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Assessing the Performance of the TURN Optimization Model in Sonae Arauco's Production Planning

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Resumo

A correta definição da melhor estratégia de produção para cada produto e o correto dimensionamento dos lotes de produção são dois aspectos cruciais que as indústrias devem ter em consideração para serem bem sucedidas.

A literatura enfatiza a importância da definição de estratégias de produção, fornecendo uma abordagem de múltiplos critérios para determinar o ponto de dissociação ótimo. Destaca também o papel dos modelos de sistemas de apoio à decisão na simulação de cenários de produção e na facilitação da tomada de decisões informadas. Estes modelos baseiam-se predominantemente em programação linear, visando maximizar ou minimizar uma função objetivo, respeitando um conjunto de restrições. A obtenção destes resultados pode ser conseguida através da utilização de softwares de otimização altamente eficazes disponíveis no mercado.

Este estudo foi realizado na Sonae Arauco, um produtor de painéis derivados de madeira, com o objetivo de parametrizar e validar o modelo desenvolvido durante o projeto TURN para a realidade industrial da empresa.

A abordagem proposta envolve um modelo de otimização concebido para determinar a estratégia de produção óptima (MTS/MTO/FTO) para produtos individuais, juntamente com os correspondentes tamanhos de lote e stocks de segurança para produtos MTS. As decisões do modelo serão orientadas por compromissos de custo entre as estratégias MTS e MTO para cada componente, incluindo placas em bruto, papel decorativo e paineís decorativos. Embora uma estratégia MTO ofereça vantagens em termos de custos de inventário mais baixos, resulta num aumento da ocupação da linha e dos custos de preparação. Por outro lado, a adoção de uma estratégia MTS implica custos de inventário mais elevados, mas oferece benefícios, como a redução dos custos de preparação e a diminuição da variabilidade do tempo de produção.

Espera-se que a aplicação das metodologias desenvolvidas resulte em poupanças significativas para a empresa. Os resultados da validação do modelo indicam que a estratégia de produção proposta resulta num aumento de 5% no nível de MTS, indicando que o modelo favorece a produção de stock para reduzir os custos de inventário, aumentando os tamanhos de lote ideais para a produção, levando a uma redução de custos mensais de 8%.

A validação deste modelo de sistema de apoio à decisão, juntamente com o seu alinhamento aos princípios da Indústria 4.0, são de extrema importância para demonstrar a eficácia e o valor de aproveitar tecnologias avançadas na tomada de decisões otimizadas em operações de produção.

Abstract

The correct definition of the best production strategy for each product and the correct sizing of the production lots are two crucial aspects that industrial companies must take into consideration to be successful.

The literature emphasizes the significance of defining production strategies by providing a multi-criteria approach to determine the optimal decoupling point. It also highlights the role of decision support system models in simulating production scenarios and facilitating informed decision-making. These models predominantly rely on linear programming, aiming to maximize or minimize an objective function while adhering to a set of constraints. Obtaining these results can be achieved through the utilization of highly powerful optimization software available in the market.

This study was carried out at Sonae Arauco, a wood-based panels producer, with the purpose of parameterising and validating the model developed during the TURN project for the industrial reality of the company.

The proposed approach entails an optimization model designed to determine the optimal production strategy (MTS/MTO/FTO) for individual products, along with corresponding lot sizes and safety stocks for MTS products. The model's decisions will be guided by cost trade-offs between MTS and MTO strategies for each component, including raw boards, decorative paper, and decorative panels. While an MTO strategy offers advantages in terms of lower inventory costs, it results in increased line occupation and setup costs. Conversely, adopting an MTS strategy entails higher inventory costs but offers benefits such as reduced setup costs and decreased variability in production lead time.

It is expected that the application of the methodologies developed will result in significant savings for the company. The results of the validation of the model indicate that the proposed production strategy result in a 5% increase in the MTS level, indicating that the model favors stock production to reduce inventory costs by increasing the optimal lot sizes for production, leading to a 8% monthly costs saving.

The validation and proof of concept for this decision support system model, along with its integration with Industry 4.0 principles and utilization of real-time data, hold significant importance in demonstrating the effectiveness and value of leveraging advanced technologies for optimized decision-making in production operations.

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Diogo Figueiredo Fernandes

“ Don’t be discouraged by anxieties and troubles.
Life is full of them.”

St. John Baptist De La Salle

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Abbreviations

AHP	Analytic Hierarchy Process
CODP	Customer Order Decoupling Point
DSS	Decision Support System
ERP	Enterprise Resource Planning
FTE	Full-time Equivalent
FTO	Finish-to-Order
GFT	Group-Family-Type
ILP	Integer Linear Programming
IT	Information Technology
KPI	Key Performance Indicator
LP	Linear Programming
MDF	Medium Density Fiberboard
MFC	Melamine Faced Chipboard
MFMDF	Melamine Faced MDF
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
MOQ	Minimum Order Quantity
MPQ	Minimum Production Quantity
MRP	Material Requirements Planning
MTO	Make-to-Order
MTS	Make-to-Stock
NEE	Northeast
OEE	Overall Equipment Effectiveness
OSB	Oriented Strand Board
OTIF	On-Time In-Full
PB	Particleboard
SAF	South Africa
SKU	Stock Keeping Unit
SWE	South-west
S&OE	Sales and Operations Execution
S&OP	Sales and Operations Planning

Chapter 1

Introduction

This introductory chapter aims to provide a framework for the dissertation, referring the context and motivations that supported the proposition of the theme in section 1.1, presenting an overview of the company in section 1.2 and the goals to be accomplished with this dissertation in section 1.3. In section 1.4, the methodology that was followed is described. Finally, in section 1.5 the structure of this document will be provided.

1.1 Context and Motivation

The supply chain concept is theorized from the formation of a value chain network consisting of individual functional entities committed to providing resources and information to achieve the objectives of efficient management of suppliers as well as the flow of parts [1]. An integrated supply chain has a clear advantage on the competitiveness of the individual companies. Supply chain management includes a set of approaches and practices to effectively integrate suppliers, manufacturers, distributors and customers for improving the long-term performance of the individual firms and the supply chain as a whole in a cohesive and high-performing business model [2].

Production planning plays a critical role in supply chain management, by ensuring that the proper amount of goods are produced at the right time and at the right cost. The value of optimized production planning within the supply chain is clear to many managers, particularly when large portions reside within one organization or the planning can be done in a coordinated way [3]. Companies must have strong production planning and forecasting techniques in place if they want to optimize their production processes, save costs, improve productivity, and boost profitability. Mathematical models are used to simulate production processes and forecast their results, enabling businesses to test various hypotheses and find the best answers.

The innovative TURN project, by Sonae Arauco in collaboration with a consultancy team, intends to provide a decision support system for production planning and forecasting in the wood-based industrial sector. By collecting data of their current planning and forecast as well as their previous production alignment and sales numbers, the project aims to develop models that optimize the production strategy, finding the best MTO, MTS and FTO production mix. One of the important components of the decision support system is the Lot Sizing, which intends to calculate the ideal lot size for each production order based on variables such as demand variability, lead time, and setup costs.

With the rise of this project the need arises to perform an evaluation of the impact this system could have on the company's daily operations, realizing whether it is more advantageous than the current methods of functioning.

1.2 Company Presentation

Founded in 1959, Sonae Indústria is a multinational wood-based panels company. From the north of Portugal it has reached the entire world, developing products for the furniture, construction and decoration industries that improve people's lives. Using wood as the raw material for everything it produces, Sonae Indústria has, from the outset, been committed to using natural resources in a sustainable way and to reducing the environmental impact of its activities as much as possible.

Sonae Indústria and Inversiones Arauco Internacional formed the joint venture in 2017 to create Sonae Arauco, which became one of the largest players in the world's wood-based panel market. These products are made from wood fibers that are mixed with resin and then pressed and heat-treated to form a solid panel. Sonae Arauco's base products are MDF, PB and OSB. These products are mainly used in furniture and decoration, with the exception of OSB, which is also used in the construction business and are presented in figure 1.1.

In the surfaced panels segment, Sonae Arauco primarily manufactures and distributes MFC and MFMDF, which are MDF panels coated with a layer of melamine paper featuring a decorative motif, providing the base panels with various finishes. The company offers more than 150 different decorative varieties and more than thirty various finishes for these products.

Figure 1.1: Types of core products, PB, MDF and OSB, respectively

In addition to its core wood panel business, Sonae Arauco also produces and sells a range of other products, including doors, flooring, and decorative laminates. The company is committed to sustainability and is actively working to reduce its environmental impact through the use of sustainable raw materials, energy-efficient production processes, and the implementation of waste reduction and recycling initiatives. In this context, the figure 1.2 depict a side-by-side comparison, with the offices of Sonae Arauco's headquarters gracefully depicted on the left, juxtaposed with the dynamic and vivid portrayal of the industrial reality of Oliveira do Hospital showcased on the right.

Figure 1.2: Sonae Arauco Facilities

Currently, Sonae Arauco has a commercial presence in more than 75 countries and has factories and distribution centers in Portugal, Germany, Spain, United Kingdom and South Africa. Sonae Arauco is the industry leader in its sector, with 4,200 million m3 of annual manufacturing capacity and about 3,000 employees worldwide [4].

1.3 Goals

This dissertation aims to assess the TURN project's MTS/MTO/FTO production forecasting stat-egy and Lot Sizes optimization model, analyzing the model developed and evaluating its effectiveness and future impact of this new decision support system on the company's production planning, enabling the company to take more informed and accurate decisions.

Therefore, and in order to fulfill the main objective exposed, there is a set of intermediate milestones to be met. This partial objectives are thus presented in the following list:

- Perform a literature review on the topic;
- Analyze and follow up the TURN project development;
- Perform a preliminary analysis on company's current situation;
- Establish an appropriate set of performance indicators and metrics for comparison;
- Formulate the mathematical optimization model and implement the model in a suitable tool;
- Validate model results for Sonae Arauco's production reality;
- Discuss implications of the model in the company production planning processes and future directions.

The goals set forth in the introduction play a pivotal role in establishing the framework for this study. The development of a comprehensive methodology to achieve these goals holds great potential in not only bolstering the company's competitiveness but also driving its overall success in the face of a rapidly evolving business landscape. By successfully addressing the objectives outlined, the study aims to bring about tangible improvements in various aspects of the company's operations. These improvements may include optimizing production strategies, streamlining processes, enhancing resource utilization, reducing costs, and ultimately improving the bottom line. Additionally, the study's outcomes may serve as valuable insights and best practices that can be shared within the industry, contributing to the broader knowledge base and advancing the field of business management.

1.4 Methodology

In order to achieve the goals described above, the different tasks to be carried out throughout the project were identified and can be seen in sequential order in figure 1.3.

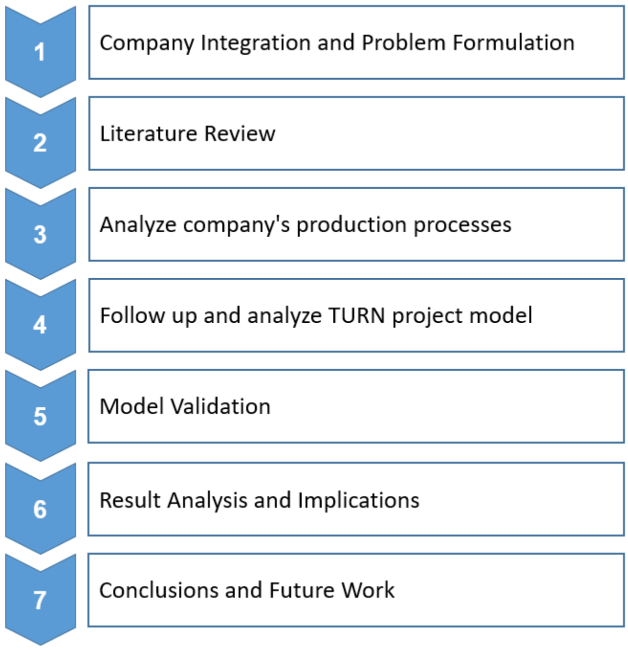


Figure 1.3: Plan of the project phases

The first phase of the project consisted in the integration into the company, obtaining general knowledge about its operation and the follow-up of the daily tasks performed, especially the meetings of the IT- Supply Chain Planning team and the TURN project. Throughout this phase, the problem that serves as the basis for the thesis was also formulated and the work plan was drawn up.

A Literature Review on pertinent topics within the project's scope was done in a second phase to address the proposed challenge.

In a third phase, relevant data on production decisions, including factors such as customer demand, delivery times, and inventory costs, were collected, filtered, and processed in order to establish comparison metrics between the models. During phase 4 and 5, the follow up and analysis of the TURN project occurs, understanding how the model was created and the knowledge behind it, followed by the validation of the data and result consistency.

The last two phases served to analyze and interpret the results, draw conclusions about the relative effectiveness of the model and understand the impact of the new model on production, ending up with the conclusion and the identification of potential areas for research or improvement.

1.5 Document Structure

This thesis is divided into six chapters, according to the sequence of the work developed throughout the project.

This first chapter, introduces the context and motivation of the dissertation, alongside the a company presentation and the objectives.

Following this, chapter 2 describes an essential theoretical background of the relevant topics for the successful execution of the project.

In chapter 3, an analysis of the company's current situation takes place, presenting all the current processes.

In chapter 4, the methodology used is explained in detail, explaining the work performed.

In chapter 5, the results are illustrated, and an analysis and interpretation of the results is presented.

Finally, chapter 6 presents the conclusions of the conducted work and difficulties encountered, pointing out topics for future work.

Chapter 2

Literature Review

This chapter exposes the theoretical concepts that support the development of the dissertation.

Various bibliographic sources were used in the literature review, with emphasis on scientific articles, books, dissertations and web pages. The search engines used were ScienceDirect, Scopus, IEEE Xplore, ResearchGate, Emerald Insight and Google Scholar.

The strategy followed for content selection consisted of reading the abstracts of scientific articles, books, and dissertations so as to understand whether or not they were relevant. Whenever possible, the most recent content was used in terms of publication date and scientific relevance.

Section 2.1 aims to provide a general review on production planning, introducing MTO and MTS production strategies and combined production models in section 2.1.1, the lot sizing problems in section 2.1.2 and finally, in section 2.1.3, the strategy of block planning. The importance of decision support systems in production planning, specially model-driven DSS, is underlined in section 2.2, followed by an overview on analytic hierarchy process for decision making in section 2.2.1. Optimization techniques in section 2.3, presents mathematical tools able to solve complex real-life problems widely used in production planning, giving greater prominence to linear programming in section 2.3.1. The last topic, in section 2.3.2, focuses on software solutions available as optimization solvers and some techniques to compare the performance of these algorithms. This chapter finishes with section 2.4, with an overview of the importance and the main steps to choose the correct performance indicators.

2.1 Production Planning

The industrial production has undergone significant changes in recent decades. The changes relate to the scale and complexity of production and technologies used. Manufacturers to be competitive must produce high-quality products at low cost while being flexible in meeting rapidly changing customer needs [5]. Production planning turns out to be crucial in tackling this issue, entailing the research and development of an effective plan to minimize waste and maximize rentability.

Production planning is almost exclusively seen in manufacturing environments; however, many of the techniques employed in production planning can be and are used by many service oriented businesses. Understanding the behavior of a process, finding bottlenecks, reducing work-in-process inventories, developing optimal scheduling, forming optimal forecasting methods and polishing inventory control methods are the main concerns of production planning [6].

However, production planning often proves itself to be a very complex task, mainly for the following reasons:

- A manufacturing resource is utilized to manufacture various product types rather than being totally dedicated to the creation of a single product.
- Customer service standards and reducing production and inventory costs are two competing goals that must be balanced in production strategies.
- Production plans are not static and must be revised before the end of the planning horizon if the actual situation deviates significantly from the plan.

