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A stock quantification of a Demand Planning process improvement, under a S&OP Context

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Professora Maria do Sameiro Carvalho

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DECLARAÇÃO

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Resumo

A indústria alimentar enfrenta muitos desafios globais, pressionando as empresas para a entrega de uma ampla gama de produtos diferentes, com a melhor qualidade possível e com tempos de entrega apertados. Como consequência, as empresas enfrentam um aumento na complexidade de suas operações, exigindo coesão extra entre as suas funções operacionais. O processo de Sales & Operations Planning (S&OP) assume uma relevância não negligenciável, como o processo responsável pela garantia de tal coesão. Se a execução operacional dos pedidos dos consumidores for fraca ou se a colaboração entre o planeamento das operações e da procura for escassa, as empresas sofrem consideravelmente em termos do seu desempenho negocial.

Apesar da importância do processo de S&OP e da excelência operacional que é derivada do mesmo, poucos casos de projetos de melhoria transformacional, oriundos do processo, são documentados e quantificados, em termos de benefícios holísticos. Normalmente, os benefícios verificados em áreas operacionais específicas são considerados de forma restrita e sem considerar os impactos sentidos noutras áreas da empresa.

Esta tese contribui para o défice identificado na literatura, ao quantificar os benefícios extraídos da melhoria do processo de Planeamento da Procura de uma empresa de bebidas Portuguesa. Concretamente, este trabalho soluciona falhas identificadas no Planeamento da Procura da empresa, melhorando consequentemente a precisão das previsões de venda, através do redesenho do atual processo e através da atualização das metodologias atualmente utilizadas. Posteriormente, os resultados são quantificados por meio de um simulador de stock e resumidos qualitativamente em termos de benefícios S&OP. Assim, esta tese responde à pergunta de pesquisa "Qual o impacto que melhorias no processo de planeamento da procura, administração e ferramentas tem numa empresa de bebidas em termos de fiabilidade das previsões de venda, stock e custos?"

Esta tese iniciou-se com um diagnóstico à empresa, medindo a eficiência e a eficácia do processo S&OP. A fiabilidade das previsões da empresa e o subsequente departamento de planeamento da procura foram identificados como áreas para potenciais melhorias, levando a uma análise crítica das metodologias de previsão atualmente utilizadas. Um novo processo de planeamento da procura foi desenvolvido, juntamente com outras interfaces de suporte, como um otimizador dos métodos de previsão estatística. Os benefícios de tais iniciativas foram quantificados, com uma simulação de stock.

As iniciativas apresentaram melhorias em termos de fiabilidade das previsões, reduzindo a cobertura total de stock, bem como o seu custo total. Mostrou-se igualmente que as novas iniciativas contribuíram para outros benefícios S&OP, como maior reatividade da cadeia de abastecimento para mudanças bruscas da procura, maior eficiência operacional das áreas de produção e maior coesão entre departamentos. Por último, é apresentado uma reflexão sobre as dificuldades sentidas na quantificação dos benefícios, destacando assim a riqueza do trabalho desenvolvido.

Abstract

The food industry faces many worldwide challenges, pressuring companies for the delivery of a wide range of different products, with the best possible quality in tight lead time/throughput scenarios. As a consequence, companies face an increase in their operations' complexity, demanding extra cohesion between their operational functions. In this context, the S&OP process assumes vital relevance, as the accountable process to ensure such cohesion. If the operational execution of expected orders is poor or if the collaboration between supply planning and demand planning is scarce, then companies suffer considerably in terms of business performance. Despite the importance of the S&OP process and of the derived operational excellence, few cases are documented of transformational improvement projects originated from the process and with its benefits quantified in a holistic perspective. Commonly, benefits withdrawn in particular operational areas are considered narrowly and without the necessary overview of its impacts.

This thesis aims at contributing to mitigate such deficit in the topic, by quantifying S&OP benefits extracted from a Demand Planning process improvement, in a Portuguese beverage company. Concretely, this work addresses flaws identified in the company's Demand Planning, improving its forecast accuracy by rehashing the department's process and updating the forecast methodology. Afterwards, results are quantified via a stock simulator and an overview is provided upon the qualitative benefits extracted in the S&OP process. Hence, this thesis answers the research question "What impact does the improvement in Demand Planning processes, governance and tools have in a beverages company forecast accuracy, stock coverage and costs?"

The work related to this thesis began with the assessment of the S&OP process, measuring efficiency and effectiveness. The current forecast accuracy, and the subsequent Demand Planning process organization and governance, were identified as potential areas for improvement leading to a critical analysis of the department's forecast methodology. A new Demand Planning process emerged from the analysis, along with other support tools, such as a statistical forecast Optimizer. The benefits of such initiatives were quantified, with a stock simulation.

The initiatives that were conducted showcased significant improvements in terms of forecast accuracy and a significant potential reduction in terms of total stock coverage and total stock cost. Moreover, it was shown that the new initiatives contributed to additional S&OP benefits, such as the reactiveness of the S&OP chain to unforeseen demand changes, the enhanced operational efficiency of Supply Planning areas and the increased cohesiveness between Demand Planning and the Master Planning area. Lastly, a reflection is provided regarding the difficulties felt in quantifying forecast benefits, and thus highlighting the richness of the work developed.

Aknowledgements

A thesis conclusion many often symbolizes the end of a life period and is, thus, a celebration of such. Knowledge, life-altering moments, friendships and hardships are all nouns commonly utilized to illustrate the impact of this academic period, and mine isn't any different.

I believe that my latest hurdle, developing this Master thesis in LTPLabs, is yet the greatest and most endearing challenge of them all. I own my appreciation to every work colleague who did and still does, support me daily with knowledge, savviness and friendship. To Andreia Cardoso, my technical coordinator, I thank you for your dedication, motivation, guidance and support during this thesis and project. Our work is in a big part successful due to your guidance and due to the many values and lessons that you continuously shared with me. To Pedro Schuller, thank you for always providing the necessary insight, as a co-worker and as a friend, regardless of the topic and environment. To Luís Guimarães and Teresa Bianchi de Aguiar, my gratefulness for all the support during my journey in LTP. It pleases me to realise that the most important value in one's organization, nurturing and caring for each other, is so vividly carried by both of you.

My path in the University of Minho is synonymous of discovery. I've discovered a world of knowledge and friendship. More than a school of words and theory, I constantly fell back realising the importance of empathy, growth and culture. Those are values taught for life. To my thesis coordinator, Professor Maria do Sameiro Carvalho, I'm grateful for your endless support to the creation of this thesis. Your guidance, structure and know-how was the backbone of this dissertation.

It was under the umbrella of such values that I've discussed and dreamt about the future and life with my friends and colleagues, specifically with the three that I've kept close throughout my journey: Diogo, José and Luís. I've learned with each that regardless of the challenge and expected outcome, an ambitious and purposeful mindset always strives for success. And indeed, it was with such mindset that I've adventured myself to discover Europe, as part of the board of the European organization ESTIEM. It was the most fulfilling, yet challenging, year of my life, who I've had the luck to spend together with 5 amazing friends: Francisca, Joonas, Minh, Sunny and Yassine. All of them, with their own culture and mindset, taught me that true happiness only comes to those who seek it together, aligned by a common purpose, greater than ourselves.

Ultimately, this thesis is a result of the effort and knowledge of many who have contributed to it since the beginning, with special emphasis in my family. I thank them all for the support they relentlessly shared during these years. To my father, my mother, my sister, my grandparents, to Luís, Marta and Bárbara, thank you for everything.

I finish by thanking the person who has had the most impact on my life. To the one, I've met along the way, and have been my support and pilar ever since. Regardless of what hardships to expect, or the size of the hurdle we may face, I keep on feeling that by your side, nothing is unsurpassable. Thank you, Mariana.

Contents

Acronyms

APS Advanced Planning & Scheduling.
C&C Cash & Carry.
DP Demand Planning.
ERP Enterprise Resource Planning.
GDP Gross Domestic Product.
HoReCa Hotels,Restaurants and Cafes.
KPI Key Performance Indicator.
MA Moving Average.
MP Master Planning.
MTO Make-To-Order.
MTS Make-To-Stock.
PP Percentage point.
PTF Planning Time Fence.
S&OP Sales & Operations Planning.
SG Statistical Group.
SKU Stock Keeping Unit.
SS Safety Stock.
SSE Sum of squared errors.

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Chapter 1

Introduction

The present dissertation falls under the scope of the Masters in Industrial Engineering and Management at the University of Minho. The thesis was developed throughout an internship in LTPLabs, an analytical management consultancy company, in a project with one of its clients.
This section aims to provide an overview of the scope and topic of the dissertation, the problems addressed, the used research methodology for its conception and the overall document structure.

1.1 Background

In the world of today, the food industry represents a significant portion of each country's Gross Domestic Product (GDP), signifying a great economic importance, to which the excellence of company's operations count (Manzini and Accorsi, 2013). As per 2015, the food and beverages industry accounted for 2.1% of the overall European GDP, with over 15% of total employment in the EU manufacturing sector. In Portugal alone, the industry generated a total of 15.6 billion euros in turnover, with over 109 thousand employees. These numbers, as well as the already documented vital importance of the industry for the population's day-to-day, aid in showcasing its relevancy (Europe, 2016). With over 294 thousand companies, in which 11 thousand are solely from Portugal, each company's product quality and supply chain coordination are important factors dictating success against fierce competition. Moreover, the increasing complexity of operations, the conditioning of food and drinks, the ever-demanding lead and throughput times, the supply and demand uncertainty and the increasing interest for more variety and product customisation are some of the issues that each company has to deal in a daily basis (Laurent Lim et al., 2014; Van der Vorst, 2000). To cope with these challenges and to remain competitive in today's economic world standards, companies search for a high level of integration between their functional sectors, looking for a planning approach that coordinates sales, production, supply and distribution. This aggregated planning approach is usually defined as the S&OP process.

S&OP directly contributes for improvements to the company's performance, going from developments in cohesiveness and agility as a whole to more detailed improvements in functional areas, such as in Demand Planning (DP) and Master Planning (MP). S&OP is thus highly related to success in today's terms, where a company's success is measured by its capability of delivering a wide range of products to a wide audience, at the lowest cost, with a high degree of customisation. In short, integration of sales and operations, high accuracy on demand forecasting and an efficient and effective master plan is required to sustain such success.

Despite the recent increment in interest for the S&OP process (Affonso et al., 2008), and despite the notorious necessity for flexibility, responsiveness and adaptability of the food industry (Van der Vorst, 2000), there are still few cases documented of transformational improvement opportunities born out of the S&OP process, with verified impact at a tactical/business level (Thomé et al., 2012). This thesis aims at contributing to the extensiveness of that knowledge, by quantifying the benefits extracted from a DP process improvement project, in terms of stock reduction and qualitative indicators, derived from an S&OP assessment in a multinational beverages company.

DP is an established forecasting process, that aims to support decision making at the areas of procurement, production, distribution and sales, through accurate predictions of the demand for the company's products or services (Haberleitner et al., 2010). DP can thus be segmented into two components: forecasting of the demand and the subsequent planning of actions to be taken, based on these forecasts. The described developments will be mostly related to these two components.

The multinational beverages company behind this thesis, has in itself incorporated an S&OP process, where the DP team elaborates monthly a detailed forecast for the next 4 months. The dynamic of the company and the whole S&OP chain is dependent on the performance of the DP team, since better forecast accuracy translates into better company performance: less end-product and production materials stock excess/shortage, Safety Stock (SS) reduction, optimised production campaigns, optimised cost/service level trade-off, improved medium-term budgets, among others. The whole process has big improvement opportunities left to be explored, specifically in the DP functional area.

1.2 Project scope

The company where the project was undertaken is a national leader in the non-alcoholic drinks sector. It employs innovative concepts for its beverages and currently benefits from a reach of over 70+ countries. The company produces over 15+ different brands in different owned factory units and distributes them widely through the use of distribution centres and decoupling points. Each brand's sales units are forecast, in a 4-month span, for further use of the MP and every Supply Planning area to themselves plan their own operational necessities. Figure 1.1 provides a simplified overview over the overall process.

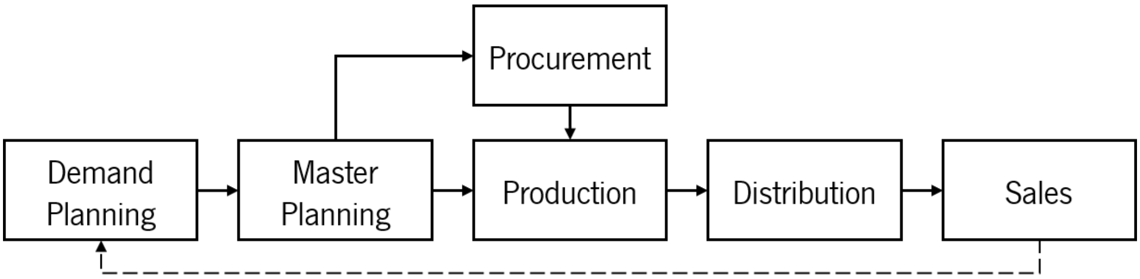


Figure 1.1: Simplistic company's process view

The project initiated with an assessment of the company's S&OP process, qualitatively evaluating the efficiency and effectiveness of the process. The scope was narrowed afterwards, as tactical improvement opportunities are identified within two main functional areas: DP and MP. As a consequence of the assessment, a transformational project is undertaken on the DP department, while the MP area is simulated to allow stock quantification of the benefits extracted from forecast improvement. Since these two functional areas belong to the first layer of the S&OP chain, their own developments lead to substantially added general improvements.

This thesis describes a S&OP assessment, performed at the start of the project, the work, solutions and results extracted from the improvement opportunities identified in the DP department and the quantified benefits, in terms of forecast accuracy, stock and cost reduction. The analysis and improvements verified were done so considering all brands and all the different products sold by the company.

1.3 Goals

The three main objectives for this thesis are the identification of improvement opportunities in the DP area, based on an S&OP assessment, the subsequent improvement of the DP department[1] and the quantification of forecast benefits, per simulation of the company's MP. In detail, this project aims to:

- Assess the performance of the company under an S&OP context, analysing its efficiency and effectiveness;

[1] According to forecast metrics defined in chapter 2

- Improve the company's DP department, according to insights collected throughout the S&OP assessment;
- Increase the accuracy and reliability of the company's sales forecasts;
- Quantify forecast benefits in terms of stock decrease, cost reduction and qualitative gains, through a simulation of the company's MP and stock management policies;

The research question for this master thesis can be defined as:

RQ1: "What impact does the improvement in DP have in a beverages company forecast accuracy, stock coverage and costs?"

