-1	Single
Lian and Deshmukh (2009)	QF	Study of a RHP contract in which the supplier provides the buyer discount to incentive him to purchase in advance for future periods. Orders can be adjusted in each period	Single	Multiple	1-1	Single
Erhan Kesen, Kanchanapiboon, and Das (2010)	QF	Analysis of a contract in which the buyer has two options per supply cycle: (i) to place an order below the minimum quantity agreed and pay a penalty, (ii) not to place an order at all and lose sales	Single	Multiple	1-1	Single
Govindan, Diabat, and Popiuc (2012)	QF (and others)	Evaluation of different contractual models on supply chain performance in a two-echelon supply chain with a retailer and a supplier	Single	Single	1-1	Single
Feng et al. (2013)	QF (and price-only, stationary)	Modeling of a coordinated contract selection and capacity allocation problem in a three-tier manufacturing supply chain. Four types of demand contracts are studied	Multiple	Multiple	1-M	Multiple
Karakaya and Bakal (2013)	QF	Characterization of a QF policy between a retailer and a manufacturer where there are multiple related products being sold. The contract establishes that the aggregate final order quantity should exactly meet the aggregate initial order, but there is full flexibility in the quantity for each product	Multiple	Multiple (two)	1-1	Single
Chung, Talluri, and Narasimhan (2014)	QF	Characterization of a combined contractual arrangement considering the QF mechanism and a price-only discount scheme. The QFi contract introduces the possibility for the buyer to take advantage of a discount price for units sold above the QF-contracted quantity	Single	Single	1-1	Single
Soo Kim, Il Park, and Young Shin (2014)	QF	Modeling of a multi-period QF model between a buyer and multiple heterogeneous suppliers selling the same product	Single	Multiple	M-1	Multiple [3]
Araneda-Fuentes et al. (2015)	QF (capacity reservation)	Presentation of a contract that coordinates capacity decisions of two manufacturers (B2B) collaborating under a buyer-supplier relationship	Single	Single	1-1	Multiple [3]
Cai, Abdel-Malek, Hoseini, and Rajaei Dehkordi (2015)	QF	Characterization of the ordering and replenishment policies for a QF contract in which the retailer commits to a minimum order quantity at the beginning of the season. The supplier offers an expedited-delivery option at a premium	Single	Multiple (two)	1-1	Single

Yuan, Chua, Liu, and Chen (2015)	TMQ	Study of an inventory review policy based on a minimum total commitment contract. The paper brings a simpler approach that considers the unsold commitment instead of the unbought commitment	Single	Multiple	1-1	Single
X. Li, Lian, Choong, and Liu (2016)	QF	Characterization of the optimal replenishment strategy for a retailer and the optimal pricing scheme for a cosmetic manufacturer using a QF contract	Single	Multiple (two)	1-1	Single
He and Yang (2018)	QF	Study of a buyer's procurement decisions when sourcing a product from two suppliers: the major supplier is random yield whereas the other supplier provides reliable fulfillment under a QF contract	Single	Single	2-1	Single
Heydari, Govindan, Ebrahimi Nasab, and Taleizadeh (2020)	QF	Characterization of a QF contract where a retailer is allowed to update the initial order both upwards and downwards. The manufacturer may outsource part of the production	Single	Multiple (two)	1-1	Single
J. Li et al. (2020)	QF (and capacity reservation)	Study of QF and capacity reservation contracts in a decision-making setting where one manufacturer and one retailer develop innovative products, capacity cost is high and lead time is long	Single	Multiple (two)	1-1	Single

1 Supply chain members considered. E.g., 1-1: one supplier-one buyer; 1-M: one supplier-multiple buyers

2 Sales segments characterized. A single segment means a context where only contract sales exist. In problems with multiple segments, spot or non-contract sales are introduced

3 Not studied from the supplier's perspective. In these cases, the buyer can resort to the spot market if contractual capacity is insufficient

4.B Formulation of the scenario-based robust model

Indexes and sets:

$t \in T$	Set of periods
$p \in P$	Set of products
$s \in S$	Set of production stages
$m \in M$	Set of machines
M_s	Set of machines belonging to the production stage s ($M_s \subset M$)
$M_{s,p}$	Set of machines belonging to the production stage s where product p can be produced ($M_{s,p} \subset M_s$)
$k \in K$	Set of markets (composed by several non-contract customers)
$c \in C$	Set of contract customers
P_k	Set of products potentially sold in market k ($P_k \subset P$)
P_c	Set of products potentially sold to contract customer c ($P_c \subset P$)
$\xi \in \Xi$	Set of demand scenarios

Parameters:

Operations:

$\beta_{p,m}$	Production time in machine m per unit of product p
$r_{m,t}$	Amount of regular time available at machine m in period t
$o_{m,t}$	Amount of overtime available at machine m in period t
ρ_m	Cost per unit of time in machine m
γ_m	Additional production cost (incremental rate) per unit of overtime in machine m
$h_{p,t}$	Holding cost of one unit of product p in period t
c_p	Cost per unit of product p (other than production costs: raw materials, administrative variable costs...)