Production planning is thus a difficult and recurring problem for industrial companies and there is a strong need for decision support systems [7]. During the decision-making process of production planning, there is an imbalance between two sorts of costs: setup and inventory storage costs. Setup costs are the costs incurred when changing the resource configuration from one type of products to another one. Inventory holding costs account for the opportunity costs of capital as well as for the direct costs of storing goods [7].

2.1.1 Make-to-Stock and Make-to-Order Production Strategies

Product classification into MTS or MTO has a substantial impact on production planning. Each product type necessitates a unique strategy to production scheduling, inventory management, and consumer demand forecasting. The major difference between MTO and MTS is that MTS makes standard products using a standardized process, which do not exist for MTO at the time of capacity planning. Unlike in MTS, which hold finished goods in inventory as a buffer against variations in customer demand, MTO operations hold capacity in reserve to meet customer demand [6].

Pure MTS and pure MTO products are defined by characteristics that indicate the best manufacturing plan for each product. Some of these characteristics include demand volatility, level of customization and the ratio of manufacturing lead time to delivery lead time. For example, when dealing with higher levels demand volatility, an MTO strategy may be the best option. This is due to the fact that MTO production is tailored to market demand and real customer requirements, rather than relying on possibly untrustworthy historical data. MTS strategy does not require production to begin until orders are received, resulting on a higher ratio of manufacturing lead time to delivery lead time. MTO production, on the other hand, begins production only after an order is received, resulting in longer production wait times. Although, MTO production is better suited to customized orders with a wide range of needs and preferences. To successfully handle a business's complex and diverse demands, requirements, and product types, combined systems that integrate multiple production strategies may be necessary. The solution needs to consider the trade-offs between product-process characteristics and the demands from the market [8].

In supply chains using a combined system, holding inventory at some of the stages of the chain and using an MTO strategy at other facilities might decrease the costs dramatically without increasing the lead times. Because of this, companies are starting to employ a hybrid approach, a ”push-pull” strategy (i.e. a combined MTO-MTS system), holding inventory at some of the facilities in their supply chain and producing to order in other [9].

The point at which the switch from MTS to MTO production steps occurs is called the customer order decoupling point (CODP). The CODP defines the stage in the manufacturing process where a product is linked to a customer order. When both MTS and MTO production steps can be used insequence, a decision must be made where to place the CODP [10]. In essence, as shown in the next figure 2.1 the decoupling point is the point that indicates how deeply the customer order penetrates into the goods flow [11].

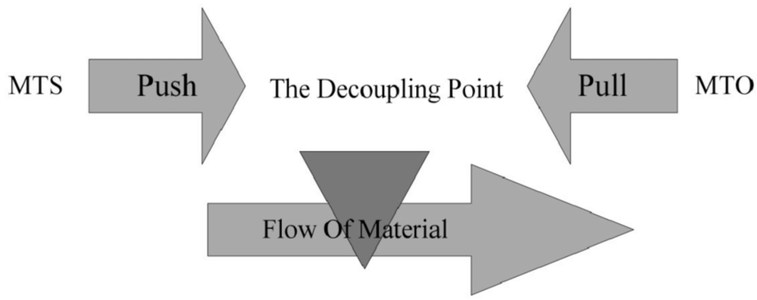


Figure 2.1: The Decoupling Point between MTS and MTO [12]

The decoupling point is important for a number of reasons, as it separates the order-driven activities from the forecast-driven activities, it is the main stock point from which delivery to customers are made and the amount of stock should be sufficient to satisfy demand in a certain period and the upstream activities can be optimized in some ways, as they are based on forecasts and are more or less independent from irregular demands in the market [11].

2.1.1.1 ABC Analysis

Nowadays many projects show the same 80/20 distribution of yield vs. costs. This is often attributed to Pareto’s observation and is called Pareto’s 80/20-law or the law of the trivial many and the critical few. ABC-analysis means to classify subprojects into three classes A, B, and C. Subprojects are ordered in decreasing order of yield. Typical proposals for the limits of yield in class A range from 5% to 33%. Proposals for class B range from 15% to 33%, for class C from 25% to 50% [13].

The first studies on hybrid MTS-MTO systems, focus on the definition of production strategy for each product. Considering the demand and lead times, the first step is to perform a pareto (ABC) analysis to the product portfolio. The items classified as A, high demand items, are classified as pure MTS and in contrast the items classified as C, corresponding to low demand, are classified as MTO. The remaining part, B items, are subjected to a decision-making process. The objective is to identify the boundary, the CODP, between the two policies in ascending demand order, taking into account a variety of factors, such as holding costs, setup costs and stockout costs [14].

2.1.1.2 Hierarchical Multiple Criteria Approach

More recently, another study proposes a hierarchical decision-making model as a reasonable approach to solve the issues involved. This framework combines a three-level decision model with contributions from MTO–MTS literature that can be observed in figure 2.2.

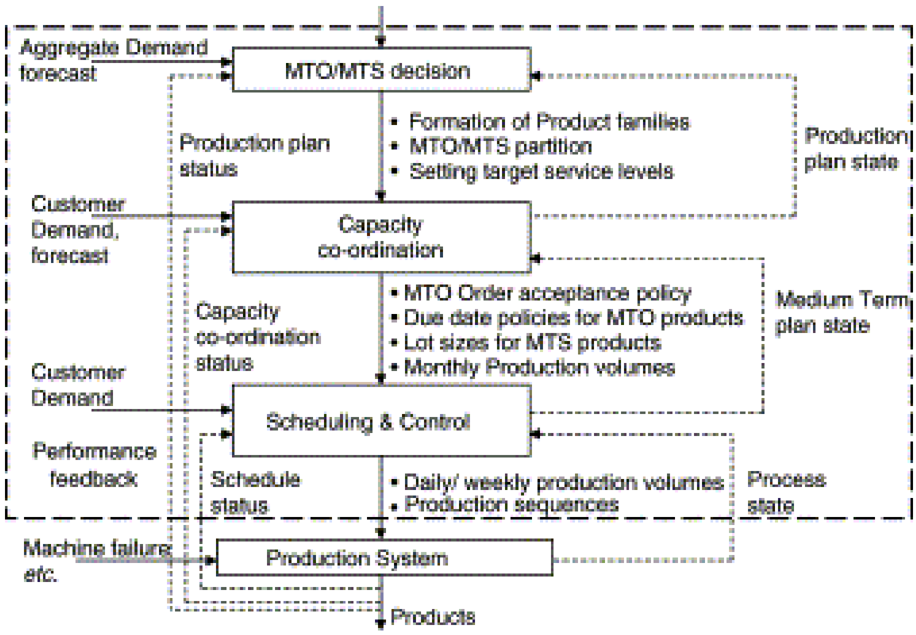


Figure 2.2: Hierarchical approach to MTO–MTS problem [8]

It is possible to conclude that the framework is a valuable contribution to both the description of the MTO– MTS production situation and possibly to the managerial decision-making in organizations [8]. At the first level, there are decisions that relate to determining which products to manufacture to order and which products to manufacture to stock. The information needed for locating the decoupling point will be used to decide on MTO/MTS partitioning [11][8]. At the second level, the decision for allocation of production orders for both MTO and MTS products to planning periods is made based on factors such as orders on hand and forecast, available capacity and stocks, realized efficiency in previous periods, and feedback about plan realization, when demand and supply are balanced. Finally, in the last level, the daily operations decisions on scheduling and control are taken.

2.1.2 Lot Sizing Models

The scheduling of production lots, as well as their sizing, is an area of increasing research attention within the wider field of production planning and scheduling [15]. Lot-sizing problems aim to find the optimal timing and level of production of each product to minimize the sum of these two costs [16]. There is a debate about whether or not lot sizing as a trade-off between setups and stocks is still an issue. Nonetheless, a high number of production processes are characterised by strong fluctuations of seasonal demand (with not enough capacity in some periods to process all the orders), by significant setup times and costs and by the economical advantage of holding stock rather than maintaining a capacity surplus [15]. The advances observed in mathematical programming in recent years combined with the increase in computational power (hardware) and in the quality of general purpose mixed-integer programming commercial solvers (software) allowed sequence independent Lot-Sizing problems to be solved efficiently using exact methods for reasonable size instances [17].

Upon initial examination, is possible to divide this issue in continuous lot sizing problems and dynamic lot sizing problems. Dynamic lot sizing problems assume a discrete time scale, deterministic dynamic demand and a finite time horizon [18]. In contrast, continuous lot sizing problems assume a continuous and infinite time scale, not divided into discrete periods/buckets [19]. Small bucket lot sizing models consider very small time periods, on which only one product can be produced per period. Given the problem company's complex production setting of sequence-dependency, numerous non-identical machines, a longer time horizon, and a large number of products, these models are inapplicable and will not be addressed further.

The famous Economic Order Quantity model as been defined as the ordering quantity which minimizes the balance of cost between inventory holding cost and reorder cost. The basic model assumes a continuous time scale, constant demand rate and infinite time horizon [20].

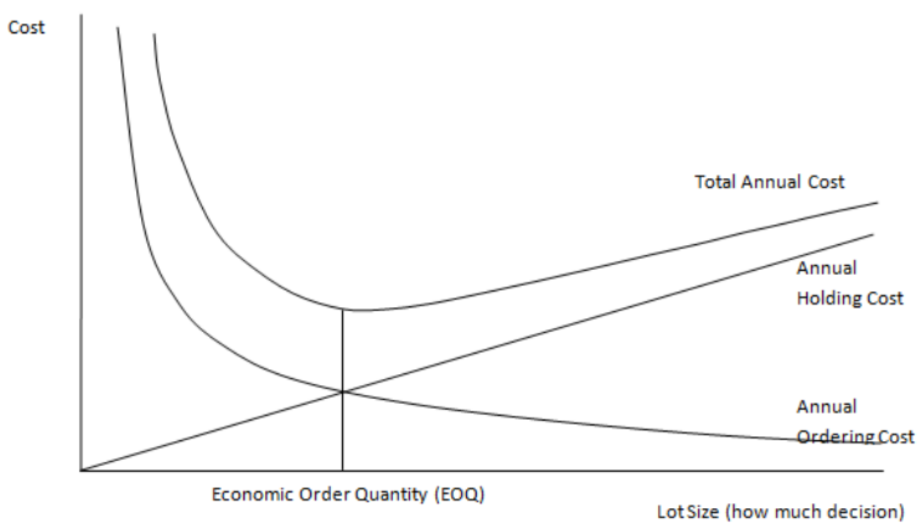


Figure 2.3: The Economic Order Quantity optimal value [20]

The extension to multiple items and constant production rates is known as the Economic Lot Scheduling Problem [18]. The goal is to determine the optimal production plan that minimizes total production and inventory costs while meeting customer demand and not exceeding machine capacity. Although, these problems frequently include non-identical parallel machines, sequence-dependent setups or stochastic demand, making extremely challenging to find an optimal solution.

The Capacitated Lot Sizing Problem is a widely recognized topic associated with big bucket modeling. Initially, the issue was defined as determining the best production plan for a single machine with multiple items while taking capacity limitations and sequence-independent setup costs into account. Setup times, on the other hand, were added afterward to improve the model's accuracy. Of course, companies do not have an unlimited capacity and usually they make more than one product. Any realistic model has to take this into account [18]. The problem has evolved over time to include more complex and realistic production settings. Multiple machines, multiple products, multiple stages of output, and various constraints such as backlog, safety stocks, and lead times are among these extensions.

2.1.3 Block Planning

Block planning is a strategy for production planning that includes categorizing products into families based on their setup dependencies. A natural sequence of producing products often occurs in process industries, which can be integrated into a product family and scheduled as a single block. This eliminates the need for major setups between blocks and instead needs only minor setups between individual products within a block, providing a higher degree of flexibility regarding the time-phasing and sequencing of production orders compared to classical dynamic lot sizing models [21].

Block planning can be divided into two categories: rigid and flexible. The length of an entire block is variable in the flexible method, whereas it corresponds to the length of a period, such as a week, in the rigid approach. Mixed integer linear programming formulations, whose definition will be discussed in more depth in the following sections, are frequently used to model these problems [22]. As a result, it is a promising method for modeling complicated real-world situations while still finding optimal solutions in short computational times.

2.2 Decision Support Systems

Decision support systems (DSS) are computer technology solutions that can be used to support complex decision making and problem solving [23]. Production planning, as mentioned previously, is a complicated and recurring challenge for industrial organizations since it entails managing many constraints and restrictions relating to materials and resources. To tackle this problem, there is an immense need for decision support systems that can give effective solutions and optimize production processes, assuring resource efficiency and meeting client requests.

The DSS role is to facilitate an efficient analysis of various decision alternatives as well as to analyze manufacturing performance in production system [24]. Typically, this systems are designed so a user can manipulate model parameters to examine the sensitivity of outputs or to conduct a more ad hoc "what if?" analysis [25].

Model-driven DSS include computerized systems that use accounting and financial models, representational models, and/or optimization models to assist in decision-making. Model-driven DSS use data and parameters provided by decision-makers to help in analyzing a situation, but such systems are not data intensive [25]. The usual cycle of this decision making process in a DSS is expressed visually in figure 2.4.

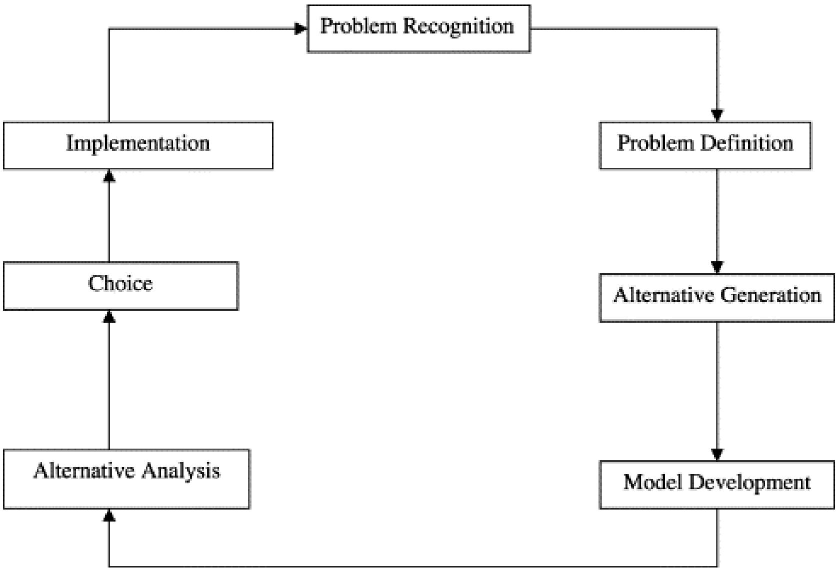


Figure 2.4: The DSS decision-making process [23]

Typically, the phases overlap and blend together, with frequent looping back to earlier stages as more is learned about the problem, as solutions fail, and so forth [23].

Models in a model-driven DSS should provide a simplified representation of a situation that is understandable to a decision maker. In the manufacturing sector, this systems can help planners to make more informed decisions, improve planning accuracy, and ultimately improve overall operational performance. A study conducted in the Kellogg Company, proved that using an optimization and financial model-based planning system can reduce production, inventory, and distribution costs, in this case, multi-million dollar savings [26].

An emerging supply chain application for model- driven DSS is termed demand optimization or demand chain management. The idea is to employ optimization models that incorporate uncertainty, product relationships, and stock levels to decide prices for thousands of products that a retailer may have. Some software vendors have developed model-driven DSS that may include stochastic programming, integer programming, and modeling language interfaces to enable rapid model modification, and large-scale data integration capabilities [25].

Two main difficulties arise in developing the decision making system: the uncertainty and inaccuracy of the data (quantities and composition of raw material, time for delivery, etc.) [27]. As companies become more capable of utilizing huge databases, high bandwidth networking to convey data in real time, and faster processors to provide solutions for very large models, the use of artificial intelligence can significantly improve the decision-making process, making it less subjective and less time-consuming. Model management systems and knowledge-based decision support systems have used techniques from artificial intelligence and expert systems to provide smarter support for the decision-maker [23].