1.4 Research methodology

Under the context of this master thesis, a literature review was carried to the S&OP area and into the DP and MP theory in particular. Moreover, similar problems to the ones this thesis addresses were also researched, to benchmark best practices and methodologies that could be useful for the final solutions.

The methodology utilised for this thesis is the *Action Research*, also referred to as the *"learning by doing"*, as it had the best fit with the problem faced (Brien, 1998). The researcher assumed a proactive approach during the research, with the purpose of trying to identify and solve a specific problem from the organisation. The methodology is divided into 5 stages: diagnosis, action planning, taking action, evaluating and specifying learning (Brien, 1998).

Diagnosis: the company's S&OP process is evaluated, specifically in the DP and MP areas. Using the frameworks defined by Thomé et al. (2012) and Hulthén et al. (2016), and with a practical approach, the process was analysed, first holistically, to identify connection points between the different departments and secondly with a thorough assessment to the two functional areas previously mentioned. The insights withdrawn from the diagnosis were used throughout this thesis.

Action planning: the insights withdrawn from the S&OP diagnosis are used to draw an action plan to tackle identified problems at the DP area. The plan takes into consideration possible synergies with the MP area, as well as the overall S&OP process, when defining best practices.

Taking action: the problems identified within the DP department are addressed and solved. Concretely, state-of-the-art approaches and methodologies are utilised, with a focus on the use of *analytics* and of historical sales data to achieve the best result.

Evaluating: the results are analysed and reviewed in two separate views: qualitative results, felt within the S&OP process, DP and MP department; Quantitative results, measured in terms of forecast accuracy, stock reduction and cost benefits. A final assessment is made over the work developed, inquiring if the problems initially detected were improved based on the taken actions.

Specifying learning: the main results and conclusions are withdrawn from the project. The results, methodology and the process used to improve the problems are recorded. It is expected that afterwards, as the work of this thesis is finalised, another cycle of learning starts regarding the S&OP process and specifically, the DP department.

1.5 Thesis outline

This thesis is organised into six chapters, with the following outline:

Chapter 1 introduces the purpose of the thesis, contextualising the problem and defining the main objectives to be pursued;

Chapter 2 provides a theoretical background on relevant subjects to the work. An S&OP literature review is initially provided, explaining the concept behind the process and providing an overview of different measurement methods. A literature review on DP, forecasting models and supply Planning follows to complement the solutions developed afterwards. Lastly, research on methods for forecast quantification is displayed;

Chapter 3 describes the assessment conducted at the S&OP process of the company, including the main insights withdrawn from such. A critical analysis of the DP department is then described, indicating its performance and limitations. Finally, the results of an assessment conveyed to the company's inventory management and MP is reported;

Chapter 4 explains the various methodologies adopted to address the identified key issues. A novel forecast prioritisation methodology is described, followed by sequential explanations of the newly defined DP process, of the statistical forecast optimiser and of the commercial, validation and re-validation interfaces. A final section is dedicated to depicting the approach employed to quantify the forecast accuracy gains;

Chapter 5 showcases the solution's results. In particular, the chapter describes the results of the simulation performed to quantify forecast benefits;

Chapter 6 is a summary and a reflection on the findings of this thesis.

Chapter 2

Literature review

This chapter intends to make a bibliographical review of the concepts and tools that served as the foundation for the accomplishment of this thesis. An introduction and historical evolution to S&OP is provided, as well as analysis to concepts and themes regarding DP, forecasting, MP, stock management and forecast quantification.

2.1 Challenges faced by the food industry related to operational excellence

As mentioned in the introductory chapter of this thesis, the food and beverages industry is in the midst of the new industrial revolution, facing many external challenges capable of affecting their daily operations. Companies are required to have a higher integration between functional layers of the company, higher responsiveness to customer/supplier demands and agility to quickly re-adapt to newer circumstances. Some of these external factors affecting the industry are described below:

Globalization: The way customers are served and products are provided changed majorly following the impact of globalization. The increment in distribution channels, contact points and even the sole increase in the number of customers in reach for each product requires flexibility in the supply chain and on the manufacturing network (Rudberg and Olhager, 2003).

Market competitiveness: Competitiveness is fiercer than before and is currently increasing in the global industry. Margins shrink, success opportunities diminish and there is a need for companies to develop newer strategies and methods of operation (Azevedo and Almeida, 2011).

Product portfolio diversification: the customer interest for customized products has dramatically increased over the course of the last decade. Distinctive features, flavours and details are continuously demanded from products and a vast array of different options and features are usually demanded. The food & drinks industry is similarly affected, as more product variety is necessary to tailor specific customer tastes and demands (Chen et al., 2015).

Food safety and quality excellence: recent changes to the food sector defined safety and quality as a top priority in the field. As such, strict regulations and specifications need to be met, indulging the industry in higher production costs and more control (Lehmann et al., 2012; Holleran and Bredahl, 1999).

Such factors contribute directly to the need for operational excellence and business integration, as several operational problems are created: high demand and supply variability, increased number of orders, lower production quantities, higher order uncertainty, production restrictions, higher perishability of goods and supplies.

All of the aforementioned problems affect sales, forecasting, production, replenishment and distribution:

1. **Sales** become more unpredictable and forecasting less accurate as demand variability increases. Thus, higher efforts are required from demand planners and commercial teams to deliver accurate forecasts.
2. **Production** teams are demanded to meet stricter quality restrictions and tougher planning schedules. Stock management is carefully planned to keep in mind order productions and product's perishability.
3. **Replenishment** is affected by the high demand and supply variability, stock necessities and product perishability. As product variety increases, so does the variety required of different raw materials and auxiliary products.
4. **Distribution** becomes complex, with a higher network of customers to serve. An efficient use of decoupling points and distribution routes is required to maximize delivery value.

S&OP becomes a necessity to ensure coordination between the four areas and to provide the necessary flexibility and agility to maintain competitiveness (Ivert et al., 2015). The following section introduces the concept of S&OP.

2.2 Sales & Operations Planning

S&OP is considered a tactical business process, that unifies strategic plans with the daily operations of the company, searching for balance between the demand and supply of the company's products, towards profit optimization (Grimson and Pyke, 2007). Thus, the S&OP process aims to level the manufacturing output of the company, the replenishment of goods and the distribution of the end-product to best satisfy the product sales forecast, while ensuring that business objectives are successfully accomplished. A holistic overview over the processes and planning of the company is necessary for the success of such endeavour, carefully ensured by the nature of S&OP: it enables vertical and horizontal alignment between the different layers of the company (Thomé et al., 2012). Essentially, the primary role of S&OP is to facilitate information sharing from the DP area to a final MP, that considers the finer details of operations, such as purchasing, production and distribution (Oliva and Watson, 2011).

The first reference to the need for such process, remotes back to 1998 when a formal mechanism that could integrate operational and strategic decisions, both horizontally and vertically, was seen as a solution for problems such as lack of coherence, communication and integration between departments, and at a company-wide level (Longoni and Raffaella, 1998). In fact, most of the issues already identified in 1998 have been greatly amplified throughout the past two decades.

S&OP has since matured towards a complete business process, encompassing company-wide objectives and specific departmental metrics such as ones related to sales, production, replenishment and distribution. The first iteration of the S&OP process was initially proposed by Wing (2001) and benefited from further developments over the years, with Lapide (2005), Grimson and Pyke (2007), Feng et al. (2008), Cecere et al. (2009), Wagner et al. (2014) and Hulthén et al. (2016) proposing significant changes as well.

The framework in Figure 2.1, inspired by the work of Thomé et al. (2012), summarises the environment surrounding the S&OP process, encompassing four key elements: context, inputs, the S&OP process and the desired outcomes.

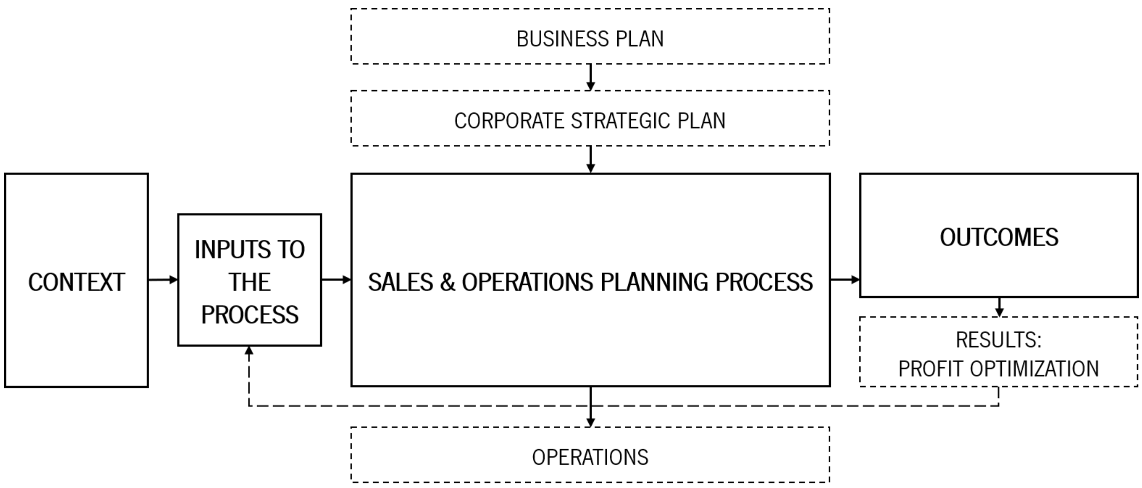


Figure 2.1: S&OP Framework (in Thomé et al. (2012))

The following subsections provide a description of the S&OP process and of its main surrounding elements, context, inputs and desired outcomes.

2.2.1 Context

Context considers the planning environment of each company, including all the variables that could potentially affect the conception of the S&OP process. In fact, there is still to be found a common conceptual process implemented across different countries, industries and manufacturing strategies. Most research is tailored to its own context, be it through the difference in approach between Make-To-Order (MTO) and Make-To-Stock (MTS), to the format used for product aggregation, which affects the communication between DP and other functional areas. Pedroso et al. (2016) and Ivert et al. (2014) provide examples of S&OP implementations in distinctive contexts.

2.2.2 Inputs

Inputs to the S&OP process can be separated into individual plans and constraints to the process. The following Table 2.1 summarises, not exhaustively, the fundamental plans and constraints:

	Plans	Constraints
Demand	marketing and sales plan demand forecast	
Replenishment	procurement/supply plan purchasing data	supply lead time supplier constraints
Production	production/capacity plan inventory	production capacity production lead time operational constraints
Distribution	distribution plan	delivery capacity delivery lead time service level targets other delivery constraints
Finance	financial plans	budgets

Table 2.1: S&OP inputs: plans and constraints (in Thomé et al. (2012))

The inputs are provided by the functional areas involved (demand, production, replenishment, distribution and finance), coordinated by an aggregated tactical planning, who seek the aforementioned alignment by coordinating their work. It is by comparing the predicted demand with the master plan, containing the planned production, the end-product stock, raw materials provisioning and the distribution plans, that meaningful assessment is made.

Transformational projects with improvements in specific S&OP areas, such as the one this thesis documents in the DP area, are important drivers to the success of the S&OP process. Other functional areas of the process also benefit from such transformaltional projects, as their own performance improves significantly.

2.2.3 Process

The S&OP process is commonly described as a five-step process (Wagner et al., 2014; Wallace and Stahl, 2008; Grimson and Pyke, 2007), with high emphasis on collaborative actions between correlative departments (Nakano, 2009). Figure 2.2 exemplifies a typical S&OP process.

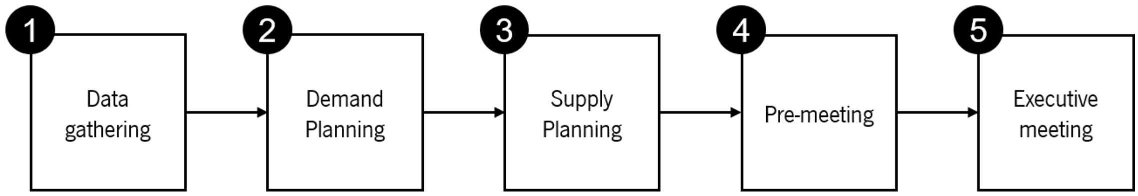


Figure 2.2: S&OP Process (in Wallace and Stahl (2008))

The S&OP process starts by gathering the necessary inputs, provided by the involved departments. The data is then used for step 2 and 3, Demand and Supply Planning. DP is often considered the most challenging step (Wallace and Stahl, 2008), due to the high importance of the forecasts at an aggregated sales level and at a granular level, such as the SKU level. The accuracy of the forecasts and the certainty of what is being predicted highly influences the creation of the operational plans and the end-results of their implementation. Following the DP step, Supply Planning follows, with a master plan coordinating the different operational areas, production, distribution, replenishment and sales. Each area plans their own operational needs and set their monthly targets, based on the monthly master plan. Meetings then occur to perfect the plans and to establish agreement upon their implementation: an initial pre-meeting to spot necessary adjustments and then a final executive meeting to ensure alignment at a higher level. The S&OP process is usually executed in monthly time-periods. Simultaneously, an assessment to the process is conducted each month, including measurements of financial and business results, to forecast accuracy, operational metrics and overall S&OP effectiveness.

The steps 2 and 3 of the S&OP process are described with more detail in section 2.3 and section 2.5, respectively.

2.2.4 Outcomes and results

As for the outcomes and goals expected from the S&OP process, these can be resumed by the three following points, as described by Thomé et al. (2012):

- **Alignment and integration**, which seek the balance between demand and supply, horizontal alignment within the supply chain and adjustments to functional plans;
- **Operational improvements**, as improvements on forecast accuracy, in operational performance, inventory reduction, production mix management or constraints management;
- **Results focused in a single perspective**, such as improving revenue, reducing supply chain costs, diminishing demand distortion and achieve the expected service level;

Many drivers for improvement are derived from, or attached to, the S&OP process, towards the same end result of profit optimization (Thomé et al., 2012). Drivers such as stock optimization, improvements of the forecast accuracy or even improved capacity levelling, as mentioned before, are important complementary actions to the S&OP process and to the overall success of the company. It is thus wise to consider the specific improvement of these functional areas of the company for a better holistic performance.