Sales:

$d_{\xi,p,k,t}$	Demand of product p in period t for non-contract customers from market k under scenario ξ
$\phi_{p,k,t}$	Sales price of product p in period t in non-contract sales in market k
$d_{\xi,p,c,t}$	Demand of product p in period t for contract customer c under scenario ξ
$\overline{d}_{p,c,t}$	Expected demand (forecast) of product p in period t for contract customer c
$\psi_{c,\alpha}$	Level of discount offered to customer c over the sales price $\phi_{p,k_c,t}$ under a QF contract with flexibility α_c (assuming the same flexibility upwards and downwards, measured as a percentage deviation over the expected demand). k_c is the market the contract c belongs to. α_c is a decision variable

Robust formulation:

p_ξ	Probability of occurrence of scenario ξ
λ	Weight attributed to the solution variance term (solution robustness)
ω	Weight attributed to the infeasibilities penalty term (model robustness)

Decision variables:

Operations:

$X_{\xi,p,m,t}$	Production quantity of product p in machine m in period t under scenario ξ
$E_{\xi,m,t}$	Overtime used at machine m in period t under scenario ξ
$I_{\xi,p,t}$	Inventory of product p at the end of period t under scenario ξ

Sales:

$Q_{\xi,p,k,t}$	Quantity sold of product p to market k in period t under scenario ξ
W_c	Binary variable, 1 if a QF contract is offered to contract customer c, 0 otherwise
α_c	Flexibility of the QF contract offered to customer c, valid if $W_c = 1$
$Z_{p,c}$	Binary variable, 1 if product p is sold to contract customer c, 0 otherwise
$Q_{\xi,p,c,t}$	Quantity sold of product p to contract customer c in period t under scenario ξ
$A^{min}_{\xi,c,t}/A^{max}_{\xi,c,t}$	Auxiliary binary variable, 1 if the sum of the demand of the products included in the contract ($\sum_{p\in P_c:Z_{p,c}=1} d_{\xi,p,c,t}$) reaches the minimum/maximum agreed quantity in the QF contract established with the customer c in period t, 0 otherwise

Robust formulation:

$U_{\xi,p,c,t}$	Shortage on demand satisfaction of product p ordered by customer c in period t under scenario ξ
θ_ξ	Auxiliary variable, required to replace the quadratic term of the objective function by an absolute deviation term (Yu & Li, 2000)

Constraints:

Operations:

$$\sum_{p\in P} X_{\xi,p,m,t}\beta_{p,m} \le r_{m,t} + E_{\xi,m,t}, \quad \forall \xi \in \Xi, m \in M, t \in T$$

$$E_{\xi,m,t} \le o_{m,t}, \quad \forall \xi \in \Xi, m \in M, t \in T$$

$$\sum_{m\in M_{s,p}} X_{\xi,p,m,t} \le \sum_{m\in M_{s-1,p}} X_{\xi,p,m,t}, \quad \forall \xi \in \Xi, p \in P, s \in S : s > 1, t \in T$$

$$I_{\xi,p,t} = I_{\xi,p,t-1} + \sum_{m\in M_{s,p}:s=S} X_{\xi,p,m,t} - \sum_{c\in C} Q_{\xi,p,c,t} - \sum_{k\in K} Q_{\xi,p,k,t}, \quad \forall \xi \in \Xi, p \in P, t \in T$$

Sales:

$$Q_{\xi,p,k,t} \leq d_{\xi,p,k,t}, \quad \forall \xi \in \Xi, k \in K, p \in P_k, t \in T$$

$$Z_{p,c} \leq W_c \quad \forall c \in C, p \in P_c$$

$$Q_{\xi,p,c,t} \leq d_{\xi,p,c,t} Z_{p,c} A^{min}_{\xi,c,t} + \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t} Z_{p,c}(1 - A^{min}_{\xi,c,t}), \quad \forall \xi \in \Xi, c \in C, p \in P_c, t \in T$$

$$Q_{\xi,p,c,t} + U_{\xi,p,c,t} \geq d_{\xi,p,c,t} Z_{p,c}(1 - A^{max}_{\xi,c,t}), \quad \forall \xi \in \Xi, c \in C, p \in P_c, t \in T$$

