A Decision Support System for the Definition of a Mixed Make-to-Stock/Make-to-Order Production Strategy

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Master's Dissertation

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Mestrado Integrado em Engenharia e Gestão Industrial

2018-07-02

Abstract

This study was motivated by a manufacturer following a make-to-order strategy and facing difficulties to fulfill customer orders on time. This has a massive impact on the company since it incured in penalties for late deliveries.

While adopting a hybrid make-to-stock/make-to-order strategy could bring significant service level improvements, it is not so trivial to define the ideal combination of both approaches, since the problem is combinatorial and policy changes introduced to one product have impact on the remaining products.

We propose a methodology to redefine the production strategy, by selecting the ideal policy for each product, between make-to-order, assemble-to-order or make-to-stock and to set an inventory management policy for make-to-stock products. The determination of the customer order decoupling point was based on the principle that placing it after the bottleneck of the process would allow for better efficiency of the bottleneck production stage.

The job-shop production environment, characterised by setup times, limited capacity and congestion effects, was modeled to assess the impact of changes to the strategy at the product level and the intermediate product required for the assemble-to-order scenario. By modeling the two most congested production stages by M/G/1 queues, a nonlinear, integer programming formulation of the problem was developed. A greedy heuristic was developed to iteratively switch the manufacturing policy of first, the individual intermediate products, the boards, from make-to-order to make-to-stock and afterward the production strategy of the final products from make-to-order to make-to-stock. Selection of ideal candidates for policy change is based on an objective function that assesses the cost trade-off between inventory and failed deliveries. The heuristic goal is to minimise the overall cost of the system.

By applying the developed methodology, it is expected that the company increases on-time fulfillment rates while minimizing total cost. Through the implementation of the solution on a decision support system tool, some experimental results were obtained. The obtained results point to an increase of 60 perceptual points on the service level with the modeled cost function presenting a reduction in total cost of 76%.

Resumo

O estudo apresentado neste trabalho teve como motivação a dificuldade que uma empresa, que seguia uma estratégia de produção *make-to-order*, estava a ter em cumprir os prazos de entrega requeridos pelos clientes. Os atrasos dessas entregas têm um grande impacto económico para a empresa, uma vez que esta tem de suportar elevados custos de penalização. Embora a aplicação de um sistema de produção híbrido *make-to-stock/make-to-order* possa trazer melhorias significativas do nível de serviço prestado ao cliente, a definição da combinação ideal de ambas as estratégias não é um problema de fácil resolução dada a sua natureza combinatória, resultante do facto de uma mudança de estratégia de produção de um determinado produto ter impacto nos restantes produtos.

É proposta uma metodologia para a redefinição da estratégia de produção, selecionando a melhor política de produção para cada produto de entre *make-to-stock*, *assemble-to-order* ou *make-to-order*, e especificando uma política para a gestão de stocks dos produtos *make-to-stock*. A determinação do ponto de desacoplamento da encomenda do cliente foi baseada no princípio que colocá-lo após o gargalo do sistema permitirá uma melhor eficiência da etapa produtiva do gargalo.

O ambiente produtivo *job-shop*, caracterizado pela existência de tempos de setup, capacidade limitada e congestionamentos, foi modelado de maneira a ser possível avaliar o impacto da mudança de estratégia de produção de um produto final, ou de um produto intermédio, para o cenário da estratégia *assemble-to-order*. Através da modelação das duas etapas produtivas com maior congestionamento através de filas de espera M/G/1, foi formulado um problema não linear de programação inteira. Posteriormente, foi desenvolvida uma heurística gulosa para iterativamente mudar a estratégia produtiva, numa primeira etapa, dos produtos intermédios e, numa segunda etapa, dos produtos finais. A seleção dos melhores candidatos para a mudança de estratégia é baseada numa função objetivo que avalia o *trade-off* entre os custos de inventário e os custos de penalização no atraso das entregas. O objetivo da heurística é minimizar o custo total do sistema.

Através da aplicação da metodologia desenvolvida, é expectável que a empresa melhore o seu nível de serviço, ao mesmo tempo que minimiza o custo total. Com o desenvolvimento de uma ferramenta de apoio à decisão, baseada na proposta de solução desenvolvida, foi possível obter alguns resultados experimentais. Esses resultados, quando comparados com a situação atual, apontam para um aumento do nível de serviço em 60 pontos percentuais, enquanto que o custo total apresenta uma redução de 76%.

Acknowledgments

First and foremost I would like to thank my supervisor José Fernando de Oliveira for all the mentoring provided during the development of this dissertation and for always inciting me to improve my work. The way you manage to help me even though the project was delayed will not be forgotten.

I am thankful to Paulo Sousa for the rigorous review of my work and for always being there to help me grow. Besides the academic mentoring, thank you for your friendship and for being a great role model.

To Raquel and Pedro, I would like to thank you for bearing with me and always being there to lend a hand and to guide me through the intricate world of real-life problem-solving.

I am incredibly overwhelmed by the brilliant and inspiring people I met at LTPlabs. Thank you all for the opportunity to be a part of your family and for embracing me so promptly. Without all of you, this last couple of months would not have been nearly as good as they were.

At the end of my college-era, I have to show the gratitude I have for the friends that undertake this journey with me. To the best, that made this journey worthwhile and the reaching of its end so enriching. I would like to thank all of them.

To my team and all the supporting staff for always understanding that sometimes I had to miss practice and for still protecting my back no matter the adversity. Your understanding and companionship will always be remembered.

To all my family that always believed in me and looked at no obstacles to help me. To my sister for always caring for me and for being a source of continuous support and inspiration. To my parents for guiding my path and for always giving everything to allow me to pursue my dreams. Mãe, Pai, thank you for everything.

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Acronyms and Symbols

B2B	Business to business
MTO	Make-to-order
MTS	Make-to-stock
OTIF	On time and in full
DSS	Decision support system
ATO	Assemble-to-order
ETO	Engineer-to-order
CODP	Customer order decoupling point
OPP	Order penetration point
MFS	Make-from-stock
HPP	Hierarchical production planning
AHP	Analytic hierarchy process
SWOT	Strengths, weaknesses, opportunities and threats
WIP	Work in progress
TOC	Theory of constraints
FCFS	First-come-first-served
KP	Knapsack problem
EOQ	Economic order quantity
MAPE	Mean absolute percentual error
MPE	Mean percentual error
ERP	Enterprise resource planning

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Chapter 1

Introduction

1.1 Motivation

The company where this project was undertaken is one of the world leaders in the visual communication sector. The company's product range is vast, ranging from all kinds of shapes, colours and sizes of whiteboards and cork boards to vitrines, flip charts and tripods. The company is present in more than 82 countries and its exports amount to 98.7% of total sales. It operates in a market where the competition is increasingly global and aggressive, hence the only way to achieve a sustainable growth is to be efficient. The company operates in a B2B environment where fulfilment rates are of the utmost importance, because customers seek reliable suppliers.

The company had been operating under a MTO system since its beginning. Throughout the years, as its business volume grew, it always reacted in order to cope with that growth, but it never tried to anticipate the future nor prepare for it. The range of products also increased, but the company stuck to the same production strategy.

For quite some time, the company struggled to solve a problem of poor delivery performance. A diagnostic conducted to assess the magnitude of the problem determined that its on time and in full (OTIF) service level to its clients, in the period[1] under assessment, was 16%. Furthermore, the diagnostic determined that the OTIF service level from the production corresponded to 29%. Looking at these values, it is almost self-evident that something was wrong. In a market where clients are increasingly demanding and impatient, a performance such as the one presented may diminish a company's competitiveness and thus cause it to lose market share. As Mason-Jones and R. Towill (1999) point out, market performance metrics such as high service rate and short lead times of customised products are a unique selling proposition and, subsequently, bring value to a company.

The poor service level shown had a considerable impact on the company since it incurred penalties for late deliveries. In fact, there was a significant discrepancy between the needs of the clients and the company's capabilities. The company was incapable of fulfilling the requests of its customers within the required time. Its inability to fulfil these requests was directly related

[1] Between July 2016 and July 2017

with the fact that all production was done under a make-to-order strategy. As it stood, since the company was working almost at its maximum capacity, it was not only impossible to improve the situation, but also to accept more orders from clients.

A change in production was needed in order to improve the operational performance of the company. The implementation of a hybrid MTS/MTO production system was considered in order to help the company to increase its OTIF, therefore allowing it to become more competitive. In cases such as the one addressed in this work, where the company has a diverse product line and customer base, the best way to serve it is through an appropriate combination of MTS/MTO systems (Kaminsky and Kaya, 2006). As Kaminsky and Kaya (2006) concluded, hybrid systems yield much better performance than pure MTO or MTS systems when product characteristics and product demand characteristics vary highly from one another.

Moreover, the company had recently started selling to the final consumer through e-commerce. This, in addition to the change of the order paradigm from business clients, led to a tendency to increase order granularity. In fact, B2B clients are trying to optimise their inventories. Hence, they want to order fewer quantities more often and with shorter lead times.

An appropriate redefinition of the production strategy can lead to an increase in production efficiency and to a better responsiveness to customer requests. Assuming that a proper strategy partition is implemented, the redefinition of the strategy may lead to large-scale savings on penalty costs and lost sales.

1.2 The project

This study was conducted as part of a consulting project. The project began when the company realised that a change of strategy was essential in order to increase the service level and that it needed help to redefine and implement this new production strategy.

The key stakeholders of this project were the production planning department and the sales department. However, as the project span the entire company, several other teams were included in the project, with the intent of gathering all the information required and of not leaving out teams that might potentially have to interact with the changes.

In order to approach this problem holistically, several stages of production and the range of products and their demands had to be analysed. Furthermore, besides the definition of the strategy, all the auxiliary activities required for its implementation had to be developed and seamlessly integrated into one system.

The final goal was to provide the company with a Decision Support System (DSS), as a tool, enabling it to redefine the strategy whenever necessary. The system also helps to decide the replenishment policy by defining the reorder level and the reorder quantity for the products set to operate on an MTS basis, with the aid of insights provided by a demand forecast module.

The project can be divided into six main stages, as seen in figure 1.1. The first stage is the analysis of the environment and data and the system modelling. The second stage is the development of a methodology for the partition policy. Next, the third stage is selecting the best forecast technique, which is then used in the fourth stage: the definition of the replenishment policy. Finally, the fifth stage is checking the preliminary results with the company for final tuning of the methodology and model. In parallel as some of the final stages, the DSS is developed.

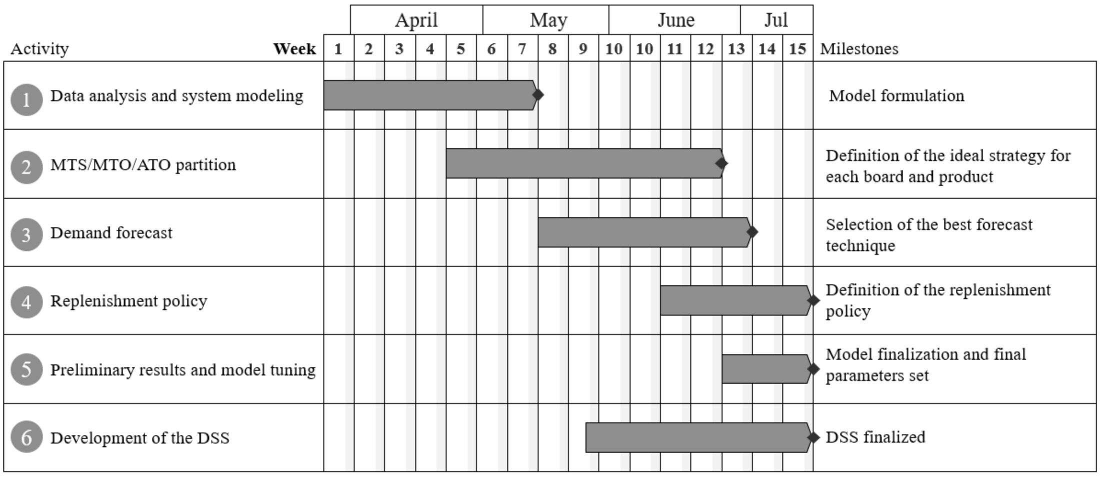


Figure 1.1: Project's timeline

1.3 Thesis outline

This dissertation is structured as follows. Chapter 2 provides an overview of the current state of the art in hybrid production strategies, as well as a review of the mostly used production strategies. In addition, it broadly covers the most common forecast techniques and replenishment policies. Chapter 3 describes the problem that the company was facing. Chapter 4 describes in detail the methodology developed to solve the problem. Chapter 5 presents part of the preliminary results. Finally, chapter 6 draws the main conclusions, discusses future improvements to the work developed and presents some of the shortcomings of the methodology.

Chapter 2

Literature review

This chapter has three goals. First, it seeks to provide the reader with an overview of the current state of the art in hybrid production strategies, particularly in what concerns the selection of the strategy by elaborating on the decision process itself. Secondly, it aims to present the features of the most used policies. Lastly, it focuses on the other stages influenced by the production strategy change. Section 2.1 introduces the types of production strategies most used by the industry in order to contextualise the current problem. Section 2.2 addresses the production strategy decision. Section 2.3 generally covers some of the current replenishment methods. Finally, section 2.4 broadly addresses forecasting.

2.1 Production strategies

Nowadays, when selecting a production strategy, manufacturing companies tend to choose between make-to-stock (MTS), make-to-order (MTO), assemble-to-order (ATO) or even engineer-to-order (ETO) strategies (Tashakori, 2015). Each one of the mentioned strategies has its specific advantages and disadvantages and suits specific applications. Among the abovementioned policies, MTO and MTS strategies have been widely applied in production companies (Tashakori, 2015). Although MTS and MTO approaches are still extensively used, pure strategies cannot cope with the increase in customer needs for higher customisation in products (Maheut et al., 2014) and with the growing predominance of e-commerce, where end costumers are expecting high levels of service, as well as prompt and on time deliveries. Therefore, the hybrid MTS/MTO strategy presents a policy that combines the advantages of both MTS and MTO approaches and that tries to overcome some of the shortcomings of both strategies. In fact, this hybrid production system has recently attracted the attention of academicians and practitioners (Rafiei and Rabbani, 2012). The trend is for fewer production systems to be entirely MTS or MTO (Adan and van der Wal, 1998).

Pure MTS manufacturing systems, also defined as push systems, have been widely studied. In a policy such as this one, customer demand is fulfilled from stock (Nagib et al., 2016). Hence, the items are processed in advance and stocked until customer orders arrive (Rafiei and Rabbani, 2012). This kind of systems are associated with low production flexibility and customisation and offer a good approach for less expensive products (Soman et al., 2004). Therefore, their primary goal is to anticipate future demand through forecasting and to plan to fulfil that demand. The success of the strategy deeply depends on the market analysis and on the quality of demand forecasting (Tashakori, 2015). This system is appealing due to the high capacity utilisation of resources and short lead times (Rafiei and Rabbani, 2012), providing an opportunity to take advantage of economies of scale (Günalay, 2011). Thus, by incurring inventory holding costs and losing flexibility, speedy fulfilment of orders and high service levels are possible. As Soman et al. (2004) point out, the main operational obstacles are planning inventories, determining lot sizes and forecasting demand. The performance of a MTS approach is measured by product-focused metrics such as fill rate, average inventory levels, stockouts, back orders and service level, among others.

On the other hand, the MTO policy enables a reduction in the inventory holding costs at the expense of reducing the service level, increasing lead times and making customers have to wait for their products to be produced (Claudio et al., 2010). The MTO systems, also referred to in the literature as pull systems, offer more production versatility, allowing for higher product customisation, which is usually related with highly customised solutions or expensive products (Soman et al., 2004). The manufacturing process of a MTO policy only begins after an order is received from the customer (Noorwali, 2014). As Nagib et al. (2016) explain, in some cases, MTO policy begins at the starting point of the production process, while in other cases, some parts are assembled in advance, and the process continues from this point when an order is collected. The latter cases are also known as assemble-to-order (ATO) and are discussed ahead. A MTO approach, in contrast to MTS, does not require a replenishment policy or a demand forecast since it does not hold inventory. Regarding measures to assess the performance of such systems, (Soman et al., 2004) refer that those are usually order-focused, and they provide as examples the average response time and average order delay. Since this policy is almost at the other end of the spectrum in comparison to MTS, it presents its own set of operational challenges. Accordingly, capacity planning, order acceptance/rejection and accurate due-date quotation are the main operational issues identified by Soman et al. (2004).