2.2.5 S&OP performance assessment

Companies generally perform the process described in Figure 2.2, albeit differently. While the described steps are the same regardless, the effectiveness and efficiency are related to the company's maturity level in such process. Current literature presents different measurement methods to assess the company's S&OP performance. Many authors developed maturity models with different evolutionary stages, with each stage signifying a better S&OP performance (Wagner et al., 2014; Cecere et al., 2009; Feng et al., 2008; Grimson and Pyke, 2007).

Grimson and Pyke (2007) described their model through 5 stages: no S&OP process, reactive, standard, advanced and proactive. Each stage was described through five categories: meetings & collaborations, organization, measurements, information technology and S&OP plan integration. Generally, each stage symbolizes a more efficient S&OP process than the previous. In stage 1, companies lack an S&OP process and have very few collaboration points. In stage 2, companies are generally more reactive than proactive, with sales plans dominating over operational plans or requirements. In stage 3, the first integrated measures emerge as well as the first holistic perspective of the overall process. Stage 4 adds in advanced metrics and discussions, such as trade-offs between functional areas and new product's planning. Finally, stage 5 adds in a wider perspective, with increased profitability appended as a set target, while the integration of all plans seems now a seamless effort.

The S&OP process is also assessed by other authors through operational metrics, instead of holistic maturity levels. A Key Performance Indicator (KPI), or many, such as forecast accuracy, inventory levels, production/distribution costs, capacity utilisation and delivery reliability are commonly used for monitorization (Thomé et al., 2012; Godsell et al., 2010; Feng et al., 2008; Lapide, 2004).

Hulthén et al. (2016) considered both distinctive perspectives when designing their own S&OP assessment framework. In their framework, components assessed by previous maturity models are now utilised as key areas to measure the efficiency of the process, while operational metrics are utilised to measure the effectiveness of the process towards business success. Figure 2.3 illustrates Hulthén et al. (2016) framework. The efficiency is qualitatively measured in three main dimensions, S&OP process, organisation and people, while the effectiveness is measured across the S&OP process, at each different stage, regarding the expected output quality and performance.

Notwithstanding the use of components from other methodologies, Hulthén et al. (2016) aims at providing a holistic assessment, pinpointing action points conjointly to the process's categorisation. Hence, their methodology allows for a complete analysis of different dimensions of the S&OP process, identifying what could be potential improvement opportunities.

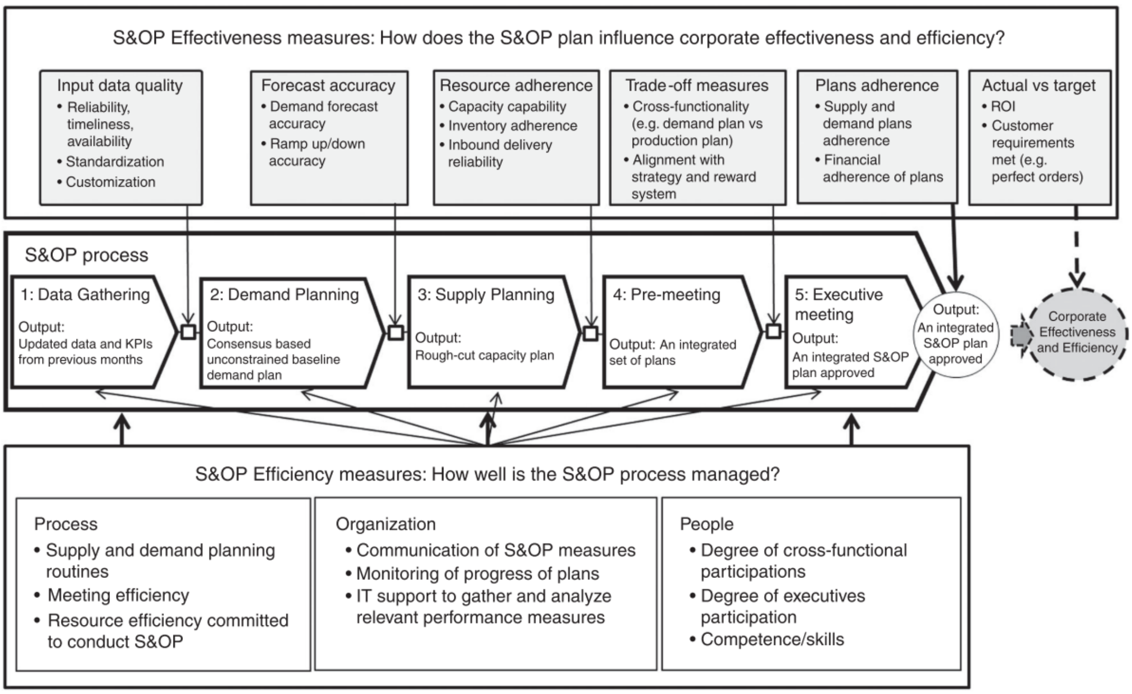


Figure 2.3: Framework to measure performance of the S&OP process (in Hulthén et al. (2016))

2.3 Demand Planning

DP is an established forecasting process, that aims to support decision making at the areas of procurement, production, distribution and sales, through accurate predictions of the demand for the company's products or services (Haberleitner et al., 2010). Thus, DP represents the second stage of the S&OP process, from which is expected a consensus-based unconstrained baseline demand plan (Hulthén et al., 2016). The execution of the DP plan is vitally important. When well executed, the process enables: managers and executives to make sound decisions when balancing demand and supply; Integration of operational plans with supply and financial results; Discussions upon strategy, policy and risks regarding companies' decisions (Wallace and Stahl, 2008).

Figure 2.4 summarizes a typical DP process, presenting the major steps required for the forecasts' elaboration.

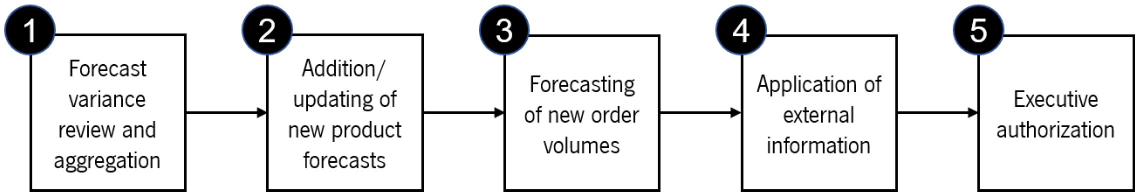


Figure 2.4: Demand Planning process (in Wallace and Stahl (2008))

The DP process starts with a review of past causes for significant forecast variance and with the generation of a statistical forecast (mostly automatic) for each SKU. The usual forecast range for most companies is between one to three months, albeit such time-span is highly conditioned by the Planning Time Fence (PTF), the necessary time required for a master plan to be drafted, according to procurement and production own operational plans. If necessary, forecasts are generated within a longer time period. During this step, detailed forecasts are aggregated within sub-groups, such as brands, product families or components, and reconciled with an aggregated forecast. The second step generates or updates forecasts for new products. These cases are often treated differently due to the unavailability of sufficient historical data and due to special correlations between other products, such as cannibalisation of sales or complete substitution of previous versions. For these cases, automatic forecast generation isn't available, requiring manual forecasting using qualitative techniques or considering extra information besides historical data. Step three, forecasting of new order volumes, is intrinsically connected with predicting future sales with major accounts and business, such as the retail industry. Usually performed by salespeople and commercial teams, this step blends in client projections and their order volumes with the existing forecasts, ensuring a better compromise with what is already expected to be sold. Step four considers external factors and assumptions to correct forecasts. Factors such as promotions, internal budgets, environmental causes, new product launches, price changes or other external factors are all added in this stage. Different industries carry different assumptions due to specific behaviours felt in their own market. Each company has their own factors to consider when forecasting future sales. The process finishes with executive validation, often conducted through meetings in which past results are analysed and the new forecasts are fine-tuned and discussed.

This process is often cyclical and highly affected by its automation. As one of the factors evaluated in many S&OP assessment frameworks (Hulthén et al., 2016; Wagner et al., 2014; Wallace and Stahl, 2008; Lapide, 2005), the level of integration within the Enterprise Resource Planning (ERP)'s system changes considerably the effectiveness of the DP process. The better the system's match between SKUs and forecast models and the higher the inclusion of extra information, such as promotional activity or weather conditions, the better is the accuracy expected from forecasts.

2.4 Forecast

The forecast is the science of predicting future events. It involves analyzing historical data, patterns and trends for a projection of a future situation, influenced by the factors that hinder our ability to forecast: how well do we understand the factors that affect demand, how much data do we have available and whether our own forecast affects what we are trying to forecast (Hyndman and Athanasopoulos, 2018). Demand is predicted based on forecasting models, with its accuracy being measured through statistical methods. Gonçalves (2000) divides forecasting models into qualitative and quantitative methods, as exemplified in Figure 2.5.

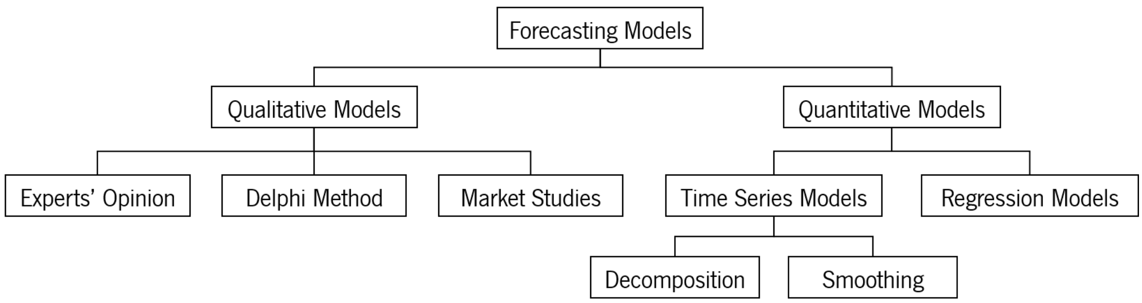


Figure 2.5: Forecasting Models (in Gonçalves (2000))

Qualitative methods use subjective views and perceptions to base the forecast and are often used either in a long-term spectrum or in situations whose data available isn't enough for statistical models to extract viable results. Market studies or the Delphi method are examples of qualitative models. Quantitative methods, on the other hand, are used for short-term decisions and in situations whose data has enough quality to extract valuable insights from. These methods are divided into Time Series methods and Causal/Regression models. Time Series methods base the forecast on historical data, patterns and trends identified in the past, while Causal or regression methods produce forecasts based on cause and effect relationships between explanatory variables and the demand variable itself.

Causal and Regression methods are very useful in situations where there is good knowledge over the impact of strong causal relationships, that may impact demand if their value changes considerably (Green and Armstrong, 2012). The method that investigates functional relationships among variables are commonly referred as Simple Linear Regressions, in case of modelling a linear relationship between two variables, multiple Linear Regressions, in case of modelling the relationship between three or more variables, or non Linear Regressions if the relationship is better explained through a nonlinear functional form (Casella et al., 2009). Cases of inclusion of causal information, such as promotional activity or weather information, often benefit from the use of Machine Learning concepts for forecasting, such as Random Forest (Breiman, 1984) or Gradient Boosting machine algorithms, as defined by Friedman (2002).

The choice of a specific forecast method is restricted by nature to the issue expected to be forecast. In cases of the nature indicating a necessity for prediction based on historical data, Time Series methods are often utilised, while Causal methods are applied for cases when prediction is based on other significant causal variables. Furthermore, the selection between models belonging to the same category is equally restricted by patterns and characteristics respective to the case. For instance, time series indicating a seasonality pattern require a different model than time series without such underlying pattern category. The assignment of the best-fit forecasting model requires thus prior knowledge upon the data.

Appendix A provides a deep look upon complementary concepts for forecasting and a description of commonly utilised Time Series methods: Naïve forecasting, Weighted Moving Average, Exponential Smoothing and Classical Decomposition. Despite ARIMA models not being explored through the course of this thesis, due to their inadequacy to the context, these are also relevant forecasting models in the literature. Box et al. (2016) provides a good explanation to the different models available under the methodology.

Table 2.2 illustrates the applicability of each method, depending on the problem's context and characteristics. For cases where various models can be applied, the choice isn't always straightforward. Each model has different levels of interpretability, easiness of implementation, reliability and performance. The choice of the correct model is often affected by the conditions surrounding the decision (e.g. choosing a machine learning method highly conditions the interpretability of its results). Thus, testing various different methods, measuring each method's accuracy and decide the method of choice based on the mentioned conditions is a common practice (Hyndman and Athanasopoulos, 2018).

Methods	Lack of data	Historical data	Intermittent data	Trend	Seasonality	Causal variables
Qualitative	x					
Naïve		x				
Moving average		x				
Simple exponential smoothing		x				
Holt's		x		x		
Holt-Winter's		x		x	x	
ARIMA		x		x	x	
Cronston		x	x			
Regression models		x				x

Table 2.2: Forecast method's ideal use cases

2.4.1 Forecast performance measurements

Regardless of the methodology used to forecast future observations, it is very likely that the forecast won't be fully accurate. Most forecasts induce errors: the difference between the verified sales and its forecast. Forecast accuracy is measured by summarizing forecast errors through different methods (Hyndman and Athanasopoulos, 2018).

Mean Squared Error or MSE: represents the average of the squared forecast errors and is used in cases where frequent and small errors are preferred to bigger deviations. n is the total number of observations.

$$MSE = \sum_{i=1}^{n} (Forecast - Sales)^2/n \tag{2.1}$$

Mean Absolute deviation or MAD: represents the average forecast error of the model and is calculated by dividing the sum of the individual forecast errors through the number of observations.

$$MAD = \sum_{i=1}^{n} |Forecast - Sales|/n \tag{2.2}$$

Mean Percentage Error or MPE: often referred as Bias, is mostly used to measure the tendency of the forecasts by ascertaining if they continuously underestimate or overestimate.

$$Bias = \sum_{i=1}^{n}((Forecast - Sales)/Sales)/n) * 100\% \tag{2.3}$$

Mean Average Percentage error or MAPE: represents the average absolute forecast error of the model, and is expressed as a percentage of the sale.

$$MAPE = \sum_{i=1}^{n}(|Forecast - Sales|/Sales)/n) * 100\% \tag{2.4}$$

Often, forecast performance is interpreted per its accuracy, instead of per its deviation.

$$Accuracy = 1 - MAPE \tag{2.5}$$

MAPE is often preferred to MAD and MSE, due to its independence of the magnitude of the values being forecast. Since MAPE is a percentage value calculated through the absolute difference between forecast and sales, the order of the values doesn't have any influence on its result. MAD and MSE, by considering individual forecast errors, are prone to the order magnitude. These measurements can also be weighted according to certain variable importance. Considering their superior interpretability, MAPE and Bias will be used throughout the course of this thesis as measurements.