$$\sum_{p\in P_c} d_{\xi,p,c,t} Z_{p,c} - \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 - \alpha_c) \leq \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t} A^{min}_{\xi,c,t}, \quad \forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} d_{\xi,p,c,t} Z_{p,c} - \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 - \alpha_c) \geq -\sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t}(1 - A^{min}_{\xi,c,t}),$$
$$\forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} d_{\xi,p,c,t} Z_{p,c} - \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 + \alpha_c) \leq \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t} A^{max}_{\xi,c,t}, \quad \forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} d_{\xi,p,c,t} Z_{p,c} - \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 + \alpha_c) \geq -\sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t}(1 - A^{max}_{c,t}),$$
$$\forall \xi \in \Xi, c \in C, t \in T$$

$$\alpha_c \leq max_\alpha W_c, \quad \forall c \in C$$

$$\sum_{p\in P_c} (Q_{\xi,p,c,t} + U_{\xi,p,c,t}) \geq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 - \alpha_c), \quad \forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} Q_{\xi,p,c,t} \leq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 + \alpha_c), \quad \forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} Q_{\xi,p,c,t} \leq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 - \alpha_c) + \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t} A^{min}_{\xi,c,t}, \quad \forall \xi \in \Xi, c \in C, t \in T$$

$$\sum_{p\in P_c} (Q_{\xi,p,c,t} + U_{\xi,p,c,t}) \geq \sum_{p\in P_c} \overline{d}_{p,c,t} Z_{p,c}(1 + \alpha_c) - \sum_{c\in C}\sum_{p\in P_c}\sum_{t\in T} d_{\xi,p,c,t}(1 - A^{max}_{\xi,c,t}),$$
$$\forall \xi \in \Xi, c \in C, t \in T$$

Robust formulation:

$$\Gamma_\xi - \sum_{\xi\in\Xi} p_\xi \Gamma_\xi + \theta_\xi \geq 0, \quad \forall \xi \in \Xi$$

Domain constraints:

$$X_{\xi,p,m,t}, E_{\xi,m,t}, I_{\xi,p,t} \geq 0, \quad \forall \xi \in \Xi, p \in P, m \in M, t \in T$$

$$\alpha_c, Q_{\xi,p,c,t}, Q_{\xi,p,k,t} \geq 0, \quad \forall \xi \in \Xi, c \in C, p \in P, k \in K, t \in T$$

$$W_c, Z_{p,c}, A^{min}_{\xi,c,t}, A^{max}_{\xi,c,t} \in \{0,1\}, \quad \forall \xi \in \Xi, p \in P, c \in C, t \in T$$

$$\theta_\xi, U_{\xi,p,c,t} \geq 0, \quad \forall \xi \in \Xi, p \in P, c \in C, t \in T$$

Objective function:

Profit function for each scenario:

$$SalesQF_{\xi} = \sum_{c \in C} \sum_{p \in P_c : Z_{p,c}=1} \sum_{t \in T} Q_{\xi,p,c,t} \phi_{p,k_c,t} (1 - \psi_{c,\alpha}), \quad \forall \xi \in \Xi$$

$$NonContractSales_{\xi} = \sum_{k \in K} \sum_{p \in P_k} \sum_{t \in T} Q_{\xi,p,k,t} \phi_{p,k,t}, \quad \forall \xi \in \Xi$$

$$ProductionCost_{\xi} = \sum_{p \in P} \sum_{s \in S} \sum_{m \in M_{s,p}} \sum_{t \in T} X_{\xi,p,m,t} \beta_{p,m} \rho_m + \sum_{m \in M} \sum_{t \in T} E_{\xi,m,t} \gamma_m, \quad \forall \xi \in \Xi$$

$$OtherCosts_{\xi} = \sum_{p \in P} \sum_{t \in T} I_{\xi,p,t} h_{p,t} + \sum_{p \in P} \sum_{s \in S : s = S} \sum_{m \in M_{s,p}} \sum_{t \in T} X_{\xi,p,m,t} c_p, \quad \forall \xi \in \Xi$$

$$Profit_{\xi} = \Gamma_{\xi} = SalesQF_{\xi} + NonContractSales_{\xi} - ProductionCost_{\xi} - OtherCosts_{\xi}, \quad \forall \xi \in \Xi$$

Overall function:

$$Max \sum_{\xi \in \Xi} p_{\xi} \Gamma_{\xi} - \lambda \sum_{\xi \in \Xi} p_{\xi} \left[\left(\Gamma_{\xi} - \sum_{\xi' \in \Xi} p_{\xi'} \Gamma_{\xi'} \right) + 2\theta_{\xi} \right] - \omega \sum_{\xi \in \Xi} \sum_{c \in C} \sum_{p \in P_c : Z_{p,c}=1} \sum_{t \in T} p_{\xi} U_{\xi,p,c,t}$$