As mentioned earlier, sometimes the assemble-to-order system might be confused with a specific type of make-to-stock approach. On an ATO approach, the manufacturer produces standardised parts or components that have been made according to the demand forecasts and that are then assembled when an order is placed, according to customer specifications (Tashakori, 2015). An excellent example of this kind of production system is the car industry, where the assembly of the model according to customer specifications only starts after receiving the orders, although they already have stock of all the parts needed. Assemble-to-order is a very appealing strategy in industries where the need for customisation is high and lead times are long (Atan et al., 2017). Using this strategy, companies can reduce their customer lead time response by holding component inventories, benefiting from pooling component inventories and decreasing the cost of having multiple end products. Thus, this approach finds itself between a MTS and a MTO approach, and it can be either closer to a MTS or MTO strategy depending on the positioning of the customer order decoupling point (CODP). The CODP, sometimes called order penetration point (OPP), is defined as the point at the product production value chain where the product becomes linked to a specific order. Therefore, the CODP separates the manufacturing stages that are forecast-driven (upstream of the CODP) from the ones that are customer driven (downstream of the CODP) (Olhager, 2010). Based on this concept, Samadhi and Hoang (1995) categorise the four production environments mentioned in the first paragraph according to their customer order decoupling point. Figure 2.1 portrays the CODP for each of these production environments.

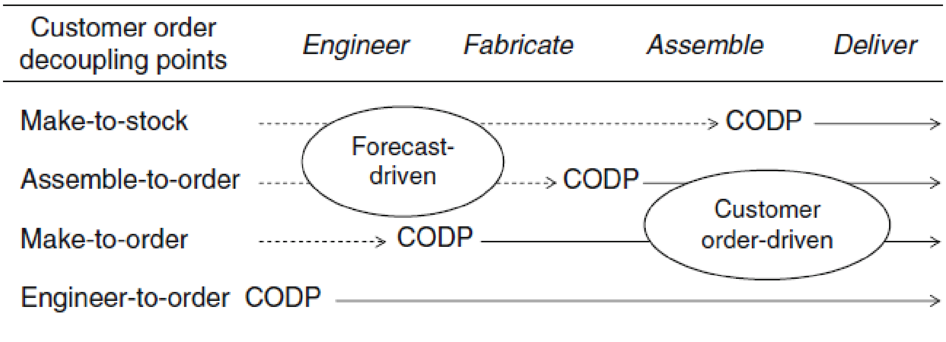


Figure 2.1: Different customer order decoupling points. Source: Olhager (2010)

Regarding the assessment of the performance of an assembling system, the process is divided into two stages. Firstly, the operations upstream of the CODP are evaluated in the same way as a MTS system. Secondly, the remaining operations are treated as if they were a MTO system. The main operational challenges faced by the implementation of an ATO, besides the ones present in the MTS and MTO systems, are determining the correlation between component demands and the ideal CODP that minimises the total cost of the system.

Inspired by both MTS and MTO approaches, hybrid systems are used to balance those policies. The hybrid MTS and MTO policy is widely used in the food and beverage processing industry (Nagib et al., 2016) and is usually suitable for multi-product environments, where products experience very different demands: while some have high and stable demands, others have low and variable demands. In a policy like this one, while some products are made-to-stock and kept in inventory to promptly respond to customer orders, others are made-to-order and only start being produced after an order is received. Adan and van der Wal (1998) state that combining MTO and MTS effectively reduces production lead times, leading to a more efficient system. When evaluating the performance, the criteria of this type of system are very similar to the ones of MTS and MTO, where the performance of MTS products and MTO products is assessed according to their strategy, and compound metrics such as overall fill rates are determined. Even though this might seem like a promising strategy for companies, implementing a hybrid system can be daunting. Firstly, it is not an easy task to select an ideal strategy for each product that defines the whole system, and after overcoming this step, decisions such as order prioritisation, production scheduling, and due-date quotation must be tackled and solved before deploying the system.

2.2 Production strategies decision

The literature review regarding the issue of MTO vs. MTS goes back to the 1960s (Rajagopalan, 2002). Although many papers address the issues of pure MTO (e.g. Kingsman et al. (1996)) and pure MTS (e.g. Silver et al. (1998)) policies, only a few take into account the hybrid MTS/MTO approach in a production system. Furthermore, from the scarce literature available concerning the hybrid solution, the vast majority of MTO/MTS models assume that the decision of production strategy for each product is made in advance and they try to find the best way to operate under such a system. Hence, they focus on order prioritisation (e.g. Tashakori (2015)), admission control and sequencing (e.g. Carr (2000)). Only a few approach decision-making and attempt to determine the importance of the factors involved in such a decision, and which ones should affect that decision. Since the core of this work is the policy decision, that will be the main focus of the literature review.

The strict set of articles that focus on partition policy present a somewhat limited range of solution approaches and tend to consider different factors for decision-making. While some authors propose quantitative frameworks for product classification according to the best strategy between MTS and MTO, others discuss this decision from a qualitative point of view. Another category of the literature is case studies where the authors undertake the decision process and the implementation of a hybrid system in specific companies.

2.2.1 Quantitative frameworks approaches

Williams (1984) conducted one of the first studies on combined MTO-MTS production systems. Williams (1984)'s research tries to answer multiple questions raised by hybrid systems, such as what products should be stocked, what MTO business should be accepted and what the ideal batch sizes for MTS products should be. Conversely to the research conducted in this area before this study, Williams (1984) does not assume that product demand and production times are deterministic. He proposes a method for the analysis of a single-stage production system that takes into account both the stochastic nature seen in practice and the interactions between products and capacity using queuing theory, modelling the queue as an M/G/m system. Williams (1984) begins by performing an ABC analysis and defines at the start that lower demand items (C items) are MTO and higher demand items (A items) are MTS. Hence, he orders the remaining items based on ascending demand, trying to determine the threshold where an item with lower demand is MTO and the others are MTS. The total costs function used to assess the performance of each strategy is composed of stock holding costs, setup costs, and stockout costs. By using this technique, it is possible to measure the impact of a strategy change on the whole system. This can be seen in many other subsequent works using an approach also based on queuing systems. By changing the policy of one product from MTO to MTS, there is a reduction in the number of setups and, consequently, the occupation of the process is reduced, leading to a reduction in the mean waiting time on the queue, which, in turn, leads to faster production time for all other products. Even though this study was conducted more than thirty years ago, it has its merits and must still be taken into account by everyone who attempts to undertake an endeavour such as policy partitioning. This is a novel approach, that drops some limiting assumptions, making the model closer to what we can find in the real world. Moreover, by taking into consideration the interactions between products and capacity, through the use of queuing concepts, the approach tracks the impact of the strategy change on the overall system.

Arreola-risa and DeCroix (1998) provide optimality conditions for the MTO/MTS partitioning for a multi-heterogeneous product scenario with random manufacturing times where products can have different manufacturing-time distributions, product demand is independent and a Poisson distribution with different arrival rates is followed. A single-machine environment with a first come first serve (FCFS) scheduling rule is considered. Regarding the cost structure, the authors assume that the costs of managing either system are stationary and they appraise the performance of each strategy based only on the minimisation of the sum of inventory holding costs and stockout costs. Therefore, in order to determine such conditions, they created a mathematical formulation of the problem at hand. The optimality conditions are inferred for two cases of backorder costs: cost per unit and cost per unit per unit of time. Besides providing insights for optimal selection among both strategies for different scenarios and factors, their results demonstrate how the reduction in production time randomness leads towards MTO production. Although this study might be useful as a general rule selection in cases where the real environment closely relates to the one assumed here, the authors are the first ones to recognise ways to improve on several fronts. Firstly, they suggest that a generalisation of the Poisson process would be beneficial due to its practical applicability. Secondly, they admit that they should have analysed a manufacturing setting with multiple production stages and machines. They also recognise the very limited scope of application of their study due to its dependency on stringent initial setting assumptions. Moreover, the existence of a queue system in the machine could have been studied, as well as the inclusion of setup times, since this is an essential factor that should be taken into account during the strategy selection. Finally, this model fails to incorporate the relationship between the strategy election and the impact on the policy performance of other products. This can be seen later in the review of other articles.

Li and O'Brien (2001) propose to model the decision process under different operational conditions through the development of a multi-objective optimisation model. They present a quantitative analysis where they compare product types and supply chain strategies. The production strategies under assessment are MTO, MTS, and make-from-stock (MFS), and the performance of each strategy is measured as the weighted sum of three factors related to profitability, responsiveness and reliability through the expected total cost, the expected lead time and the expected delivery delay, respectively. By performing a sensitivity analysis, the impact of the product attributes is determined based on the performance of each strategy. The critical factors considered are demand uncertainty and value-added capacity, here defined by the costs that the materials add to the price of the finished product. Based on the analysis performed, the authors conclude that the performance of the three strategies varies according to the factors analysed. In cases where demand uncertainties are lower, a MTS approach outperforms the other two strategies. However, as the demand uncertainty increases, both the performance of MTO and MFS surpasses the one from

MTS. Furthermore, it was demonstrated that the value-adding capacity has a minor impact on the performance of strategies for lower values of demand uncertainty, although the performance becomes highly dependent as the uncertainties in demand increase. Accordingly, in cases where it is hard to predict the demand and the value-adding capacity is low, the priority should be to employ a MTO strategy, since it tries to avoid waste in stocks at the expense of longer lead times. Despite proving some proper empirical conclusions, this paper only provides us with some indications whether a product should be made-to-stock or made-to-order based on their demand predictability and value-added, and does not consider the implications that such a decision has on the choice of strategy for the other products. Furthermore, it does not take into consideration setup costs nor does it address the hybrid system approach directly.

Unlike the other models in the literature, Kaminsky and Kaya (2006) conduct an analytic study that delves into inventory decision, strategy selection, scheduling and lead time quotation in a MTS/MTO supply chain context, while also exploring the influence of the supplier-manufacturer relationship on such a system. Their research covers a variety of models with the intent of providing a holistic insight into the operation of combined MTS/MTO systems. By mathematically modelling the systems, they acquire optimality conditions under which a MTS or MTO system should be used for each product. They also present algorithms to determine the optimal inventory levels for MTS products. Through their research, they conclude that costs can be dramatically reduced by using a hybrid system instead of a pure strategy, and also that information exchange between the suppliers and the manufacturer is of paramount importance for an effective due date quotation. Although this research goes more in-depth than Li and O'Brien (2001), presenting a broader range of factors and systems, and even though it is based on more solid models, it has almost the same shortcomings. By not considering setup times and costs as well as how the decision of a strategy for one product impacts the performance of the remaining products' strategy, it is not a suitable approach to follow in our case.

Contrary to Kaminsky and Kaya (2006) and Li and O'Brien (2001), Rajagopalan (2002) proposes a heuristic procedure to solve a non-linear, integer programming formulation of the MTS/MTO decision problem and to define batch sizes. In addition, the author also takes into account the impact that a change in product production strategy has on the performance of the whole system. The suggested model was developed for an environment characterised by a large number of different items with stochastic demand and variable processing times, significant setup times, limited production capacity and congestion effects. The objective of the heuristic is to ensure that the MTO orders are fulfilled on time with a given probability while minimising the inventory costs of MTS products. By modelling the queue as a M/G/1 system, it is possible to obtain the mean queue time that in turn affects the production lead time. By doing this, when applying the heuristic and upon changing the product production strategy, the queue is recalculated and, consequently, the profitability of changing the strategy for the remaining products is also updated according to the new queue meantime and variance. The starting point is that all the products are MTS and, one by one, following a greedy approach where the most profitable MTS product is picked, is passed to an MTO production strategy and all the costs are recalculated. The procedure is repeated until the global system gains nothing from changing the strategy for another product. Hence, the designed approach copes with the influences that a change of strategy for one product implies, reaching a near optimal solution for the decision problem. Although this model surpasses a lot of the shortcomings of other studies, it is more suitable for a flow-shop environment where the vast majority of the products follow the same manufacturing sequence passing through the bottleneck. Thus, for different environments, this approach probably will not yield such good results. Unlike Williams (1984), Rajagopalan (2002) allows every item to follow one of both policies and thus achieves a broader analysis.

Soman et al. (2004) propose a hierarchical production planning (HPP). Through this approach, a decision is made over different decision levels with distinct attributes. The three distinct levels are strategic, tactical and operational, respectively. In the first level, the most important for our research, some decisions relate to determining which products to manufacture to stock. Firstly, product families are formed based on product similarities and on process and market characteristics. Afterwards, the location of the CODP is used to decide on MTO/MTS partitioning for each family, using the information provided by Van Donk (2001). The second level focuses on production capacity coordination. The last level determines the sequencing and the detailed production plan. The main drawback of the solution proposed by Soman et al. (2004) is that the framework is conceptual and the authors only considered questions focused on a single level. Therefore, it lacks decision-making models to answer defined questions.

Tavakkoli-Moghaddam (2008) develops a fuzzy analytic hierarchy process (AHP) combined with a strengths, weaknesses, opportunities, and threats (SWOT) approach as a decision-making method to tackle the first level, MTS/MTO partitioning, from Soman et al. (2004). Firstly, the procedure identifies the SWOT factors that define the MTO production by carrying out surveys at the different levels of a company. The next step consists in defining the weights of each of the SWOT groups using fuzzy pair-wise comparison. Finally, if strengths and opportunities are higher than weaknesses and threats, a product can continue to be manufactured according to a MTO policy. Otherwise, the product is suitable for a MTS solution. Although the method is complete and can be easily implemented, the data is subjective, and the firms' manufacturing capacity is not taken into account.

Most of the approaches only consider demand characteristics and ignore production and market characteristics such as manufacturing time, response time and so on. Even though the abovementioned models propose novel approaches to tackle the MTS/MTO partition problem, they have one main drawback. They all have too many assumptions and thus hamper application in scenarios where the production environment is not the same. These assumptions were proposed either to simplify the models or to make them compatible with some well-known models in theoretical aspects. Furthermore, most of the times, the developed models had a considerable computational complexity making them intractable. Finally, due to the complexity of these models, managers are seldom able to comprehend and apply them with success (Rafiei and Rabbani, 2012).

2.2.2 Qualitative research

In addition to the mathematical models depicted in section 2.2.1, a new trend of qualitative research started to emerge nearly two decades ago. Papers authored by Van Donk (2001) and Olhager (2003) were the first steps taken from this point of view.

Van Donk (2001) describes the application of the CODP concept in the food processing industry. This paper develops a frame that aims to serve as an aid for managers in balancing the factors and characteristics of the marketing and production process, which influence the decision of strategies. Van Donk (2001) introduces eight criteria to help to determine the CODP, divided into two categories: process and stock, and product and market. Hence, his framework offers a systematic tool for food processing companies to find the market and production system factors that play a significant role in the decision process. Besides being a very qualitative approach with a focus on the food processing industry, Van Donk (2001)'s study provides useful insights into how a manager can implement a hybrid strategy when mathematical models are not a feasible approach, due to a lack of skills, data or even resources.

Olhager (2003) presents an extension to Van Donk (2001)'s framework by defining more criteria in three categories: market, product, and production. The significant factors that affect the strategic positioning of the CODP are demand volume and volatility, and the relationship between delivery and production lead times (P/D ratio). An interesting cut-off point for the P/D ratio occurs when the value is one. At this point, if the value is lower, a MTO strategy starts to be viable, since the production will be able to manufacture the product quicker than the lead time demanded by the customer. When the relative demand volatility of a product is high, it is not reasonable to use a MTS policy, since this would lead to excessive inventory. In his approach, a firm that operates in an ATO system must differentiate between MTS operations (upstream of the CODP) and MTO operations (downstream of the CODP). Regarding production-related factors, one of the most critical is the position of the CODP in relation to the bottleneck of the production. From a resource optimisation point of view, it is beneficial to position the CODP after the bottleneck, so that the bottleneck does not have to deal with volatile demand and a variety of different products. In his framework, Olhager (2003) also addresses the consequences of moving the CODP forward and backward. He concludes that the position of the CODP is the core of the trade-off between maximising the production efficiency in the pre-CODP operations and minimising the investment in inventories on the post-OPP while maintaining a high service level.

2.2.3 Case studies

Kerkkänen (2007) deals with the question of which MTO items could be MTS on a small steel mill company that operates strictly on a MTO basis. The decision process that the author presents is tightly related to the case study at hand. In that sector, most of the products are MTO even though setup costs have a significant impact on the cost structure. The objective is to define which products are eligible for MTS in order to reduce the required number of setups. Several factors are taken into account to help with the decision, such as setup costs, the degree of customisation of the product, production volume and customer fidelity. The decision method starts by picking out, from the pool of all products, the most standard ones and the ones that are produced in more significant quantities. The choice obeys some feasibility criteria such as material testing or potential losses of material. Even though the solution procedure is simple, this study is relevant to demonstrate how the environment where the decision is going to be made affects and restrains the solution approach.