2.4.2 Optimization of forecasting modules

Any exponential smoothing method requires the definition of its parameters to properly predict future happenings. The parameters can be defined subjectively, considering the context of the time series and also previous experiences. However, the most reliable way to estimate parameters is by estimation from past data. The method commonly used is the minimization of the Sum of squared errors (SSE) (Hyndman and Athanasopoulos, 2018).

$$\textbf{SSE} = \sum_{t=1}^{T}(y_t - \hat{y}_{t|t-1})^2 = \sum_{t=1}^{T} e_t^2, \tag{2.6}$$

The method works by calculating the squared difference between data points and their predictions, for a large number of observations. The model and parameters with the lowest sum of SSE is the one with higher "fit" to the observed time series. The test is applied to different versions of the same method, with different coefficients. Finally, the coefficients that have presented the best result, are used to predict future values. Since such a test requires heavy computational effort, especially when dealing with complex formulas, with many different coefficients, an optimising algorithm is usually used to solve this non-linear minimisation problem (Hyndman and Athanasopoulos, 2018).

2.4.3 Hierarchical forecasting

It is a common necessity to forecast in different levels of aggregations. Either through different attributes of interest, such as brands - families - components, geographic divisions (country - district - city) or through sales channels, forecasts naturally group together in hierarchies of different levels. Due to the natural necessity and the accuracy benefits that can arise from performing aggregation and disaggregation, a section will be dedicated to the topic.

2.4.3.1 Hierarchical time series

SKU's have a natural tendency to group together through hierarchies, with different hierarchical levels. Commonly, as exemplified in Figure 2.6, hierarchies follow a pattern of individual sales per product at the most basic level, followed by one or many intermediate levels and finally, a top level with total sales (Pennings and Dalen, 2017).

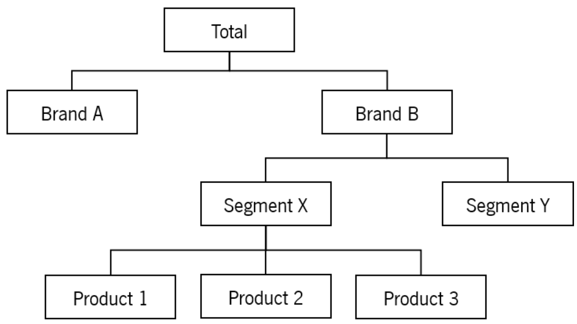


Figure 2.6: An example of an SKU Hierarchy

In many situations, there is often the need to forecast in different levels of the hierarchy. Production often requires forecasts at the SKU level, sales departments often perform their daily duties per sales channel output and management reports under a brand scope. Such differences upon granularity are often the main reason for the aggregation and disaggregation of forecasts. Moreover, performance benefits in terms of forecast accuracy can also arise from forecasting at different hierarchical levels (Widiarta et al., 2009). The two most common strategies for hierarchical forecast are the Bottom-Up and Top-Down approaches.

2.4.3.2 Bottom-up approach

When forecasting through the bottom-up approach, base forecasts are initially forecast at the lowest level of the hierarchy. if needed, each component is then aggregated to obtain the forecast of the next aggregated level. The process can be replicated until the higher level of the hierarchy. The aggregation is made by the sum of the forecasts of each component, represented by:

$$\hat{Y}_h = \hat{y}_{AA,h} + \hat{y}_{AB,h} + \hat{y}_{AC,h} + \hat{y}_{BA,h} + \hat{y}_{BB,h} \tag{2.7}$$

Where $\hat{Y}_h$ is the aggregated level of forecast for period h and $\hat{y}_{AA,h}; \hat{y}_{AB,h}; \hat{y}_{AC,h}; \hat{y}_{BA,h}; \hat{y}_{BB,h}$ being exemplary components.

An advantage often associated with this approach is its loss less property. Since the forecasts are generated at the most granular level, when aggregated, no information from the time series is lost. However, bottom-level data can be noisy and harder to model and forecast, since trends and seasonality patterns may be mixed with random variability (Hyndman and Athanasopoulos, 2018).

2.4.3.3 Top-down approach

This approach follows the contrary path to the Bottom-Up approach. Time-series are initially aggregated, or pre-existent aggregated information is used to forecast demand. Forecasts are then disaggregated to different hierarchical levels. The disaggregation process requires a method capable of distributing the forecast through the newer, finer, components. Commonly, proportion coefficients are assigned to each component, to allow the forecast to be distributed accordingly.

Gross and Sohl (1990) compare different methods to determine allocation proportions. A common method, is to average the historical sales proportions:

$$p_j = \frac{1}{T} \sum_{t=1}^{T} \frac{y_{j,t}}{Y_t} \tag{2.8}$$

Where p_j is the unweighted proportion, for each product j, $y_{j,t}$ are the sales relative to the total sales, y_t, in the product category y over time period T

An alternative is to weight the allocation, with a single, total proportion over all time periods:

$$p_j = \frac{\sum_{t=1}^{T} y_{j,t}}{\sum_{t=1}^{T} Y_t} \tag{2.9}$$

Both approaches have similar practical benefits (Gross and Sohl, 1990).

A benefit from the Top-Down approach, is the offset of data fluctuation and variability between time series. The aggregation, reduces noise, emphasizing trend and seasonality patterns and thus improving forecast accuracy (Widiarta et al., 2009).

Hyndman et al. (2011) also developed a middle approach, not as widely used as the other two approaches, in which the forecast happens at a middle level of the hierarchy, being afterwards aggregated bottom-up and disaggregated top-down to the rest of the hierarchy levels.

Despite the benefits that each method has, there isn't concrete results proving superiority by any of the three methods. Bahman et al. (2015), Giacomo and Andrea (2013) and Widiarta et al. (2009) have reached similar conclusions, in which the different methods produce similar results and their success is highly dependent on the context of the problem.

2.5 Supply Planning

Figure 2.2 showcases the next step in S&OP following the elaboration of the necessary forecasts: Supply Planning. Commonly, Supply Planning occurs across different functional areas (Production, distribution, replenishment and sales) and is the operational planning of each section, based on the company needs. These are coordinated through a tactical plan, the company's blueprint, which indicates the necessary quantities required to be produced, distributed, sold and provisioned for. That tactical plan is often known as MP or Aggregated Planning.

The main goal of the MP is to satisfy demand while maximizing profit, by determining planned levels of capacity, production, subcontracting and inventory. It is commonly defined at an aggregated level, per product's families or other recognizable patterns that ensure similarity, in a process aiming to synchronize the flow of materials along the supply chain (Chopra and Meindl, 2015). It supports mid-term decisions, across all functional departments, and ensures efficient utilization of resources, as a result of the usage of sales forecasts (Stadtler and Kilger Christoph, 2005).

MP obtains its maximization of profits by minimizing the overall costs while considering every constraint, such as limitation with overtime, payoffs, capital availability and others. Each constraint has an impact on one of the three main cost categories: production, inventory holding and stock out or backlog cost. Production costs refer to expenditures incurred with the production of the materials, inventory holding costs refer to expenditures due to inventory that is held and stockout costs are associated with the cost of not fulfilling a client order (Chopra and Meindl, 2015). MP balances out each signature, aiming to find the best solution that minimizes overall cost.

It is through these cost categories that forecast improvements are quantified. The smaller the forecast error, less erratic is the MP, fewer production plans are changed mid-through, less stock is required to be kept as a prevention measure and fewer deviations exist between expected and realised sales (Stadtler and Kilger Christoph, 2005). Forecast performance is directly connected to inventory holding and stockout cost, since a better performance can reduce the cost of both, as further explained in section 2.7.

Due to the importance of inventory management in forecast improvement quantification, a deeper look to the topic is presented in the next section.

2.6 Stock management

The presence of finished good stock is often a necessity for most companies. The main reasons behind it, however, may vary according to the industry, type of product production and external factors that a certain company may face. Nahmias and Olsen (2015) identified some of the main reasons for stock holding, highlighting in particular the relevancy of demand uncertainty and forecast error.

The higher the forecast error, the bigger the deviation between expected and verified stock levels. The impact felt with such deviation varies according to its nature, if overstocking or understocking. To overstock is to hold more stock than required, inducing in unnecessary inventory holding and obsolescence costs. On the opposite, to understock is to hold less stock than necessary, often inducing the company in costumer order delays and, in a worst case scenario, lost sales.

However, benefits are expected, from a business perspective, from holding higher levels of inventory. Nahmias and Olsen (2015) indicates that a higher stock investment, leads to higher product availability, which in turn contributes to higher client satisfaction, due to smaller delivery lead time and finally, to additional revenue. It is at the MP that the trade-off between inventory holding costs and service level/client satisfaction is considered. Nevertheless, a perspective over the value that stock carries is necessary for an ideal judgment and for the elaboration of an optimal plan.

Stock fulfills different necessities and may be segmented accordingly (Chopra and Meindl, 2015):

Category	Description
Cycle stock	The average amount of inventory required to satisfy demand until the next batch production. The size of the cycle stock is a result of the needs in production, transportation, and replenishment for that time interval.
Seasonal stock	Utilised to cover predictable seasonal variability in demand. It is often built during low demand periods and stored during high demand periods.
Safety stock	Inventory held for cases in which demand or the delivery lead time exceeds expectations. It is the stock utilised to face both demand and production uncertainty.

Table 2.3: Stock categories

While the presence of cycle stock is commonly expected in any industry scenario, the same can't be said from seasonal and safety stock, only present if necessary for the scenario in question. Regardless of stock category, improvements verified in forecast error is likely felt in terms of inventory. For instance, a higher forecasting MAPE and error's variance requires a bigger quantity of SS, to cover for the unexpected variability, while systematic forecasting errors are mostly felt in cycle stock. If the forecasting Bias is positive, the cycle stock level is higher than required, increasing inventory levels. On the contrary, in case of negative Bias, the company is consistently producing less quantity than the expected demand (Enns, 2002).

2.6.1 Safety stock

In a scenario without uncertainty, only cycle and seasonal stock would be necessary to cover all needs, with forecasting errors's variability being zero. However, demand variability plays a major factor in most supply chains, requiring the existence of SS, to cover for unpredictable excessive demand. SS contributes directly to production scheduling, since the SS level can potentially impact the quantity and frequency of SKU's production orders (Jacobs and Chase, 2013). Hence, in case of its presence, the method used to calculate SS has a big impact on Production Planning and on inventory holding costs.

Most methods for SS calculation are embedded in determining production re-ordering points and replenishment moments, due to the synergies between SS and Production Planning. Consequently, a selection of methods bases their SS calculation methods on service level requirements and on demand's standard deviation (Jacobs and Chase, 2013; Nahmias and Olsen, 2015). Other authors, such as Barrow and Kourentzes. (2016), suggest a different approach, using forecast error's standard deviation, instead of demand variability. Silver et al. (2009) base their approach on the mean and variability in demand, using polynomial approximations to calculate the ideal SS.

Zinn and Marmorstein (1990) verified which methodology wields the best results in terms of stock management, concluding that the use of forecasting errors offer significant advantages in cases of high-quality forecast and high demand variability. In the case of using a metric based on forecasting errors, the methodology requires the forecasting error's normality and centricity.

The measurement of SS policies and of its impact in supply chain is often restricted in practical scenarios. Henceforth, current literature often discuss the applicability of different methodologies theoretically, utilising result simulations. Bottani et al. (2014) and Galal and El-Kilany (2016) are examples of the applicability of the SS methodology in the food industry.

2.7 Quantifying forecast gains

It is common to assume that the minor the forecast error the greater. In the majority of cases, forecast accuracy and the minimization of forecast error are the common measurements used to assess the performance of the forecasting methods and DP in general. However, in an S&OP context, DP and forecast accuracy play a major role, by supplying the MP with the necessary information to plan out operational tasks and overall product production. The success at that role is, per itself, hard to measure based simply on forecast errors, since most of the impact is felt in various dimensions. The error measurements previously defined in section 2.4.1 are ideal to illustrate variation and systematic forecasting errors but are unable to properly explain a result or damage in Supply Planning (Wright, 1988). As Ha et al. (2018) exemplifies, two forecasts of equal MAPE, may have very different consequences in Supply Planning. Thus, the benefit of quantifying forecast benefits: it ensures that the forecast gain is reflected in the S&OP chain and contributing, with certainty, for better operational performance. Kerkkänen et al. (2009) breakdowns in Table 2.4 the different potential impacts that sales forecast error can have in the S&OP chain.

Planning Impacts	**Capacity impacts**	**Inventory impacts**
Schedule instability	Lost capacity	Excess inventory
	Uneconomical use of capacity	Inventory holding cost
		Obsolescence
		Reduced margin
		Lost sales cost

Table 2.4: Potential impacts of sales forecast errors (in Kerkkänen et al. (2009))

Kerkkänen et al. (2009) divides forecast error's impact into three main areas: planning, capacity and inventory. Planning impacts include the extra planning work and the associated costs that are derived from producing more quantity than required. Capacity impacts are due mostly to uneconomical use of capacity and lost capacity, while inventory impact is felt both with excessive inventory and lost sales. Kahn B. Kenneth (2003) divides forecast error impact into over-forecast and under-forecast. The consequences are the same as the ones illustrated by Kerkkänen et al. (2009), clarifying the importance of striking for balance in the topic.

Despite the fact that many studies have considered the impact of forecasting on financial and inventory performance, quantification of that same impact is still to be explored. Everette S. Gardner (1990) and Kahn B. Kenneth (2003) initially represented the impact of forecasting models through a trade-off curve between inventory investment and service level, and by measuring the financial value of accurate sales forecasting, respectively. Furthermore, the research developed through various different proposals, with Xie et al. (2004), Pennings et al. (2017) and Ha et al. (2018) contributing each to the topic. Xie et al. (2004) looked at the connection between schedule instability, service level and forecast errors, however, the method doesn't offer a solution applicable to a wide variety of scenarios. Pennings et al. (2017) proposed a new forecasting method that concerns service level, stock investment and lost sales. However, the model is only applicable to intermittent demand forecasting and only explores lightly the quantification area. Ha et al. (2018), on the other hand, proposes a broad view of the effects of forecasting in MP, considering inventory costs and production costs for forecast gain quantification. Equation 2.10 provides a simplified illustration of the formula utilized by Ha et al. (2018).

$$\begin{aligned}
\textbf{Total cost} \quad & TC_k = \sum_{t=1}^{n}(c_w * W_t + c_o * O_t + c_h * H_t + c_l * L_t \\
& + c_i * I_t + c_s * S_t + c_m * P_t + c_c * C_t), \\
\textbf{Inventory units} \quad & I_t = Max(SS + I_{t-1} + P_t + C_t - D_t - S_{t-1}, 0), \\
\textbf{Units stocked out} \quad & S_t = -Min(SS + I_{t-1} + P_t + C_t - D_t - S_{t-1}, 0).
\end{aligned} \tag{2.10}$$

Where c_w represents the workforce cost per unit, W_t the workforce size, c_o the overtime cost per unit, O_t the number of overtime hours, c_h the hiring and training cost per unit, H_t the number of employees hired, c_l the layoff cost per employee, L_t the number of employees laid off, c_i the inventory holding cost per unit, I_t the inventory units, c_s the marginal stock-out/backlog cost per unit, S_t the units stocked out, c_m the material cost per unit, P_t the units produced, c_b the subcontracting cost per unit, C_t units subtracted and D_t the actual demand, all in month t.