2.2.1 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a multiple criteria decision-making tool. AHP helps to incorporate a group consensus. Generally this consists of a questionnaire for comparison of each element and geometric mean to arrive at a final solution [28]. It is used to derive ratio scales from both discrete and continuous paired comparisons [29].

In supply chain system, AHP is used to evaluate and compare different suppliers, production facilities, and transportation options, and to determine the most appropriate choices based on the organization's priorities. It can also be used to assess the potential risks and uncertainties associated with different production scenarios, and to develop contingency plans to mitigate those risks.

2.3 Optimization techniques

Optimization techniques are effective mathematical tools that use the power of math to find the best possible solution to a complex, real-life problem, determining the optimum solution to a problem given a set of constraints. These techniques entail developing a mathematical model that reflects the problem and then employing algorithms to calculate the optimal set of decisions [30].

Naturally, increasing realism turns the mathematical models larger and more complex. This added complexity, and the need to increase the size of instances solvable to near-optimality, requires the integration of existing methods with novel and efficient optimisation algorithms, along with the development of tighter models and stronger valid inequalities based on the model polyhedral structures. Moreover, there is a continuing need to trade off the complexity of reality in planning models with mathematical and computational tractability [15].

85% of the world's leading companies use mathematical optimization to make optimal business decisions. For example, Air France uses it to build the most efficient schedule for its entire fleet, in order to save on fuel and operational costs, while reducing delay propagation [30].

This mathematical optimization techniques can be divided into several categories such as linear or nonlinear, depending on the objective function. Within the linear side, there is also a split in continuous or discrete. Continuous optimization problems involve variables that can take on any real value, whereas discrete optimization problems can only assume integer values for its variables. Another classification concerns on the the values of the input parameters. Some of the parameters may not be known values, due to uncertainty, increasing the level of difficulty of the model. This problems are called stochastic problems. On the other side in deterministic problems, all the parameters values are given.

An optimization process begins by carefully observing and formulating the problem, including gathering all relevant data. The next step is to construct a scientific (typically mathematical) model that represents the problem under study. It is then hypothesized that this model is a sufficiently precise representation of the essential features of the situation that the conclusions (solutions) obtained from the model are also valid for the real problem. Next, suitable experiments are conducted to test this hypothesis, "modify it as needed, and eventually verify some form of the hypothesis. (This step is frequently referred to as model validation.) Finally, implement the model [31].

2.3.1 Linear Programming

Linear programming studies the optimization of a linear function over a feasible set defined by linear inequalities, hence a polyhedron. The problem is in some sense trivial, since it is only necessary to examine a finite number of vertices (and possibly edges) [32]. When all variables are discrete (belonging to the set of integers) integers) we are faced with an Integer Linear Programming (ILP) problem. If some decision variables are not discrete, the problem is known as a mixed-integer programming problem (MILP). These problems are typically NP-hard, meaning that there are no efficient algorithms that solve it in polynomial time.

MILP, because of its rigorousness, flexibility and extensive modeling capability, has become one of the most widely explored methods for process scheduling problems. Applications of MILP based scheduling methods range from the simplest single-stage single-unit multiproduct processes to the most general multipurpose processes [33].

The simplex algorithm, firstly developed by George Dantzig in 1947, is the most commonly used method for solving LP problems. The inequalities are first transformed into equations by adding slack variables, and then the optimum, if any, can be found by obtaining new bases and writing the variables as a function of those in the new base [32].

A linear program can take many different forms. First, we have a minimization or a maximization problem depending on whether the objective function is to be minimized or maximized. The constraints can either be inequalities or equalities. Some variables might be unrestricted in sign, while others might be restricted to be non-negative. A general linear program in the decision variables $x1,...,xn$ is therefore of the following form [34]:

$$\text{Maximize or Minimize} \quad z = c_0 + c_1 x + \cdots + c_n x_n$$

subject to:

$$a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n \begin{matrix} \leq \\ \geq \\ = \end{matrix} \qquad i = 1, \ldots, m$$

$$x_j \begin{cases} \geq \\ \gtrless \end{cases} \qquad j = 1, \ldots, n.$$

2.3.2 Optimization Solvers

Optimization solvers help improve decision-making around planning, allocating and scheduling scarce resources. They embed powerful algorithms that can solve mathematical programming models, constraint programming and constraint-based scheduling models [35]. Some examples of the most popular and well-known commercial solvers are:

- **IBM ILOG CPLEX Optimization Studio:** can find answers for linear programming, mixed integer programming, quadratic programming and quadratically constrained programming problems [35].

- **Gurobi Optimizer:** is a powerful optimizer which is designed from scratch to run in multi core with capability of running in parallel mode [36]

Although there are other free and commercial software solutions in the market, this two are known to be the ones that provide the best competitive results on real life problems [36].

The design and development of these solvers depends upon the nature of particular problem to be handled. Only one optimization solver is unable to solve all types of real-life problems. Hence, there is a need to study the performance of optimization solvers [36]. In general, performance measures fall into three categories: efficiency, reliability, and quality of algorithmic output [37]. The following table illustrates the the criteria used to evaluate each category.

Table 2.1: Comparative metrics to measure performance of optimization algorithms

Performance category	Example criteria
Efficiency	1. Number of fundamental evaluations 2. Running time 3. Memory usage
Reliability	1. Success rate 2. Number of constraint violations 3. Percentage of global solutions found
Quality of solution	1. Fixed-cost solution result 2. Fixed-target solve time 3. Computational accuracy

The efficiency refers to the computational effort required to run the model, where the number of fundamental evaluations, concerning the objective function value and the running time are the main measures. For the comparison between solvers that will be done in this paper, the efficiency is the most important aspect. Reliability relies on the ability of the model to be successful, depending if the model is deterministic or non-deterministic. Last but not least, the quality of the solution may also be taken into account, understanding if the solution given is accurate. Although, in real-world applications, is not possible to know the real solution, becoming it difficult to evaluate. In this situation is possible to use the as-is situation to compare with the new solution.

2.4 Key Performance Indicators Selection

A performance measurement system is important. It consists of a set of procedures and indicators that precisely and constantly measure the performance of activities, process-es and the organization as a whole, and is a vital aspect in regard to the management of companies KPI systems have been developed to support business management at the highest levels of business. In the last decade, indicators on the process and production level of management are being implemented. Optimal operation of the management systems can be achieved by automatically collecting process data and mapping these data into KPIs [38].

The improvement in performance comes from efficient definition and selection of appropriate measurement. Before the KPIs are selected, it is necessary to identify and to clarify the criteria which are going to influence the choice of these indicators. The choice makes a difference. If the wrong KPI is measured, or if it is measured in the wrong way, the information may be misleading and the quality of decisions could be affected [39].

The selection of a set of key performance indicators is directly associated with the organizational strategic goal and vision. Identify the criteria that are relevant to evaluate and measure progress towards the objectives as well as creating a hierarchical structure that represents the relationships between objectives and criteria are the following definitional steps, respectively [40]. The significance of the objectives and criteria is then compared against one another at each level using pairwise comparisons, assigning weights to each objective and criteria. These weights are essential for combining the findings and determining the most important performance evaluation criteria.

The modern digital transition and the utilization of Industry 4.0 technologies offer companies significant opportunities to establish and operationalize sustainability initiatives by effectively correlating production processes with relevant metrics. The digital transition enables companies to collect real-time data from various sources within the production environment, facilitating the measurement and analysis of sustainability-related metrics. KPIs can be established to track resource consumption, energy efficiency, waste generation, and carbon emissions. This data-driven approach allows organizations to identify inefficiencies, set targets for improvement, and make informed decisions to optimize sustainability performance.

Chapter 3

Current Situation Analysis

This chapter describes how the company is currently working. It begins by describing all the current processes of the company in section 3.1, from the manufacturing processes, through the current modes of planning. The chapter ends with a preliminary analysis of these practices in section 3.2.

3.1 Characterization of the Company's Production Process

As a multinational company with businesses all over the world, Sonae Arauco has production and distribution units in several countries and is divided internally into three regions: SWE, NEE and SAF. Adding all the regions mentioned, Sonae Arauco has ten industrial plants producing wood-based panels.

The scope of this project will focus only on the NEE region, more specifically on the germany production units of Beeskow, Nettgau and Kaisersesh. Each of these plants, has different characteristics, with a specific process map. Beeskow and Nettgau are the main units in this region and are responsible for the production of the core products of Sonae Arauco's portfolio in this region,, with a production capacity of approximately 860 000 cubic meters and 1 000 000 cubic meters per year, respectively, while Kaisersesch is a smaller unit that produces only impregnated paper, which serves as an overlay for the rawboards. In the following table it is possible to verify what products are produced in each of the factories.

Table 3.1: Product distribution between the plants of Nettgau and Beeskow

Plant	PB	MFC	MFMDF	MDF	OSB
Beeskow	x	x	x	x	
Nettgau	x	x	x		x

Based on this information, we realize that the main difference between these two plants is in the production of MDF and OSB.

Each of the company's SKUs corresponds to a unique material with a particular type, shape, length, width and thickness. This SKU's are represented by a code that follows a specific configuration for identification and tracking purposes. Each code contains information about the group, family, and type of material of the product. Besides the group, family, type, the product "recipe" is completed by the set of 15 characteristics that defines it. The first letter of an SKU represents the product group, such as A for raw boards, while the next two characters represent the product family, for example B0 corresponds to the family SONAEPAN, and the following two characters denote the material type, like S1 for SUPERLAC. The remaining five numbers of the SKU code differentiate a specific product from others within the same group, family, and material type. The set of numbers is unique to that specific product and helps to track sales data, and restock products as needed. As this stands, one possible example of a SKU is AB0S104027.

3.1.1 Production Environment and Process Mapping

The process of creating a wood-based panel depends on what finish good we want to achieve. In some cases, raw boards may be considered as finish good product and are directly sold in this format. Other times, these panels go through other extra processes such as cut to size, where panels are cut to the desired dimensions. The edges may also be trimmed or machined to create a smooth finished edge, and the surface may be sanded. Another fairly common approach is to apply an extra layer. In this case the panels move to another line where the impregnated paper is laminated to the board and then coated with a layer of melamine. This lines are internally called as melamine lines.

In general, the process of creating a raw board starts with the preparation of raw materials, which depends on what product is expected to be produced. For MDF products, the wood fibers are prepared, in the case of PB and OSB the particles are prepared. This involves shredding and refining logs or waste wood materials that are then dried to reduce their moisture content and are screened to remove any oversized or undersized particles.

Once the wood fibers or particles are prepared, they are mixed with a binder material, typically a synthetic resin. After being spread out thinly on a forming machine, the resin-coated wood fibers or particles are compacted into a surface of the required thickness and density. The conveyor is transported to a hot press, where heat and pressure is applied, bonding the fibers or particles together into a solid panel. The temperature and pressure are carefully controlled to ensure that the panel has the desired properties and characteristics.

As already stated, the process map of each plant is quite different among them. Each plant has an associated code in the system and a specific set of production lines, thus creating a process map specific to each plant, so there are SKUs that can be produced in any plant and others that can only be produced in a specific plant due to its constraints.

Another very important aspect of the production process is that the same product can be made in different production lines. At the same time, the same production line, can make several different products. This fact, combined with the existence of intermediate products that can originate more than one final product, make this production environment a multi-resource and multi-level problem.

3.1.1.1 Beeskow Plant

Beeskow refers to the P542 plant and the core production in this plant is PB and MDF, each one containing specific production lines associated. This plant also contains a cut to size line and melamine line. In terms of storage, there are two intermediate storage points for raw boards prior to the sanding line, one for PB and one for MDF, one storage for raw boards going to melamine lines and for finished goods, such as MFC and MFMDF. There is also one last storage for cut to size products and finished goods also. The complete production process in Beeskow is represented in the following figure 3.1.

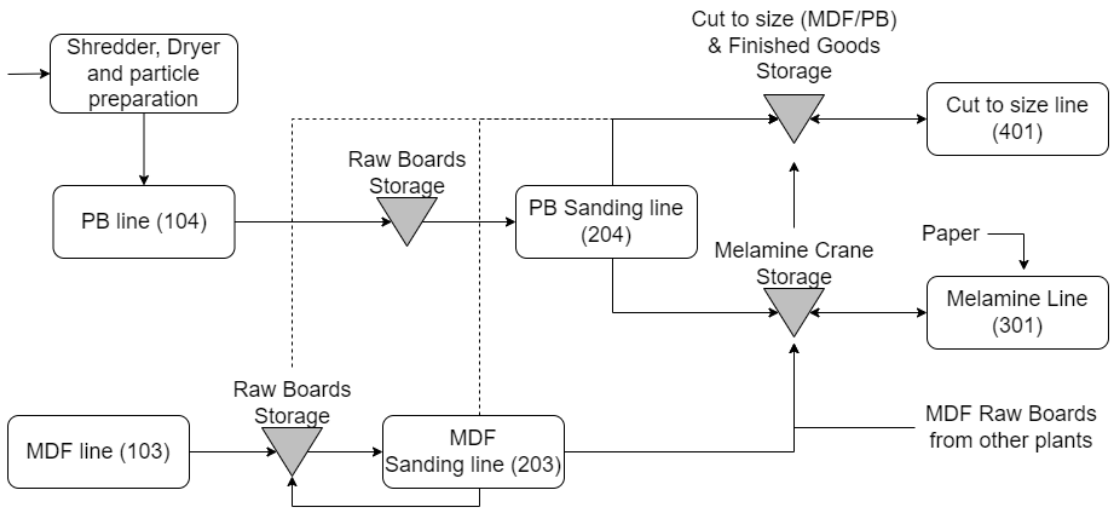


Figure 3.1: Process Map of Beeskow Plant

The processes in this plant are easy to understand, noting only that moving boards from melamine crane storage to cut to size and finished goods storage rarely happens, only when a board that has left the melamine line needs to go to the cut to size line.

3.1.1.2 Nettgau Plant

P661 corresponds to the plant of Nettgau. In contrast to Beeskow, this plant produces OSB panels but does not produce MDF. However, this plant receives MDF boards from other plants, from the Oliveira do Hospital facility, for example. These boards are semi-finished products, which are stored in this plant, to be later finished. P661 is made up of a PB line, OSB line and a sanding line that serves both types of materials. There are also two melamine lines and two Cut to Size lines, a Tongue & groove area, where OSB boards are attached and a packing line. Regarding storage, there is a paper storage serving the melamine lines, a crane storage and a final storage that allocates all finished goods from PB, OSB and MFC and also semi-finished boards used in

Sanding and Cut to size. In figure 3.2, it is possible to observe all the processes that take place in this plant.

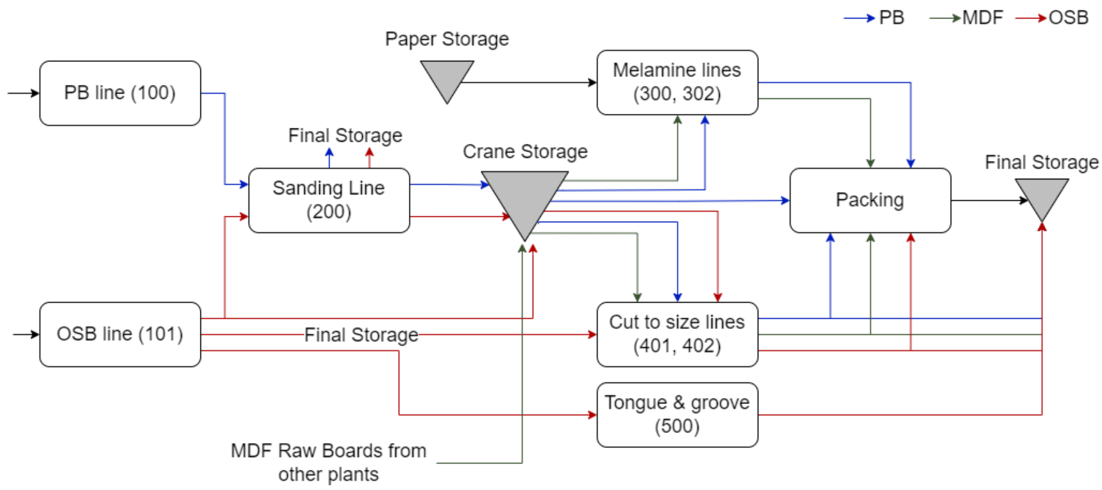


Figure 3.2: Process Map of Nettgau Plant

Noteworthy that, due to the complexity in this plant, a legend was included at the top of the figure with the colors that correspond to each type of board formed, understanding in this way which alternatives they can pursue. In addition, despite the fact that the end storage appears more than once mentioned in the scheme, they all represent the same space, the mentions were only used to simplify the scheme. It should also be mentioned that products leaving the cut to size line can either go directly to final storage or go through the packing process first, depending on their shape.