Halawa et al. (2017) tackle the problem of implementing a hybrid MTS/MTO system in the automotive industry, motivated by the increased market volatility in this sector. By using discrete event simulation and optimisation, they manage to increase the responsiveness of the supply chain to the volatile customer demand, while achieving significant cost savings. To appraise the merit of each solution, inventory, work in progress (WIP), non-fulfilment and penalty costs are considered. Starting from a 100% MTO solution, the strategy of the most promising product is iteratively changed and, through optimisation, the optimum decoupling point is determined.

Köber and Heinecke (2012)'s work aims to define a methodology to implement a hybrid system. The evaluation of the production policies is based on an industrial case of a global manufacturer of agricultural machinery and is achieved with the help of system dynamics. The market under study is characterised by its mass production nature, low and seasonal demand volume, increasing product variety and globalisation of operations. Moreover, due to the its current landscape, the market requires high customisation of products, quality, service, price, delivery reliability and short delivery times. Their approach is based on Olhager (2010)'s framework, and they adapt it to their problem specifications. One of their main conclusions is that in order to successfully develop an implementation plan for a hybrid strategy, it is essential to have a holistic view on the supply chain behaviour and the resulting performance for operational and market targets. Their partition of products among MTS and MTO policies and relating CODP is validated by a simulation model developed by the authors.

In the illustrative case study of Soman et al. (2007), the authors test the implementation of the conceptual production planning and inventory control framework developed for such combined situations by Soman et al. (2004), described above. They observe that the framework suggested by Soman et al. (2004), although generic and straightforward, is a handy tool for designing the planning and scheduling hierarchy for the combined MTO/MTS production scenarios, yielding excellent results. As pointed out earlier as a drawback of this framework, the authors conclude that the proposed solution methodology lacks analytic decision aids. Thus, they identify and provide a few possibilities to overcome these shortcomings. They focus on providing a heuristic for the MTO/MTS short-term batch-scheduling problem.

2.3 Replenishment methods

Companies that aim to fulfil demand through inventory must use a replenishment system in order to have high delivery performance.

Wagner (2002) presents and analyses the evolution of inventory models throughout history. The earliest publications on replenishment policies date back to almost one century and refer to the Economic Order Quantity (EOQ), which is still researched today. Back then, the main struggles were the acquisition of historical demand data and testing the developed stock models, as a result of the lack of computing power. According to Silver (1981), inventory management seeks to answer three questions:

1. How often should we review our inventory?
2. When should a replenishment order be placed?
3. How large should the replenishment order be?

The answer to these questions depends on the policy applied. Two of the most common stock management practices are the continuous and the periodic review. While the continuous review tracks the inventory status continuously and an order of a certain quantity, Q, is placed whenever the inventory reaches a certain predefined level, the periodic review only tracks the inventory position at regular periodic intervals and an order to bring the inventory level to a predefined level can only be placed at those intervals. While the continuous review might be attractive for a single item due to its lower inventory levels, periodic review systems offer the advantages of coordinating the replenishment of different products (Eynan and Kropp, 2007).

The four most well-known inventory management policies for a single item are the periodic (R,S) system, the continuous review based (s,Q) and (s,S) systems and a hybrid approach that is both time and quantity based (R,s,S). In the R,S policy, the inventory level is compared with the determined S level at each R period, and the replenishment quantity is obtained by calculating the difference between the current stock and S level. This model is widely used due to its simple and static solution, although it yields some higher holding costs (Smits, 2003). For s,Q systems, a minimum quantity level, designated as reorder level, s, is defined, and when the inventory falls below that level, a replenishment order, with a fixed quantity size, Q, is placed. According to Smits (2003), the risk of this scheme is potentially running out of stock if the s level is not high enough to cover the lead time of the placed order. The s,S approach is very similar to the s,Q, with a minor variance: the replenishment quantity is not a fixed Q quantity. Rather, the quantity will be the difference between the current stock upon triggering and an S level (Smits, 2003). Finally, the R,s,S combines the advantages of both continuous and periodic policies (Smits, 2003). In every cycle, if the current inventory level is lower than s, a batch size equal to the difference between the current stock and S is needed.

Silver et al. (2009) study a periodic review, reorder point, and order-up-to level (R,s,S) replenishment policy. The authors present a novel approach capable of determining the reorder point and order-up-to-level in order to achieve the desired fill rate as well as a desired average time between replenishments. By using a diffusion model, the periodic review with constant lead time setting is converted into one with random lead times and a continuous review. The proposed method is simple to implement and yields quite reasonable results.

Wagner (2002) focuses on why stockouts continue to occur even though the development of technology should have led to a better comprehension and use of inventory models. Some of the problems identified relate to seasonal demands, and when new SKUs are introduced, there is not enough data to proceed to an accurate forecast.

Inderfurth and Vogelgesang (2013) consider an inventory problem under periodic review and present methods to determine safety stocks that cope with uncertainties caused by stochastic demand and other different types of yield randomness. The approaches suggested in this work are easy to apply in practice, and the performance of the proposed safety stock variants are assessed through a simulation study.

Prak et al. (2017) state that the practical applications to determine safety stocks when demand is forecast are flawed. Typically, for safety stock calculations, the variance of the lead time demand is obtained by multiplying the estimated demand variance by the lead time. Nevertheless, as Prak et al. (2017) point out, since forecast errors for different periods of the lead time are correlated, even if the demand process in itself does not show auto-correlation, this method is incorrect. Hence, in their study, Prak et al. (2017) present lead time variance expressions and reorder levels for inventory systems where demand fluctuates around a constant level. They find that conventional approaches can lead to safety stocks that are up to 30% below the ideal one and to service levels that are up to 10% below target.

Finally, regarding the optimal reorder period in periodic review systems, Silver and Robb (2008) provide some insights. The normal and gamma distributions are discussed in the paper, since they are the two most commonly used to model demand in periodic review systems. The authors show that the determination of the best value for the review interval can be tricky, because the total cost function does not always behave as a function of the review period. They demonstrate and provide an explanation for the changes of the best review period as the values of different parameters change.

2.4 Forecasting

Forecasting demand is unquestionably one of the main challenges in supply chain management (Beutel and Minner, 2012). As stated before, the lack of forecast accuracy leads to overstocks or shortages that have a negative impact on the operational performance of companies. Hence, an improvement of forecast accuracy leads directly to inventory savings and service level improvements (Beutel and Minner, 2012). Talluri (2004)'s work led the author to conclude that an extra effort should be made in order to improve the accuracy of forecasting models, since they have a significant impact on stock levels.

As far as forecasting models are concerned, a large number of models are proposed throughout the literature, from advanced methods like artificial neural networks to more traditional ones such as exponential smoothing. The latter methods are the ones we are going to delve into. One might choose these methods instead of more advanced ones due to its ease of implementation and comprehension by the planners.

Traditional forecasting methods were implemented in different areas, generating satisfactory results (Kuo and Xue, 1999). Nonetheless, the efficiency of such techniques depends on the area to which they are applied, the experience of the user and the forecasting horizon (Goodwin et al., 2002). Even though these methods are widely used due to their ease of computation and implementation simplicity, it is sometimes difficult to choose the most appropriate technique for the forecast in question. Meade (2000) addresses this issue. In his study, Meade (2000) tries to determine the usefulness of statistics, summarising the ability to predict the relative accuracy of different forecasting methods. He concludes that even though those statistics might not lead to the selection of the best method, they nonetheless lead to the selection of a good one. Hence, a possible solution to determine the best solution for the forecasting problem at hand is to compare the accuracy and bias of different methods and select the most promising one.

The traditional methods include the naïve approach, moving averages, regressions, exponential smoothing and a slightly more advanced method ARIMA. In the naive approach, the forecast is equal to the last sales data point, or even the analogous point of the previous year. The moving average method, as the name suggests, is a basic method where the forecast is equal to the previous k data points. Exponential smoothing is a step up from the moving average method. Whereas in the simple moving average all the occurrences are weighted equally, in exponential smoothing, an exponential function is used to attribute exponential decreasing weights to past data over time. From the original method developed by Robert G. Brown (Gardner et al., 2001) some extensions have been made to take into consideration seasonality, trend and other factors. For a deeper understanding of exponential smoothing techniques, please refer to Gardner (1985).

The autoregressive integrated moving average model, or ARIMA, makes very few assumptions and is very flexible (Ho and Xie, 1998). With the aid of the autocorrelation and partial autocorrelation functions, the stochastic nature of a time series can be modelled approximately, mainly when the series is not stationary (Ho and Xie, 1998). These models were extended with modules and factors that should be considered, e.g. seasonality (SARIMA) and external variables (SARIMAX).

Chapter 3

The challenge

This chapter describes the problem that the company was facing. Changing a production strategy is not an easy task. Such a change has repercussions in various departments of a company and sometimes requires the creation of new departments, operation routines, and support systems. Before trying to solve the problem and come up with a suitable strategy, we first had to determine the challenges to tackle and understand why the definition of a new production strategy is not an easy thing to do. These steps will be addressed in section 3.1. Afterwards, we required a holistic comprehension of the production environment in order to develop a suitable solution approach. By disclosing the production strategy and the operational structure of the company at the time of the beginning of the project in section 3.2, the reader will be provided with an overview of the situation as it stood. Finally, the approach proposed to solve the problem will be depicted in section 3.3.

3.1 The problem

At the time of the beginning of this project, the company was operating in a MTO basis only, and our goal was to redefine that production strategy with the implementation of a hybrid MT-S/MTO system. Thus, we had to define a methodology that helped the strategy partition. So, the objective was to solve the problem by defining the strategy for each product that minimised the total cost of the system.

The first challenge we have to face when we start planning a manufacturing strategy change is to figure out what the impacts on the company will be. What must change so that the company can cope with the demands that arise with the implementation of a new strategy? What are the new functions or decision support systems that must be developed? Since a hybrid operation is a new operating mode, a new method of production planning and control must be developed (Chang et al., 2003).

Changing from a solely MTO policy to a hybrid approach requires a company to develop new capabilities. Assuming that the strategy partition is already made, since the MTS products are forecast-driven, a forecast tool must be provided to the company to help it handle its needs.

Moreover, as the company will begin to handle inventory, it must develop a replenishment system to handle the needs resulting from the forecasts. Another relevant aspect is the importance of setting the desired service levels in order to help to define the safety stocks.

Besides the support tools and methods that must be developed and integrated, the main issue is the strategy definition. Upon implementing a hybrid production policy, the decision of the best production policy for each product is of the utmost importance. The levelling between MTO versus MTS is critical for the hybrid system to run smoothly, since a wrongly classified item can generate unwanted stress on the production line or take up unnecessary space in the inventory. Hence, the objective is to determine a method to select the production strategy for each product that tries to optimise the efficiency of the whole system.

To start assessing how we should set the strategy for a given product, we must understand the costs and the trade-offs involved in such a decision. Making an item to stock has a positive impact on the other items for the following reasons: there will be fewer setups, and hence less capacity utilisation, and there will also be a decrease in order processing variability. The negative impact of making an item to stock is that the company will incur inventory costs and other operational costs such as picking. Together, these two factors result in less congestion and shorter and possibly less variable lead times, resulting in both shorter cycles and safety stocks for the MTS items and in better service in fulfilling orders for MTO items. Thus, correctly modelling these effects is critical to achieve a good solution.

For the MTS items, the determination of the lot size represents a similar trade-off between decreasing the inventory of one item and increasing the cycle and safety stocks of the other items (S. Karmarkar, 1987). Decreasing an item's lot size reduces its cycle stock but increases the number of setups and machine utilisation, which will lead to an increase in production lead time and variance. Again, this increases cycle and safety stocks for MTS items and results in a poorer service for the MTO items. The objective is to minimise inventory costs of MTS items while ensuring that orders for MTO items are fulfilled within the required lead time.

Another important aspect is how to define the costs involved. By changing to a hybrid system, we diminish the penalties incurred by the company due to late deliveries as well as possible lost sales, increasing the service level and production efficiency at the expense of holding inventory. So, is it necessary to make a correct evaluation of the value attributed to the gain of service level. The costs that should be considered in the analysis are divided according to three categories: inventory costs, late delivery costs, and operational costs. Inventory costs simply correspond to the holding cost of inventory. The late delivery costs can be divided into two costs: a fixed penalty cost for each late delivery, according to the contract with the customer, and a cost of potential future lost sales. Finally, the operational costs are related to the storage costs and picking operations that will arise for the MTS items.

Aside from the strategic and operational constraints, we also have to manage some challenges regarding how we should develop our methodology and how to implement it. One of the first issues we stumbled upon in this project was the lack of data and the structure of the data provided. Due to this fact, we had to be cautious not to develop a strategy that required more data that the one that was available, or that required data that could only be obtained by committing a considerable amount of company resources.

The solution approach must be able to be run over and over again in the future since the seasonality, market trends and the introduction of new products will require an updated strategy partition. Therefore, it must be a sound methodology that empowers the company with the ability to update the best strategy for each product whenever required. It is not a one-time solution. Moreover, the model must be easy to explain to the managers and to the team responsible for implementing the solution. This is essential for the correct implementation of the solution and to have a committed team. If the team understands the proposed model, its members are more likely to stay interested in said model and take full advantage of it. So, this is an important topic to bear in mind.

The solution must also be tractable, i.e. easy to implement, and yield fast results. We are not interested in running a model to optimality if that implies a considerable processing time and the use of resources that are not at our disposal. In fact, the goal is to develop a resolution method that is not computationally intensive and that allows a strategy partition to be quickly obtained.

All in all, a problem such as this one requires a considerable effort to solve. Defining the ideal combination of both approaches is hard since the problem is combinatorial and policy changes introduced to one product have an impact on the remaining products. As seen in section 2.2, a simple framework to tackle the partition problem does not exist. Almost every approach is either context dependent or the assumptions made for the model are highly restrictive. Thus, this problem requires a tailor-made solution where the characteristics of the operations influence the solution method and a comprehensive insight of the system plays a significant role. The main decisions that have to be made can be observed in table 3.1.

Table 3.1: Main decisions to be made

Decision	**Description**
Define production strategy for each product	The goal will be to define the production strategy that each product should follow that will lead to a minimization of the overall costs of the company
Define forecast technique	Identify with forecasting technique, level of aggregation and parameters will yield the best results for the MTS products
Define Replenishment policy	Identify the must suitable replenishment policy to be implemented. Moreover, the parameters for that policy should be defined.

3.2 Environment description

3.2.1 Production environment

The production environment might be characterise as a job shop, some sequences are similar to a flow shop, like mini production lines within the job shop environment. Hence, the production environment of the company under study can be defined as a hybrid system. While some centres are process-oriented and are reserved to perform certain types of processes, working like a job shop, other centres are product-oriented, being responsible for assembly lines for some of the consecutive operation stages, operating as manufacturing cells. While some production centres are oriented towards families of products, others are focused on specific sizes, independently of the product family.

The production capacity of most of the machines and production centres is limited. Nonetheless, in the manual centres, the capacity is not so strictly limited, because by increasing the number of workers, the output of that station can be increased. The production setting suffers from congestion effects in some stations.

The products are manufactured in batches in the process centres and, sequentially, in the manufacturing cells. The batch size is decided upon the production planning and usually corresponds to the desired quantity to produce in that week. The products are aggregated by families. Within each family, they are differentiated according to the material of the frames of the boards and colour, size of the product and other personalised options. If the same product is sold to different clients that require their branding, the product will have an extension to their code to identify that personalisation. Hence, at what will be called from now on the pre-extension level, they are the same product.

Regarding the production process in itself, within the families, it is very streamlined. Actually, some products from different families even share the same production sequence, such as when the products have the same dimensions. Similar products with the same size follow the same production process.

Almost all types of boards require three different components to be assembled. First, the frames are required. A wide range of different frames can be found, from different materials to different finishes and different colours. The only process required to prepare the frames is cutting them into the correct size. Secondly, the corners of the board are needed. They do not require any process since their production is outsourced. Finally, the main component is required - the board, where the final user will write or insert drawing pins. Again, for this part, a broad assortment of options can be found. The only common process that every board undergoes is the gluing, where all the components of the board are glued together and left to dry. The gluing centre in the factory has only two machines, with different characteristics, which can perform this operation. Regarding the remaining operations, some boards have their components cut before the gluing, while others only go to the cutting stage after they are dry. The ones that follow neither of the prior sequences go through the cutting process before and after.