4.C Required production hours to meet demand (IE)

Product	Machines 543	590	324	316	338	612	530	527	375	327	325	555	Others	Total	Contract[1]
7222002	2,700	0	0	0	0	749	268	0	0	558	0	0	81	4,356	100%
7222008	0	0	0	0	0	283	102	189	895	0	0	0	532	2,001	84.1%
7222001	988	0	0	0	0	274	98	0	0	0	241	0	26	1,626	100%
7209015	0	267	547	0	0	127	108	0	0	0	175	215	0	1,438	0%
7222005	0	253	0	0	0	120	129	102	0	0	0	151	565	1,319	100%
7209013	0	224	458	0	0	106	90	0	0	0	146	180	0	1,205	0%
7202031	0	0	174	242	206	0	0	112	0	0	0	0	468	1,203	48%
7207111	0	255	0	0	0	0	335	0	0	0	0	0	374	965	100%
7182747	0	0	219	200	175	0	0	101	0	0	0	0	83	778	0%
7182881	0	202	0	135	176	0	0	145	0	0	0	0	112	770	0%
7182743	0	213	0	183	186	0	0	107	0	0	0	0	58	747	0.3%
7182748	0	0	174	201	159	0	0	98	0	0	0	0	60	693	0.2%
7182738	0	184	0	126	200	0	0	127	0	0	0	0	46	684	0%
7182506	0	0	0	0	0	0	0	0	0	259	0	0	310	569	1.1%
7182746	0	0	82	179	139	0	0	110	0	0	0	0	42	553	0%
7207088	0	0	212	0	0	0	230	0	0	0	0	0	95	536	80.2%
7182511	0	171	0	91	148	0	0	79	0	0	0	0	43	532	1.7%
72220021	330	0	0	0	0	91	33	0	0	63	0	0	10	527	100%
7222012	0	0	0	0	0	87	31	0	276	0	77	0	46	517	100%
7182745	0	0	76	139	107	0	0	64	0	0	0	0	51	438	0%
Others	0	914	337	583	521	21	264	203	47	95	51	102	2,186	5,324	42.9%
Total	4,018	2,683	2,278	2,079	2,019	1,859	1,688	1,437	1,218	975	690	647	5,189	26,780	53.4%

1 Weight of contractual segment in the total expected potential demand
Values on contract demand (m.u.) not including QF contract discount