3.1.1.3 ImPaper Plant

In Kaisersesch, the ImPaper Plant, P551, presented in figure 3.3 consists in a set of 3 production lines of impregnated paper production, where the raw-paper is processed to serve as finishing layer. This plant contains a Raw-paper storage and a finished goods storage.

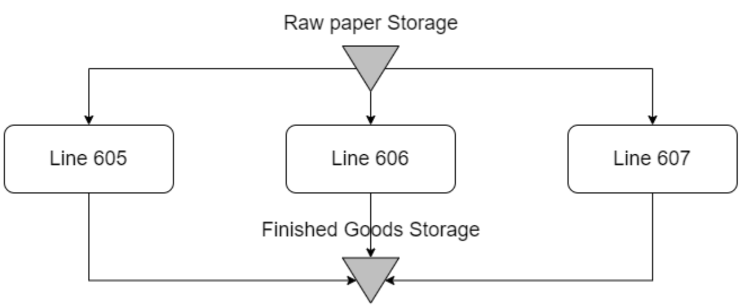


Figure 3.3: Process Map of ImPaper Plant

3.1.2 Current Planning Approach

The present business processes were mapped as part of the diagnosis project making it possible to understand all the steps and the thinking behind each decision. The corporation currently relies largely on a commercial definition to set the production strategy for each product.

The commercial department, based on its experience and on a sales analysis, defines the main products, establishing a lead time that cannot be compromised. These products are then considered as MTS and an MPQ is defined. After this classification, for the remaining products a risk analysis is performed, taking into account the number of historical customers for each product, as well as the percentage that each customer has in the sales of each product. Other scenarios are also evaluated, such as assessing which customers only buy materials at a pallet level or what percentage of sales is lost when a material changes from MTS to MTO and vice-versa. After this analysis these materials are also classified as MTS or MTO and the MPQ for MTS materials is also defined, as well as the MOQ for MTO materials.

The S&OP cycle at Sonae Arauco, displayed in figure 3.4, as well as the production strategy definition, also starts from the commercial department side, that collects, analyzes and validates the historical sales data, generating a three month statistical forecast with a one month interval. This means that with M being the current month, planning is done for M+2, M+3 and M+4. The current month and the month immediately following (M+1) are analyzed and planned in a process parallel to S&OP, in a more operational context and with a different type of granularity.

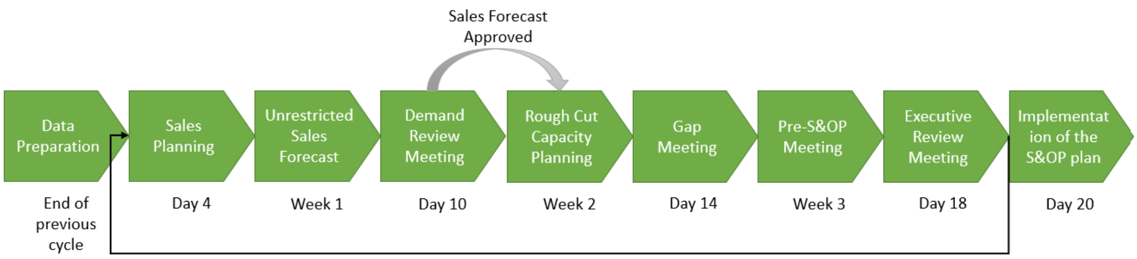


Figure 3.4: S&OP Process at Sonae Arauco

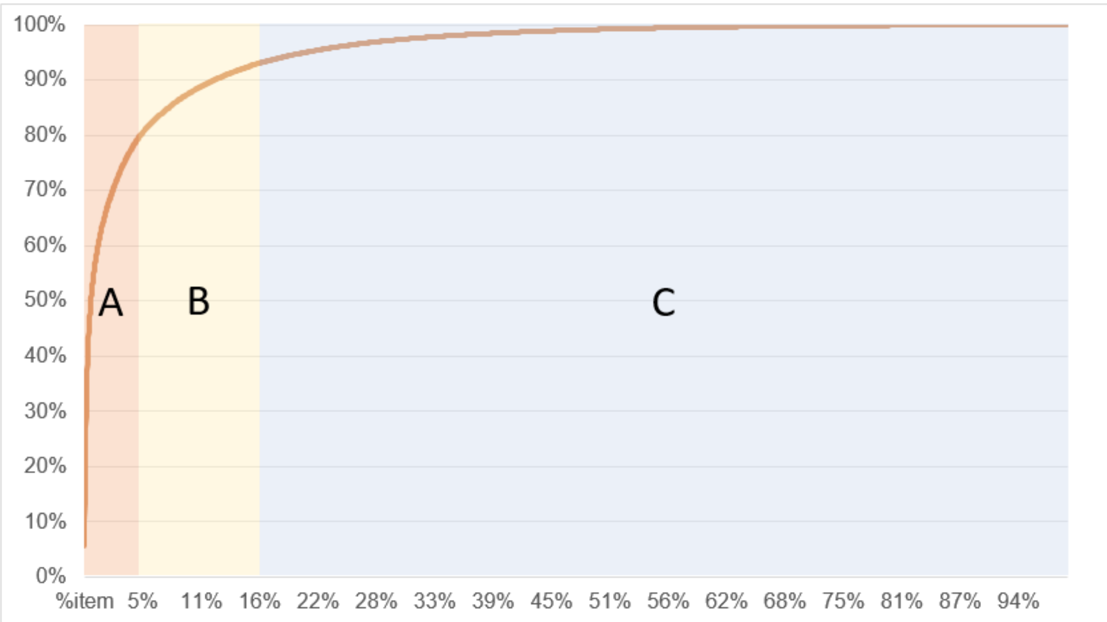
After collecting comments and forecasts from sales people and commercial directors, an unrestricted sales forecast is generated, which is reviewed and analyzed in the Demand Review meeting. After the first phase and having already the sales quantity forecast for the following months, it is necessary to adjust these same numbers to the reality of the company's supply chain.

In this context, the supply chain team prepares a rough cut capacity plan, which is a supply plan guided by the sales forecast numbers resulting from the previous phase of the process. This plan takes into account the desired stock levels in each of the industrial and distribution units, and adjusts the forecasted productivity and production capacity values for the defined time horizon. As a result, a plan is produced whose objective is to allocate the previously forecasted demand volumes to productive or logistical resources. All this analysis is done at the aggregate level of product, customer, and resource. This is followed by two business review meetings to discuss details at the business level, identify and solve allocation problems by studying different scenarios and thereby adjusting the final plan to be presented in the last step of the process, the Executive review, where performance indicators and gaps are analyzed, and the best plan is approved for the planning horizon.

3.2 Preliminary Analysis

In this section a preliminary analysis to the current planning approach took place, in order to better understand the company current performance, identify demand patterns and service levels, relating them with the MTO/MTS strategy.

Starting by analyzing the demand patterns, an ABC analysis was performed with historical demand data from the last year. This analysis had under study a set of 4231 SKUs whose demand data from the last year as well as their current classification were available. With this analysis it was possible to notice that the range of products under study suffers from a quite strong pareto effect, with very different demand patterns. The following figure 3.5 that results from the analysis, relates the volume of products with the volume of demand, confirming the accentuated difference in demand patterns as it can be seen that it follows a Pareto pattern with 80% of the demand corresponding to only 5% of the products.



	%demand	%products
A	80%	5%
B	15%	14%
C	5%	81%

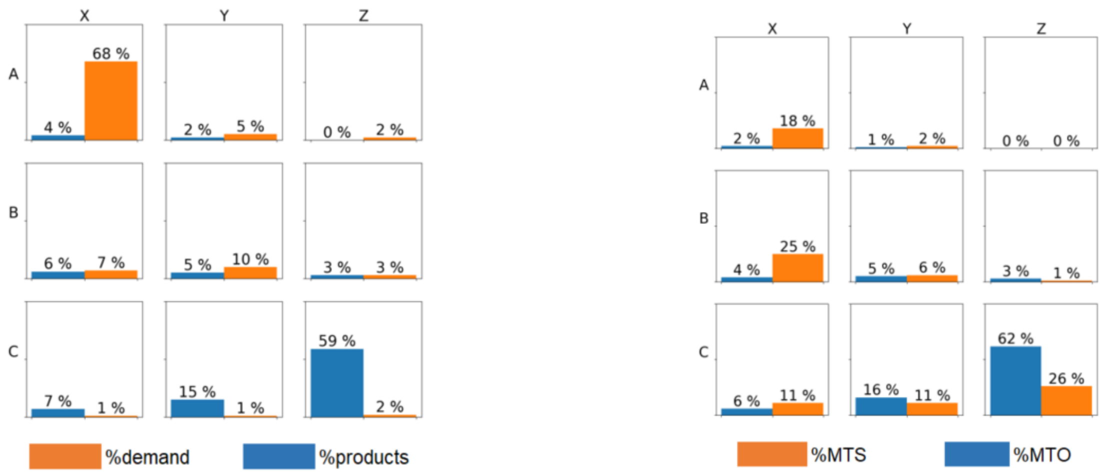
Figure 3.5: Pareto ABC analysis

To better estimate service rates and safety stock targets, we need to add another dimension. The XYZ dimension introduces the level of uncertainty, classifying products according to the variability of their demand.

Products with a very steady demand every month are represented by the X axis, while products with a highly volatile demand are represented by the Z axis. Between these two extremes we have the intermediate products represented by Y. For this study the Coefficient of variation is used as a term of comparison. The relation made was products with CV < 0.7 correspond to X, 0.7 < CV < 1.5 correspond to Y and the remaining ones, with CV > 1.5 correspond to Z.

The following figure 3.6a shows a 9 categories matrix that combines the ABC and XYZ analyses, in terms of %demand and %products. It can be seen from this figure that 59% of the demand corresponding to 2% of the materials is in the zone with the lowest volatility, and the opposite is also true. 68% of the products responsible for only 4% of the demand are in the zone with higher uncertainty.

Figure 3.6b shows where the materials classified by the company as MTS/MTO are located in the previously formulated matrix. It is therefore possible to observe the percentage of MTS and MTO materials in each of the categories. Of greater relevance is the fact that MTS materials are mostly distributed in opposite categories, with 26% being in the low demand and high volatility category, when in theory this category should focus only on MTO materials. As we can also see from the figure, MTO materials are mostly concentrated in this category.



(a) %Demand vs. %Products (b) MTS vs. MTO

Figure 3.6: ABC-XYZ analysis

Following the ABC-XYZ classification, the focus of this analysis turns to service levels. In order for this metric to be improved, it makes sense to observe the company's current lead times, which is the difference between the requested date and the date the order is created, being one of the factors that most affects the service level. The higher the lead time, the more likely it is to deliver an order on time and in full. The shorter the order lead time of a given product, the more likely the company will have to keep it in stock to be able to respond on time to the demand.

The figure 3.7 presents the orders lead times per week for the current MTS/MTO classification. It can be observed that MTS materials present on average a lower lead time, with the average for these materials being 2.5 weeks, while for MTO materials this value is 4.2 weeks.

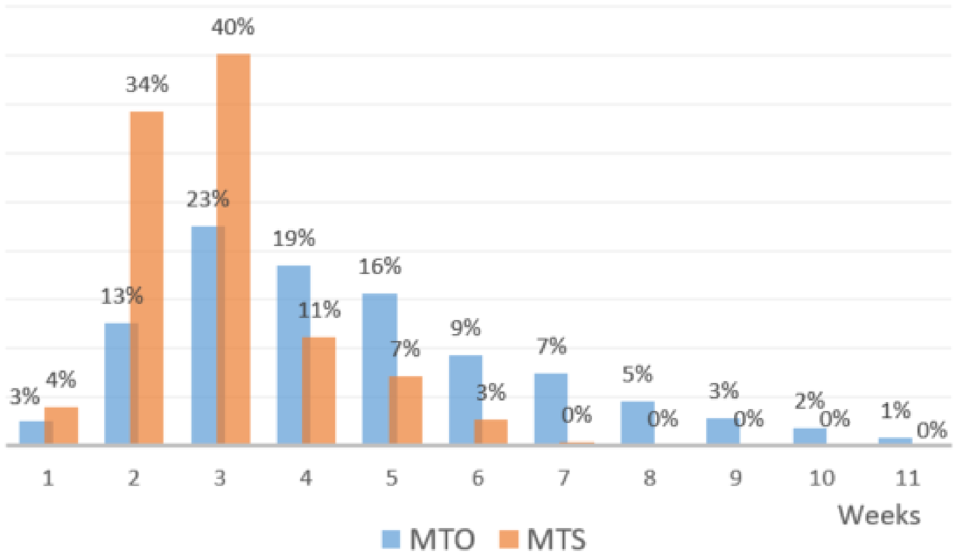


Figure 3.7: Orders lead time: MTS vs. MTO

It can also be seen that unlike MTO products that have a wider distribution, MTS products are mostly concentrated in a 2 to 3-week lead time, since these products are already in stock ready to be shipped, whereas MTO products depend on the availability of materials and production lines at the time of the purchase order and the complexity of the finished goods ordered.

Based on the preliminary analysis of the company's processes, it was possible to get a more concrete perspective of the company's processes, thus identifying which areas can be improved to increase efficiency and improve results and quantifying the company's current performance.

Chapter 4

Methodology

This chapter elaborates on the development of the methodology used during the research, describing the work performed.

Starting by section 4.1, this topic describes how the data used throughout the methodology was collected, and how it was treated for further study of the model. Next, section 4.2 presents the key performance indicators defined for evaluating the model's outputs and subsequent comparisons. Finally, in section 4.3, it is possible to observe the outline of how the model was integrated into the company's existing systems, showing its mathematical formulation, including the algorithms used, the parameters involved, the constraints and objectives considered in section 4.3.1 and the process behind the final adjustments of strategy definition in section 4.3.2.

4.1 Data Collection

For the data selection process of this study and in order to carry it out as accurately as possible, it became necessary to use several sources of information, namely, software information, interviews document analysis, and direct observation.

In a preliminary phase, to support the development of the TURN project, the IT-Supply Chain and IT-Data Analytics teams created a database exclusively for the project, in order to facilitate data processing. This database is located in a Azure Data Lake cloud, and the preparation and treatment of these is done via Databricks and SQL Server.

As stated initially, the data in this database for production, marketing, supply chain and other relevant stakeholders were collected from different sources. The following table that outlines the input data used in this study, along with their respective sources. Table 4.1 serves as a comprehensive reference for understanding the origin and characteristics of the data utilized in our analysis.

The first column lists the specific variables or data elements included in the analysis. These variables represent the key factors or parameters under investigation. The second column specifies the source of each data element. This includes the origin or provider of the data. Clearly documenting the source of each data element ensures transparency and allows for future verification or replication of the study.