Ha et al. (2018) considers a minimising objective function, and various constraints, to calculate the total MP cost, using either actual demand or forecast results. The SS is included in the model, through the I_t and S_t equations. When forecast accuracy is improved, every cost variable may be affected, directly or indirectly.

2.8 Reflection upon literature review's findings

The S&OP literature is in a stage of consolidation and gathering of potential practical leveraging points. While the benefits attached to the applicability of the process are well defined, concrete examples of operational improvements extracted from the process are still very few. The expansion of the S&OP process, from its mere formal steps to a wider spectrum, by considering the operational success of its many steps would contribute for an increase in cohesion and overall business success.

Despite the good awareness surrounding the value of DP in the S&OP process, the quantification of its results in terms of cost and its overall impact is still an area requiring major developments. The evident practical restrictions slow down the development of the topic since a proper quantification requires domain and consideration of various distinct operational functions. Ha et al. (2018) methodology, while focused on providing an overall new forecast measurement, could potentially be leveraged to extract insights on the potential benefits surrounding forecast improvement projects as well as what could be overall qualitative benefits.

This thesis strives to support literature on various heterogeneous points. It aims at assessing a company based on the S&OP process, summarised by Thomé et al. (2012), while utilising the framework developed by Hulthén et al. (2016), thus providing insights upon the benefits of utilising a holistic approach in transformational projects and what benefits could be extracted from the practical applicability of the S&OP process. Simultaneously, the potential improvements expected at the DP department, due to the utilisation of the best practices surrounding the area, would support, or refute, what is the current mindset over the revised methods and literature, culminating on what would be the quantification of such benefits. While the utilisation of the whole equation proposed by Ha et al. (2018) is unfeasible, due to time and project related restrictions, a proper quantification of forecast improvements in terms of qualitative and stock benefits, including the costs involved, is possible. Hence, the main contribution expected from this thesis is the possibility of enriching the current literature by providing a practical example of forecast quantification.

Chapter 3

Case description and critical analysis

This chapter aims at providing an overview upon the case and identifying key improvement points, based on critical analysis. The chapter is segmented into three main sections: an S&OP assessment, a DP critical analysis and a description of the company's stock management.

The S&OP assessment aims to describe and assess the company's S&OP process, based on the framework constructed by Hulthén et al. (2016). The critical analysis of the DP department and its forecasting process, are a result of the insights withdrew from the S&OP assessment, that has identified the DP area as a focal area for a transformational project. The last section provides a brief overview of the company's stock management.

Throughout the chapter, the main pain points affecting the DP department will be explored. The project benefits from a holistic approach, as the improvements undertaken in DP are expected to yield results throughout the company's S&OP chain. Such results will be quantified later, at the MP area, by simulating the impact of the new measurements in terms of inventory and associated costs.

The information depicted in this chapter is a result of a hands-on assessment conducted at the beverages company. Formal meetings and informal workshops were held with the DP and MP teams to leverage the best on their insights to frame the holistic S&OP process and to conduct critical analyses. Many of the results are due to the fundamental role that data analysis portrayed during the overall project. The DP and MP departments in-depth analysis and the S&OP qualitative assessment is a result of a close collaboration with the company's accountable teams.

3.1 S&OP process description

3.1.1 Context

The beverage company at where this project is being conducted is based in Portugal, owning 4 factory lines and over 14 warehouses / cross-docking platforms. Its production follows a MTS manufacturing strategy, in a batch process, highly dependent on sales forecasts. Its products are aggregated at an operational level depending on their components and produced in batches that respect compatibility restrictions. There is a multitude of different SKUs, with a moderate volume of each type, produced in a disconnected line flow. The MP is done with a planning horizon of four months, reviewed monthly, with an SKU-level product aggregation. Supply Planning follows the tactical plan defined by the MP, with the replenishment, production, distribution and sales basing their product needs in the 4-month forecast and their operational tasks on the next month's more precise forecast.

3.1.2 Inputs

The company's S&OP process main inputs are similar to the ones described in Table 2.1. Each functional unit considers their own constraints when drafting their operational plans. Demand forecasts and the Master Plan are used as the main alignment tool. All the company's data is stored and managed through the company's ERP system, SAP R3. The data is updated consistently and kept for over 5 years, thus supporting data analysis and treatment.

3.1.3 Process

The company has implemented a typical monthly S&OP process, as illustrated in Figure 3.1. Each stage is described afterwards with detail.

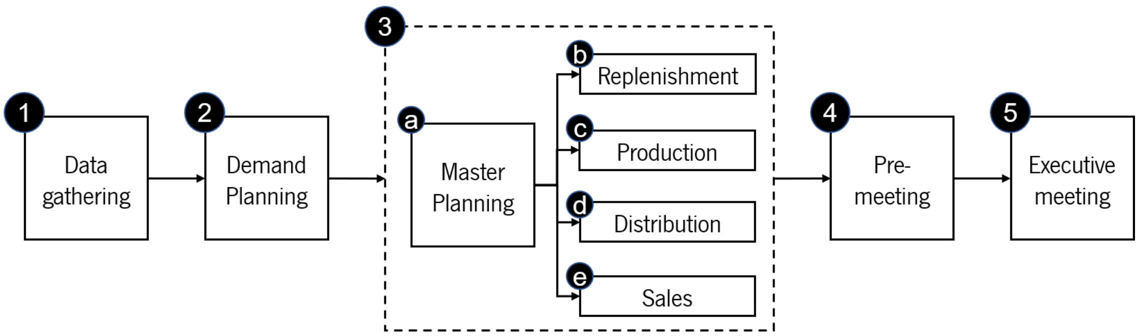


Figure 3.1: Company's S&OP Process

Data gathering

The process starts by collecting the information DP requires to forecast. The collected data spans five different categories:

- **Historical sales data**, used as the basis for the forecasting process and with a 3-year time span;
- **Forecasts from the past month's process**, still encompassing the next three months;
- **Confirmed next month sales**, related to specific sales channels;
- **Promotional activity**, proposed by the commercial department itself, related to its products, or timely informed customer's promotions;
- **Yearly and monthly sales budget**;
- **Innovations**, as in new developed SKUs and their expected first month's sales;
- **Discontinued SKUs**, no longer requiring forecasts and production;
- **Other relevant information**, such as changes in price tables or special occasions related to specific products or customers;

Commonly, necessary information for other functional units are also collected, such as raw materials delivery information, delayed production orders, or delayed customer deliveries.

Demand Planning

In the DP phase, the expected monthly sales for each sales channel is forecast in detail for each SKU. The forecast process is monitored by a DP team, who relies mostly on the input of sales commercial teams, segmented per sales channels. Each team provides the expected SKU's sales amount for the next four months, based on the statistical forecast automatically generated by the Advanced Planning & Scheduling (APS) system, SAP APO, and based on their own information and insight. The DP team consolidates the forecast information and inserts it into SAP APO, to be later used for Supply Planning. The sales' forecast is then distributed equally per each week of the month. A deeper explanation of the DP process is provided in section 3.3.

Supply Planning

The company's Supply Planning is segmented into two components: the MP, which calculates the necessary production quantities of each product, and each functional area operational plan, designed based on the calculated needs. Each SKU's production batch quantity is calculated based on 6 factors:

- Expected monthly sales;
- Current stock levels;
- Cycle stock and safety stock expected quantities;
- Operational restrictions, such as minimum lot size and sequencing;
- Product perishability;
- Expected service level;

MP considers each tactical restriction when drafting the four months production plan, with the expectation of producing the requested quantities. The plan is then sent to each factory unit as well as for the distribution and replenishment departments to support the elaboration of their own operational plans. Each factory unit design their weekly production plans based on specific factory restrictions, the replenishment department plans raw materials requirements and the distribution department sets the necessary quantities to be shipped to each company warehouse and delivery routes.

Pre-meeting & executive meeting

An Executive Meeting is held at the beginning of the month, to review past results and approve a high-level version of next month's plans.

3.1.4 Outcomes and results

The company seeks the expected main result from an S&OP process: alignment and integration between the whole company. Such alignment is mostly achieved, as functional plans tend to be crafted considering the same demand forecast, despite the presence of a clear improvement margin in the topic. Different results come as a benefit from the current integration:

- Reduced supply chain costs, as less stock is held as compensation for communication issues;
- Continuous operational improvement, as the company values global performance and seeks developments in sub-par functional areas;
- Forecast improvement is a continuous improvement process as is the search for continuous stock reduction;

- Service level of 94,3%, monitored by the company, achieved mostly due to high forecast accuracy, high operational efficiency, overcapacity and high levels of stock;

While the presence of a consistent company's S&OP process is undeniable, its effectiveness and efficiency would benefit from certain improvement actions. The following section assesses the process on those regards.

3.2 S&OP process assessment

Despite the valuable contribution that having an S&OP process provides per itself, greater effectiveness and efficiency adds in even greater benefits. However, in cases of poor efficiency, coordination and alignment suffer, as different operational functions lack the cohesiveness expected. Similarly, poor effectiveness results in a poor output, with business indicators demonstrating poorer results than expected.

The company's S&OP process is assessed for its efficiency and effectiveness in the following subsections, according to Hulthén et al. (2016) framework, illustrated in Figure 2.3.

3.2.1 Process efficiency

The efficiency of the process was assessed through formal meetings, data / process analysis and based on three hollistic aspects: process, organization and people. Figure 3.2 illustrates what aspects of the S&OP process were examined.

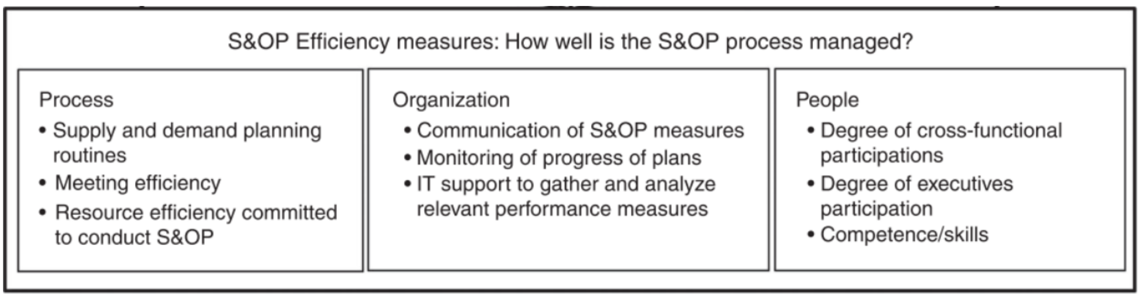


Figure 3.2: S&OP efficiency assessment

Overall, the company's S&OP process executes every step of the process, allowing for the extraction of benefits. Process-wise, both Supply Planning and DP benefit from monthly routines, to ensure their plan elaboration. Meetings are formally established, with two main meeting types: reporting of past month results and planning of next month's objectives between DP and MP; Operational plans coordination, between MP and the distribution, production and replenishment departments.

Each department distributes accountability to ensure the quality of the process and of the information shared. Despite each department being accountable for their own metrics related to their expected performance in the process, there is no shared responsibility for holistic metrics, potentially enforcing a strong internal view for each department. In spite of it, each department tracks the accomplishment of their own plans, considering the impact that they will have on the rest of the company. Executives are involved in the process, in the meetings and in ensuring the success of the process. Of worth noting, is the lack of an S&OP overall KPI.

3.2.2 Process effectiveness

The effectiveness of the process was analysed considering the expected outputs from each stage. Figure 3.3 shows what are the expectations of each phase.

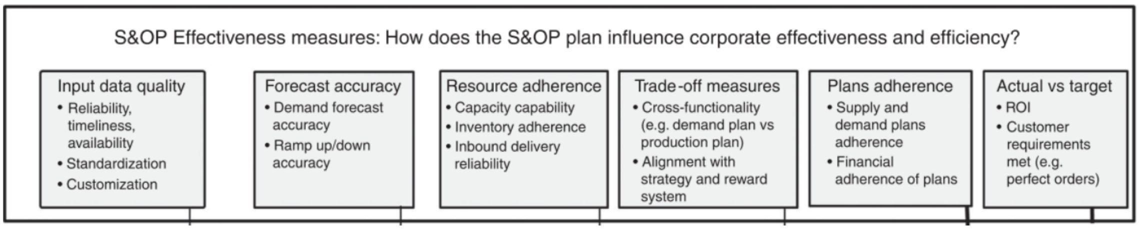


Figure 3.3: S&OP effectiveness assessment

Input data quality

The monthly input data collected for the process is reliable and updated under the expected time frame. The data is always provided in the same standardised format, facilitating integration with business modules and the creation of specific tools that benefit from such data sets. Customisation, on the other hand, is a lacking feature, mostly due to the data integration process of the ERP system. Big struggles are involved if it is required a different format to the data set or if newer information should be added. For DP, mostly historical sales data is currently being used to forecast, as promotional activity and causal variables aren't easily available. It is expected that the inclusion of this information would highly benefit the forecasting process.

Forecast accuracy

DP provides a forecast accuracy of 71,8% and a systematic Bias of 7,9%, per SKU x Sales channel x Month (per each month, for each sales channel of each SKU), according to the company's data. At the granularity required by MP, SKU x Week, the forecast accuracy is of 60,7%. A benchmark from previous forecasting projects held in other beverages companies from the same country, indicates a non-negligible potential for improvement, as competitors may rack up from 79% to 91,1% of monthly forecast accuracy, and up from 66% to 87,1% at a weekly time span. The competitor's data, utilised solely for the benchmark are a result from similar assessments conducted by the consultant's team. Such a difference towards its competitors could be explained by deficiencies in the client's DP process and by the low accuracy demonstrated by the statistical APS's forecast.