4.D Products details

Product	Market	Customers	Prod. stages	Machines	Prod. time[1]	Price[2]	Cost[3]	Prod. cost[3]
7182506	#6;#3	1358	4	327;357;605;761	9.34	1.14	0.68	0.17
7182757	#6;#3	1571	4	327;357;605;761	7.42	1.03	0.57	0.13
7182511	#6;#3	1571	6	316;338;527;590;605;619	14.95	1.83	1.12	0.21
7207030	#5;#3	1358;1571	5	530;590;605;728;761	9.77	0.80	0.65	0.09
7207088	#3	1358	4	324;530;605;761	13.25	2.97	1.93	0.27
7182731	#6	-	6	316;338;590;605;727;761	13.05	1.41	0.96	0.21
7207074	#6	-	4	605;711;728;761	7.54	0.88	0.35	0.14
7207076	#6	-	4	387;605;728;761	6.07	0.45	0.12	0.10
7182733	#6;#3	-	5	316;338;590;605;619	12.59	1.15	0.74	0.19
7182738	#6;#3	-	6	316;338;527;590;605;619	17.83	2.16	1.45	0.27
7182736	#5;#6;#3	1571	7	316;338;527;590;605;727;761	15.09	1.44	0.95	0.23
7182739	#6	-	6	316;324;338;527;605;619	19.57	2.83	1.89	0.42
7182743	#6;#3	1571	6	316;338;527;590;605;619	16.79	2.30	1.51	0.27
7182747	#6;#3	-	6	316;324;331;338;527;605	18.60	3.14	2.12	0.45
7182744	#6;#3	1571	6	316;324;338;527;605;616	30.41	5.08	3.55	0.80
7222005	-	3291;3622;3971	8	304;318;510;527;530;555;590;612	31.33	2.99	2.00	0.57
7182745	#6;#3	-	6	316;324;338;527;610;616	30.17	6.50	4.48	0.76
7182746	#6	-	6	316;324;338;527;605;616	44.30	10.17	7.16	1.07
7182762	#5;#6;#3	-	5	316;338;590;605;761	11.82	0.93	0.57	0.16
7182881	#6;#3	-	7	316;338;527;590;605;727;761	15.65	1.71	1.11	0.23
7207075	#6;#3	-	4	387;605;728;761	8.98	1.30	0.71	0.20
7182748	#5;#6;#3	1571	6	316;324;331;338;527;605	20.82	4.07	2.83	0.50
7202031	#3	1358;1571	9	316;324;330;331;338;527;605;616;727	57.70	7.24	5.40	1.23
7207109	-	3622;4012	4	530;590;605;618	12.50	1.22	0.67	0.13
7207110	-	3622;4012	4	530;590;605;618	15.12	2.10	1.24	0.18
7207111	-	1358;3622;4012	4	530;590;605;618	15.12	3.86	2.48	0.18
72071121	-	4012	4	530;590;605;618	15.12	2.01	1.34	0.18
7209013	#6	-	6	324;325;530;555;590;612	32.29	3.00	1.70	0.70
7209015	#6	-	6	324;325;530;555;590;612	32.29	3.32	2.22	0.70
7222001	-	3291;3622;3971	6	304;325;510;530;543;612	16.94	1.22	0.93	0.27
7222002	-	3291;3622;3971	6	304;327;510;530;543;612	16.59	1.90	1.32	0.26
72220021	-	4012	6	304;327;510;530;543;612	16.43	1.72	1.32	0.25
7222008	#1	3291;3971	7	375;377;397;510;527;530;612	20.13	3.72	2.41	0.33
72220081	-	4012	7	375;377;397;510;527;530;612	20.13	3.02	2.41	0.33
7222011	#1	3971	8	334;377;397;510;527;530;590;612	35.13	5.19	3.20	0.54
7222012	-	3291;3971	7	325;375;397;460;510;530;612	16.87	2.43	1.77	0.26
7225112	#5;#3	-	3	316;605;616	6.68	2.04	2.09	0.20
7225125	#5;#6;#3	-	6	316;338;527;590;605;619	15.68	1.74	1.19	0.24
7225201	#5;#6;#3	1571	4	327;357;605;761	6.71	0.81	0.51	0.11
7225248	#5;#6;#3	-	4	327;357;605;761	6.00	0.63	0.38	0.10
7225271	-	2750	8	304;324;338;377;510;545;605;620	38.29	3.74	2.36	0.9
7225272	-	2750	8	304;324;377;510;545;605;618;727	39.77	5.38	3.29	0.96
7225273	-	2750	9	304;324;338;377;510;545;605;618;727	40.49	6.32	4.33	1.00
7225277	-	2750	8	324;331;338;510;545;555;605;616	63.48	14.42	10.94	1.74
7229001	-	3291	9	304;316;325;510;545;590;605;727;761	27.61	2.19	1.41	0.57
7229008	-	3291	8	304;316;324;338;510;545;610;616	39.87	9.16	7.06	1.05
7229010	-	3291	9	304;316;325;510;545;590;605;727;761	27.93	2.36	1.72	0.58

1 seconds/meter; 2 monetary units/meter. Average sales price, not including QF discount (in contract sales); 3 monetary units/meter

4.E Comparison of the basis plan (A) against a business rules-based plan (B)

Table 4.E.1: Average non-contract demand satisfaction and sales

Market	Demand satisfaction		Sales (m.u.)	
	(A)	(B)	(A)	(B)
#5	13.1%	16.7%	4,179	8,217
#6	90.5%	91.6%	4,521,772	4,570,496
#1	99.7%	100.0%	238,852	240,308
#3	67.2%	69.1%	361,620	348,673
Total	88.0%	89.2%	5,126,424	5,167,695

Table 4.E.2: Average contract demand satisfaction and sales (detail of the demand satisfaction under scenario OE to illustrate the 'basis' plan greater robustness)

Market	Customer	Avg. demand satisf. (contract only[1])		OE Demand satisf. (contract only[1])		Average Sales (m.u.)	
		(A)	(B)	(A)	(B)	(A)	(B)
#1	3622	111.3%	100.9%	88.3%	55.8%	1,672,428	1,306,025
	3971	104.7%	109.8%	92.5%	86.2%	1,084,007	1,802,575
	4012	109.7%	115.6%	91.5%	88.5%	925,848	637,584
#2	3291	103.5%	86.1%	95.8%	70.2%	562,932	832,473
#3	1358	105.2%	104.0%	92.8%	90.5%	523,670	493,356
	1571	104.4%	104.4%	88.4%	88.4%	53,360	54,167
#4	2750	100.7%	100.7%	94.0%	94.0%	441,650	438,186
Total		107.7%	101.3%	91.0%	74.8%	5,263,894	5,564,368