Almost every final product follows the same production process. After every required part is available, the products follow the sequence illustrated in figure 3.1. In some special cases, the product can also be filmed before going to the packaging stage.

Figure 3.1: Production process of final products

Odd sizes, products, and personalised requests are treated separately in a manual production centre.

Regarding setup costs, only those resulting from stopping time are relevant. In every operation, upon changing the product being manufactured, a setup is required in order to prepare for another product. The setups vary from quick one-minute stops to longer half an hour stops.

Finally, it is relevant to disclose the different production locations. Besides the main production facility, the company also owns three other smaller manufacturing facilities to help it cope with the growth it has been experiencing. The raw materials and parts required for the products made in these facilities are sent from the main production location. After production is finished, except for special cases, the final product is shipped back to the main facility to be dispatched to the customers.

3.2.2 Demand characteristics

The company faces some challenges regarding its production due to the characteristics of its products and overall growth trend. Between 2011 and 2016, the company's revenue grew roughly 10%. This growth has continued thus far and is expected to continue in the following years. To further complicate the situation, the company presents a vast range of products. In fact, between July 2016 and June 2017, 8033 different stock keeping units (SKUs) were sold. Finally, orders have become increasingly more granular. In the abovementioned period, nearly 21% of the orders had only one item per SKU.

By analysing the demand characteristics of the products, a strong Pareto effect is noticeable. As seen in figure 3.2, 11% of products concentrate 80% of the sales, in order quantity. So, we can see that the products present a wide variety of demand volume. Through an ABC analysis, we can classify them according to their demand as shown in figure 3.2.

Besides presenting very different quantities, products also present very different demand patterns. As observed in figure 3.3, the products cover a broad range of the number of weeks in a year with orders. More than 90% of the products are only ordered in half of the weeks during the year.

Regarding the variance associated with the demand patterns, we can also see that there is a considerable disparity between the products. An analysis of the coefficient of variance was done and can be observed in figure 3.3. This assessment, which covers both the coefficient of variance and the order frequency, is critical because it correlates with the feasibility of accurately forecasting future demands. The peaks that are observed represent the products that are seldom

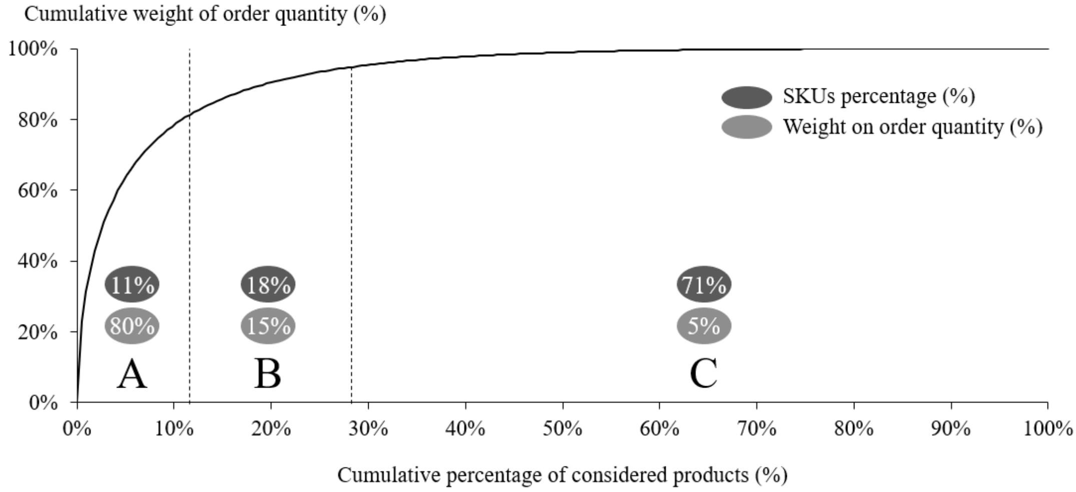


Figure 3.2: Cumulative distribution of sales.

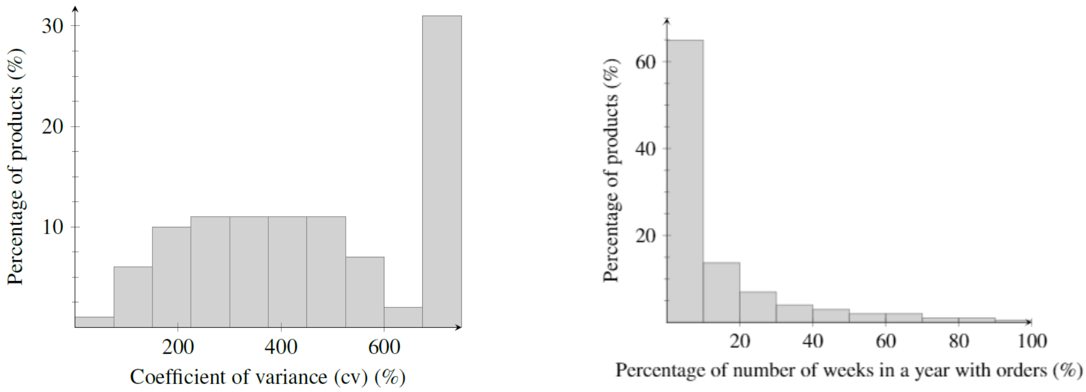


Figure 3.3: Distribution of products according to their coefficient of variance and order frequency

sold, type C products. It is important to mention that the coefficient of variance was calculated for the weekly sales.

Another aspect that is relevant to the discussion is the mean lead time required by customers. As seen in figure 3.4, the vast majority of the orders have a lead time of less than two weeks. In fact, 41% of the orders, constituted by 38% of the SKUs, require a lead time of less than eight days.

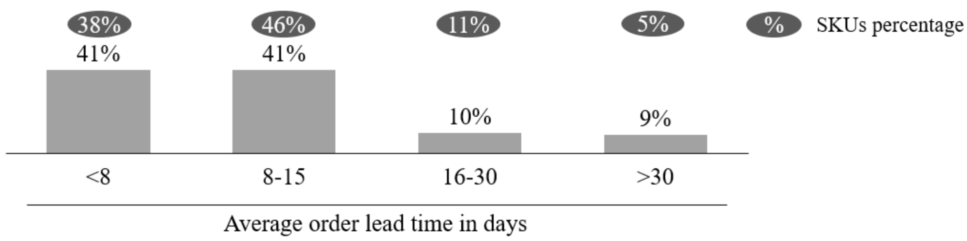


Figure 3.4: Distribution of required lead times

As we can see through the analysis of the product demand data, it is possible to categorise the products according to their weight on the total sales and demand variance. Hence, due to the high number of SKUs, to the wide variety of demand characteristics and to the different lead times required by the customers, setting a single production policy for all the products cannot yield high performance when the company is operating almost at full capacity. By analysing the value attributes mentioned above, a tendency starts to unfold. In principle, the products that have a shorter lead time required by the customer have high and more predictable demands, and thus are better served by a MTS strategy.

3.2.3 Current practices

Until the start of the project, the company had been operating exclusively under a make-to-order (MTO) production strategy. The company only initiated the procedures involved in the manufacturing of the products requested by the customer after the order was received, independently of the quantity or product. The orders were buffered during the week, and the production started at the beginning of the following week. By doing this, the goal of the company was to try to slightly smooth the demand, making the production less reactive to the demand. With this method, the granular orders received throughout the week will be grouped for production. Hence, many setups will be saved, avoiding an excess of downtime of the machines.

More recently, the company started to manage the production quantities to create some stock of specific products. The goal was to have a production strategy that tried to come closer to a hybrid MTS/MTO approach, hoping to reduce the production lead times, increase service level and on-time order fulfilment.

Although the company reduced inventory levels, the set of criteria that determined whether products should be stocked, and if that is the case, the corresponding stock level, was not explicitly established. Furthermore, there were no decision-support tools to assist the process of defining the proper production quantities, which relied mainly on unstructured and *ad-hoc* decisions. Upon the generation of weekly production orders, it was typical for the production team to increase the quantities to produce in order to guard against unexpected peaks in demand. Nonetheless, the vast majority of the production served the sole purpose of fulfilling customer orders that had already been placed.

Once the request for an order was received, the sales team tried to settle with the customer a date for the delivery. After this process, the final date was determined. That due date was then used to assess the service level and OTIF. Afterwards, the production order was created and queued for production.

Concerning the measurement of its operational performance as a company, the metric of choice was the OTIF. This measurement evaluates if the company was able to deliver the expected product, in the quantity ordered by the customer and at the time expected by the customer. The company treated this value as a binary variable, where if the delivery was successful, the value is one, and if not, the value is zero. Even if only a few units were missing from the order at the time required by the purchaser, that order would be considered as missed, and a value of zero was given to the OTIF.

3.3 The proposed approach

The proposed approach followed a five-fold methodology as seen in table 3.2. In the first step, there was a strong focus on the treatment of the data provided by the company. Afterwards, to gain a more in-depth knowledge of the production and gain on-site insights, some visits to the facilities of the company were required. Then, the data available was identified and studied in order to determine its quality. Finally, opportunities for the successful development of the solution were identified.

The second step concerned modelling the congestion effects, the costs of the change in strategy and the way this change would impact the whole system. Furthermore, in this step, possibilities of the placement of the CODP were considered in order to assess the feasibility of a hybrid MTS/ATO/MTO system.

The third step concerned the optimisation of the strategy partition. The goal was to define the production strategy for each product that minimises the total cost of the system. In this step, some insights into the expected gains of the newly defined strategy were obtained.

The fourth step focused on determining the best forecast technique to predict the forecast of the products set to be under a MTS policy, as well as on establishing the parameters for the replenishment policy.

The final step proposed the development of a decision support system to provide the company with a tool that allows it to perform a new strategy partition whenever required. This tool also allows the company to generate the reorder points and quantities for the products that, based on the monthly forecast, will require stock.

Table 3.2: Proposed approach

Data Treatment	Data request
	Data analysis
	Visit facilities and identify opportunities
System modeling	Identify congestion centers
	Model congestion through queuing systems
	Identify and quantify costs
	Identify impacts of strategy change
Optimization model	Minimize the total cost of the model
	For each scenario and parameters identify the expected gains
	For each SKU define the best production strategy
Forecasting and replenishment policy	Identify the best forecasting technique
	Define replenishment policy
Decision support system	Requirements definition: interfaces and usability
	Programming of the tool
	Automatic data extraction

Chapter 4

Methodology

This chapter addresses the methodology developed for the strategy partition and the implementation of the hybrid production system. The first part, section 4.1, describes the analysis made to identify the bottleneck of the production and the solution opportunities. Section 4.2 formulates the problem according to the insights provided in section 4.1. Section 4.3 describes the heuristic developed in order to solve the formulated problem. Finally, sections 4.4 and 4.5 address the forecasting technique selection and the replenishment policy definition, respectively.

4.1 System analysis

The first task is to fully understand the production processes and the performance of the company, so as to identify the production constraints. This identification process is described in subsection 4.1.1. Then, after the constraints have been identified, the proposed solution model must be developed. Hence, subsection 4.1.2 explains the proposed hybrid model and its reasoning in detail, using the information gathered in the previous section.

4.1.1 Bottleneck identification

Having a holistic vision of the production processes and an understanding of how a company is performing is of paramount importance to identify the best approach to solve the problem. Thus, an analysis should be performed to assess which constraints do not allow the company to meet customer needs. Since the problem faced by the company was the lack of responsiveness to customer orders, we had to investigate why the manufacturing process was taking so long.

So, the first step is to identify the production lead time without any other constraints, only considering the time that the product needs in every stage in order to be produced. The goal of this assessment is to understand if the product can be produced within the required time. If that is not the case, the change of production strategy alone will not be enough to solve the problem. After this study was conducted, it was determined that the time required to manufacture every product was more than enough to cope with the lead times required. Hence, the delays were due to the setups and the existence of congestion effects in some stage of the production process. This, in turn, led to an increment of the production lead time, making it impossible to reach the targeted service level.

The existence of a large number of setups was expected, due to the production strategy in use, and we were able to easily ascertain the number of setups made. However, for the congestion effects, the analysis was not so straightforward. Upon accepting the challenge, we were informed that some stages might be suffering from congestion effects, due to their high occupation rate. Thus, the next step was to identify the production stages that were causing these problems.

Production volatility and limited manufacturing resources inevitably lead to bottlenecks that restrict the maximisation of system throughput (Wang JQ, 2006). Each manufacturing system has bottlenecks that constrain its performance (Lei and Li, 2015), and our case was not an exception to that rule. According to the theory of constraints (TOC), bottlenecks control the circulation of the system, and, consequently, the output rate of bottlenecks determines the output of the system (Watson et al., 2007).

Finding bottlenecks is a difficult task. Furthermore, if the data needed in order to conduct an intensive identification study is lacking, or if the quality of the data is questionable, numerical approaches will not yield excellent results. Instead, they will indicate possible bottlenecks that are far from the real situation. In fact, for such cases, when the data required is not available, according to James F. Cox (1997), the best approach is often to go to the production floor and ask knowledgeable employees what they see as the bottleneck. Another way to identify the bottleneck is through equipment loads and queue lengths of unprocessed jobs in front of each machine.

So, we were able to find the critical production steps by combining the approaches advocated by James F. Cox (1997) and by determining equipment loads and the amount of unprocessed work waiting in each production stage. The vast majority of the employees pointed out that the gluing station was the bottleneck of the system. Because there were only two machines able to carry out this process, and as a result of 60% of the products sold requiring a board that was processed there, this was an expected critical stage. Another critical step identified in the production was the final assembly of products. The analysis showed that this point required a high amount of weekly labouring hours. Furthermore, having products waiting to be assembled was a recurring situation. This step was also identified as a critical stage by the employees that worked in it and also by the ones that worked in the downstream stages.

4.1.2 The model

After identifying the critical stages of the production, we were in a position to develop a strategy selection for each product that tried to reduce the congestion effects in those areas. The proposed methodology tried to classify the production strategy for each product according to one of three strategies: MTO, ATO or MTS. As the first critical stage is the gluing, and this is a differentiation point, since many products share the same board, the idea was to have stock of the intermediate product - the boards. This is an interesting point for the positioning of the CODP, because, from a resource optimisation point of view, it is advantageous to have the bottleneck upstream of the CODP (Olhager, 2003). The goal was to reduce the congestion effects in the gluing by having more extended series with fewer stops for setups. Thus, from that point on, if a product had its board or boards stocked, it could be assembled to order without dealing with the queuing time of the gluing. Hence, the first decision that had to be made was which boards to stock and which boards to only manufacture to order.

As we decreased the congestion effects of the gluing and increased its throughput, the next critical stage, the assembly, became even more critical. Eventually, the assembly might become the new bottleneck of the system. Since almost every product passed through this stage (90% of the products sold), we also had to increase this stage's efficiency. Thence, we also had to increase the production series to reduce the number of setups, by selecting some products to follow a MTS system.

As a result, we modelled two queues to emulate the two critical production stages. Regarding the production strategy, we had to select the boards produced for stock. Furthermore, we had to select the final product production strategy. The product can follow a MTO approach, as was the case then, an ATO approach if the board or boards that the product requires are selected to have stock, and finally, the product can be MTS. It is worth noting that the products that do not go through any of the critical stages are not burdened by any obstacle, because we assume that the other production steps are not under full occupation,. Hence, the production is rapid, reducing the tendency to become MTS or even ATO.

4.2 Strategy partition problem formulation

We developed a nonlinear, integer programming formulation of the problem. Table 4.1 contains all the notation used in the mathematical model. First, the assumptions made to model the problem are stated. Secondly, the modelling of both the gluing and assembly queues are addressed. Afterwards, the costs to consider and the way they are computed are explained. Finally, the mathematical formulation of the problem is concisely stated.

Although our formulation was based on Rajagopalan (2002)'s work, we made some extensions to his model for it to fit our scenario. The main difference was that we considered two queuing systems, sequentially placed, instead of just one, and we also considered the possibility of a product following an ATO policy.

The production orders of both MTS, ATO and MTO were processed according to a first-come-first-served (FCFS) policy. Both the queues considered, the gluing and assembly, were modelled by a M/G/1 approximation. The waiting time distribution resulting from this model had an impact on the total production lead time used to determine the safety stocks for MTS items and the service level for MTO and ATO items. When demand in a period for a MTO item occurred, a production order was initiated for a batch size equal to the demand quantity.