Resource adherence

The company's production capacity is sufficient for current demand, as Production Planning benefits from an excessive capacity to cover for hard setups and restrictive production requirements. The distribution and replenishment areas, while having sufficient capacity, do not benefit from the same excess. Furthermore, inbound raw material deliveries are reliable and functioning as expected. Stock management, however, is influenced negatively by the poorer alignment between MP, distribution and replenishment. While demand forecasts are sent from MP to such operational areas and considered, their inventory system is managed based on specific historical data from the particular sector. These inventory silos may impact negatively the company as a cohesive and holistic look over its total stock would benefit the company in terms of taking integrated actions. Internal steps have been taken to address the issue and its resolution is out of the scope of this thesis.

Trade-off measures, plans adherence & actual vs target results

Each operational plan is properly aligned with MP and the expected demand. There's a continuous effort towards strategic alignment and in ensuring the expected customer service level. As a policy, ensuring the satisfaction of every delivery is prefered to cost-saving decisions. Hence, often Supply Planning caters for such a mindset, by encouraging a higher stock level.

Every plan is followed through as expected, with changes communicated on time. Customer requirements are continuously met, considering the trade-off between costs and revenue when necessary.

3.2.3 Assessment's conclusions

From an S&OP standpoint, the competitor's benchmark regarding DP indicates a significant margin for improvement. As expected, the more accurate the forecast, the less the stock required to be held and the smoother the MP is. Such benefits have a clear impact cost-wise and the expected efforts to achieve them are highly appreciated by the company. Furthermore, efforts are already being undertaken to ensure a deeper alignment between the replenishment and distribution functional areas and the rest of the S&OP chain. However, until such alignment is evident, the process will benefit the most from actions undertaken within the connection DP-MP, as their integration can be better leveraged. The current process supports the quantification of forecasting benefits in the MP inventory management. Inventory quantification adds depth to forecast measurement metrics, as it quantifies the benefit the company will undertake, cost wise. Due to the verified independent stock management of the distribution and replenishment areas, the same quantification can't be expected in their inventory system and materials.

Hence, considering the leveraging opportunities DP appears to present, a deeper look to the department is provided in the following section.

3.3 Demand Planning critical analysis

This section provides a detailed analysis of the DP department process and of its overall performance. The main struggles of the department are identified, of which improvement opportunities are further leveraged. The result of the analysis is due to the work developed in the field, based on historical data and employee's perceptions.

The DP department is accountable for ensuring a monthly SKU x sales channel forecast delivery, aggregated according to its needs. Figure 3.4 illustrates the scope within the department. The project was conducted together with the DP team and with various contact points with members from commercial teams.

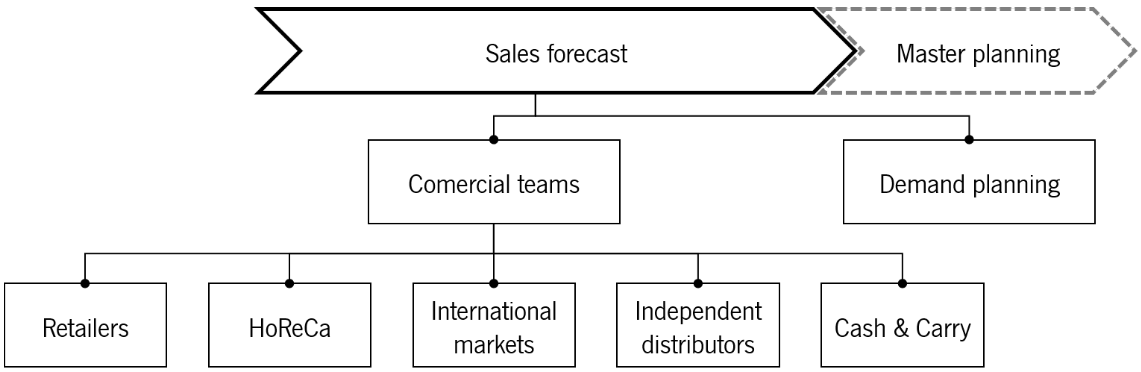


Figure 3.4: Teams involved into the sales forecast generation

The following section analyses the department in terms of its KPIs: total Sales, its forecast accuracy and deviation.

3.3.1 Demand Planning performance analysis

The company benefits from a very dynamic assortment list, with over 500 different SKUs, of which 60 are renewed every year and replaced by new innovative beverages. Each SKU is sold through one or more sales channels of the company. There are five different sales channels, each with their own commercial team. Figure 3.5 showcases the relative importance of each channel, in terms of total units sold[1]:

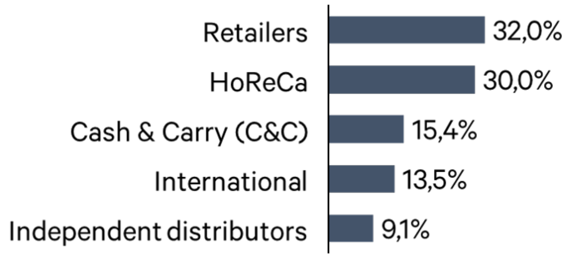


Figure 3.5: Sales Channels distribution

Forecasts are generated for each channel, at different granularities. Figure 3.6 illustrates the forecast accuracy for the different granularity levels[2], required as so due to company needs. The notation indicates the granularity of the information (e.g. SKU x Month is measured with sales aggregated per SKU, for each month).

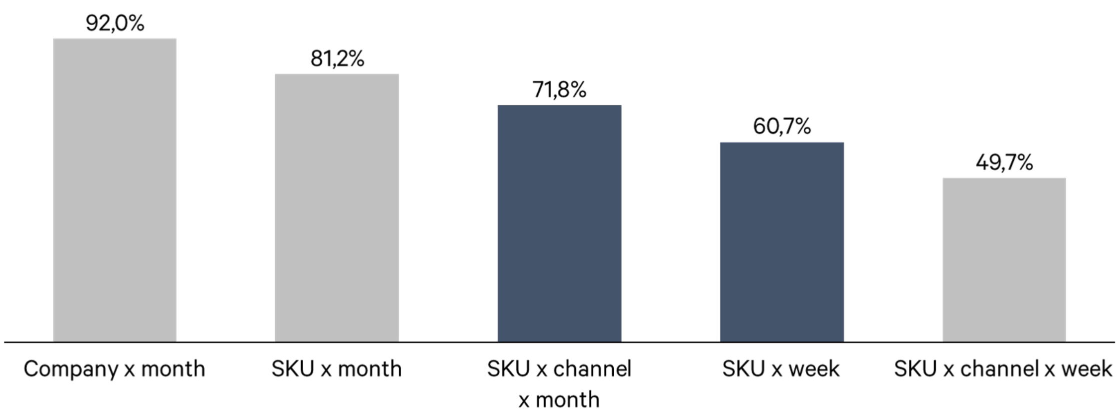


Figure 3.6: Forecast accuracy at different granularities

As expected, the bigger the granularity required, the lower the accuracy. DP provides such forecasts with the aid of the company's sales commercial teams, accountable for achieving the sales results. Each team provides their monthly forecasts based on their expectations for the following

[1]Sales units from Jun 2015 to May 2018
[2]Accuracy and Bias measured considering a data-set from Jan 2017 to May 2018

months and their own interpretability of the statistical automatic forecast, provided by SAP APO. Figure 3.7 indicates the system and commercial (final) forecast accuracy (SKU x Month), segmented per sales channels: retail, Hotels,Restaurants and Cafes (HoReCa), C&C, international markets and independent distributors.

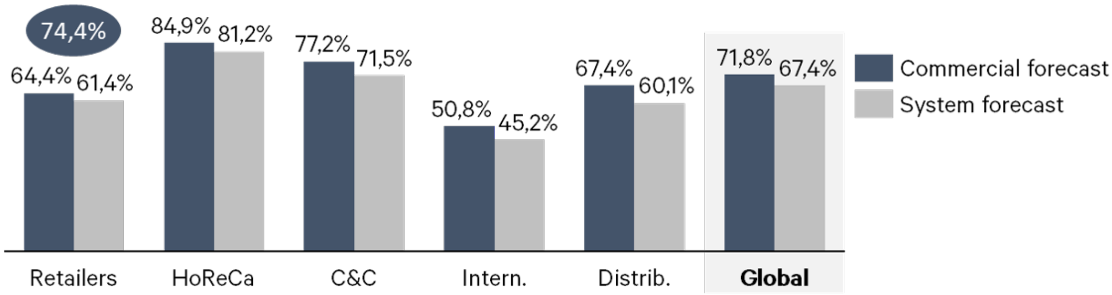


Figure 3.7: Sales channel's forecast accuracy

HoReCa consistently registers the higher accuracy, due to its regular demand pattern. In contrast, international markets have the lowest accuracy, due to the sales erratic nature. Retail's accuracy of 64,4% is displayed in a SKU x client x month granularity, since the client's internal policies consider that segmentation for the sales channel. Nevertheless, under the same granularity as the other channels, the accuracy value is the one displayed in the blue ellipse, 74,4%. Forecasts tend to be more accurate for those channels with a higher percentage of the company's total units sold. Aditionally, the system's forecast accuracy is consistently lower than the commercial forecast, due to the poor parametrization of SAP, conditioning the quality of its forecasts, and due to the extra qualitative information that the commercial teams leverage on, when generating their own forecasts.

In a similar manner, forecast Bias was also analysed and segmented accordingly to their sales channel. Figure 3.8 illustrates the global Bias and its respective segmentation.

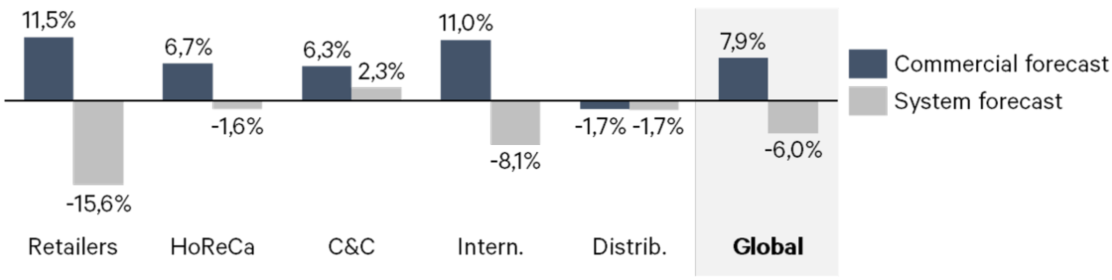


Figure 3.8: Sales channel's forecast Bias characterization

As illustrated by the Figure 3.8, the system forecast assumes a systematic average negative error of 6%, while commercial forecast reveals a tendency to overestimate sales, by 7.9%. Accordingly, margins for improvement are possible to identify for both types of forecasts, as both would benefit from correcting systematic errors and thus, reducing the DP negative impact on the MP, currently affected by sales overestimation, causing stock excess.

3.3.2 ABC-XYZ analysis

The DP process does not distinguish the company's products in any way. Regardless of their importance for the company, or statistical predictability, each SKU is forecast with the same method: initially with the statistical forecast, followed by the commercial forecast. However, there are significant differences between products. Some are naturally responsible for a bigger share of the company's sales volume than others and thus potentially deserving more attention and effort. A similar rationale can be applied related to forecasting predictability. A product with stable and small demand fluctuations, or with a clear sales pattern, is easier to predict through statistical methods, potentially indicating benefits, in case of leveraging statistical forecasting for those cases. Kourentzes (2016) mentioned in his blog an analysis that considers both the sales importance of an SKU, with the common ABC analysis, and the forecasting predictability, with an XYZ analysis. "A" products have a cumulative sales weight of 80% of the company's total sales, "B" products have the remaining 15%, until a cumulative total sales weight of 95% and "C" products comprises of the remaining 5% percent. The distribution follows the Pareto principle. The XYZ analysis utilized for this case was slightly different from what Kourentzes (2016) suggests. Instead of using the Coefficient of Variation[3], the SKUs were segmented according to their naïve[4] forecast accuracy. If an SKU had above 85% of forecast accuracy, it is classified as an "X", if it has between 85% to 70%, "Y", and if below that threshold, "Z". The Coefficient of Variation, while it identifies the overall variation, poorly acknowledges seasonality, despite its easiness to forecast. Hence, the reason to use a different metric.

The methodology was applied, segmenting the company's SKUs per nine different quadrants. Figure 3.9 indicates the % of the company's SKUs in each of the quadrants, the % of sales per quadrants and the approved forecast accuracy (system in brackets).

[3] $C_v = \sigma/\mu$

[4] Naïve forecast as the best option between 1) moving average of three most recent months and 2) the sales of the same month in the previous year

Sales Volume / Difficulty to forecast

% of SKUs	X	Y	Z
A	13,0%	10,6%	4,1%
B	6,8%	11,1%	7,9%
C	13,6%	11,7%	21,2%

% of sales	X	Y	Z
A	45,3%	26,7%	8,2%
B	4,3%	6,2%	4,3%
C	1,3%	1,1%	2,5%

Approved (system) forecast accuracy	X	Y	Z
A	89,2% (86,4%)	81,0% (69,7%)	66,2% (54,9%)
B	82,0% (82,1%)	76,5% (74,6%)	49,8% (45,0%)
C	85,7% (81,9%)	73,8% (77,9%)	52,5% (50,6%)

Figure 3.9: ABC-XYZ Analysis

These three matrixes allow a deep analysis of the forecast impact in the assortment of the company. 45,31% of sales are obtained by selling 13,0% of the products, for which the company has 89,2% of forecast accuracy. Intuitively, it is expected that the products with higher sales volume are easier to predict and the opposite is equally true. Similarly, the impact of the commercial validation increases has the SKUs become harder to predict. For products belonging to the ”X” quadrants, the commercial impact is of +2.58percentage point (PP), +9,09PP for the ”Y” quadrants and +7,87PP for the ”Z” quadrants. The impact measurement is weighted by the sales value and could serve as a foundation for superior usage of the statistical and commercial forecasts.

Past experience with other multinational beverage producers endorse the notion that there is a possibility of improving the current client’s forecast accuracy. Henceforth, the DP department process is analysed to identify pain points and improvement opportunities. The following subsection explores those findings.