1 Demand satisfaction considering the products in the contract only

Table 4.E.3: Contract offering for each customer

	Plan	1358	1571	2750	3291	3622	3971	4012	Total
Products included	(A)	4/5	8/9	4/4	6/8	6/6	3/6	6/6	37/44
	(B)	4/5	8/9	4/4	7/8	5/6	4/6	4/6	36/44
Estimated dem. (m.u.)	(A)	584,636	58,678	455,623	609,487	1,668,278	1,155,892	982,023	5,514,618
	(B)	564,644	58,678	455,623	975,786	1,544,859	1,852,014	726,212	6,177,818
Flexibility level	(A)	0.5	0.5	0.5	0.5	0.4	0.5	0.4	
	(B)	0.5	0.5	0.5	0.5	0.3	0.4	0.3	

Estimated demand (m.u.) not including the QF discount

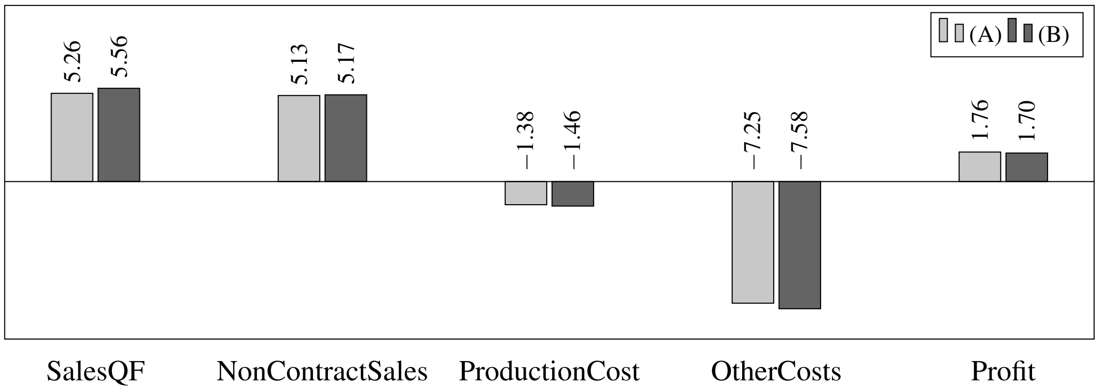


Figure 4.E.1: Profit comparison and drill-down, in monetary units (millions). Values resulting from the average of the three scenarios: AE, OE, UE

4.F Comparison of the basis plan (A) against a deterministic-based plan (B)

Table 4.F.1: Average non-contract demand satisfaction and sales

Market	Demand satisfaction		Sales (m.u.)	
	(A)	(B)	(A)	(B)
#5	13.1%	14.0%	4,179	4,577
#6	90.5%	93.0%	4,521,772	4,705,544
#1	99.7%	100.0%	238,852	240,308
#3	67.2%	70.3%	361,620	401,105
Total	88.0%	90.5%	5,126,424	5,351,535

Table 4.F.2: Average contract demand satisfaction and sales (detail of the demand satisfaction under scenario OE to illustrate the 'basis' plan greater robustness)

Market	Customer	Avg. demand satisf. (contract only[1])		OE Demand satisf. (contract only[1])		Average Sales (m.u.)	
		(A)	(B)	(A)	(B)	(A)	(B)
#1	3622	111.3%	99.7%	88.3%	71.1%	1,672,428	1,371,712
	3971	104.7%	108.2%	92.5%	96.2%	1,084,007	1,827,723
	4012	109.7%	105.8%	91.5%	96.3%	925,848	725,291
#2	3291	103.5%	101.8%	95.8%	93.4%	562,932	406,712
#3	1358	105.2%	105.8%	92.8%	88.8%	523,670	313,915
	1571	104.4%	104.0%	88.4%	94.9%	53,360	11,630
#4	2750	100.7%	100.7%	94.0%	94.0%	441,650	446,012
Total		107.7%	104.0%	91.0%	86.8%	5,263,894	5,102,995

1 Demand satisfaction considering the products in the contract only

Table 4.F.3: Contract offering for each customer

	Plan	1358	1571	2750	3291	3622	3971	4012	Total
Products included	(A)	4/5	8/9	4/4	6/8	6/6	3/6	6/6	37/44
	(B)	3/5	7/9	4/4	4/8	5/6	4/6	5/6	32/44
Estimated dem. (m.u.)	(A)	584,636	58,678	455,623	609,487	1,668,278	1,155,892	982,023	5,514,618
	(B)	351,492	11,179	455,623	456,571	1,544,859	1,852,014	783,360	5,455,098
Flexibility level	(A)	0.5	0.5	0.5	0.5	0.4	0.5	0.4	
	(B)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	