The inventory control and replenishment system for MTS items and boards was represented by an (s,Q) policy. This policy was chosen because, as pointed out by Rajagopalan (2002), it is simple and easy to implement and facilitates the analysis. Moreover, it fit the requirement made by the company.

The developed model, like many others in the literature, relied on some assumptions. Our model was based on the following assumptions:

1. We assumed the demand and production processes to be stationary, uncorrelated over time, and across items.

2. We assumed that the demand of both the boards and the products follow a normal distribution.

3. Given the large number of items, we approximated the arrival rate for the queuing system using a Poisson process, even though this might not be appropriate when the system utilisation and the coefficient of variation in arrivals are high (Ward, 1993).

4. We ignored work-in-process and raw material inventories and costs.

5. We ignored material-handling times and differences across items in processing and material handling times.

6. Setup and processing times were assumed to be deterministic.

7. For MTS items, we specified a type 1 (α) service level (Hopp, 1997) for two reasons. First, because this measure is conservative and is consistent with the company's philosophy. Secondly, because this makes the analysis more tractable as the computation of batch sizes (q_i) and reorder points (or safety stocks) is decoupled.

8. We made all the assumptions that modelling the congestion effects through the queuing theory entail.

9. We only recognised the existence of congestion effects in the two mentioned stages, neglecting the fact that the other stages might also suffer from these effects.

There are N items to be produced and M different boards. The MTS/MTO decision for each item is represented by a binary variable, z_i, with $z_i = 0$ if the item is MTO or ATO and $z_i = 1$ if the item is MTS. For the board decision, the reasoning is the same. The decision is represented by a binary variable, y_j, with $y_j = 0$ if the board is MTO and $y_j = 1$ if the board is MTS. For the cases where $z_i = 0$, in order to identify if a product will follow a MTO or ATO policy, the binary variable x_i is used. For cases where $x_i = 1$ the item will be ATO and otherwise it will be MTO.

Let $\mathcal{C}_i$ be the set of boards of product i, and $\mathcal{P}_j$ be the set of products that require the board j. It is worth noting that, for $\mathcal{C}_i$, in case the product does not require any board, the set will be empty. Having this notation, we can detail how the ATO scenario works.

An item will be MTS if $z_i = 1$, ATO if $z_i = 0$ and $x_i = 1$ and MTO if $z_i = 0$ and $x_i = 0$. To ensure the consistency of the model, and to ensure that a product will only be ATO instead of MTO if all the boards that the product requires are MTS, the model will be subject to:

$$x_i = \begin{cases} \prod_{j \in \mathcal{C}_i} y_j & \text{if } |\mathcal{C}_i| > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

Let μ_i be the expected demand per unit of time for the final product i and σ_i the standard deviation of the demand per unit of time. Even though the demand and standard variation of the boards are correlated to the ones of the products that require the board, for ease of exposition, we will refer to the expected demand of the board j as μ_j and to the standard deviation as σ_j. α_i will denote the setup time at the start of production of item i in the assembly stage and α_j the setup time at the start of the production of board j in the gluing. Similarly, β_i will denote the assembly processing rate of product i and β_j the processing rate of board j at the gluing. Let m_i be the probability of demand being greater than 0 for product i during a unit interval, and m_j the probability for board j.

Finally, for ease of exposition, let's consider both c_i and a_i as binary variables that indicate if the product i goes through the gluing and assembly, respectably. If the product i goes through the gluing, $c_i = 1$, and if it goes through the assembly, $a_i = 1$; otherwise, $c_i = 0$ and $a_i = 0$.

Gluing queue

Let us start by modelling the queue for the first stage, the gluing. The time required for processing a batch of a MTO board is:

$$T_j = \alpha_j + (\mu_j / m_j)/\beta_j \tag{4.2}$$

The average number of setups or batches, λ_j, per unit of time, is simply m_j.

For the cases where the board is MTS, the average number of batches per unit of time is $\lambda_j = \mu_j / Q_j$. The average batch processing time is given by:

$$T_j = \alpha_j + (Q_j / \beta_j) \tag{4.3}$$

Let $\lambda = \sum_j [(\mu_j / Q_j) y_j + m_j (1 - y_j)]$ be the total number of batches to be processed at the gluing stage. The mean service time is given by:

$$\overline{Y} = \mathbb{E}(Y) = \frac{\sum_j \lambda_j T_j}{\lambda} \tag{4.4}$$

and:

$$\mathbb{E}(Y^2) = \frac{\sum_j \lambda_j T_j^2}{\lambda} \tag{4.5}$$

Then, the mean waiting time in the queue in a M/G/1 system is (Galton, 1990):

Table 4.1: Table of Notation

Decision Variables:	
z_i	Binary variable that indicates whether a product i is MTS(1) or MTO/ATO(0)
y_j	Binary variable that indicates whether a board j is MTS(1) or MTO(0)
x_i	Binary variable that indicates whether a product i with $z_i = 0$ is ATO(1) or MTO(0)
Q_i	MTS batch size of product i
Q_j	MTS batch size of board j
Sets:	
N	Set of different products
M	Set of different boards
$\mathcal{C}_i$	Set of boards required by product i
$\mathcal{P}_j$	Set of products that require the board j
$\mathcal{D}_i$	Set of order lines for product i, indexed by m
Auxiliary variables:	
T_j	Time required for processing a batch of the board j
T_i	Time required for assembling a batch of the product i
λ_j	Number of setups per unit of time at the gluing for board j
λ	Total number of setups per unit of time at the gluing
γ_i	Number of setups per unit of time at the assembly for product i
γ	Total number of setups per unit of time at the assembly
Y	Service time at the gluing
W	Queue time at the gluing
Z	Service time at the assembly
A	Queue time at the assembly
$TPLT_j$	Total production lead time of board j
$TPLT_i$	Total production lead time of product i
$TRLT_I$	Total remaining lead time of product i in an ATO strategy
τ_j	Standard deviation of the mean demand during the lead time for board j
τ_i	Standard deviation of the mean demand during the lead time for product i
v_i	Variance of the production lead time of the product i
ss_j	Safety stock of board j
ss_i	Safety stock of product i
IC_j	Inventory cost of board j
IC_i	Inventory cost of product i
WC_j	Warehousing cost of board j
WC_i	Warehousing cost of product i
TDC_{MTO}	Total cost for late deliveries of MTO products
TDC_{ATO}	Total cost for late deliveries of ATO products
TDC_{MTS}	Total cost for late deliveries of MTS products

Parameters:

μ_i	Expected demand per unit of time for the product i
σ_i	Standard deviation of the expected demand per unit of time of product i
μ_j	Expected demand per unit time for the board j
σ_j	Standard deviation of the expected demand per unit of time of board j
m_i	Probability of demand being greater than 0 for product i during a unit interval
m_j	Probability of demand being greater than 0 for board j during a unit interval
α_i	Setup time at the start of production of item i at the assembly stage
α_j	Setup time at the start of production of board j at the gluing stage
β_i	Assembly processing rate of product i
β_j	Processing rate of board j at the gluing
c_i	Binary parameter that indicates whether the product i goes through the gluing, 1, or if not, 0
a_i	Binary parameter that indicates whether the product i is assembled, 1, or if not, 0
PT_j	Total machine production time plus setup times for the board j
PT_i	Total machine production time plus setup times for the product i
TRT_i	Total production time and setups required to finish the product i in an ATO strategy
sl_j	Desired MTS service level for board j
LT_m	Lead time required in order $m \in \mathcal{D}_i : i \in N$
Qt_m	Quantity required in order $m \in \mathcal{D}_i : i \in N$
PM_m	Profit margin of order $m \in \mathcal{D}_i : i \in N$
PC_m	Penalty cost of order $m \in \mathcal{D}_i : i \in N$
h_j	Annual holding cost for board j
h_i	Annual holding cost for product i
WPC	Annual cost of storing a palette
P_j	Number of boards j that fit on one palette
P_i	Number of products i that fit on one palette
LS	Percentage of lost margin
$MaxP$	Maximum number of pallets that can be stored in the warehouse

$$\mathbb{E}(W) = \frac{\lambda E(Y^2)}{2(1-\rho_c)} \tag{4.6}$$

Where the utilisation of the gluing $\rho_c = \sum_j \lambda_j T_j = \sum_j (\alpha_j (z_j \mu_j / Q_j + (1-z_j) m_j) + \mu_j/\beta_j)$ = $\sum_j (\alpha_j \lambda_j + \mu_j/\beta_j)$. Having $\mathbb{E}(Y^3) = \frac{\sum_j \lambda_j T_j^3}{\lambda}$, the variance of the waiting time in the queue is given by:

$$v(W) = \mathbb{E}(W)^2 + \frac{\lambda \mathbb{E}(Y^3)}{3(1-\rho_c)} \tag{4.7}$$

Hence, the parameters of the distribution of the waiting time in the gluing queue can be determined from 4.6 and 4.7. Accordingly, we assume that the distribution will have a mean and variance equal to $\mathbb{E}(W)$ and $v(W)$ and is the same for all boards.

Assembly queue

The modelling of the assembly queue follows the same process as the gluing one. Similarly as before, the time required for processing a batch Q_i of a MTO board is $T_i = \alpha_i + (\mu_i/m_i)/\beta_i$. The average number of setups, γ_i, per unit of time, is simply m_i.

For the cases where the product is MTS, the average number of batches per unit of time is $\gamma_i = \mu_i/Q_i$. The average batch processing time is $T_i = \alpha_i + (Q_i/\beta_i)$. Let $\mathcal{D}$ be the set of products that undergoes the assembly process, and $\gamma = \sum_{i\in\mathcal{D}}(\mu_i/Q_i)y_i + m_i(1-y_i)$ the total number of batches to be processed at the assembly stage. Then, the mean assembly service time is given by:

$$\overline{Z} = \mathbb{E}(Z) = \frac{\sum_{i\in\mathcal{D}}\gamma_i T_i}{\gamma} \tag{4.8}$$

and:

$$\mathbb{E}(Z^2) = \frac{\sum_i \gamma_i T_i^2}{\gamma} \tag{4.9}$$

Then, the mean waiting time in the queue in a M/G/1 system is:

$$\mathbb{E}(A) = \frac{\gamma\mathbb{E}(Z^2)}{2(1-\rho_a)} \tag{4.10}$$

Where the utilisation of the assembly $\rho_a = \sum_{i\in\mathcal{D}}\gamma_i T_i = \sum_{i\in\mathcal{D}}(\alpha_i(y_i\mu_i/Q_i + (1-y_i)m_i) + \mu_i/\beta_i)$ = $\sum_{i\in\mathcal{D}}(\alpha_i\gamma_i + \mu_i/\beta_i)$. Having $\mathbb{E}(Z^3) = \frac{\sum_{i\in\mathcal{D}}\gamma_i T_i^3}{\lambda}$, the variance of the waiting time in the queue is given by:

$$v(A) = \mathbb{E}(A)^2 + \frac{\gamma\mathbb{E}(Z^3)}{3(1-\rho_a)} \tag{4.11}$$

Thus, the parameters of the distribution of the lead time of the assembly stage can be determined from 4.10 and 4.11. Accordingly, we assume that the distribution will have a mean and variance equal to $\mathbb{E}(A)$ and $v(A)$ and is the same for all products.

Costs

Different costs must be considered to build the objective function. On one side, we have the inventory and warehousing costs for the MTS products and boards. The cycle and the safety stock form the total stock held.

Let PT_j and PT_i be the total production time for the boards and products, respectively. These times are given by the sum of the setups required in each production step plus the processing time at each stage of production. Our total production lead time for a board is $TPLT_j = PT_j + \mathbb{E}(W)$ and the variance is $v(W)$. Thus, the mean demand during the lead time for board j is $\mu_j TPLT_j$ and the standard deviation, τ_j, is given by:

$$\tau_j = \sqrt{TPLT_j \sigma_j^2 + v(W)\mu_j^2} \tag{4.12}$$

Then, the safety stock, ss_j, for a certain service level, sl_j, and for the board j, is $ss_j = k_s \tau_j$, where k_s is the inverse of the cumulative standard normal distribution function computed for the given sl_j. Thus, the average inventory level is $\frac{Q_j}{2} + ss_j$. By having h_j as the holding cost of board j, the inventory cost is $IC_j = h_j(\frac{Q_j}{2} + ss_j)$. With WPC as the cost of storing one palette, P_j as the number of boards j that fit on one palette, and $NP_j = \left\lceil \frac{\frac{Q_j}{2}+ss_j}{P_j} \right\rceil$, the warehousing cost for board j is $WC_j = WPC \cdot NP_j$.

For the products, the process is similar. For the MTS products, the total production lead time is dependent on whether the product goes through the assembly process and if it requires a board:

$$TPLT_i = PT_i + \mathbb{E}(W)c_i + \mathbb{E}(A)a_i \tag{4.13}$$

The mean demand during the lead time is $\mu_i TPLT_i$. The standard deviation, τ_i, is also depend on the product requiring a board or needing to be assembled. Thus, the variance of the production time for the product i is $v_i = v(W)c_i + v(A)a_i$. The standard deviation during the lead time is:

$$\tau_i = \sqrt{TPLT_i \sigma_i^2 + v_i \mu_i^2} \tag{4.14}$$

Following the same reasoning as for the boards, the inventory holding cost is given by equation 4.15. The warehousing costs for the final product i can be seen in equation 4.16. Let $ss_i = k_s \tau_i$, where k_s is the inverse of the cumulative standard normal distribution function computed for the given sl_i.

$$IC_i = h_i(\frac{Q_i}{2} + ss_i) \tag{4.15}$$

$$WC_i = WPC \cdot NP_i \tag{4.16}$$

Next, we have to compute the costs related to late deliveries. Upon a late delivery, the company incurs contractual penalty costs for each line of the order placed. For each SKU in an order, an order line will be generated. Thus, if an order from a customer requires three different products, three line orders are generated with the same order id. The penalty cost varies from costumer to costumer, being 0 for the cases where no penalties were defined. Moreover, we also consider a percentage of lost margin, LS, to account for possible lost sales.

Let $\mathcal{D}_i$ be the set of order lines for product i, indexed by m. Then, for each order, m, within the set $\mathcal{D}_i$, we have the required lead time, LT_m, the order quantity, Qt_m, the profit margin, PM_m, and the penalty cost, PC_m.

For a MTO and ATO product, the probability of failing an order is given by the probability of the production lead time being higher than the required lead time. In case the product is MTO, that probability is calculated from a normal distribution with $\mu = TPLT_i$ and variance $v_i = v(W)c_i +$

$v(A)a_i$. So, for the MTO case, the total cost for late deliveries is given by:

$$TDC_{MTO} = \sum_{i \in N} \sum_{m \in \mathcal{D}_i} P(TPLT_i > LT_m)(Qt_m PM_m LS + PC_m)(1 - z_i)(1 - x_i) \tag{4.17}$$

For the ATO products, the total remaining lead time is $TRLT_i = TRT_i + \mathbb{E}(A)a_i$, where TRT_i corresponds to the total production time and setups required to finish the product. The variance of the production time only exists if the product has to go through the assembly stage. Hence, the variance is $v_i = v(A)a_i$. Thus, the total cost for late deliveries of ATO items can be obtained analogously to the MTO case. The total cost is depicted in equation 4.18. Note that, for this case, we have to consider the service level of the boards, because upon receiving an order, there is the possibility of having no boards available for production. In such a case, the probability of late delivery is considered to be equal to 1.

$$TDC_{ATO} = \sum_{i \in N} \sum_{m \in \mathcal{D}_i} [P(TRLT_i > LT_m) \cdot \prod_{j \in \mathcal{C}_i} sl_j + (1 - \prod_{j \in \mathcal{C}_i} sl_j)]\,(Qt_m PM_m LS + PC_m)(1 - z_i)x_i \tag{4.18}$$

Finally, for the cases where the product is MTS, the probability of failing an order is equal to one minus the defined service level for that product. Accordingly, we can define the total cost of late delivery as in equation 4.19.

$$TDC_{MTS} = \sum_{i \in N} \sum_{m \in \mathcal{D}_i} (1 - sl_i)(Qt_m PM_m LS + PC_m)z_i \tag{4.19}$$

Optimization

Having formulated and defined all costs involved and how the dynamism of the queue systems affects them, the objective is to minimise the total cost of the system.

$$\text{Minimise} \quad TCS = \sum_{j \in M} (IC_j + WC_j)y_j + \sum_{i \in N} (IC_i + WC_i)z_i + TDC_{MTO} + TDC_{ATO} + TDC_{MTS} \tag{4.20}$$

Besides being subject to restrictions (4.1), (4.6), (4.7), (4.10), (4.11), the system also has limited storage space in the warehouse. Let $MaxP$ be the maximum number of pallets that can be stored. We have the system subject to:

$$\sum_{j \in M} NP_j y_j + \sum_{i \in N} NP_i z_i \leq MaxP \tag{4.21}$$

$$Q_i \geq 0, \ \forall i \in N \tag{4.22}$$

$$Q_j \geq 0, \ \forall j \in M \tag{4.23}$$

$$Q_j \text{ and } Q_i \ \in \mathbb{N} \tag{4.24}$$

4.3 Heuristic

The problem in question is difficult to solve because it is a mixed-integer nonlinear program. So, for the instances we have, it can be impossible to reach the optimal solution within a useful time. Mixed-integer nonlinear problems are hard to solve because they are not generally convex (Michalewicz, 2010). For these cases, a heuristic or a metaheuristic yields good solutions in a much shorter period of time.