3.3.3 Demand Planning process analysis

The DP process is segmented into three main key activities: forecast generation, forecast validation and monitoring. Appendix B is a high-level process mapping of the DP process, segmented per its three main activities and per the three involved departments: DP, sales & marketing and MP. The inputs for each activity are identified as well. The process mapping is a result of a close interaction with the DP team, identifying the key activities that were performed throughout the month to provide the company with the necessary forecasts. Key improvement opportunities were extracted from the process mapping.

Forecast generation

A system and a commercial forecast are generated sequentially, through a five-step monthly process, illustrated in Figure 3.10.

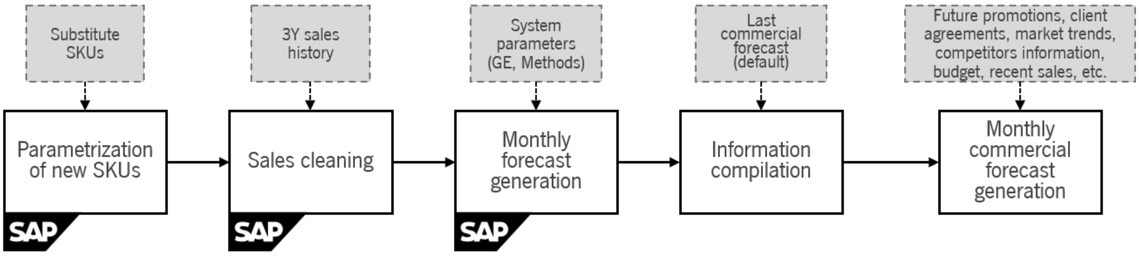


Figure 3.10: Forecast generation process

The system forecast is the first one to be generated, based on a statistical procedure. Primarily, SAP APO requires the aggregation of each SKU into a Statistical Group (SG), manually inserted into the system. Each SG has assigned a forecasting method, automatically or manually defined, that considers seasonality or tendency if justified. A twelve-month rolling forecast is generated for each SG and afterwards desegregated per SKU x channel, based on the sales percentage of the last twelve months of each SKU in the total SG sales units. SAP (2006) provides a list of the available forecasting methods and appendix A presents a description of the used methods.

The forecast performance of SAP APO is dependent of the SGs created and the methods that are assigned to them accordingly. The SGs have to be manually defined and periodically updated, indicating which SKUs belong to each. Forecasting models can be automatically defined or manually parametrized if prefered. SAP can only generate forecasts for parametrized SGs with automatically or manually defined statistical methods and parameters. However, since SAP isn't capable of automatically assign SKUs to SGs, the system is always in risk of becoming outdated and losing forecast accuracy, if the SKUs within the same SGs start to lose their similarities in terms of sales patterns. Currently, SAP parameters and SGs are not updated systematically.

The forecast generation requires two preceding steps:

1. Parametrization of new SKUs, for cases where a new SKU is added to the assortment. If the SKU is a direct substitution of other (e.g. change of package), then the Sales and SG of the previous model are implemented in the new version. In case of a new innovative SKU, with at least six months of sales, SAP parametrizes a statistical model, automatically through the use of the methods defined in SAP (2006), to forecast for the new SKU. This step is manually applied by the DP team;
2. Sales history cleaning, for every SKU. While outliers are detected and removed from the sales pattern, promotions and other relevant events are not identified by the system;

After the statistical forecast generation, the DP team compiles additional information, such as budget information, last commercial forecast and past sales, sending a file to the commercial teams, containing the necessary information for their forecast generation. However, only the commercial forecast is utilized by the MP, overriding the benefits of the statistical system forecast, since the same isn't considered by the commercial teams.

Each commercial team generates their own judgemental forecast, for every SKU in their channel, considering qualitative information, such as future promotions, client agreements, market trends and competitors information. Each team applies their own independent methodology, manually, and inserts the forecasts in files similar to the one illustrated in Figure 3.11. In total, there are over 20 plus separate files for forecasting. Each commercial is expected to explore the excel file SKU per SKU, cross-checking between the different similar rows, without the aid of any analysis or graphical support. The commercial forecast generation process is highly prone to error, with high output variability in quality terms.

Table

C		Ma	Package	Capacity	Family	SKU	Description		M 09.2017	M 10.2017	M 11.2017	M 12.2017	M 01.2018	M 02.2018
01	Client	Brand	CANS	1.5	Light	90000	Product A	Sales	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	8	Light	90000	Product A	System Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	14.5	Light	90000	Product A	Budget	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	21	Light	90000	Product A	Previous Comercial Forec	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	27.5	Light	90000	Product A	Commercial Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	34	Original	90001	Product B	Sales	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	40.5	Original	90001	Product B	System Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	47	Original	90001	Product B	Budget	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	53.5	Original	90001	Product B	Previous Comercial Forec	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	CANS	60	Original	90001	Product B	Commercial Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
									0 TAB	0 TAB	0 TAB	0 TAB	0 TAB	0 TAB
			Subtotal						0 TAB	0 TAB	0 TAB	0 TAB	0 TAB	0 TAB
01	Client	Brand	GLASS	1.5	Original	90002	Product C	Sales	1,000	1,001	1,002	1,003	1,004	1,005
01	Client	Brand	GLASS	8	Original	90002	Product C	System Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	14.5	Original	90002	Product C	Budget	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	21	Original	90002	Product C	Previous Comercial Forec	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	27.5	Original	90002	Product C	Commercial Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
			Subtotal						0 TAB	0 TAB	0 TAB	0 TAB	0 TAB	0 TAB
01	Client	Brand	GLASS	40.5	Light	90003	Product D	Sales	1,000	1,001	1,002	1,003	1,004	1,005
01	Client	Brand	GLASS	47	Light	90003	Product D	System Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	53.5	Light	90003	Product D	Budget	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	60	Light	90003	Product D	Previous Comercial Forec	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	66.5	Light	90003	Product D	Commercial Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	73	Original	90004	Product E	Sales	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB
01	Client	Brand	GLASS	79.5	Original	90004	Product E	System Forecast	1,000 TAB	1,001 TAB	1,002 TAB	1,003 TAB	1,004 TAB	1,005 TAB

Figure 3.11: Example of a file for commercial forecast input

Forecast validation

Forecast validation involves the MP and commercial teams alongside DP, to ensure that the expected demand is aligned with the company's production capabilities and the latest information. The process starts with a DP forecast validation and integration into SAP, after receiving the final commercial forecast. The validation is done manually, at a high level of aggregation. In case of an overly deviated value, the disaggregated forecasts are cross-checked to identify which one assumes an unreasonably deflected value. Despite the commercial forecast validation, no system alerts or other validation process are utilised to validate the system forecast of SAP. Hence, often the system forecasts that are sent to the commercial teams carry overly deviated values, affecting the system's credibility and their usability when commercial forecasts are generated.

Reporting meetings are conducted between DP and MP, to adjust the forecasts if necessary. Weekly, throughout the month, manual adjustments are performed by the DP team to forecasts, in cases of orders exceeding the expected forecast. However, such updates are dependent on the informal information sharing by the commercial team, lacking a standardized method to identify and recalculate deviated forecasts. The recalculation process is based on empirical evidence. The following Figure 3.12 illustrates the steps involved in the process.

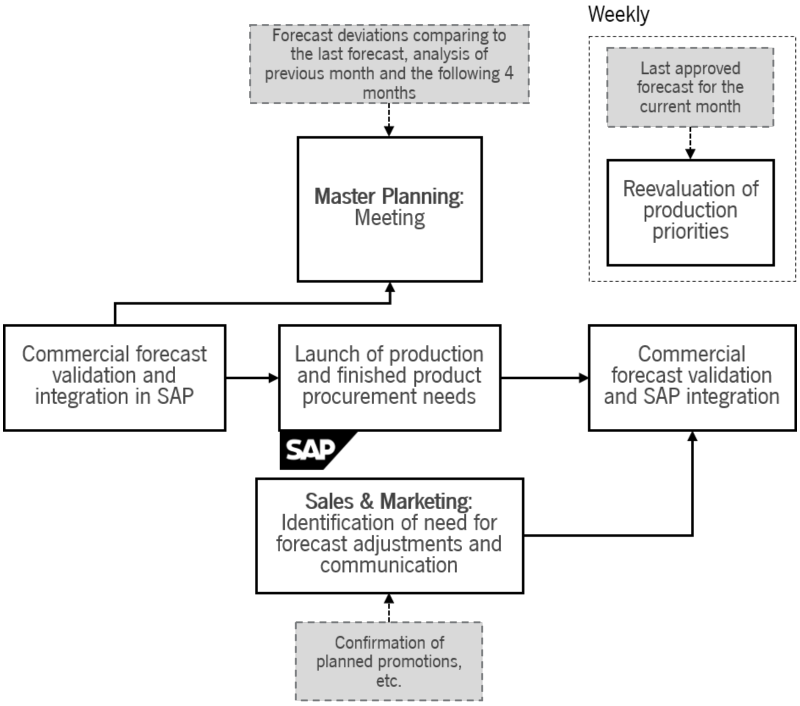


Figure 3.12: Forecast validation process

Forecast monitoring

Forecast performance is measured by two KPIs: Accuracy and Bias of the approved final forecast. The indicators are calculated monthly and reported monthly to the commercial teams and executives. Simultaneously, DP provides a weekly report of the forecast concretization to the commercial teams, albeit no action is commonly withdrawn from such conclusions. The monitorization of system performance is for reporting purposes only, reducing the incentives for improvement of the system's forecast accuracy. Similarly, no accuracy targets are defined for the forecast KPIs and no systematic analysis is performed to evaluate forecast error trends and systematic errors. Generally, forecast monitoring indicates big leveraging opportunities. The following Figure 3.13 illustrates the steps involved in the process.

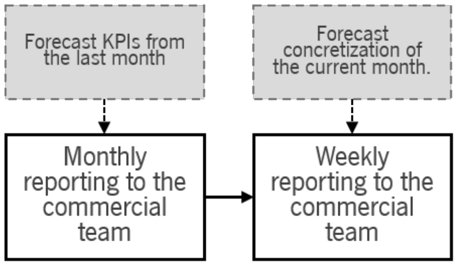


Figure 3.13: Forecast monitoring process

Reflexion & insights

The overall process benefits from periodic formal meetings with the planning department and formal communication with the various commercial teams. The forecast generation is decentralized, since each commercial team is accountable for their own channel, with the DP team as the main connection point. On the opposite, forecast validation and monitorization processes are both centralized, with DP assuming accountability. Overall, the process is considered redundant and time-consuming. The system's forecast is underappreciated and lacks confidence within the commercial teams, with many preferring to not consider the system's suggestions in any regard. The current process lacks standardized tools that could potentially support the generation and the validation of the forecasts. Consequently, the DP team doesn't validate system forecasts, since it would requires an extensive manual validation. Similarly, every commercial team member has to forecast for every SKU, in their own tools, regardless of the SKU's importance for the company and regardless of the system's accuracy for that same product. Often, and due to the mentioned reasons, the forecast provided by the commercial teams, and used by the MP, are qualitatively based, disregarding the benefits of statistical forecasts, and distributing their effort through a myriad of different products, regardless of the quality of their input in comparison to the statistical forecast. Such a process, full of inefficiencies, potentially leads to reduced accuracy, or to the inefficient use of the available resources.

3.4 Inventory management

The company's stock management is a direct result of the MP, accountable for considering expected demand, product restrictions and required production orders when drafting the master plan. Product's stock necessities are then carefully planned, in order to satisfy the expected service level until the next possible SKU's production order.

Each weekly stock necessity is defined per SKU, segmented in three different components: cycle stock, SS and production constraints. The later contributes with stock buffers to compensate for the following restrictions:

- Production frequency: the periodicity until a new batch of an SKU can be produced again;
- Minimum batch quantity: minimum necessary production quantity for a given product;

Figure 3.14 summarises the effect of each stock component and their relative importance in the final stock quantity. The blue colour highlights the two components affected by potential improvements in the DP department: the SS and the sales deviation component (Consequence of overestimating monthly sales).

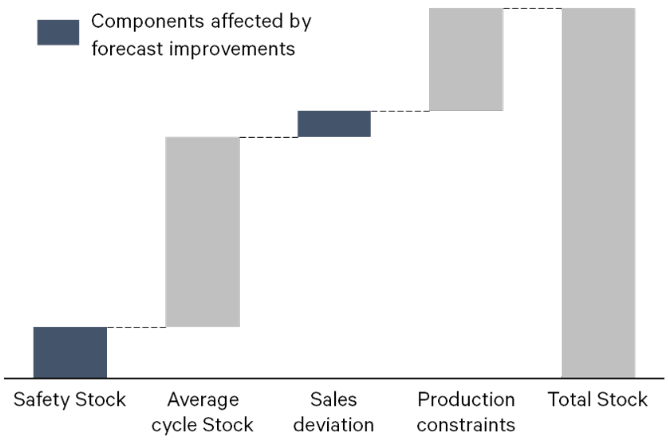


Figure 3.14: Stock components

Each product has a SS quantity, defined according to the methodology presented in Silver et al. (2009). The greater the company's forecast error's variability, the greater the SS value. The positive sales deviation illustrated in Figure 3.14 is correlated to the company's tendency to overforecast. For the cases where the company underforecasts, the deviation reduces the overall stock quantity. Ideally, the sales deviations, positive or negative, should be minimised.

Stock necessities are calculated per SKU, each week. Afterwards, production orders are drafted based on the difference between held stock and what is required, with a weekly updated version.

Table 3.1 summarises the service level, measured as the percentage of fulfilled orders, and stock coverage, in days, per ABC-XYZ quadrant, at the beginning of this project. The data was provided by the company and was calculated based on the components defined in Figure 3.14, per SKU x Week.

Quadrant	Service Level	Total Stock	Cycle Stock	Safety Stock
AX	98.90%	19.5	18.8	0.7
AY	99.17%	25.2	21.1	4.1
AZ	99.53%	35.9	26.9	9.0
BX	98.50%	21.4	18.9	2.4
BY	98.67%	30.8	26.9	3.8
BZ	98.82%	45.3	35.8	9.5
CX	100%	27.1	25.5	1.6
CY	95.48%	41.6	37.2	4.4
CZ	97.03%	50.7	37.6	13.1

Table 3.1: Current State: stock coverage (in days) and service level per quadrant ABX-XYZ

Despite the well-sounded process surrounding stock management, the company would profit from a methodology capable of assessing the benefits and the impact of their actions in terms of stock quantities. Currently, there's no available method to calculate forecasting benefits in terms of service level, cycle stock, safety stock and costs. Furthermore, the current state of the S&OP process, described in section 3.1, turns incapable the stock quantification for raw materials and finished products held in the company's supply chain. At the moment of this thesis, only the relationship between DP and MP is sufficiently quantifiable.