Estimated demand (m.u.) not including the QF discount

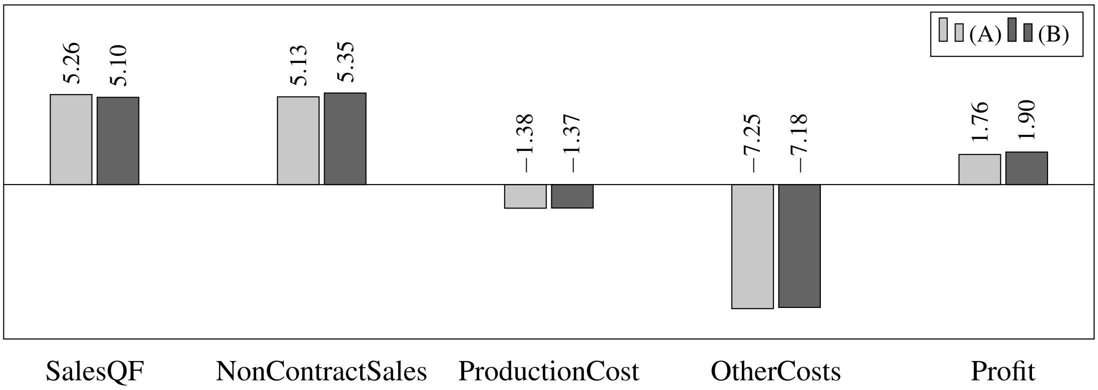


Figure 4.F.1: Profit comparison and drill-down, in monetary units (millions). Values resulting from the average of the three scenarios: AE, OE, UE

Chapter 5

Conclusions and Future Work

This thesis tackles the mid-term integrated planning of sales and operations teams known as Sales and Operations Planning. We are particularly interested in the contribution that advanced planning models can bring to the richness of this cross-functional and tactical planning layer. The field of literature is sparse and multiple domains have been studied since the origin of the concept. Therefore, in Chapter 2, we start by reviewing the existing literature, and framing the problem by developing a holistic framework that depicts the problem from a decision-making perspective. Past literature is also framed regarding the modeling approaches and solution procedures employed by past researchers. From here, relevant opportunities and avenues for further research are identified. In brief, there are opportunities to: extend the models to cope with a more complete decision-making spectrum, and enrich the models to consider more complex dimensions, such as multistage operations processes or multi-objective concerns. New models developed shall be devised with generality concerns to be widely applied, be assessed in different sectors of activity, and be sophisticated enough to include uncertain parameters. From a solution procedures' perspective, applying such models in real-world sized problems may need to be accompanied by the implementation of heuristic solution procedures to ensure solvability in acceptable time frames.

We address some of these opportunities developing innovative S&OP decision-making models. In Chapter 3, a new mathematical programming approach is proposed, coupled with a business-framing matrix, to help hybrid companies with a flow shop/batch process to manage S&OP decisions if some products are produced to stock while the remaining are produced to order. We demonstrate how the model and the multi-objective rationale proposed can be leveraged by providing an in-depth analysis of an illustrative instance. In Chapter 4, the integrated sales and operations planning context describes a setting where demand is grouped around two different segments, composed by contract and non-contract customers. A mathematical programming model is proposed to deal with operations planning, sales planning, contract design, and portfolio selection. The model is extended to account for scenario-based robustness, as the contract design decisions, to be considered at the beginning of the planning horizon, are subject to demand uncertainty that may arise in later periods. The model's usefulness is demonstrated through a series of extensive computational experiments, from which some key managerial insights are generated.

To sum up, the major contributions are as follows: a distinctive and thorough framework that sets the Tactical Sales and Operations Planning problem, and the definition of an agenda for further research in the field; two rich decision-making models that enlarge the scope provided by the existing S&OP literature, accompanied by a complete description on how they can be used to ensure an effective implementation by decision-makers facing such challenges in their real-world planning problems. The results of the contributions above are three research papers:

Pereira, D. F., Oliveira, J. F., & Carravilla, M. A. (2020). **Tactical sales and operations planning: A holistic framework and a literature review of decision-making models.** *International Journal of Production Economics*, 228, 107695. doi:https://doi.org/10.1016/j.ijpe.2020.107695

This paper comprises the content presented in Chapter 2 of this thesis. In more detail, the review leads to four contributions. First, a holistic framework depicting the overall S&OP problem contains all the decisions that can be potentially tackled in mid-term supply chain planning. The relationship between all the decisions is addressed. The review also indicates the parameters that have been modeled as uncertain variables by past research. Second, existing papers are organized according to the framework, identifying the streams of literature that contributed to the extension of the tactical production planning. Third, the review presents the modeling approaches and solution procedures that have been employed. Fourth, the current body of literature is classified according to its capability of integrating all the decisions presented, and a future agenda for more advanced and integrative S&OP is stated.