The heuristic proposed to solve the problem is divided into two main steps and follows a greedy approach, similarly to a greedy heuristic solution of the knapsack problem (KP). Firstly, it decides the production strategy for the boards between MTS and MTO. Secondly, it addresses the strategy partition for the products. Each of the stages of the heuristic will be explained separately.

Ideally, the batch sizes for both the boards, Q_j, and the products, Q_i, should be optimised to minimise the overall cost of the system between each iteration of the heuristic, in the first or second step. Since this would jeopardise the advantages of using a heuristic, a compromise was made. To determine the batch sizes, we used an Economic-order-quantity (EOQ) proxy. As for the setup cost, C_{setup}, the profit lost due to products not being produced during the setup times per period of time was used. Thus, the EOQ formula used to determine the lot size can be depicted in equation 4.25, where C is the price of the board or product. At this point, it is important to mention that the unit of time used was a week. Therefore, since the EOQ is calculated for the yearly demand, we multiplied the weekly demand, μ, by 52 weeks in order to get the annual demand.

$$Q = \sqrt{\frac{2 \cdot \mu \cdot 52 \cdot \alpha \cdot C_{setup}}{C \cdot h}} \tag{4.25}$$

Boards strategy partition

Since holding an excessive stock is an issue, we put a cap on the maximum batch size. A parameter defined as *Coverage*, that sets the maximum batch size to $Coverage \cdot \mu_j$, was applied. We can determine the batch size for each board, j, through equation 4.27, where the determination of the setup cost at the gluing, C^c_{setup}, is obtained in equation 4.26. Having that, the $AvgProfit_j$ corresponds to the average profit of all $i \in \mathcal{P}_j$ obtained for each j.

$$C^c_{setup} = \frac{\sum_{j \in M} (AvgProfit_j \cdot \beta_j) \mu_j}{\sum_{j \in M} \mu_j} \tag{4.26}$$

$$Q_j = \max\left(Coverage \cdot \mu_j \, , \sqrt{\frac{2 \cdot \mu_j \cdot 52 \cdot \alpha_j \cdot C^c_{setup}}{C_j \cdot h_j}}\right) \tag{4.27}$$

Note that if Q_j is such that $\frac{\mu_j}{Q_j} \geq m_j$, the number of expected setups will be higher than if the board stayed MTO. In those cases, it is preferable to still make it to order, since less capacity will be used and no inventory costs will be incurred. Thus, for any board that violates this condition, the possibility of changing its strategy from MTO to MTS will not be considered.

We have to determine the costs involved in the strategy change for each board, to rank them and proceed to greedily change the strategy of such boards, as in some greedy strategies used to solve the KP. In the board decision, we assume that by changing the strategy from MTO to MTS we will incur inventory and storage costs for that board, but all the products that require it will pass from MTO to ATO, thus reducing their total production lead time and reducing the tardiness costs. With the help of the auxiliary binary variable, $z_{i,j}$, we can determine which products, i, should be considered in the tardiness costs of board j. The approach to determine the value of $z_{i,j}$ can be depicted in the system 4.28. Here, if the product requires only the board, j, considered, it shall be contemplated in the tardiness. Otherwise, it shall only be considered if all the other boards that the product requires are already selected to follow a MTS approach. The total cost for late deliveries for a board, $Tard_{cost_j}^{y_j=0}$, when the production strategy is MTO ($y_j = 0$), can be deduced as shown in equation 4.29. The total cost of late deliveries for a board, $Tard_{cost_j}^{y_j=i}$, when the production strategy is MTS ($y_j = 1$), can be deduced as shown in equation 4.30. Thus, equation 4.31 shows the expected gain of changing the production strategy of board j from MTO to MTS.

$$z_{i,j} = \begin{cases} \prod y_k \quad ,k \in \mathcal{C}_i \backslash \{j\} & \text{if } |\mathcal{C}_i \backslash \{j\}| > 0 \\ 1 & \text{otherwise} \end{cases} \tag{4.28}$$

$$Tard_{cost_j}^{y_j=0} = \sum_{i \in \mathcal{P}_j} \sum_{m \in \mathcal{D}_i} P(TPLT_i > LT_m)(Qt_m PM_m LS + PC_m) \tag{4.29}$$

$$Tard_{cost_j}^{y_j=1} = \sum_{i \in \mathcal{P}_j} z_{i,j} \sum_{m \in \mathcal{D}_i} P(TRLT_i > LT_m)(Qt_m PM_m LS + PC_m) \tag{4.30}$$

$$E_{Gain_j} = Tard_{cost_j}^{y_j=0} - Tard_{cost_j}^{y_j=1} - ICj - WCj \tag{4.31}$$

Since we have to respect the space restriction, 4.21, as in the KP solution, we shall choose to change the strategy firstly for the boards that present the higher ratio between expected gain and warehouse space occupation. The ratio is given by $\phi_j = \frac{E_{Gain_j}}{NP_j}$.

Algorithm 1 provides the pseudocode of the first step of the heuristic. The first thing to do is to initialise the system with $z_i = 0 \ \forall i \in N$, $x_i = 0 \ \forall i \in N$, $y_j = 0 \ \forall j \in M$ and determine the batch sizes for all the j boards (line 1). Afterwards, the queue performance measures should be estimated, and consequently, the cost of late delivery for each $m \in \mathcal{D}_i$,$\forall i \in N$, should be determined. The step described in line 2 is completed upon the calculation of $\phi_j \ \ \forall j \in M$.

The optimal total cost of the system, C_{opt}, is set as the current cost of the system, provided by 4.20 (line3). Since all the boards in this stage are MTO, the initial cost is only due to tardiness. Next, we set the available space, $P_{available}$, as the $MaxP$ (line 4).

Let $\mathcal{G}$ be the set of boards where $y_j = 0$, $\frac{\mu_j}{Q_j} < m_j$, $\phi_j > 0$ and $NP_j < P_{available}$. The steps in lines 5 and 19 are the same. This command leads to an update of the set $\mathcal{G}$ in order to respect the restrictions.

Thus, while set $\mathcal{G}$ is not empty, and while we have not reached the space limitation or gotten a total cost superior to the current best, we keep picking the board from the set $\mathcal{G}$ with the highest ϕ_j

and changing that board's strategy to MTO (lines 7-9). We then recalculate the queues and costs, similarly to line 2, and get the new total cost of the system (lines 10-11). In case the new cost is higher than the current best cost, we reverse the strategy change for the same board and set the flag to false in order to stop the cycle (lines 12-15). Otherwise, the new best cost, C_{best}, will be equal to the current total cost of the system (line 17). Then, we have to update the remaining space to store palettes (line 18). The final step before proceeding to another iteration is to update the set $\mathcal{G}$.

1 Initialise system
2 Calculate queues and costs
3 $C_{best} \leftarrow TCS$
4 $P_{available} \leftarrow$ MaxP
5 Update $\mathcal{G}$
6 $Flag \leftarrow true$
7 **while** $|\mathcal{G}| > 0$ ***And*** $Flag{=}true$ **do**
8     $j \leftarrow \text{argmax}_{j\in\mathcal{G}} \quad \phi_j$
9     $y_j \leftarrow 1$
10   Recalculate queues average size and costs
11     $C \leftarrow TCT$
12   **if** $C > C_{best}$ **then**
13         $y_j \leftarrow 0$
14   Recalculate queues average size and costs
15         $Flag \leftarrow false$
16   **else**
17         $C_{best} \leftarrow C$
18         $P_{available} \leftarrow P_{available} - NP_j$
19   Update $\mathcal{G}$
20   **end**
21 **end**

Algorithm 1: Strategy decision for the boards

Products strategy partition

This step follows the same methodology as the first one, with some slight changes. First, we compute the setup cost at the assembly, C^a_{setup}. Here, instead of having $AvgProfit_j$, we have $Profit_i$, which corresponds to the profit of product i. Thus, C^a_{setup} is obtained through equation 4.32 and the batch size of product i, Q_i, by equation 4.33.

$$C^a_{setup} = \frac{\sum_{i\in N}(Profit_i \cdot \beta_i)\mu_i}{\sum_{i\in N}\mu_i} \tag{4.32}$$

$$Q_i = max(Coverage \cdot \mu_i\, ,\, \sqrt{\frac{2\cdot\mu_i\cdot 52\cdot\alpha_i\cdot C^a_{setup}}{C_i\cdot h_i}}\,) \tag{4.33}$$

Similarly to the first step, we also have to define the expected gain of changing strategy for each product. Upon changing the strategy from MTO to MTS, we will incur inventory and storage costs with the intent of increasing the service level, since we will already have the product ready to fulfil the demand. Then, if the product requires boards, and if all required boards are MTS, the product will follow an ATO strategy instead of a MTO one. To check if the product i follows either a MTO or ATO strategy, we have to compute the variable $x_i \ \forall i \in N$ using 4.34. Thus, the expected gain from the strategy change for product i, E_{Gain_i}, is determined as observed in 4.35. The tardiness costs if $z_i = 0$, $Tard_{cost_i}^{z_i=0}$, are given by 4.36. It should be noted that the probability of failing the delivery depends on the value of x_i. The tardiness costs if $z_i = 1$, $Tard_{cost_i}^{z_i=1}$, can be observed in 4.37.

$$x_i = \prod_{j \in \mathcal{C}_i} y_j \tag{4.34}$$

$$E_{Gain_i} = Tard_{cost}^{z_i=0} \ - \ Tard_{cost}^{z_i=1} - IC_i - WC_i \tag{4.35}$$

$$Tard_{cost_i}^{z_i=0} = \sum_{m \in \mathcal{D}_i} [P(TPLT_i > LT_m)(1 - x_i) + P(TRLT_i > LT_m)x_i](Qt_m PM_m LS + PC_m) \tag{4.36}$$

$$Tard_{cost_i}^{z_i=1} = \sum_{m \in \mathcal{D}_i} (1 - ss_i)(Qt_m PM_m LS + PC_m) \tag{4.37}$$

In this step, the space restriction must also be verified. So, to change the strategy, we first pick the product that yields the highest $\phi_i = \frac{E_{Gain_i}}{NP_i}$

Algorithm 2 provides the pseudocode of the second step of the greedy heuristic. Since this step will follow immediately after the first one, we start by computing the values of x_i for all the products (line 1). It should be noted that C_{opt} and $P_{available}$ have the same values as the ones they had upon finishing algorithm 1.

Let $\mathcal{T}$ be the set of products i where $z_i = 0$, $\frac{\mu_i}{Q_i} < m_i$, $\phi_i > 0$ and $NP_i < P_{available}$. The steps in lines 3 and 17 are the same. This command leads to an update of the set $\mathcal{T}$ in order to respect the restrictions. Afterwards, we need to compute the production batch sizes for all products (line 2).

While set $\mathcal{T}$ is not empty, and while we have not reached the space limitation or gotten a total cost superior to the current best, we keep picking the product i from the set $\mathcal{T}$ with the highest ϕ_i and change the strategy of that product (lines 5-7). Afterwards, we calculate the queue parameters and costs and get the new total cost of the system (lines 8-9). If the new cost is higher than the current optimal cost, we reverse the strategy change and set the flag to false to stop the cycle (lines 10-13). Otherwise, the new best cost, C_{best}, will be equal to the current total cost of the system (line 15). Then, we have to update the remaining space to store palettes (line 16). The final step before proceeding to another iteration is to update the set $\mathcal{G}$ (line 17).

Calculate $x_i \quad \forall i \in N$
Calculate $Q_i \quad \forall i \in N$
Update $\mathcal{T}$
$Flag \leftarrow true$
while $|\mathcal{T}| > 0$ ***And*** *Flag=true* **do**
    $j \leftarrow \text{argmax}_{i \in \mathcal{T}} \quad \phi_i$
    $z_i \leftarrow 1$
    Recalculate the queue's average size and cost
    $C \leftarrow TCT$
    if $C > C_{best}$ **then**
        $z_i \leftarrow 0$
        Recalculate the queue's average size and cost
        $Flag \leftarrow false$
    else
        $C_{best} \leftarrow C$
        $P_{available} \leftarrow P_{available} - NP_i$
        Update $\mathcal{T}$
    end
end

Algorithm 2: Strategy decision for the products

4.4 Demand forecasting

Having defined the MTS/MTO partition for both the boards and final products, the next step is to determine the best forecast technique to predict future demands and help in stock management.

We picked a monthly window of forecast due to two reasons. First, the weekly variance for almost all MTS products and boards is too high, leading to poor forecast predictions. Secondly, since the production lead time is high, it would not be logical to produce to stock on a weekly basis, since the entire goal is to increase the length of the production series while avoiding the setups required in frequent productions.

Some of the traditional methods with different levels of aggregation and desegregation criteria were compared, optimising them to get the best parameters. After some careful analysis of the sales, it was determined that we should analyse the following techniques:

1. Naïve method
2. Average of the three homologous months from the previous year
3. Moving average
4. Exponential smoothing
5. Moving average, one year with seasonality factor

6. Exponential smoothing with seasonality factor

We studied each method regarding both the forecast of the boards and the products, even though their demand is correlated. Regarding the level of aggregation, we studied the performance of each method with no aggregation, with aggregation to the pre-extension and finally with the aggregation at the family level.

The mean absolute percentual error (MAPE) (4.38) of the forecast was used as a metric of evaluation in order to determine forecast accuracy. To estimate the bias, the elected metric was the mean percentage error (MPE) (4.39).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|EP_t| \tag{4.38}$$

$$MPE = \frac{1}{n}\sum_{t=1}^{n}EP_t \tag{4.39}$$

The first technique is very straightforward. With this method, the forecast is simply set to its value from the homologous month of the previous year. Although this method might seem too simplistic, sometimes, if the demand pattern does not present a clear trend or seasonality and if the demand does not fluctuate too much, it might yield good results without requiring too much effort.

The second technique, the average from the three homologous months of the previous year, is a combination of a moving average with the Naïve method. The idea is to make the forecast of the next month equal to the average of the same month from the previous year and its two adjacent months (month before and month after). With this method, the goal is to capture the seasonality in the period right before and after the month, as well as a small trend in that period.

To try to capture the trend of sales, the moving average for one year was used. This method is self-explanatory, basically consisting in calculating the average of the prior twelve months to predict the following one.

We also tested the exponential smoothing technique as the more elaborate method capable of identifying the trend and seasonality. The goal was to have a method that does not put the same weight on past occurrences.

Moreover, we also tested the exponential smoothing without seasonality and the yearly moving average with a seasonal correctional factor on the two peaks experienced by the company.

Finally, the forecast should be validated by a sales manager. This aspect is very relevant in our case, because by operating in a B2B environment, sometimes the company has advanced visibility of the needs of the customers that the forecast model cannot predict. Other times, the company has new contracts or knows about customers that are having troubles with their businesses. Hence, by adding this validation level, the forecast accuracy is expected to increase. In fact, as supported by Tan (2008) and Rekik et al. (2017), enriching the forecasts with managerial information by adjusting the expected demand forecast according to the managers might lead to significant improvements in forecast accuracy.

The detailed explanation of how the data analysis was conducted and the accuracy results for each method will be described in the next chapter.