Table 4.1: Input Data updated to Azure Data Lake and SQL Server

Data	Source
Catalogue	SAP
Product Portolio (MOQs/Lead time)	Sharepoint - Portfolio NEE
Master material	SAP
Material description	SAP
Design Group	SAP
Master Customer	SAP
Sales/Orders	analyticspwesa02-container01
MTS-MTO-FTO Current Classification	SAP
Demand Forecast	SAP
Downtime	SAP
Production Orders	SAP
OEE	analyticspwesa02-container01
Stock	Excel File
Safety Stock	analyticspwesa02-container01
Routing	SAP
Holding Costs	Excel File
Storage Costs	Excel File
Production Costs	SAP
Setup Costs	Excel File
Product Margin	analyticspwesa02-container01
Transportation Costs	SAP
Block Definition	Excel File
Block Lot Frequencies	Excel File

Based on this table, it can be identified that most of the data was obtained from the SAP ERP, however, in some cases, the data was collected directly from calculation files used in production planning in the factories by the master planners.

The identification of resources, activities, cost objects and cost drivers were carried out by cross-referencing different accounting statements associated with each of the projects, as well as based on the interviews.

4.2 Performance Indicators and Comparison Metrics

In order to understand the value of the optimization model in the planning strategy, a series of performance metrics for later comparison and evaluation is established in this section. These metrics provide quantifiable measures that enable to evaluate with accuracy the performance, efficiency, feasibility, and cost savings associated with the project. The careful selection of performance indicators and comparison metrics ensures a comprehensive evaluation framework that addresses the research objectives of the study.

Therefore, the following set of key metrics have been identified in order to evaluate the TURN project and assess the impact on the company's planning processes.

- **Objective Function Value:** The objective function value serves as a primary performance indicator that measures the value achieved by the optimization models. This metric provides insights into the overall performance and success of the optimization models in achieving the desired objectives.

- **Computational Time:** Computational time is a critical metric that measures the time required by each model to solve the optimization problem. This metric reflects the efficiency and practicality of the models in providing timely solutions assessing their suitability for real-time decision-making.

- **Cost Savings:** Cost savings metrics quantify the potential cost savings achieved through the implementation of the TURN project. By comparing the cost savings between different models, we can evaluate the impact of the optimization approaches on cost reduction and financial performance.

- **Lead time:** Measures the time it takes for a process or product to move through a system from start to finish. It helps assess the efficiency and effectiveness of operations and identifies bottlenecks or areas for improvement. Monitoring lead time allows organizations to optimize workflows, reduce cycle times, and enhance customer satisfaction by delivering products or services more quickly.

- **Average production lot sizes:** This metric calculates the average quantity of items produced or ordered per cycle, by evaluating how well the models proposes production lots and comparing it with company's last 1º trimester 2023, indicating the variability and dispersion of lot sizes.

The selected performance indicators and comparative measures are in line with study goals and offer insightful information about the effectiveness, efficacy, viability, and cost savings of the optimization models. A comprehensive evaluation framework can be presented using these metrics that supports evidence-based decision-making, improves to the body of knowledge in optimization modeling, and has practical applications.

4.3 Production Strategy Optimization Model

This section presents an optimization model based on a linear mixed-inter programming formulation that optimizes the production strategy in order to improve efficiency and/or service level. The model operates under a SKU + Pack Type + Boards per Pack + Plant granularity level and was developed during the TURN project, adapted and parameterized to Sonae Arauco's production conditions.

The final output of the production strategy definition module is a list with the production strategy for each of the company's SKU under scope. The output should contain the MTS/MTO/FTO strategy definition, production lot sizes and safety stocks for the MTS items, as well as indicating the service level and lead time accomplished.

Model decisions will be based on the cost trade-off between MTS and MTO strategies for each component (raw board, paper, MFC finished good). An MTO strategy results in lower inventory costs but higher line occupation and setup costs. On the other hand, the MTS strategy leads to higher inventory costs, but lower setup costs and reduced variability in the production lead time.

The production strategy output optimizes the next 12-month strategy using a rolling horizon approach, considering historical data from the previous 12 months. The S&OP forecast will be used to estimate the demand for a one-year period at the GFT level. The forecast is disaggregated to the product and region levels based on material codes and customers' weights from previous year sales. Products without a forecasted demand will be automatically classified as MTO, indicating no expected demand. This can occur when the GFT forecast is zero or when a product had no sales in the previous year.

The model incorporates the consideration of non-bottleneck operations, bottleneck operations, and limitations in storage capacity. Non-bottleneck operations are represented by calculating the anticipated production time and setup time based on the demand for products. On the other hand, bottleneck operations are modeled with more intricate details, taking into account the production time, queue time, and corresponding variance, considering the production mix and projected workload. Additionally, the expected total production time for non-bottleneck operations is computed in accordance with the anticipated demand.

The determination of bottleneck lines is based on their occupancy during the last year of 2022. Lines with an occupancy rate exceeding 95% are considered bottleneck lines. Occupation is calculated at the production line level and represents the portion of time that is utilized for manufacturing activities. It reflects the actual utilization of the production line, taking into account factors such as production time, downtime, and maintenance stops. Occupation provides insights into the efficiency and utilization of the production line, indicating how effectively it is being used for production purposes. Equation 4.1 represents how this value is obtained.

$$Ocupation = \frac{(Total\ Capacity - Yearly\ Maintenance) - (Total\ Planned\ Downtime - Yearly\ Maintenance)}{(Total\ Capacity - Yearly\ Maintenance)} \tag{4.1}$$

The identified bottleneck operations in both the Beeskow and Nettgau plants are the Sanding Lines. Conversely, in Impaper, no production bottlenecks have been identified. This is attributed to its single-stage continuous production process, which involves operations at lines 605, 606, and 607, setting it apart from the Beeskow and Nettgau plants.

Regarding storage operations, the capacity of the storage facilities plays a crucial role in accommodating finished and intermediate goods, depending on the strategy employed for MTS, MTO and FTO products. In the Nettgau plant, the storage operations of crane storage and finished goods storage are taken into account. In the Beeskow plant, the storage operations encompasses raw and finished boards storage, cut-to-size and finished goods storage, as well as melamine crane storage. These storage facilities are crucial in effectively managing and organizing the inventory and ensuring a smooth flow of materials within the production process.

The setups associated with the production strategy selection are specifically related to the changeovers required for the bottleneck operations. It is important to note that the setup considerations also account for the unique characteristics of the production system, where production is planned in blocks. This implies that there are both inter-block and intra-block setups, which need to be taken into consideration when determining the production strategy and optimizing the production process.

4.3.1 Model Formulation

Formulating the problem as a mathematical model makes it amenable to various optimization techniques, simulation methods, or analytical approaches. The formulation serves as a bridge between the real-world problem and the mathematical representation, providing a systematic and structured framework for analyzing and solving the problem.

The mathematical model used in this study encompasses various indexes, sets, parameters and decision variables that are crucial for defining and solving the optimization problem. To provide a comprehensive overview, Table 4.2 presents the indexes and sets employed in the mathematical model.

Table 4.2: Indexes and Sets for the production strategy problem formulation

Indexes	
p	Product
u	Utilization
e	Production strategy
l	Line
j	Preceding product
s	Storage unit
b	Block
Sets	
L	Set of production lines
L_{bn}	Set of bottleneck production lines
L_{nbn}	Set of not bottleneck production lines
P	Set of Products
P_{bn}	Set of products whose preferred line is a bottleneck
T	Type of products
P_T	Set of products from type T
U_l	Set of possible utilizations in line l
P_l	Set of products produced in line l
E_p	Production strategies allowed for product p
D_p	Set of products derived from product p
S	Set of all storage units
P_s	Set of products that can be stored in storage unit s
S_p	Set of storage units where product p can be stored
B	Set of all Blocks
P_b	Set of products produced in block b

Each entry in the table represents a unique index or set that captures a specific aspect of the problem. These indexes and sets act as reference points for defining and constraining the decision variables, constraints, and objective function. These components provide a systematic way to categorize and reference the entities under consideration. Parameters play a significant role in the mathematical model used in this study, as they serve as inputs that influence the behavior and outcomes of the model. In Table 4.3, an overview of the parameters employed in the model is provided. Each parameter is meticulously defined and assigned specific values, which are carefully determined based on the characteristics and requirements of the problem under investigation.

Table 4.3: Parameters for the production strategy problem formulation

Parameters	
$\lambda_{p,u,e}$	Number of setups for product p, using line u and production strategy e
α_p	Setup time for product p
β_p	Processing Ratio for product p
$q_{p,u,e}$	Quantity produced, per unit of time, of product p with the utilization u in strategy e
$d_{p,u,e}$	Quantity delivered for product p in strategy e using u (pieces)
$sc_{p,u,e}$	Cycle stock for product p in strategy e using u (pieces)
$ss_{p,u,e}$	Safety stock for product p in strategy e using u (pieces)
cs_p	Setup cost for product p
cp_p	Production cost for product p (per unit produced)
ci_s	Inventory cost of storage unit s (per unit in stock)
$clms_p$	Cost of losing margin on the trade by switching from MTS to MTO for product p
csb_b	Setup cost for block b
γ_b	Setup time for block b
$lb_{u,l}$	Lower Bound of utilization u in line l
$ub_{u,l}$	Upper Bound of utilization u in line l
sm_t	Maximum stock quantity for products of type T
a_l	availability in line l
$r_{p,j}$	Constant between 0 and 1 that regulates the intensity of the relationship between product p and its precedent j
ad	Total average monthly demand
f_b	frequency for block b

In addition to the parameters, Table 4.4 includes the decision variables of the model. These variables represent the key choices and decisions that must be made to optimize the objective function while satisfying the given constraints.

The decision variables are the values that the model seeks to determine in order to achieve the desired outcome. They are typically represented as unknowns in the mathematical formulation and are subject to optimization or decision-making processes. The values of these decision variables directly impact the behavior and outcomes of the model. By adjusting the values of the decision variables, the model can explore different scenarios and determine the optimal or near-optimal solution that maximizes the objective function while adhering to the constraints.

Table 4.4: Decision Variables for the production strategy problem formulation

Decision Variables	
$Y_{l,u}$	1 if the utilization of line l is u, otherwise 0
$X_{p,u,e}$	1 if product p is produced with the utilization u and the strategy e, otherwise 0
T_l	Time produced on the line l
G_l	Gap in line availability l
$CProd$	Production Cost
$CSetup$	Setup Cost
$CStock$	Stock Cost
$Clms$	Cost of lost margin on trade for lost strategy
Q	Quantity delivered
$Nbins$	Number of bins used
ssf_p	Final safety stock of product p
$ssfc_p$	Corrected final safety stock of product p .It differs from the previous one by not allowing negative SS.
Bp	Auxiliary binary variable for the restriction that sets $ssfc_p$ to be $Max(0, ssf_p)$
$aloc_{p,s}$	Percentage allocation of the stock of product p to the storage unit s
$alocb_{p,s}$	Quantity of product p stock to allocate to storage s for bins management
$alocx_{p,s}$	1 if the aloc of product p for storage s is greater than 0, otherwise 0
$NbinsL_{p,s}$	Number of large bins used by product p in storage s
$NbinsS_{p,s}$	Number of small bins used by product p in storage s
Bs_s	Auxiliary binary variable that is 1 if storage s is used, otherwise 0
$Bl_{b,f}$	1 if block b is produce with frequency f
$Gstock_s$	Stock gap in units for storage unit s
$GstockB_s$	Stock gap in number of bins for storage unit s
$GstockL_s$	Stock gap in number of large bins for storage unit s
$GstockS_s$	Stock gap in number of small bins for storage unit s
$Gotif$	Gap in the OTIF

4.3.1.1 Objective Function

In this mathematical formulation, the primary choice for the company is to maximize operational efficiency, which can be translated as minimizing total production costs while ensuring a minimum OTIF rate.

Minimize the total production costs comprises various components such as setup costs, stock costs, and the cost of lost margin on trade resulting from a lost strategy. However, it is necessary to penalize the model for the gaps found in stock, line capacity, and OTIF, with penalty values calibrated by the company. For this, the objective function comprises two parts: minimizing all gaps (Equation 4.2 to Equation 4.6) and minimizing total costs (Equation 4.7), with the final objective being to minimize these two values (Equation 4.8).

$$Minimize\ X1 = \sum_{l} G_l * 20 \tag{4.2}$$

$$Minimize\ X2 = \sum_s Gstock_s * 2000 \tag{4.3}$$

$$Minimize\ X3 = \sum_s GstockB_s * 1000 \tag{4.4}$$

$$Minimize\ X4 = \sum_s GstockL_s * 1000 \tag{4.5}$$

$$Minimize\ X5 = \sum_s Gotif * 50000 \tag{4.6}$$

$$Minimize\ X6 = \sum CSetup\ +\ CStock\ +\ Clms \tag{4.7}$$

$$Minimize\ X = X1 + X2 + X3 + X4 + X5 + X6 \tag{4.8}$$

By minimizing these cost factors, we strive to optimize the efficiency and profitability of the production process.

4.3.1.2 Model Restrictions

Once the objective function has been determined, we can move on to the formulation of the problem's restrictions. In this section, all the relevant restrictions included in the model are presented.

The first fundamental restriction imposed by the model is the inherent constraint of having only a single utilization option for each bottleneck line (Equation 4.9). This restriction acknowledges the limited capacity and resource allocation within the system. By enforcing this constraint, the model ensures that each bottleneck line is dedicated to a specific utilization purpose, minimizing the potential for conflicts or inefficient resource allocation.

$$\sum_u Y_{l,u} = 1,\ \forall l \in L_{bn} \tag{4.9}$$

Next, the model entails the imposition of a restriction wherein each product that has a bottleneck line in its routing, is associated with a singular strategy, and the chosen strategy aligns precisely with the utilization of the respective production line (Equation 4.10). However, if a product does not go through a bottleneck line, the line where it is made must have the same usage for all products (Equation 4.11).

$$\sum_{e \in E_p} X_{p,u,e} = Y_{l,u},\ \forall l \in L_{bn}, u \in U_l, p \in P_l \tag{4.10}$$

$$\sum_{e \in E_p} X_{p,u,e} = 1,\ \forall l \in L_{nbn}, u \in U_l, p \in P_l \tag{4.11}$$

An auxiliary restriction is defined below to calculate the time used in production per line (Equation 4.12).

$$\sum_{p\in P_l,u\in U_l,e\in E_p} X_{p,u,e} * [\lambda_{p,u,e} * \alpha_p + \frac{q_{p,u,e}}{\beta_p}] = T_l,\ \forall l \in L \tag{4.12}$$

In order to ensure the fulfillment of capacity for Non-Bottleneck lines, a constraint is imposed in equation 4.13.

$$T_l \leq a_l,\ \forall l \in L_{nbn} \tag{4.13}$$

In this context, it is necessary to position the utilized time within the bounds of utilization, considering two distinct restrictions: one for lower bounds (Equation 4.14) and another for upper bounds (Equation 4.15). These restrictions ensure that the time utilized falls within the specified limits, thereby providing a framework for effective resource allocation and capacity management.

$$T_l \geq (1 - Y_{l,u}) * (-M) * lb_{ul} * a_l,\ \forall l \in L_{bn}, u \in U_l \tag{4.14}$$

$$T_l \leq (1 - Y_{l,u}) * M * lb_{ul} * a_l,\ \forall l \in L_{bn}, u \in U_l \tag{4.15}$$

A restriction on the maximum stock per storage unit is enforced in the model (Equation 4.16). This constraint ensures that the quantity of items stored in each storage unit does not exceed a predetermined maximum limit.

$$\sum_{p\in P_s,u\in U_l,e\in E_p} [X_{p,u,e} * \frac{sc_{p,u,e}}{2} * aloc_{p,s}] + \sum_{p\in P_s} [ss_{fc} * aloc_{p,s}] \leq sm_t,\ \forall s \in S \tag{4.16}$$