We believe that the proposed framework and the resulting contributions will play an important role in guiding future research on models supporting S&OP for industrial companies. Before this work, no review of the state-of-the-art modeling approaches to tackle S&OP existed, complicating the development of structured advances in the field.

Pereira, D. F., Oliveira, J. F., & Carravilla, M. A. (2021). **Merging Make-to-Stock/Make-to-Order decisions into Sales and Operations Planning: a multi-objective approach.** Submitted and under the second round of review at *Omega*.

Chapter 3 of the thesis corresponds to the content of this paper. This work's contributions are essentially twofold. First, the proposed model constitutes an innovative decision-making S&OP model for hybrid MTS/MTO production context. The framework offers the analytical support for a manufacturer to optimize its medium-term sales and operations decisions, addressing the co-existence of different production types, and dealing with the challenge of managing multiple routes and production possibilities arising in flow shop/batch environments. None of the models presented in Chapter 2 deals with such setting. Second, the paper proposes a new multi-objective planning rationale, because other reasons that financial concerns may impact mid-term decisions. The strategic committee sometimes must abdicate from profits to satisfy a specific set of customers or reinforce the company's position in the market. Our approach brings the trade-off that emerges between profitability and service level explicitly.

We foresee that this approach can be of extreme value in settings where the definition of the S&OP plan is constrained by conditions that limit the conventional prosecution of the most profitable plan. In such a case, S&OP meetings should agree on a commercial trade-off between different demand segments. Although the research is motivated by a real world case, we believe that our framework is generic enough to be easily adaptable to any company with a hybrid production strategy, and that operates in a flow/shop batch process.

Pereira, D. F., Oliveira, J. F., & Carravilla, M. A. (2021). **Design of a sales plan in a hybrid contractual and non-contractual context in a setting of limited capacity.** Submitted at *Production and Operations Management*.

This paper is presented in Chapter 4 of the thesis. The contribution of this paper lies in a decision-making model to support the sales and marketing teams to define the sales acquisition plan in a setting of limited capacity to serve multiple customers that can be either non-contractual or operate under quantity-flexibility arrangements. We extend the literature on the fields of Sales and Operations Planning and contract management by merging them, which has not been common. Contract management literature has focused more on the study of optimal policies of a single or a few products, and do not consider the complexity behind a sales ecosystem where contract and non-contract customers compete for the same capacity, in a multi-period and multi-product context.

As additional contributions of the work, we highlight the managerial insights that we derive from our work, and the application of robust optimization to Sales and Operations Planning, which our initial literature review indicates that has not been usual.

This approach is completely replicable to other business contexts. We formulate the model considering a multi-stage production process, to make it more comprehensive. However, it can be adapted to tackle more simplified production processes, where the operations' capacity can be analyzed around a bottleneck operation. As a pre-requisite for the application of our approach, we point out the need that the supplier-buyer relationship can be governed by a multi-product quantity-flexibility (QF) arrangement, which might not be always the case. Nevertheless, the QF arrangement is among the most common approaches in contract management, reinforcing our proposal's usefulness.

Overall, this thesis sustains that there is still much to do in the field of quantitative approaches to support more advanced and integrated S&OP. From the research directions presented in Chapter 2, the remainder of the thesis only focuses on advancements in some axes. There is still an opportunity to integrate more advanced demand shaping strategies or understand how different inventory management policies influence the mid-term stock targets, just to name a few. Hopefully, as progresses in computational power are developing fast, we view such topics to be further explored in the future. Until this day, the question of realism while planning (that is, granularity) versus planning scope (that is, the number of decisions included in the models) has been carefully managed by researchers and practitioners to ensure models are implementable in practice. As computer processing capacity improves and more effective heuristic procedures are designed, we expect the scientific community to move towards developing models to support more complex decision-making contexts.

When focusing on the models we propose in Chapters 3 and 4, we would be thrilled to see case studies of implementation of the frameworks in multiple business realities, to grasp the potential benefits such approaches bring to the S&OP practice. Furthermore, another interesting research direction would be combining the models with different matheuristic or metaheuristic procedures, to reduce the models' solving times even for larger instances. The work presented in this thesis focuses more on the mathematical modeling and framework development rather than on the solution procedures. However, as the applicability of such approaches depends on the efficiency of the decision support system containing such models, it is something deserving further attention.