4.5 Replenishment policy

It was proposed to the company that a periodic (R,s,S) replenishment policy should be followed, where R is the review period, s is the reorder level and S the reorder quantity. So, at every period, if the inventory level is below the reorder level, a production order of quantity S is placed. This policy choice is due to two main factors. First and foremost, for ease of implementation on the enterprise resource planning (ERP) of the company, it was desirable to have the reorder point and reorder quantity for each MTS product and board to input as parameters in the software. Secondly, since the production plan is made weekly, there would not be any gain from having a continuous replenishment policy. Thus, the proposed policy has a weekly periodic review, and the reorder parameter is updated monthly according to the new forecasts. Given that the demand is stochastic and is highly variable, a constant value of s would imply a significant loss of warehouse space and excess of stock.

For that reason, the reorder point (s) is determined every month, and the reorder quantity (S) is the same as the one estimated for the batch sizes Q_j and Q_i. The reorder level is given by the sum of the safety stock and the cycle stock. The cycle stock is determined as the expected forecast demand during the protection period, where the protection period is equal to the production lead time of the product or plan plus the review period.

The safety stock policy is based on the assumption that a business has stochastic demand and lead time. Thus, a model that incorporates demand and lead time variability should be used. Such a model is widely used, and its formula can be observed in 4.42, as seen in Talluri (2004). Where L is the protection period, and it is equal to the $TPLT_i$ or $TPLT_j$ plus the review period. The R_L is the demand during the protection period, σ_L is the demand variance in the protection period, σ_R is the standard deviation of the demand, and s_L is the standard deviation of the total production lead time. Finally, $F_s^{-1}(CSL)$ is the inverse of the cumulative normal distribution for the desired safety level.

$$R_L = RL \tag{4.40}$$

$$\sigma_L = \sqrt{\sigma_R^2 L + R_L^2 s_L^2} \tag{4.41}$$

$$SS = F_s^{-1}(CSL)\sigma_L \tag{4.42}$$

Since we have our forecast, we can apply the formula mentioned above. However, instead of using the standard approach, we will use the forecast error in the variance calculation, as advocated by Zinn (1990). With the application of this procedure, the objective is to minimise the safety stock, since the variance of the forecast errors will be inferior to the demand variance.

This approach can be easily generalised and simplified if a normal distribution of the errors is considered. Such assumption should be verified by performing hypothesis tests to the expected value of the errors, the normality of the errors and the correlation between errors.

All the developed solutions where implemented in a DSS tool that can be seen in appendix A. In that appendix, both the tools requirements, interfaces, and functionality are explained.

Chapter 5

Experimental results

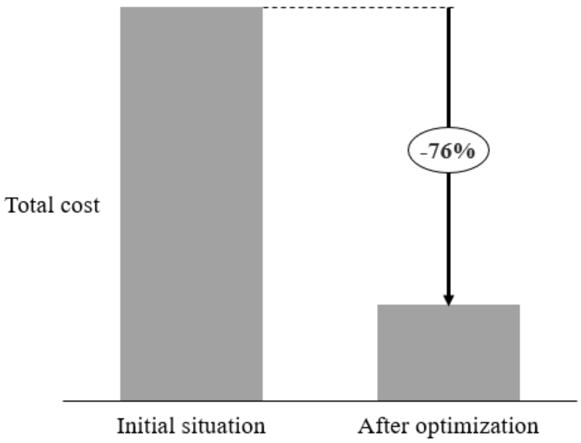
At the time this study was completed, the strategy redefinition was yet to be implemented. Accordingly, all results presented concern experimental results obtained by the model and sensitivity analysis. Therefore, this chapter shows the computational results and expectations from applying the methodology defined in the previous chapter. The results were obtained through the developed DSS tool showcased in appendix A. Section 5.1 presents the results and cost expectations of applying the methodology. Finally, section 5.2 shows the results of the comparison between forecasting techniques.

5.1 Strategy partition results

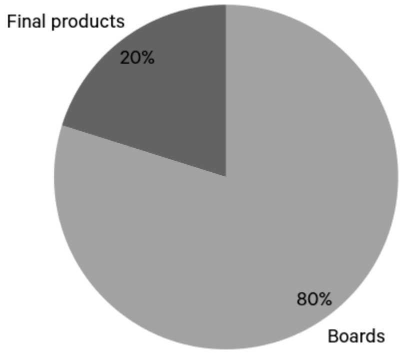
As can be seen in figure 1.1, at the end of the dissertation, the project had not yet been finished. Therefore, it is only possible to present preliminary results provided by the developed model.

A decrease of nearly 76% in the total costs is expected with the use of the optimised solution. This percentage concerns the total cost of the system, given by expression 4.15, before optimising the strategy partition, i.e. by having a 100% MTO production system. This can be seen in figure 5.1(a). Concerning inventory and storage costs, the boards represent 80% of the costs (figure 5.1(b)).

After running the heuristic, we got the partition for the boards and the final products according to table 5.1. It can be concluded that it is more advantageous to have a higher percentage of boards than final products. This is not unexpected because the gluing was the more congested centre of the two modelled queues. As expected, the products selected to follow a MTO production strategy are the ones with the highest demand and only 2% of the products are responsible for 12% of the sales. The weight of the selected boards on sales is also really impressive, as 52% of the sales are due to products that require the boards considered to change the strategy. Once again, we can see the advantages of having an ATO strategy. Furthermore, the boards set to change the manufacturing strategy have a significant impact on the gluing, which makes sense since the goal is to decrease the number of setups. The future MTS broads represent 37% of the gluing occupation. Similarly, the MTS products have an impact of 9% on the assembly.



(a) Total cost comparison



(b) Comparison of inventory and storage costs of boards versus final products

Figure 5.1: Analysis of system costs

Table 5.1: MTS partition of the boards and products

MTS:	Boards	Final products
Weight on the range of boards/products	21%	2%
Weight on sales	52%	12%
Weigh on the critical stage	37%	9%
	Gluing	Assembly

The system goes from a 100% MTO strategy to a 77% MTO, 21% ATO and 2% MTS hybrid strategy. As a sanity check, it can be seen, in figure 5.2, that as expected, the partition makes sense as the MTS products are the ones with higher and more frequent demand, less demand frequency and shorter required lead times. The ATO items may present somewhat of a surprise since for some metrics they do not seem as suitable for that strategy as the MTO. However, there is an explanation for the unexpected results. All the products that require the boards will benefit from the fact that the boards are MTS. Thus, even though products with minimal demands will not have a significant individual impact on the strategy change of a board, they might benefit from the change. Since other products have a significant weight on the costs, which leads to the change of the board manufacturing strategy, products with weak MTS potential will be ATO. Sometimes, when many products with small demand require the same board, the sum of all the demands will have a significant weight on the cost, leading to a change of the board production strategy.

The preliminary results can be observed in table 5.2. The service level, concerning quantity, has an expected increase of 15 percentage points. If we compare the increase of service level in terms of value, which is what we are trying to optimise, since it is correlated to the loss margin and penalties, the gains are even higher, more specifically 38 percentage points. As a consequence, a reduction of about 58% in the penalty costs is expected. Furthermore, the weekly number of batches is expected to decrease by 37% at the gluing and by 8% at the assembly. With the reduction

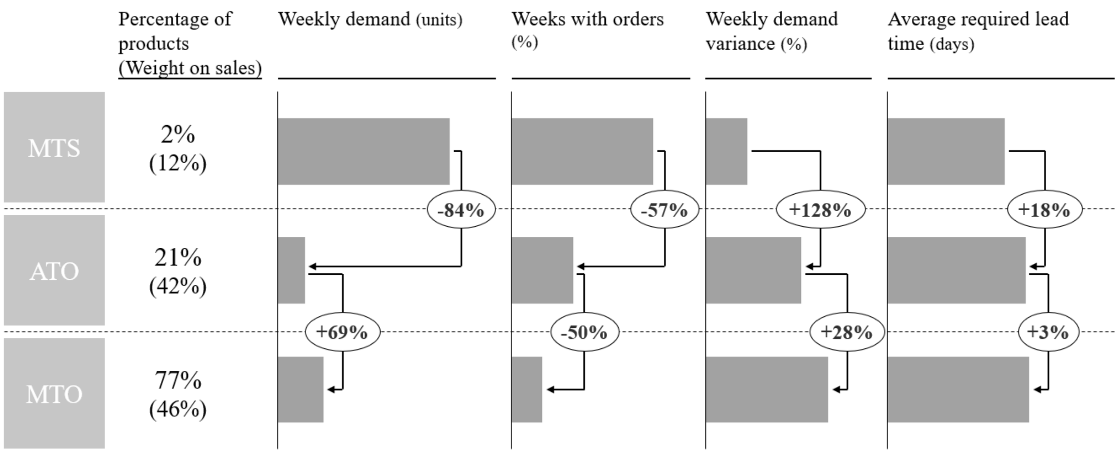


Figure 5.2: Comparison between MTS, ATO and MTO prodcuts

in the number of batches, the occupation at the gluing is expected to decrease by 15 percentage points and the occupation of the assembly by 5 percentage points.

Table 5.2: Changes to some indicators after optimisation

Indicator	**Change**
Service level in quantity	60 pp
Service level in value	65 pp
Penalty costs	-80%
Number of batches processed at the gluing	-37%
Number of batches processed at the assembly	-8%
Occupation of the gluing	-15 pp
Occupation of the assembly	-5 pp

An important point to analyse is how close the initial situation of the model is in comparison to the actual scenario. Here, we have an initial positive validation, as the initial service level estimated by the model only differs by 2 percentage points from the real-life scenario.

An important aspect to bear in mind is that the final output of the optimisation is highly dependent on the parameters set. For example, the desired service level for both the boards and the products was set by the company; however, a change in these parameters will lead to a different solution and, inherently, different gains and costs. Another parameter that plays a major role in the solution given is the percentage of loss margin. A sensibility analysis of this parameter can be observed in figure 5.3. As expected, as the percentage increases, the total cost of stock held also increases, since the service level gains more weight on the total cost than the inventory and storage costs, leading to more products becoming MTS and ATO. As expected, as the percentage of the lost sales margin increases, the delay in the orders also decreases, at the expense of incurring more inventory and storage costs.

Finally, it should be stated that, even though the primary goal of the company is to increase its OTIF, since it calculates it as a binary variable, our estimation would not be a good comparison,

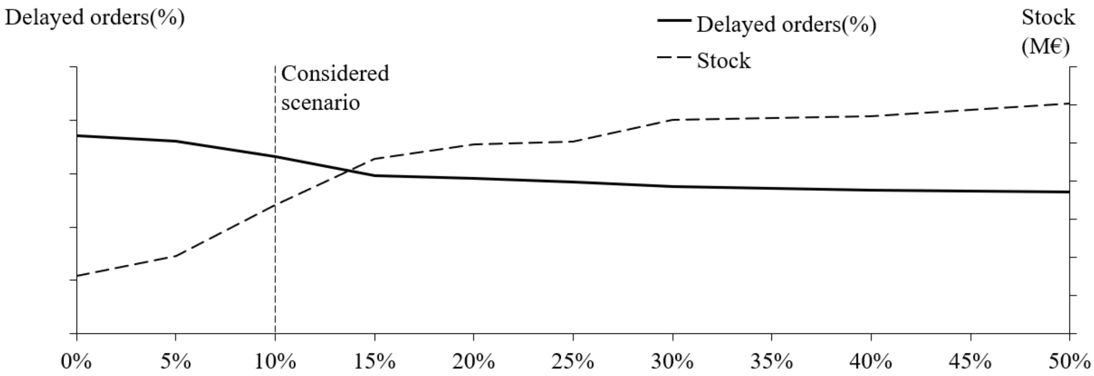


Figure 5.3: Percentage of the lost sales margin considered

because our model is based on continuous probabilities for each different SKU of each order. Accordingly, the best metric to assess the expected improvement is the service level, because it allows for a straightforward comparison. Furthermore, by increasing the service level, the OTIF also inevitably increases, though it is not a direct relation.

5.2 Demand forecast

The main conclusions from the comparison between the forecasting techniques can be observed in figure 5.3 (for the boards comparison) and in figure 5.4(for the final products).

As we can see, the best method for predicting boards' demand is using the simplistic moving average for a time window of twelve months. For predicting final product demand, the best option is using the moving average with a seasonality factor correction including an aggregation to the pre-extension.

Table 5.3: Forecast MAPE for the boards demand

Aggregation:	Naïve method	Avg 3 homologous months	Moving average	Exponential smoothing	Moving Average + Seasonality	Exponential Smoothing + Seasonality
Boards	17.7%	19.6%	17.1%	19.7%	18.2%	18.6%

The seasonality effect correction factor added to the moving average and exponential smoothing was determined by studying the sales data from the previous three years. Even though a clear seasonality was not detected, there were two months that periodically presented a value considerably below average and another month that presented a value systematically above average. The idea of considering the seasonal correction factor of both the moving average and exponential smoothing resulted from this observation.

The desegregation criteria for both the family and pre-extension was the same. The idea is to use the data from the six months before the forecast to determine the weight of the final product

Table 5.4: Forecast MAPE for the final product demand

Aggregation:	Naïve method	Avg 3 homologous months	Moving average	Exponential smoothing	Moving Average + Seasonality	Exponential Smoothing + Seasonality
Final Product	26.8%	27.8%	30.1%	30.3%	28.8%	29.9%
Pre- -Extension	32.9%	28.1%	31.0%	29.0%	24.6%	25.2%
Family	34.0%	32.0%	32.3%	31.0%	28.0%	28.6%

on the sales of the family and pre-extension, respectively. Then, we multiply that factor by the aggregated forecast to get the individual product forecast.

The selected time frame was six months, since it was the time frame that presented the best results. This is because there are no seasonality effects among products within families and pre-extensions. Thus, the most important thing to capture is the trend of a product within its respective family and/or pre-extension. A six months period presented the best compromise of capturing the trend of the product without being too reactive, which was the case if the period was shorter.

Chapter 6

Conclusions and future work

The work carried out intended to redefine the production strategy of a company from make-to-order to a mixed make-to-order, assemble-to-order, and make-to-stock strategy. The goal was to propose and develop a methodology that would then be implemented in a decision support system to help the company perform the strategy change by defining the ideal production policy for each product. Another goal was to help with the stock management required due to the production strategy change. The change was motivated by the poor delivery performance of the company, which was jeopardising its position in the market and its ability to continue to grow and increase sales.

The current state of the art in the hybrid production strategy, more specifically the decision partition part, is not very vast, and only a few restrict papers have addressed such topics. Among them, they share something in common: they all make many assumptions to relax some of the real-life constraints, which makes the novel approaches not so suitable for different scenarios of production environments. Thus, a tailor-made solution capable of addressing the specifications of this company's production environment and characteristics was required.

The methodology developed proposes changing from a MTO production to a hybrid MTS, ATO, MTO production strategy. Through the application of the hierarchical heuristic developed to solve the problem, it is possible to select the best production strategy for the intermediate products, the boards, and afterwards, the best production strategy for the final products.

According to some experimental results, the proposed approach is expected to produce good results. Even though we have yet to see the practical results of the strategy change, the comparison of the model costs of the initial solution, 100% MTO, and the final solution, 77% MTO, leads us to believe that a 76% reduction in the total cost can be achieved. An increase in the service level of 60 percentual pints in quantity and 65 percentual points in value can also be expected. So, the expected results show that the goals of the work will be accomplished. The increase in service level will mean that the company will drastically increase its delivery performance, allowing it to be more competitive and accept more orders.

By using the developed tool, the company will have full autonomy to redefine the strategy and be able to cope with market changes such as the introduction of new products, seasonal demands of specific products, products at the end of their life span, and so on. Moreover, the company will be able to determine the reorder level and reorder quantity, based on the demand forecast, for every MTS product and board. This will allow the company to efficiently manage its inventory.

This work is expected to have a significant impact on the future growth of the company, providing it with the tools needed to redefine the strategy and manage its inventory autonomously. Besides the relevance of this work regarding the company, the work also constitutes another point of view to address problems of strategy redefinition and application of hybrid production strategies. By providing a systematic approach, this work proposes a strategy for an environment that has not yet been seen in the literature. Thus, it is helpful for anyone that might want to do the same in a similar setting. Furthermore, even though the production environment might not be similar, the solution approach might be followed to create a better methodology for other hybrid production implementation problems.

Despite the expected gains that this solution will bring to the company, this approach, as many others in the literature, is not without its faults. First, even though the model is based on the actual production, it relies on numerous assumptions that try to relax some real constraints in order to be able to model the problem. So, theoretically, the ideal scenario would have been to model the entire production as a simulation model of the real production environment. Secondly, the heuristic is not perfect. Due to its hierarchical nature, by separating the decision process between the boards and the final products, the system has no visibility of the solution as a whole. This ultimately leads to some boards being classified with a manufacturing policy that, even though at the moment of its choice was the best, will not correspond to the best strategy in the end.