The allocation of stock for each product must not exceed 100%. This constraint ensures that the total allocated stock for any given product remains within the bounds of its available quantity (Equation 4.17).

$$\sum_{s\in S_p} aloc_{p,s} = 1,\ \forall p \in P \tag{4.17}$$

In addition, there are a set of restrictions aimed at costing the solution generated by the model. In equation 4.18, the restriction imposed pertains to costing the production solution, while in equation 4.19, the restriction relates to costing the stock solution. Equation 4.20 presents the restriction that defines the cost of lost margin on the trade, due to the change of strategy from MTS to MTO. Lastly, equation 4.21 refers to the costing of total setups solution, being the sum of changeovers setup costs and blocks setup costs.

$$\sum_{p,u\in U_l,e\in E_p} X_{p,u,e} * [\lambda_{p,u,e} * \alpha_p * cs_p + \frac{q_{p,u,e}}{\beta_p} * cp_p] = Cprod \tag{4.18}$$

$$\sum_{s\in S}[\sum_{p\in P_s,u\in U_l,e\in E_p} X_{p,u,e} * \frac{sc_{p,u,e}}{2} + \sum_{p\in P_s} ssfc_p] * ci_s = CStock \tag{4.19}$$

$$\sum_{p,u\in U_l,e\in E_p} X_{p,u,e} * clms_p = Clms,\ \forall p \in P_{T\in[FINISHEDGOODS]} \tag{4.20}$$

$$\sum_{p,u\in U_l,e\in E_p} X_{p,u,e} * [\lambda_{p,u,e} * \alpha_p * cs_p] + \sum_{b\in B} Bl_{b,f} * [f_b * \gamma_b * csb_b] = CSetup \tag{4.21}$$

Similarly to the previous restriction, the following restriction serves to calculate the delivered quantity.

$$\sum_{p,u\in U_l,e\in E_p} X_{p,u,e} * d_{p,u,e} = Q \tag{4.22}$$

Following this categorization, there exists a constraint that relates the strategy of a product to the strategy of its predecessor, which can be visualized through equation 4.23.

$$\sum_{p\in P_s,u\in U_l,e\in E_p} ss_{p,u,e} * X_{p,u,e} - \sum_{p\in P_s,u\in U_l,e\in E_p} ss_{p,u,e} * X_{p,u,e} * r_{p,j} = ssf_p,\ \forall p \in P_t \tag{4.23}$$

The next restriction ensures that each block is assigned exactly one frequency by setting the summation of frequencies for each block equal to 1 (Equation 4.24).

$$\sum_{b} f_b * Bl_{b,f} = 1,\ \forall b \in B \tag{4.24}$$

The following set of constraints ensures that the allocation of stock for a product does not exceed the total quantity of that same stock.

$$ssfc_p \geq ssf_p,\ \forall p \in P \tag{4.25}$$

$$ssfc_p \geq 0, \forall p \in P \tag{4.26}$$

$$ssfc_p \leq ssf_p + M * b,\ \forall p \in P \tag{4.27}$$

$$ssfc_p \leq 0 + M(1-b), \forall p \in P \tag{4.28}$$

Finally, the following restriction ensures a minimum global OTIF value, which is parameterized.

$$\frac{Q}{ad} \leq Min_{OTIF} \tag{4.29}$$

After defining and incorporating these restrictions into the mathematical model, it is possible to solve the production optimization problem, leading to improved operational efficiency.

4.3.2 Additional Adjustments in Production Strategy

A comprehensive approach also involves modeling the influence of the production strategy for a specific product on other products manufactured within the same production line. To accomplish this, a waiting queue is modeled at the bottleneck of each production stream. The mean waiting time and its variance are directly affected by the utilization of the production line and the mix of production strategies employed. When there are more MTO products in the system, congestion effects on a particular line increase, leading to longer production lead times. These lead times are determined by the waiting time, as well as the production and setup times. Figure 4.1 presents a diagram that can provide an overview of the production strategy is selected based on a cost analysis and aims to fulfill lead time and service level objectives, considering an average demand profile and industrial utilization.

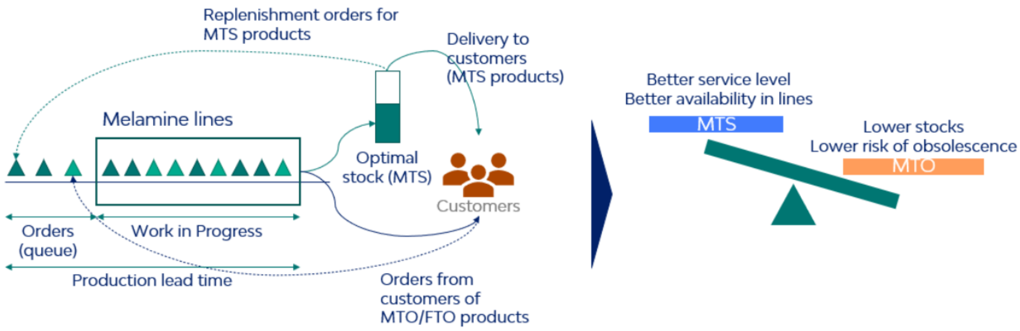


Figure 4.1: Production strategy selection process based on a comprehensive cost analysis

When it comes to finished goods, their classification can also change as they can be classified as FTO. This classification is determined based on the routing of the product, which includes the intermediate products it may utilize. If one of its preceding products, such as rawboard or paper, is classified as MTS, then the finished good will be classified as FTO.

This classification decision considers the dependencies and relationships between the various components involved in the production process. If any of the intermediate products have an MTS classification, it indicates that they are produced and stocked in advance, ready for use in the production of other products. In such cases, the finished goods that rely on these intermediate products would then be classified as FTO.

Chapter 5

Results and Analysis

This chapter presents the experimental results obtained through the application of the proposed methodology. The results obtained from the experiments are presented and analyzed in detail. The performance metrics, such as solution quality, computational time, and convergence behavior, were evaluated to assess the effectiveness of the methodology. In section 5.1 the computational results of the parameterized scenario executed in the chosen software are presented. In section 5.2 an analysis is made of the output generated from the production strategy for each product. Finally, in section 5.3 the model's impact on the company's processes is evaluated to find out whether it optimizes operational efficiency and minimizes costs.

5.1 Computational Results

The TURN project, conducted within the framework of Microsoft Azure, involved the implementation of an optimization model using Python, specifically utilizing the PuLP library. The presented instance was solved using the commercial solver Gurobi, version 10.0.0.

Table 5.1 displays the specific instance that was employed for comprehensive analysis, tailored to the scenario parameters of Sonae Arauco. The objective was to attain a service level of 90% for MTS products, while ensuring a minimum production OTIF threshold of 80%. The overarching aim was to maximize overall efficiency. The table outlines the dimensions of the original instance as well as the resulting dimensions of the MIP problem. The dataset utilized encompassed 4321 products, leading to a total of 125158 variables and 78933 constraints.

Table 5.1: MIP Problem Dimensions

Constrains	Continuous Variables	Integer Variables
78933	33817	91341

The execution results of the model are presented in Table 5.2. The optimizer iterated through 30517 simplex iterations before converging to the optimal solution. The MIP gap indicates that the current solution obtained by the optimization algorithm is very close to the optimal solution. The computational time required for the execution was 3196 seconds, indicating that the model can be seamlessly incorporated into production decision makers routine activities for scenario simulation. These findings contribute valuable insights for the practical applicability and efficiency of the proposed model in real-world planning scenarios.

Table 5.2: Solution Results

Solution Time	Objective Function Value	Iterations	MIP Gap
3196 sec	2515870.90785	30517	0.0829

These computational results hold significance as they shed light on the performance and outcomes of the implemented model.

5.2 Production Strategy Definition Results

By implementing the proposed approach, a comprehensive list of production strategies was generated for each item in the company's product assortment. The model returns an optimal production strategy (MTS/MTO/FTO) for each product, as well as the lot sizes and safety stocks of MTS Products. Model decisions are based on the cost trade-off between MTS and MTO strategies for each component (raw board, paper, MFC finished good). An MTO strategy results in lower inventory costs but higher line occupation and setup costs. On the other hand, the MTS strategy leads to higher inventory costs, but lower setup costs and reduced variability in the production lead time.

Preliminary results indicate that a significant portion of demand is concentrated within a very small percentage of the product range. However, the production strategy does not fully align with this effect. It is expected that increasing the number of MTS products would enhance overall efficiency. Figure 5.1 provides a comparison between the current strategy definition and the optimized solution, demonstrating that the model successfully addresses this issue by showcasing an increased number of MTS products.

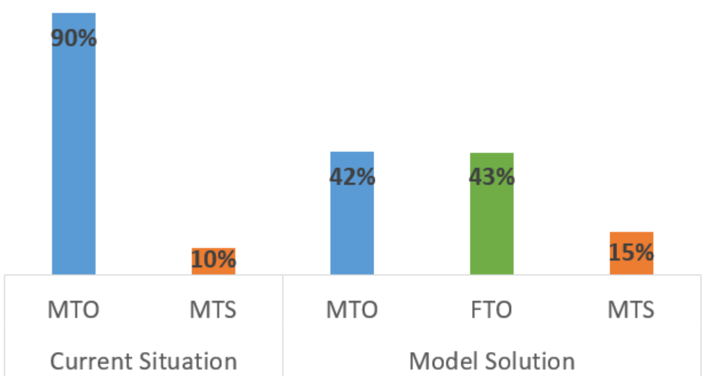


Figure 5.1: Comparison of the Production Strategy between Current Situation and Model Solution

When comparing the production strategies recommended by the model to the strategies currently employed by the company, a 5% increase in the number of MTS items was observed. It is noteworthy to mention that 5% of the previously categorized MTS products had their production strategies modified to MTO or FTO in the optimized solution. Conversely, a proportion equivalent to 10% of the initial quantity of MTS items shifted their production strategies from MTO to MTS. These values can be consulted and corroborated in figure A.1.

Another crucial aspect of production strategy optimization is the evaluation and improvement of lead times, which play a significant role in meeting customer expectations. Figure 5.2 illustrates a comparison between the lead times proposed by the model and the lead times associated with the current solution.

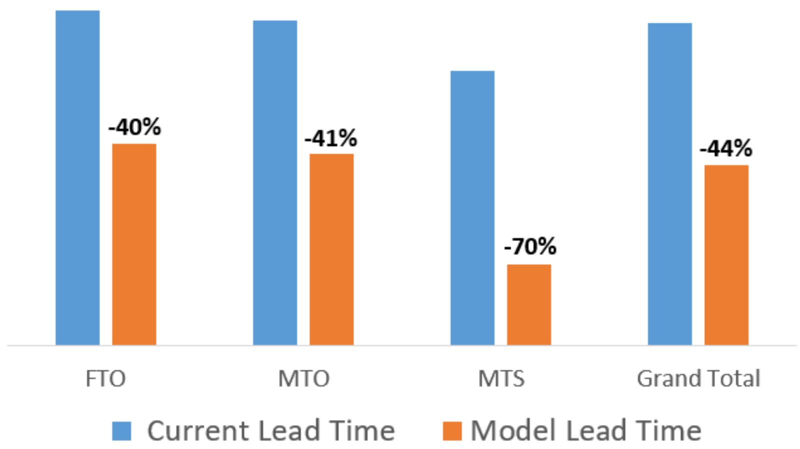


Figure 5.2: Comparison of current lead times and model lead times

The findings depicted in the figure indicate that the lead times suggested by the model outperform the lead times of the current solution, leading to an overall decrease of 44%.

5.3 Evaluation of Model Impact

As part of the impact assessment of the model, an analysis is conducted to evaluate the effect of the new solution on lot sizing and inventory levels. A key objective of this analysis is to determine whether the proposed solution is more efficient than the current one by assessing if the combined costs of setup and inventory are lower. The evaluation focuses on 2197 SKUs, as data on block frequency were unavailable for the remaining products. This evaluation is crucial to understanding the potential benefits and cost savings associated with implementing the optimized solution compared to the current approach. By considering lot sizing and inventory levels, this analysis provides valuable insights into the efficiency and effectiveness of the proposed model and its potential impact on overall operational costs.

The findings from this analysis are documented in Annexes A.2 and A.3, providing a foundation for subsequent analyses. It is important to note that the results presented in these annexes have been altered to ensure confidentiality of business-sensitive information. As a result, the absolute values have been masked, but the relative results have been preserved. This approach allows for the exploration and interpretation of the data while safeguarding proprietary information.

Regarding the lot sizes, the model calculates lot sizes for MTO items as a recommendation based on the minimum cost-effective production quantity. However, it is important to note that the model does not consider factors such as selling price, the size and dispersion of sales orders, and the ability to accurately predict them. Consequently, only the lot sizes for MTS items are considered in the analysis.

In Figure 5.3, the comparison of lot size calculations for MTS items in each Plant per Type is presented. These lot sizes are determined by establishing an inverse proportion between the average monthly demand and the production frequency. By considering the relationship between demand and production frequency, the model aims to determine optimal lot sizes that strike a balance between minimizing production costs and meeting customer demand efficiently.

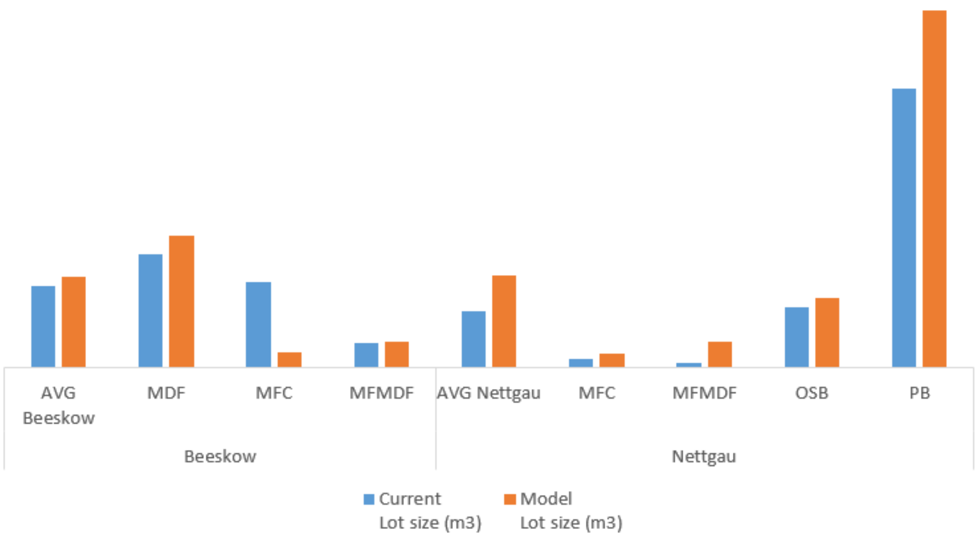


Figure 5.3: Comparison between Current Lot Sizes and Model Lot Sizes for MTS Products in Beeskow and Nettgau per type

The visualization of this figure provides insights into how the lot sizes for MTS items vary across different Plants and Types and the comparison as well as comparing the current strategy with the proposed one. It is important to highlight that the model's recommendations for MTS products result in an anticipated increase in overall lot sizes of 46%. This increase is attributed to the model's emphasis on maintaining higher stock levels, which in turn reduces line stoppages and allows for larger production batches. Consequently, this leads to a reduction in setup times, as fewer changeovers are required. By optimizing the lot sizes, the model aims to strike a balance between minimizing setup costs and maximizing production efficiency, ultimately enhancing overall operational performance.

Notably, the most significant increase in lot sizes is observed in the PB category in Nettgau plant. Intriguingly, certain products within this category, despite already being classified as MTS, exhibit even larger lot sizes. This strategic decision by the model aims to further minimize setup times by allowing for more extended production runs. The optimization of setup times resulted in a reduction of 34%, which is equivalent to 1.15 FTE.

The primary objective of this analysis is to ascertain whether the implementation of the new model results in cost savings for the company. Figure 5.4 provides a comprehensive cost comparison between the optimized plans and the plans based on historical practices.