Therefore, in order to overcome some of the acknowledged shortcomings, we will offer some recommendations for future work. To overcome the drawbacks of the heuristic and gravitate towards an even better solution, a metaheuristic should be applied using as an initial solution the solution provided by the heuristic described in this work.

To address the model constraints, the production environment can be developed in a simulation program to mimic the real production. If the resources and data needed to carry out such an endeavour are available, a simulation optimisation approach can be undertaken. The goal is to optimise an objective function subject to constraints, both of which can be evaluated through stochastic simulation. Although approaches such as this to a problem similar to the one addressed in the dissertation have not be found, it will be a perfect candidate for this solution approach and might yield excellent results, as it will be as close as possible to the real scenario.

Additionally, the use of advanced demand information can be taken into account to improve forecast accuracy, which in turn will lead to a reduction in the safety stocks required for the same service level. Moreover, the location of the CODP could also be further studied to make sure that its locations is the best one for each product.

Finally, it is important to mention that this area of study is still quite unexplored, but extremely pertinent, now more than ever. With markets growing at a fast pace and with the increase in online business, the demands that production companies face are very dynamic and can change dramatically in a heartbeat. Accordingly, always sticking to the same production strategy and opposing a hybrid and reactive solution might lead some companies to be unsuccessful. It is our hope that this work succeeds in showing the enormous impact that such a manufacturing strategy change can have on a company, which in turn might encourage new developments and studies in this field.

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Appendix A

Decision support system tool

From the beginning of the project, the deliverable of the project was a decision support system to be used by the company to help with the strategy partition and the necessary auxiliary modules, forecast and inventory management.

According to Marek J. Druzdzel (2009), decision support systems are defined as computer-based systems that aid the users in judgment and choice activities. Its acceptance is more substantial when the available information is exorbitant for the human analysis, and when accuracy and optimality are required.

In the current project, the amount of data that had to be treated is considerable and requires an appreciable amount of processing and analysis capacity. So, the tool must be able to cope with that. The tool was developed using MS Excel®.

The present chapter is organized as follows. In section A.1, the customer's requirements to be included in the DSS are declared. In section A.2, the architecture and functionality of the DSS is detailed as well as the approach taken in his development

A.1 Requirements

To develop the model into a tool to be used by the people that will have to plan the production and manage the inventory position, understanding the requirements required by the company is the first step. While some requirements of the DSS were stated as crucial at the beginning of the project, the functionality requirements were iteratively drawn during the development of the tool.

A first requirement is related to the fact that the company wanted the decision support system tool in a software that they already had, where the people that will have to interact with it are familiarized with. Thus, the selected software was MS Excel®. Even though it might be not the fastest software for optimization problems, specially for big sets, the performance in terms of running time is not the principal concern since the strategy partition is not planned to be performed often. Thus, the firm sacrifices some potential performance gains for having the tool developed in an environment that they are already acquainted.

Some of the most important requirements gathered until the moment of the dissertation writing were:

1. Develop tool in MS Excel®

2. Intuitive interface.

3. Ability to change model parameters.

4. Easy integration of new data.

5. Output of strategy partition must be a list of products and boards.
6. Capability of manually override the strategy partition for some specific products and/or boards.
7. Possibility of adjusting the forecast.
8. Output of the inventory management must be the reorder level and reorder quantity for facilitating the integration with the MRP.

A.2 DSS architecture

The architecture of the DSS is organized into three major modules. The first module corresponds to the strategy partition. The second module is the forecast module. The last module is to deal with the replenishment policy. The optimization part was developed in VBA within MS Excel®. The input and output will also be MS Excel® files. The DSS tool follows a logic of having an interface in which the user can interact with its modules. Then, the optimization is called using the information and parameters provided. After the optimization is finished, the outcome can be observed by the user. This logic is exhibited in figure A.1.

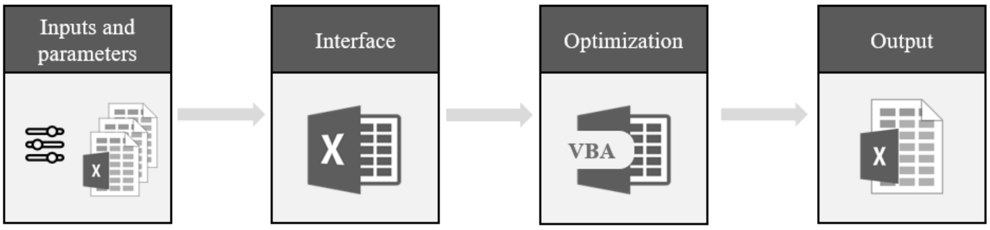

Figure A.1: DSS Architecture

Interfaces

The application starts with a home page that works as the main interface of the application. As seen in figure A.2 the three major modules are grouped. The first step will be to import the data required to perform the strategy partition optimization. Afterward, the parameters for the model must be set according to the desired specifications. The parameters can be changed by the users in the interface that can be seen in figure A.3.

Now, the optimization can be made. The output of the optimization will be divided into two separate sheets, one for the boards' strategy partition and another for the final products, with the same structure with some slight changes. Hence, the output of both will be similar. The output of the final products sheet can be depicted in figure A.4.

The result of the optimization can be analyzed in an abstract page. In that page, the primary KPIs and a myriad of analysis are presented in a graphic-friendly formula similar to a dashboard.

To be able to use the second module, the forecast module, first, the user must import the more recent data of the sales. Then, by clicking the button to generate the forecast ("Prever Vendas"), the forecast will be outputted to the page that can be observed in figure A.5. Note that at this point, the user will have the chance to correct the forecast manually.

The final module will be destined to generate the reorder level and reorder quantity for the MTS boards and final products. The final page can be observed in figure A.6.

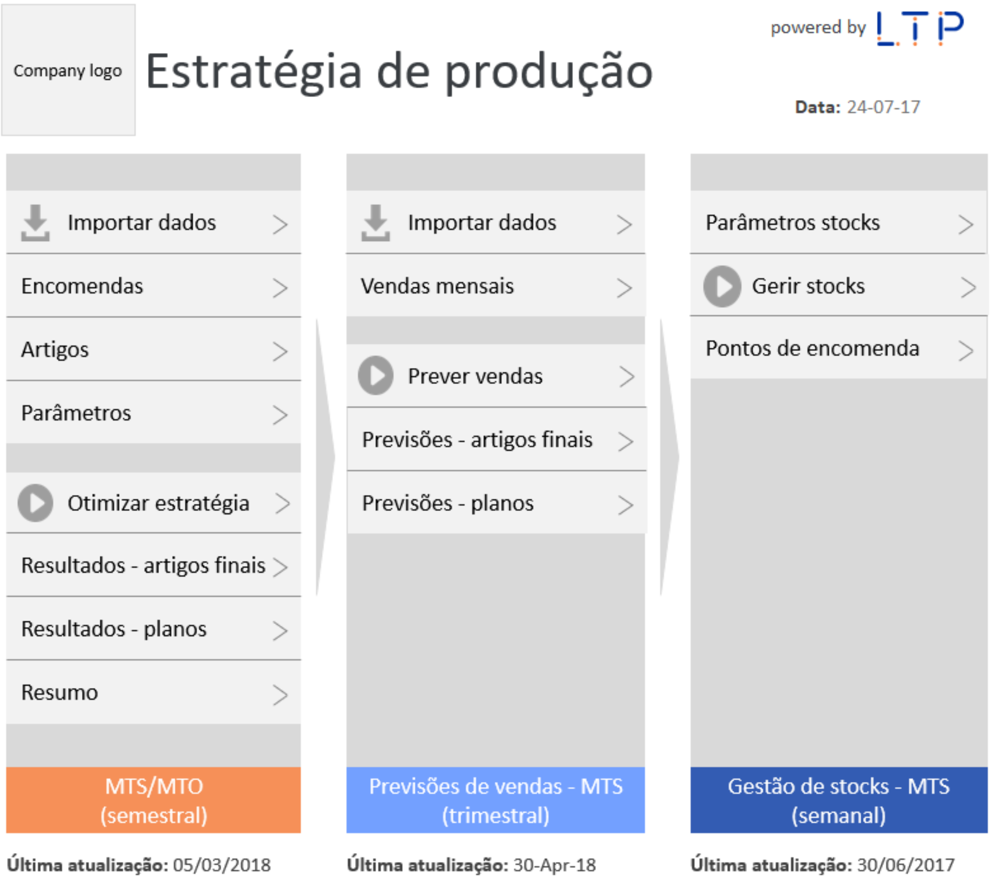

Figure A.2: Home page

Parâmetro	Valor
Produção	
Tempo de setup - outras operações (min)	99
Tempo de setup - gargalo (min)	99
Tempo de setup - segundo gargalo (min)	99
Tempo de cura (h)	99
Nº horas trabalho / dia - gargalo	99
Nº dias por semana	99
Nº máquinas - colagem	99
Nº máquinas - 2º gargalo	99
Cobertura máxima lote fabrico (nº semanas)	99
Custeio	
Custo anual do stock (%)	99%
Custo dos planos (% PVP)	99%
Margem média (%)	99%
Peso perda margem de encomendas (%)	99%
Penalidade por linha de incumprimento (€)	€ 99.00
Custo unitário armazenamento palete (€)	€ 99.00
Custo unitário de picking (€)	€ -
Admissibilidade MTS de planos	
Semanas com encomenda	99%
Vendas semanais (unidades)	99
Admissibilidade MTS de produtos finais	
Semanas com encomenda	99%
Vendas semanais (unidades)	99
Nível de serviço (MTS)	
Artigos finais	99%
Planos	99%

Clientes especiais
Lorem ipsum dolor
Lorem ipsum dolor
Lorem ipsum dolor

Figure A.3: Parameters sheet

Dados								
Artigo	Qtd (u) media semanal	DesvPad procura (u)	Prob Encomenda	Lote ideal - EOQ (unid)	MTS?	Custo total MTO (€)	Custo total MTS (€)	Poupança -> MTS (€)
XXXXXXXXX-1	4,882	4,285	77%	7,826	1	440 €	8,329 €	-7,889 €
XXXXXXXXX-2	3,351	7,183	21%	14,864	1	0 €	12,526 €	-12,526 €
XXXXXXXXX-3	2,117	1,883	79%	9,526	0	133 €	6,092 €	-5,959 €
XXXXXXXXX-4	1,847	2,021	72%	0	1	74 €	383 €	-309 €
XXXXXXXXX-5	1,810	1,910	72%	8,143	1	28 €	5,414 €	-5,386 €
XXXXXXXXX-6	1,727	1,992	74%	7,773	1	31 €	5,260 €	-5,229 €
XXXXXXXXX-7	1,316	1,715	62%	5,922	0	111 €	4,188 €	-4,076 €
XXXXXXXXX-8	1,279	1,141	77%	5,757	0	82 €	3,724 €	-3,642 €
XXXXXXXXX-9	1,273	1,235	77%	5,730	1	18 €	3,819 €	-3,801 €
XXXXXXXXX-10	1,156	1,018	81%	5,203	1	83 €	3,333 €	-3,250 €
XXXXXXXXX-11	1,091	1,441	55%	2,525	0	310 €	1,163 €	-853 €
XXXXXXXXX-12	963	1,917	64%	0	0	0 €	38 €	-38 €
XXXXXXXXX-13	872	2,776	9%	0	0	0 €	99 €	-99 €
XXXXXXXXX-14	825	951	64%	0	1	0 €	134 €	-134 €
XXXXXXXXX-15	823	1,863	23%	3,704	1	1,244 €	571 €	672 €
XXXXXXXXX-16	754	497	94%	1,883	1	834 €	2,296 €	-1,461 €
XXXXXXXXX-17	679	1,516	19%	3,057	0	0 €	2,455 €	-2,455 €
XXXXXXXXX-18	676	1,117	32%	0	0	0 €	40 €	-40 €
XXXXXXXXX-19	647	1,027	43%	1,825	1	136 €	1,273 €	-1,137 €

Figure A.4: Final product strategy partition sheet

Dados	Vendas últimos 6 meses							Previsão			Validação comercial		
Artigo	M-6	M-5	M-4	M-3	M-2	M-1	Média	M	M+1	M+2	M	M+1	M+2
XXXXXXXXX-1	1,296	1,394	1,726	1,236	1,756	1,728	1,523	1,523	1,523	1,523			
XXXXXXXXX-2	3,316	4,372	7,291	4,326	4,595	4,118	4,670	4,670	4,670	4,670			
XXXXXXXXX-3	365	977	1,088	516	434	629	668	668	668	668			
XXXXXXXXX-4	5,401	6,254	5,185	4,293	5,179	4,216	5,088	5,088	5,088	5,088			
XXXXXXXXX-5	658	889	1,029	920	724	837	843	843	843	843			
XXXXXXXXX-6	399	280	335	200	344	238	299	299	299	299			
XXXXXXXXX-7	1,261	1,435	2,190	1,245	1,340	1,441	1,485	1,485	1,485	1,485			
XXXXXXXXX-8	284	196	397	184	130	120	219	219	219	219			
XXXXXXXXX-9	2,914	2,919	4,175	2,413	2,890	2,876	3,031	3,031	3,031	3,031			
XXXXXXXXX-10	780	380	1,468	487	249	1,052	736	736	736	736			
XXXXXXXXX-11	225	360	270	45	198	90	198	198	198	198			
XXXXXXXXX-12	224	387	389	176	296	267	290	290	290	290			
XXXXXXXXX-13	3,702	4,045	5,794	3,820	4,295	4,360	4,336	4,336	4,336	4,336			
XXXXXXXXX-14	504	595	668	361	395	580	517	517	517	517			
XXXXXXXXX-15	1,185	1,825	2,259	1,191	1,143	1,433	1,506	1,506	1,506	1,506			
XXXXXXXXX-16	232	473	552	313	396	298	377	377	377	377			
XXXXXXXXX-17	135	200	136	99	138	147	143	143	143	143			
XXXXXXXXX-18	677	489	870	552	624	1,245	743	743	743	743			
XXXXXXXXX-19	209	239	222	92	150	246	193	193	193	193			

Figure A.5: Final product forecast sheet

Dados	**Info gestão de stocks**					**Previsão**	**Dados para gerir stocks**		**Análise Coberturas**
Artigo	Lead time de produção (dias)	Periodo Protecao (dias)	Var LT Prod (dias^2)	DesvPad Erro Prev (u)	Nível de serviço	Prev Periodo Protecao	Order Point (u)	Lote de produção (u)	Cob lote de produção (dias)
XXXXXXXXX-1	48.39	56	332.31	595.36	95%	2,780	2,299	1,685	56
XXXXXXXXX-2	48.15	56	332.31	1734.33	95%	8,526	1,994	1,389	52
XXXXXXXXX-3	47.85	55	332.31	411.82	95%	1,198	1,411	273	42
XXXXXXXXX-4	48.70	56	332.31	941.64	95%	9,290	1,262	2,808	25
XXXXXXXXX-5	48.12	56	332.31	293.86	95%	1,539	2,045	1,225	52
XXXXXXXXX-6	48.03	56	332.31	48.44	95%	547	1,384	696	21
XXXXXXXXX-7	48.17	56	332.31	659.88	95%	2,712	1,893	1,432	55
XXXXXXXXX-8	47.81	55	332.31	121.48	95%	392	2,010	85	44
XXXXXXXXX-9	48.13	56	332.31	1238.30	95%	5,534	1,244	1,286	21
XXXXXXXXX-10	47.86	55	332.31	288.82	95%	1,319	1,868	219	29
XXXXXXXXX-11	47.82	55	332.31	78.33	95%	355	1,562	130	53
XXXXXXXXX-12	47.82	55	332.31	105.93	95%	520	2,201	175	55
XXXXXXXXX-13	48.47	56	332.31	1562.35	95%	7,917	1,734	2,292	34
XXXXXXXXX-14	47.83	55	332.31	146.32	95%	927	1,979	171	36
XXXXXXXXX-15	47.97	55	332.31	532.92	95%	2,699	1,694	715	33
XXXXXXXXX-16	48.03	56	332.31	206.57	95%	689	1,443	837	36
XXXXXXXXX-17	47.80	55	332.31	52.05	95%	255	1,220	160	30
XXXXXXXXX-18	48.01	56	332.31	237.45	95%	1,356	2,006	919	50
XXXXXXXXX-19	47.81	55	332.31	64.44	95%	346	1,470	176	55

Figure A.6: Stock management sheet