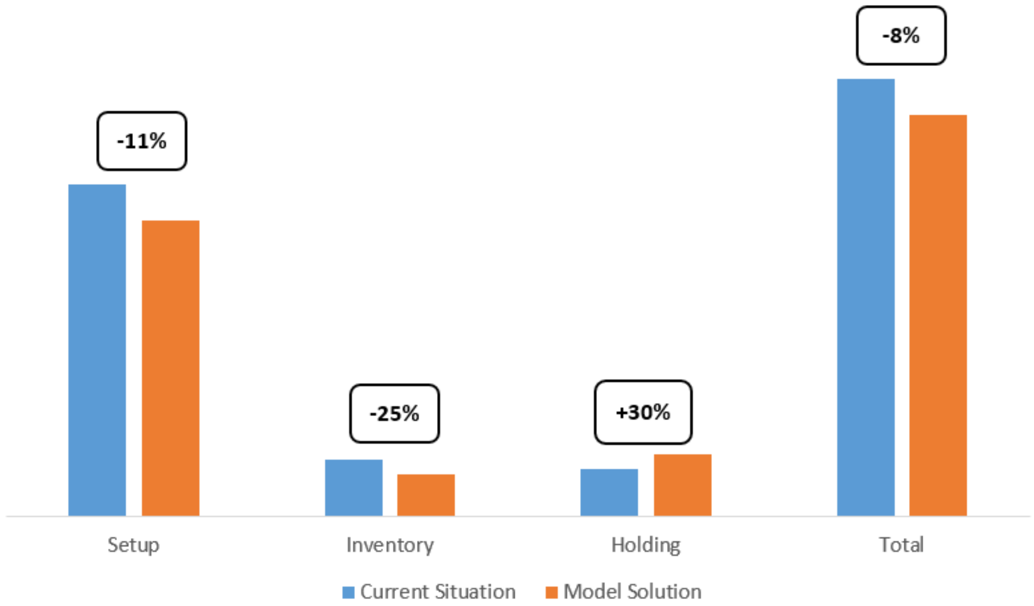


Figure 5.4: Cost comparison between the historical practices and optimized plan

The cost comparison considers various cost components, such as setup costs, inventory costs and holding costs. The setup costs encompass the aggregation of expenses within and between SKU's and blocks, while the inventory costs embody the product of the average monthly stock and the monthly storage cost. In contrast, the holding costs are calculated by dividing the costs associated with possession by the capital costs. It is important to note that all of these costs are expressed on a monthly basis.

Based on the presented graphic, it can be confidently concluded that the results of the model demonstrate a reduction in total costs. This outcome can be primarily attributed to the increased emphasis on production to stock strategies. Figure A.3 displays a comprehensive overview of the cost results, including both intermediate values, categorized according to final strategy, plant, and type. This visual representation facilitates a detailed analysis of the cost breakdown at each level, enabling a clear comprehension of the findings. Notably, the reduction in setup times plays a pivotal role in achieving cost savings, resulting in a significant decrease of 8% in the total monthly cost of the plan.

Chapter 6

Conclusions

This chapter provides the final conclusions drawn from the study conducted. Section 6.1 presents the key findings and considerations derived from the study. Section 6.2 outline the future steps that should be considered for the ongoing enhancement of the model and its implementation.

6.1 Main Considerations

In conclusion, the main objective of the dissertation, which aimed to assess the TURN project's MTO/MTS/FTO production forecasting strategy and Lot Sizing optimization model, has been successfully achieved. Through a comprehensive analysis of the developed model and its implementation, it has been possible to evaluate its effectiveness and gauge the future impact of this new decision support system on the company's production planning.

Throughout the research process, several intermediate milestones that contributed to the fulfillment of the main objective were accomplished. A thorough literature review provided a solid foundation for understanding the theoretical underpinnings of the topic. By continuously follow-up the development of the TURN project, a comprehensive understanding of its scope and potential implications has been ensured. The study delved into the underlying mechanisms and variables utilized by the model.

Additionally, a preliminary analysis of the company's current situation was conducted, enabling to contextualize and evaluate the effectiveness of the proposed model. By establishing a set of appropriate performance indicators and metrics for comparison, it was possible to measure and assess the impact of the model accurately. The formulation and implementation of the mathematical optimization model in a suitable tool was successfully accomplished. However, it is important to acknowledge that further refinement and fine-tuning could have been beneficial. For instance, conducting tests and implementing the model in different optimization solvers would have allowed for benchmarking and comparison. Unfortunately, bureaucratic obstacles hindered the opportunity to explore these possibilities, and the model ended up being implemented solely on the most robust solver available in the market.

Validating the model results against the production reality of Sonae Arauco further bolstered the credibility and applicability of the model. The results of these evaluations demonstrated a 10% increase in the MTS level, indicating that the model favors stock production to reduce inventory costs by increasing the optimal lot sizes for production. This change proves to be crucial, as, on average, the production lot sizes for MTS increase by 46%, reaching up to 100% in some cases for PB materials. As a result, there is a monthly cost reduction of 8% in overall production.

One of the challenges encountered was understanding all the wood panel formation processes and the functioning of the company's production. Furthermore, comprehending the underlying key concepts posed an additional difficulty. To overcome these challenges, several integration meetings were conducted. These meetings served as invaluable opportunities to clarify doubts and discuss operational intricacies. Additionally, a site visit to one of the company's factories was arranged, providing a firsthand experience of the production environment.

This study faced limitations that may impact the results. The collection and systematization of information were time-consuming and complex due to data dispersion. Manual input of block frequencies and the lack of well-defined production strategies in the current MRP system added to the challenges. These limitations raise concerns about data accuracy and the reliability of the findings. Efforts were made to mitigate these limitations through rigorous data validation and expert consultations. However, these factors should be considered when interpreting the study's results.

Although adjustments were made along the way, these modifications have been approached with care and deliberation. Any changes to the methodology or analysis were implemented to enhance the quality and reliability of the research, while still remaining true to the original research objectives. This flexibility in adapting the research plan demonstrated the commitment in producing rigorous and meaningful results. Furthermore, throughout the thesis, critical thinking and analytical skills were consistently applied to interpret the data and draw meaningful conclusions. The analysis and discussion sections were structured to address the research objectives directly, providing a clear connection between the collected data and the intended outcomes.

The concepts and tools acquired throughout the course have played a pivotal role in the development of my dissertation. Operational research has served as a cornerstone of my dissertation, providing a systematic and analytical approach to problem-solving. This discipline equipped me with a range of modeling techniques, optimization methods, and decision-making frameworks that proved invaluable in addressing real-world industrial challenges. By applying mathematical modeling and simulation techniques, alongside the proficiency in various programming languages, such as Python and SQL, it was possible to analyze the development and functioning of the model as well as analyze and manipulate large datasets. The knowledge gained in industrial management, with a specific focus on lean manufacturing principles and operations management, provided a solid foundation for understanding the intricacies of production processes and supply chain management.

The dissertation has contributed to the company in many ways. Firstly, it provided a clear understanding of the current production strategies. Secondly, it examined and comprehended the model's outputs, essential for future expansion considerations. Lastly, the validation of the results instilled trust in the supply chain team, enabling the implementation of new production strategies within the ERP system. These contributions enhance decision-making, improve operational practices, and bridge the gap between theory and application in the company's production environment. It facilitates scenario simulation and what-if analysis, enabling Supply Chain planners to assess the viability and potential benefits of implementing a stock-focused production policy for various materials or segments. By leveraging the model's capabilities, planners can explore alternative strategies, and gain insights into the feasibility and impact of adopting a stock-oriented approach.

However, although the validation shows a strong correlation between the model recommendations and the actual results observed in Sonae Arauco's production operations, Supply Chain Planners should always consider the realities of the production environment and approach the results with critical thinking. In order for the model to yield viable and accurate results, it is essential that the data used to feed the model are up-to-date. Planners must ensure that the input data accurately reflects the current state of the production operations, including factors such as material availability, lead times, and production capacities. It is through this balanced consideration of the DSS outputs and real-world production dynamics that planners can make informed decisions to optimize production strategies effectively.

6.2 Future Work

As observed, the model exhibits a high sensitivity to the quality and accuracy of the setup and stock data used as input. Therefore, ensuring the availability of up-to-date and precise data is imperative to achieve favorable outcomes. To improve the reliability and effectiveness of the model, further emphasis should be placed on integrating industry 4.0 technologies into the implementation process. By doing so, real-time data on setup times can be automatically and accurately captured, eliminating the reliance on approximate manual calculations. The utilization of such advanced technologies would enable the model to be fed with more precise and reliable data, subsequently leading to enhanced output and decision-making capabilities. This approach aligns with the principles of industry 4.0, emphasizing the importance of leveraging technology advancements to optimize processes and improve overall performance.

Ensuring the reliability of input data, there are several areas for improvement and expansion of the model. Firstly, the model can be extended to operate at the granular level of planning, specifically S&OE stage. By incorporating S&OE capabilities, the model would be able to generate a production wheel that effectively serves demand fluctuations. This would enable a more agile and responsive production planning process, accommodating real-time changes in demand and optimizing resource allocation.

Secondly, the model can be enhanced to provide suggestions for more efficient alternatives in terms of new production blocks. By analyzing historical data and considering various factors such as production capacities, lead times, and material availability, the model can offer recommendations for optimizing production block configurations. This capability would assist Supply Chain Planners in making informed decisions regarding the introduction of new production blocks, considering factors such as cost-effectiveness, resource utilization, and production efficiency.

Another aspect to consider is the expansion of the model to encompass other production regions, such as SWE and SAF, while adapting it to the unique production realities of those regions. By extending the model's applicability to multiple regions, the organization can benefit from a standardized and consistent approach to production planning across different locations.

The findings of this study contribute to the academic and industrial understanding of production strategy optimization. The validation and thorough analysis of the model's structure and output provide empirical evidence of its accuracy and efficacy. The insights gained from this research are not only valuable for Sonae Arauco but also have broader implications for similar companies seeking to improve their production operations through data-driven approaches.

Appendix A

Results obtained from the validation

Count of N	Final Strategy			
Current Strategy	**FTO**	**MTO**	**MTS**	**Grand Total**
MTO	1737	1655	434	3826
MTS	60	150	195	405
Grand Total	**1797**	**1805**	**629**	**4231**

	Final Strategy			
Current Strategy	**FTO**	**MTO**	**MTS**	**Grand Total**
MTO	41%	39%	10%	90%
MTS	1%	4%	5%	10%
Grand Total	42%	43%	15%	100%

Figure A.1: Results from Current Strategy and Final Strategy Comparison

Difference between historical and forecast			2%	Current Situation					Optimization Solution				
Row Labels	Number of SKU's	Sum of Historical Demand	Sum of Forecast Demand	Current Lot Size (m3)	Current Block Cycle (days)	Current Average Stock (m3)	Current Safety Stock (m3)	Current Lead Time (days)	Model Lot Size (m3)	Model Block Cycle (days)	Model Average Stock (m3)	Model Safety Stock (m3)	Model Lead Time (days)
FTO	**1031**	**2387,0**	**2227,0**	**3,9**	**156,0**	**1,1**	**0,1**	**10,9**	**3,5**	**100,4**	**0,5**	**0,0**	**6,6**
Beeskow	**186**	**945,2**	**851,3**	**8,5**	**87,3**	**2,7**	**0,0**	**10,5**	**6,3**	**129,2**	**1,3**	**0,0**	**6,7**
MFC	50	513,1	374,8	16,3	83,3	3,6	0,0	12,4	8,8	73,8	1,6	0,0	7,7
MFMDF	136	432,0	476,5	5,7	88,8	2,3	0,0	9,6	5,4	149,6	1,2	0,1	6,3
Nettgau	**845**	**1441,8**	**1375,7**	**2,9**	**170,9**	**0,8**	**0,2**	**11,0**	**2,9**	**94,1**	**0,3**	**0,0**	**6,6**
MFC	841	1441,5	1374,9	2,9	171,1	0,8	0,2	11,0	2,9	93,9	0,3	0,0	6,6
MFMDF	4	0,3	0,8	0,8	135,4	0,0	0,0	7,0	0,9	142,2	0,0	0,0	5,3
MTO	**851**	**13508,9**	**14073,4**	**30,5**	**358,7**	**7,2**	**4,8**	**10,5**	**18,5**	**341,3**	**5,8**	**0,0**	**6,2**
Beeskow	**352**	**5101,6**	**4656,8**	**34,1**	**471,3**	**9,0**	**12,8**	**12,0**	**20,9**	**622,1**	**6,2**	**0,0**	**5,9**
MDF	306	5000,2	4570,6	38,0	511,6	10,2	15,6	11,6	23,2	701,6	7,1	0,0	5,3
MFC	8	26,2	22,4	18,5	180,9	1,9	0,0	14,6	9,5	68,6	0,6	0,0	10,6
MFMDF	38	75,2	63,8	7,5	219,5	0,8	0,0	15,5	5,2	99,2	0,4	0,0	9,4
Nettgau	**499**	**8407,3**	**9416,6**	**27,6**	**271,3**	**5,8**	**0,2**	**9,4**	**16,8**	**143,2**	**5,5**	**0,0**	**6,5**
MFC	218	135,0	136,1	2,7	194,8	0,4	0,0	8,9	2,2	114,0	0,1	0,0	8,9
OSB	55	403,4	985,7	21,0	34,1	0,5	0,0	19,8	20,9	37,7	4,3	0,0	3,3
PB	214	7652,0	8141,4	54,7	390,4	12,5	0,5	9,4	30,3	201,6	11,2	0,0	4,8
PB Shuttering	12	217,0	153,3	41,9	42,2	11,2	0,2	13,4	22,9	117,9	6,9	0,0	6,2
MTS	**315**	**7208,4**	**7295,0**	**18,6**	**135,2**	**10,4**	**0,5**	**8,9**	**27,0**	**18,4**	**20,5**	**5,2**	**2,6**
Beeskow	**81**	**2214,9**	**2421,1**	**24,0**	**53,2**	**16,2**	**0,0**	**8,5**	**26,9**	**15,2**	**16,8**	**2,2**	**2,6**
MDF	50	1982,5	2126,7	33,2	46,3	23,0	0,0	9,1	38,9	13,5	24,4	3,1	2,6
MFC	3	8,3	6,7	25,3	114,6	0,6	0,0	7,3	4,5	22,6	5,9	3,7	2,6
MFMDF	28	224,1	287,7	7,4	58,8	5,8	0,0	7,6	7,7	17,5	4,3	0,4	2,6
Nettgau	**234**	**4993,5**	**4873,9**	**16,6**	**165,2**	**8,4**	**0,6**	**9,1**	**27,0**	**19,4**	**21,8**	**6,3**	**2,6**
MFC	154	555,0	596,0	2,8	242,3	2,3	0,0	8,8	4,4	19,4	2,8	0,6	2,6
MFMDF	3	0,4	24,6	1,6	138,2	0,0	0,0	8,6	7,7	10,6	3,9	0,0	2,6
OSB	4	36,8	78,0	17,9	27,1	2,9	15,3	7,7	20,4	18,3	12,9	2,5	2,6
PB	72	4382,4	4161,1	45,1	17,7	21,9	0,7	9,9	76,6	19,9	63,7	18,9	2,6
PB Shuttering	1	19,0	14,2	36,6	21,8	14,7	0,4	13,2	28,4	22,6	26,4	8,5	2,6
Grand Total	**2197**	**23104,3**	**23595,5**	**16,1**	**229,5**	**4,8**	**1,9**	**10,5**	**12,7**	**182,0**	**5,4**	**0,8**	**5,9**

Figure A.2: Results from Lots, Stocks and Lead time Comparison

Row Labels	Number of SKU's	Current Situation: Current Setup Costs	Current Situation: Current Inventory Costs	Current Situation: Current Holding Costs	Current Situation: Current Total Costs	Optimization Solution: Model Setup Costs	Optimization Solution: Model Inventory Costs	Optimization Solution: Model Holding Costs	Optimization Solution: Model Total Costs	Difference
FTO	**1031**	**14 477,35 TOP**	**5 000,16 TOP**	**4 893,76 TOP**	**24 371,27 TOP**	**15 542,11 TOP**	**987,54 TOP**	**2 309,54 TOP**	**18 839,20 TOP**	- 5 532,07 TOP
Beeskow	**186**	**4 913,52 TOP**	**2 332,96 TOP**	**2 430,23 TOP**	**9 676,71 TOP**	**4 675,31 TOP**	**446,49 TOP**	**1 180,12 TOP**	**6 301,92 TOP**	- 3 374,78 TOP
MFC	50	1 150,13 TOP	330,80 TOP	587,97 TOP	2 068,90 TOP	1 498,44 TOP	150,78 TOP	287,84 TOP	1 937,06 TOP	- 131,84 TOP
MFMDF	136	3 763,39 TOP	2 002,15 TOP	1 842,27 TOP	7 607,80 TOP	3 176,88 TOP	295,71 TOP	892,28 TOP	4 364,86 TOP	- 3 242,94 TOP
Nettgau	**845**	**9 563,83 TOP**	**2 667,20 TOP**	**2 463,53 TOP**	**14 694,56 TOP**	**10 866,79 TOP**	**541,05 TOP**	**1 129,43 TOP**	**12 537,27 TOP**	- 2 157,29 TOP
MFC	841	9 542,47 TOP	2 666,52 TOP	2 463,13 TOP	14 672,11 TOP	10 847,87 TOP	540,87 TOP	1 128,93 TOP	12 517,68 TOP	- 2 154,43 TOP
MFMDF	4	21,36 TOP	0,69 TOP	0,40 TOP	22,45 TOP	18,92 TOP	0,18 TOP	0,49 TOP	19,59 TOP	- 2,86 TOP
MTO	**851**	**90 821,57 TOP**	**13 193,62 TOP**	**13 008,30 TOP**	**117 023,49 TOP**	**98 203,59 TOP**	**9 438,21 TOP**	**15 031,6 TOP**	**122 673,35 TOP**	5 649,86 TOP
Beeskow	**352**	**20 227,80 TOP**	**6 318,89 TOP**	**8 060,20 TOP**	**34 606,89 TOP**	**24 083,76 TOP**	**3 995,27 TOP**	**8 435,10 TOP**	**36 514,13 TOP**	1 907,23 TOP
MDF	306	17 139,96 TOP	6 235,94 TOP	7 871,86 TOP	31 247,76 TOP	22 460,47 TOP	3 961,73 TOP	8 341,99 TOP	34 764,19 TOP	3 516,43 TOP
MFC	8	82,88 TOP	27,22 TOP	46,88 TOP	156,98 TOP	113,30 TOP	8,71 TOP	15,53 TOP	137,54 TOP	- 19,44 TOP
MFMDF	38	3 004,96 TOP	55,73 TOP	141,45 TOP	3 202,15 TOP	1 509,99 TOP	24,83 TOP	77,57 TOP	1 612,39 TOP	- 1 589,76 TOP
Nettgau	**499**	**70 593,77 TOP**	**6 874,73 TOP**	**4 948,10 TOP**	**82 416,60 TOP**	**74 119,83 TOP**	**5 442,94 TOP**	**6 596,46 TOP**	**86 159,23 TOP**	3 742,63 TOP
MFC	218	1 415,60 TOP	808,50 TOP	115,58 TOP	2 339,67 TOP	1 777,41 TOP	46,09 TOP	90,91 TOP	1 914,41 TOP	- 425,26 TOP
OSB	55	5 946,19 TOP	50,88 TOP	32,75 TOP	6 029,82 TOP	8 236,35 TOP	468,65 TOP	743,70 TOP	9 448,70 TOP	3 418,88 TOP
PB	214	61 404,15 TOP	5 749,31 TOP	4 206,66 TOP	71 360,11 TOP	60 065,64 TOP	4 762,92 TOP	5 388,97 TOP	70 217,53 TOP	- 1 142,59 TOP
PB Shuttering	12	1 827,84 TOP	266,03 TOP	593,12 TOP	2 686,99 TOP	4 040,42 TOP	165,28 TOP	372,89 TOP	4 578,59 TOP	1 891,60 TOP
MTS	**315**	**74 786,90 TOP**	**12 531,53 TOP**	**8 157,93 TOP**	**95 476,36 TOP**	**46 474,66 TOP**	**12 625,15 TOP**	**16 614,9 TOP**	**75 714,76 TOP**	- 19 761,60 TOP
Beeskow	**81**	**12 259,39 TOP**	**5 752,24 TOP**	**4 839,11 TOP**	**22 850,74 TOP**	**8 985,77 TOP**	**2 492,88 TOP**	**5 493,91 TOP**	**16 972,57 TOP**	- 5 878,17 TOP
MDF	50	9 681,33 TOP	4 358,15 TOP	3 992,39 TOP	18 031,88 TOP	7 384,17 TOP	2 239,64 TOP	4 792,48 TOP	14 416,29 TOP	- 3 615,59 TOP
MFC	3	17,82 TOP	3,27 TOP	6,74 TOP	27,82 TOP	65,66 TOP	32,71 TOP	67,47 TOP	165,84 TOP	138,01 TOP
MFMDF	28	2 560,24 TOP	1 390,82 TOP	839,98 TOP	4 791,04 TOP	1 535,94 TOP	220,54 TOP	633,96 TOP	2 390,44 TOP	- 2 400,59 TOP
Nettgau	**234**	**62 527,51 TOP**	**6 779,29 TOP**	**3 318,82 TOP**	**72 625,62 TOP**	**37 488,89 TOP**	**10 132,26 TOP**	**11 121,0 TOP**	**58 742,19 TOP**	- 13 883,43 TOP
MFC	154	5 443,80 TOP	2 812,20 TOP	977,36 TOP	9 233,36 TOP	4 777,83 TOP	851,24 TOP	1 627,12 TOP	7 256,19 TOP	- 1 977,16 TOP
MFMDF	3	438,89 TOP	0,33 TOP	0,16 TOP	439,38 TOP	101,87 TOP	23,02 TOP	61,31 TOP	186,20 TOP	- 253,18 TOP
OSB	4	682,49 TOP	22,87 TOP	33,27 TOP	738,63 TOP	686,38 TOP	102,65 TOP	141,14 TOP	930,16 TOP	191,53 TOP
PB	72	55 728,08 TOP	3 914,71 TOP	2 244,25 TOP	61 887,04 TOP	31 547,55 TOP	9 102,91 TOP	9 176,86 TOP	49 827,32 TOP	- 12 059,72 TOP
PB Shuttering	1	234,26 TOP	29,19 TOP	63,78 TOP	327,22 TOP	375,26 TOP	52,45 TOP	114,60 TOP	542,31 TOP	215,09 TOP
Grand Total	**2197**	**180 085,82 TOP**	**30 725,32 TOP**	**26 059,99 TOP**	**236 871,12 TOP**	**160 220,36 TOP**	**23 050,90 TOP**	**33 956,1 TOP**	**217 227,31 TOP**	- 19 643,81 TOP

TOP= Turn Optimization Points

Figure A.3: Results from Costs Comparison

References

[1] H.C.W. Lau and W.B. Lee. On a responsive supply chain information system. *International Journal of Physical Distribution Logistics Management*, 30:598–610, 2000. doi:10.1108/09600030010346242.

[2] Sunil Chopra and Peter Meindl. *Supply Chain Management*. Prentice-Hall, Englewood Cliffs, NJ, 2001.

[3] Stefan Voss and David L Woodruff. *Introduction to computational optimization models for production planning in a supply chain*, volume 240. Springer Science & Business Media, 2006.

[4] Sonae Arauco. História | sonae arauco. https://www.sonaearauco.com/pt/empresa/quem-somos_2455.html, 2023. Accessed on: March 1, 2023.

[5] Su Min Jeon and Gitae Kim. A survey of simulation modeling techniques in production planning and control (ppc). *Production Planning & Control*, 27(5):360–377, 2016. doi:10.1080/09537287.2015.1128010.

[6] Aboubaker Altiaieb Moussttfa and Dusan Malinzak. A finite capacity of production planning approach for industrial manufacturing. *Acta Mechanica Slovaca*, 17(1):84–88, 2013. doi:10.21496/ams.2013.013.

[7] Céline Gicquel, Michel Minoux, and Yves Dallery. Capacitated Lot Sizing models: a literature review. working paper or preprint, February 2008. URL: https://hal.science/hal-00255830.

[8] Chetan Anil Soman, Dirk Pieter van Donk, and Gerard Gaalman. Combined make-to-order and make-to-stock in a food production system. *International Journal of Production Economics*, 90(2):223–235, 2004. doi:10.1016/S0925-5273(02)00376-6.

[9] Philip M Kaminsky and Onur Kaya. Mto-mts production systems in supply chains. In *NSF Design, Service, and Manufacturing Grantees and Research Conference*, volume 36, pages 30–34. Citeseer, 2006.

[10] Kay Peeters and Henny van Ooijen. Hybrid make-to-stock and make-to-order systems: a taxonomic review. *International Journal of Production Research*, 58(15):4659–4688, 2020. doi:10.1080/00207543.2020.1778204.

[11] Dirk Pieter van Donk. Make to stock or make to order: The decoupling point in the food processing industries. *International Journal of Production Economics*, 69(3):297–306, 2001. doi:10.1016/S0925-5273(00)00035-9.

[12] Kuan Yang and Ermei Wang. Optimal control of decoupling point with deteriorating items. *Journal of Industrial Engineering and Management*, 7, 12 2014. doi:10.3926/jiem.1205.

[13] Alfred Ultsch. Proof of pareto's 80/20 law and precise limits for abc-analysis. 06 2023.

[14] T.M. Williams. Special products and uncertainty in production/inventory systems. *European Journal of Operational Research*, 15(1):46–54, 1984. doi:doi.org/10.1016/0377-2217(84)90047-X.

[15] Guest Editors Alistair Clark, Bernardo Almada-Lobo, and Christian Almeder. Lot sizing and scheduling: industrial extensions and research opportunities. *International Journal of Production Research*, 49(9):2457–2461, 2011. doi:10.1080/00207543.2010.532908.

[16] Raf Jans. Solving lotsizing problems on parallel identical machines using symmetry-breaking constraints. *INFORMS Journal on Computing*, 21(1):123–136, 2009. doi:10.1287/ijoc.1080.0283.

[17] Luis Guimarães, Diego Klabjan, and Bernardo Almada-Lobo. Modeling lotsizing and scheduling problems with sequence dependent setups. *European Journal of Operational Research*, 239(3):644–662, 2014. doi:10.1016/j.ejor.2014.05.018.

[18] Raf Jans and Zeger Degraeve. Modeling industrial lot sizing problems: a review. *International Journal of Production Research*, 46(6):1619–1643, 2008. doi:10.1080/00207540600902262.

[19] R. Ramya, C. Rajendran, H. Ziegler, S. Mohapatra, and K. Ganesh. *Capacitated Lot Sizing Problems in Process Industries*. Springer, Singapore, 2019.

[20] Sachin Agarwal. Economic order quantity model: a review. *VSRD International Journal of Mechanical, Civil, Automobile and Production Engineering*, 4(12):233–236, 2014.

[21] Bilge Bilgen and H-O Günther. Integrated production and distribution planning in the fast moving consumer goods industry: a block planning application. *Or Spectrum*, 32:927–955, 2010. doi:10.1007/s00291-009-0177-4.

[22] H.-O. Günther, M. Grunow, and U. Neuhaus. Realizing block planning concepts in make-and-pack production using milp modelling and sap apo ©. *International Journal of Production Research*, 44(18-19):3711–3726, 2006. doi:10.1080/00207540600589127.

[23] J.P. Shim, Merrill Warkentin, James F. Courtney, Daniel J. Power, Ramesh Sharda, and Christer Carlsson. Past, present, and future of decision support technology. *Decision Support Systems*, 33(2):111–126, 2002. doi:10.1016/S0167-9236(01)00139-7.

[24] Hitoshi Tsubone, Haruki Matsuura, and Kyoko Kimura. Decision support system for production planning — concept and prototype. *Decision Support Systems*, 13(2):207–215, 1995. doi:10.1016/0167-9236(93)E0037-E.

[25] Daniel J. Power and Ramesh Sharda. Model-driven decision support systems: Concepts and research directions. *Decision Support Systems*, 43(3):1044–1061, 2007. doi:10.1016/j.dss.2005.05.030.

[26] Gerald Brown, Joseph Keegan, Brian Vigus, and Kevin Wood. The kellogg company optimizes production, inventory, and distribution. *Interfaces*, 31(6):1–15, 2001. doi:10.1287/inte.31.6.1.9646.

[27] Guillermo González Rodríguez, Jose M Gonzalez-Cava, and José A Méndez Pérez. An intelligent decision support system for production planning based on machine learning. *Journal of Intelligent Manufacturing*, 31:1257–1273, 2020. doi:10.1007/s10845-019-01510-y.

[28] Omkarprasad S. Vaidya and Sushil Kumar. Analytic hierarchy process: An overview of applications. *European Journal of Operational Research*, 169(1):1–29, 2006. doi:10.1016/j.ejor.2004.04.028.

[29] R.W. Saaty. The analytic hierarchy process—what it is and how it is used. *Mathematical Modelling*, 9(3):161–176, 1987. doi:10.1016/0270-0255(87)90473-8.

[30] LLC Gurobi Optimization. Mathematical optimization FAQs. https://www.gurobi.com/faqs/mathematical-optimization/, 2023. Accessed on April 12, 2023.

[31] Frederick Hillier and Gerald Lieberman. *Introduction To Operations Research*, volume 139. 01 1969. doi:10.2307/2345190.

[32] Michael J Todd. The many facets of linear programming. *Mathematical programming*, 91(3):417–436, 2002. doi:10.1007/s101070100261.

[33] Christodoulos A Floudas and Xudong Lin. Mixed integer linear programming in process scheduling: Modeling, algorithms, and applications. *Annals of Operations Research*, 139:131–162, 2005. doi:10.1007/s10479-005-3446-x.

[34] Michel X Goemans. Lecture notes for linear programming. *Massachusetts Inst. Technol., Cambridge, MA, USA*, 2010.

[35] IBM. Ibm optimization solver. https://www.ibm.com/optimization-solver, 2023. Accessed on April 12, 2023.

[36] Rimmi Anand, Divya Aggarwal, and Vijay Kumar. A comparative analysis of optimization solvers. *Journal of Statistics and Management Systems*, 20(4):623–635, 2017. doi:10.1080/09720510.2017.1395182.

[37] Vahid Beiranvand, Warren Hare, and Yves Lucet. Best practices for comparing optimization algorithms. *Optimization and Engineering*, 18(4):815–848, 2017. doi:10.1007/s11081-017-9366-1.

[38] Simona Šarotar Žižek, Zlatko Nedelko, Matjaž Mulej, and Živa Veingerl Čič. Key performance indicators and industry 4.0 – a socially responsible perspective. *Naše gospodarstvo/Our economy*, 66(3):22–35, 2020. doi:doi:10.2478/ngoe-2020-0015.

[39] Emna Ammar El Hadj Amor and Sonia Ayachi Ghannouchi. Ahp method for selecting emergency care key performance indicators. In *2017 27th International Conference on Computer Theory and Applications (ICCTA)*, pages 83–88, 2017. doi:10.1109/ICCTA43079.2017.9497153.

[40] Carlos Eugênio Batista Da Silva, Rodrigo José Pires Ferreira, and Suzana de França Dantas Daher. Multicriteria model for key performance indicators selection applied in a transportation company. In *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2227–2231, 2021. doi:10.1109/SMC52423.2021.9659300.