3.5 Insights and key findings

The critical analysis conducted at the DP department and to the company's stock management allowed for the extraction of key findings that could potentially be leveraged for improvement opportunities. Table 3.2 provides an overview of the current situation and structures the key findings identified. The following chapter addresses the critical issues identified and describes the solutions and methodologies applied to solve the problems that were diagnosed.

	Key findings
Overall process	Redundant and time consuming Lack of confidence in SAP APO DP Forecast used only for production and procurement purposes High prevalence of qualitative inputs No clear priorities for validation
Generation	System forecast is not used SAP APO DP parameters were not updated systematically Commercial forecast mostly as manual input – process with high variability Promotions and other relevant events are not flagged in sales history
Validation	No system alerts or other validation process for SAP APO forecast validation Manual validation without automatic cross-checking mechanisms Forecast update during the month depends on the informal information sharing of the commercial team
Monitoring	Monitorization of system performance for reporting purposes only No systematic analysis of forecast error trends and systematic errors No accuracy targets and objectives alignment with forecast KPIs
Stock Management	SKU's stock quantities affected by the forecast's positive Bias Lacking a methodology for quantification of forecasting actions and benefits Replenishment and distribution stock quantities managed separately from the MP stock management

Table 3.2: Key findings

Chapter 4

Description of improvement proposals

This chapter summarises the methodologies utilised to overcome the identified issues and to improve the performance of the DP department. After a brief summary of the undertaken line of actions, a detailed description of each unfollows. Table 4.1 exposes the improvement actions, segmented per impact areas.

Impact area	Initiatives	Description
Overall process	Forecast Prioritization methodology	A method that prioritizes which SKUs benefits the most from commercial forecast.
	New DP process	New process to improve the efficiency of the department.
Generation	Forecast optimizer	External software module crafted to periodically optimize the SAP SGs and the forecasting methods assigned to each.
	Commercial interface	Clean, user-friendly interface to aid commercial teams in their tasks of forecast generation.
Validation	System forecast validation	Interface supporting the DP team with analysis and corrections to system forecasts.
Monitoring	Monitorization interface	Interface weekly monitoring forecasts, correcting deviated values.
Stock Management	Stock Simulator	A simulator of the stock management policies, allowing the quantification of forecasting gains.

Table 4.1: Improvement actions

4.1 Forecast prioritization methodology

The first two pain points addressed were the redundancy/ time-consumption of the DP process and the neglective usage of system forecast. Addressing these issues is critical to not only leverage the benefits of statistical forecasting but also to magnify the potential of the commercial input by optimizing their effort for cases with higher improvement margin. The new process should be built under the premise that each resource is leveraged at its best. Therefore, an obligatory commercial input should only be required for cases of great value for the company/sales channel, or for situations in which the system forecast is poor, while the system forecast should be sufficient for cases of low value for the company/sales channel and of high predictability. Ideally, both types of forecast should be used, for cases where both insights can contribute positively. Thus, the need for proper segmentation.

The new SKU prioritization methodology builds upon the previous justification, by segmenting SKUs into three different categories:

- **System** (S), system forecast as default forecast, with a punctual commercial validation, only in cases of applicability of special factors, such as promotions;
- **Manual** (M), no system forecast, a commercial forecast is required for every input (last commercial forecast as default);
- **System + Manual** (S+M), system forecast as default forecast, with careful commercial validation of every input;

The segmentation is performed per SKU x sales channel, based on the rationale and analysis described in Table 4.2:

Rationale	Analysis	Results
Is this an SKU of high importance because of its sales volume?	*ABC* analysis at SKU level	SKU is defined as *A*, *B* or *C*
Does my client/ channel represent a relevant share of SKU sales?	*ABC* analysis at SKU x channel/ client level	Channel /client per SKU defined as *A*, *B* or *C*
Is this a forecast that is difficult to determine?	*XYZ* based on naive forecast analysis	SKU defined as *X*, *Y* or *Z*
Is this a case of an exception such as innovative products?	Identification of exceptions	SKU classified as an *M*, in all sales channels

Table 4.2: Rationale for prioritization

Based on the results of Table 4.2, each SKU x Sales channel is defined with one of the designations. Table 4.3 illustrates all the possible designations, for four different exemplary SKUs, according to the results of Table 4.2, their classification as an A, B or C product and each channel/client classification.

SKU	ABC	Channel/ Client at SKU level	X	Y	Z
		A	S+M	M	M
1	A	B	S+M	S+M	M
		C	S	S+M	S+M
		A	S+M	S+M	M
2	B	B	S	S+M	S+M
		C	S	S	S+M
		A	S+M	S+M	S+M
3	C	B	S	S	S+M
		C	S	S	S
4		No classification	M	M	M

Table 4.3: Prioritization Matrix

The prioritization matrix follows a diagonal pattern, requesting increased commercial support in cases of greater value and higher forecast difficulty. For SKUs in the quadrants "AX","AY" or "AZ", undistinguishable of sales channel, the prioritization will be "M" or "$S+M$", due to the high importance of the SKU. Solely for the case of "AX" in a "C" channel can the prioritization be an "S", due to the low sales amount in the respective channels and the expected high forecast accuracy. For SKUs classified as "B" and "C" the rationale is maintained.

The assignment of "S", "M" and "$S+M$" per combination was defined together with the DP team, in an iterative process, searching for the ideal distribution that ensured the best trade-off between business importance and commercial team's effort. Table 4.4 illustrates the prior and novel SKU allocation per category, when utilising the established SAP SGs and statistical methods. The same allocation is provided to the DP team, aggregated per sales channel.

	As is	To be	Variation (%)
S	-	1423 (5,1%)	-
M	2.622 (100%)	217 (19,5%)	-91.7%
S+M	-	982 (75,4%)	.

Table 4.4: Number of SKUs (% of sales)

Despite the great reduction in terms of SKUs requiring manual forecast (1423 SKUs), commercial validation is still requested for 94.9% of total sales. The new prioritization methodology provides benefits in terms of reduced manual effort and diminished variability in the forecast generation process since the matrix leverages on the cases of higher accuracy for both the commercial team and SAP. Figure 4.1 illustrates a preliminary result, showing how each category exploits the best case scenario. System forecast is illustrated with the gray colour and commercial forecast with blue.

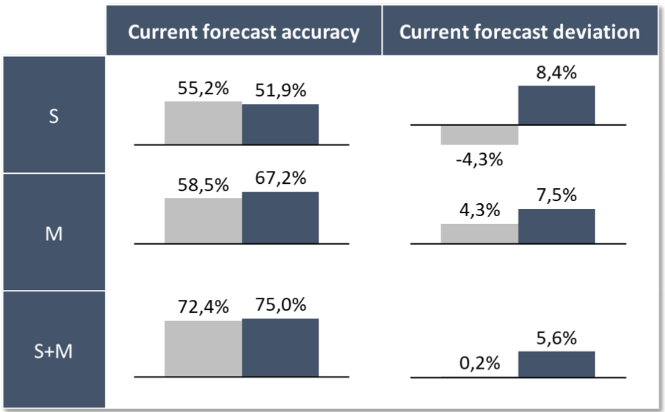


Figure 4.1: Accuracy and deviation per category

Additionally, increased usage of the system forecasts decreases the dependency of the commercial team's informal knowledge and motivates the department to continuously improve the system forecast.

The forecast prioritization matrix was utilized on the remaining line of actions due to its pivotal role in the department. An efficient department requires cohesion between its different activities, a clear effort prioritization and a well-defined process.

4.2 New Demand Planning process

The critical analysis conducted at the DP process, with the key insights described in Table 3.2, identified various improvement opportunities associated with the department's process: its redundancy, the prevalence of qualitative inputs, the non-SKU prioritization in the generation and validation activities and the absence of a monitorization subprocess.

The chosen approach to tackle the identified issues was the elaboration of a new process alongside the DP team, accountable for its execution. To assure continuous communication, iterative biweekly meetings were established with the executive team. Moreover, two group meetings were held with the sales channels' commercial teams and weekly meetings were held with the accountable DP team. The solution satisfies the following requirements:

- Process with a monthly periodicity, systematic and automated when possible;
- Statistical forecast appropriately leveraged;
- Commercial effort empowered and efficiently used;
- Governance appropriately defined across the multiple subprocesses;
- Advantage of weekly monitorization and successive forecast revalidation;
- Forecasts provided in time for MP;

The new DP process is divided into three sub-process. Table 4.5 provides a quick summary of the definition of each and their periodic time-span.

Subprocess	Description	Stakeholders	time-span
Forecast generation and validation	Generate monthly forecasts using SAP forecasts and the insights of the commercial teams	DP; Commercial teams; marketing & sales	During the 2nd, 3rd and 4th week
Forecast revalidation	Reassess the forecast of the current month for the weekly reported cases and improve the accuracy for the remaining weeks	DP; Commercial teams;	1 day at the 2nd, 3rd and 4th week
Forecast monitorization	Communicate results to the teams involved in the process and collect improvement points for the future	DP; Commercial teams; MP;	3 days at the 1st and 2nd week

Table 4.5: Subprocesses description

A detailed look will be provided to each subprocess, considering one monthly (4 weeks) cycle of the process. Figure 4.2 provides an overview of the process, schematized in a calendar view. The following subsections provide an explanation of each of the tasks illustrated.

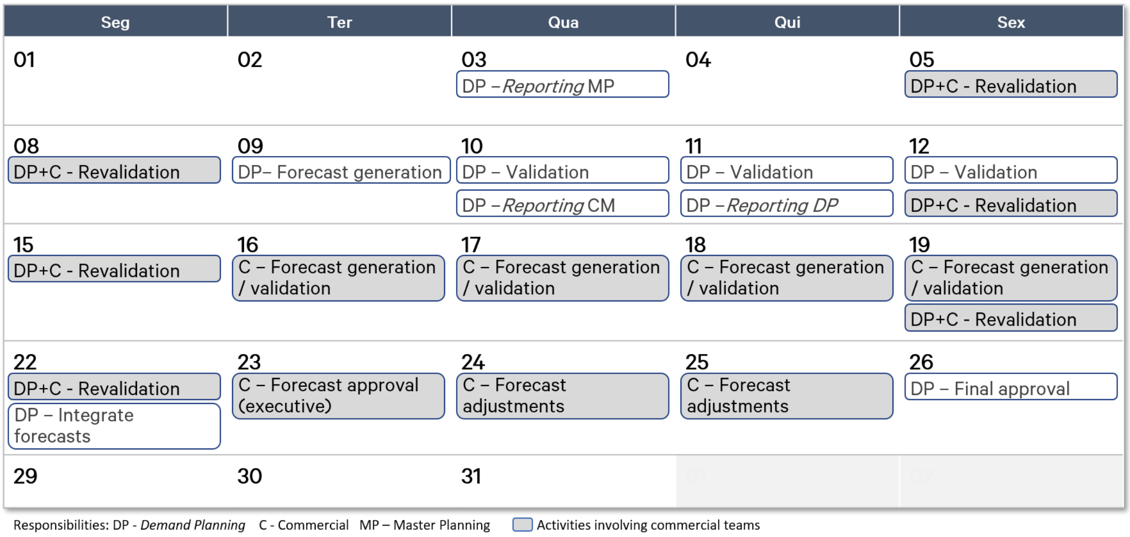


Figure 4.2: Overview of the new DP process

4.2.1 Forecast generation and validation

The forecast generation and validation process is based on the applicability of the prioritization matrix, illustrated in Table 4.3, and aims at ensuring accountability to the involved teams, focus on value-adding tasks and increased usability. Figure 4.3 shows a macro-view of the subprocess.

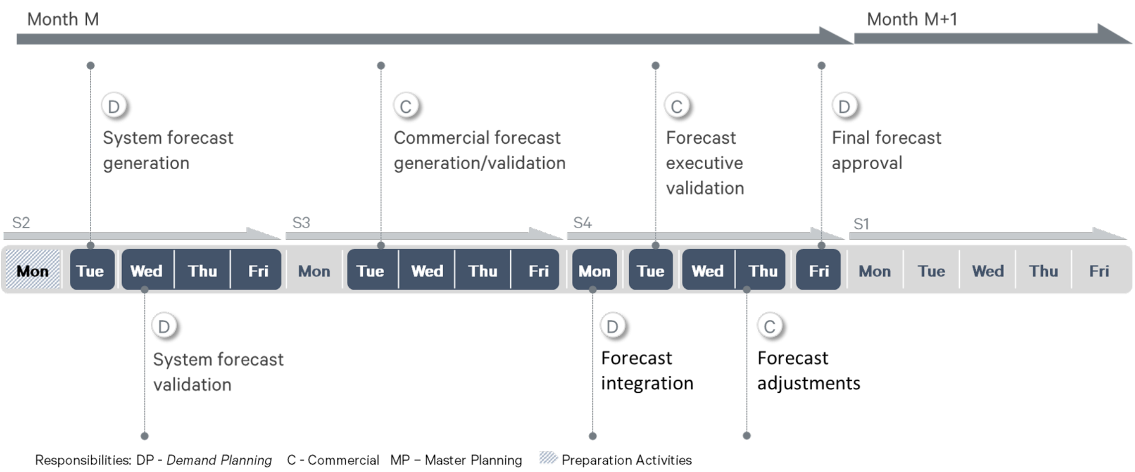


Figure 4.3: New generation / validation subprocess

The first week of the month is kept without any activity, as the S&OP's step, data gathering, requires a week to provide the latest sales results. Therefore, the subprocess is initiated Tuesday of the second week, with the generation of the system forecast and the utilization of the latest information. The system generation step requires setup activities, to ensure the most accurate results:

1. Manage new and excluded SKUs according to their status:
   a) Innovation - Product is classified as "M" and the marketing & sales initial forecast is used for the first month. For the following months, commercial teams are accountable for the forecast;
   b) Substitution - Register the new product as a substitution of the previous one. Allocate in SAP the past information, including the SG;
2. Every six months, update SAP SG's and statistical methods through the external optimizer described in subsection 4.3. New SKUs with six months of sales are added to an SGs;

Three days are reserved for system forecast validation, with the usage of a new tool, described in subsection 4.5. The most critical cases are identified and adjusted if necessary, based on a tracking signal method. Afterwards, information is prepared to be sent to each sales commercial team. The following activity is the commercial forecast generation/ validation, held until Friday of the third week. The commercial input is asked as late as possible, to ensure the highest fidelity in their insights and information. If their input was provided earlier, a significant percentage of client's deals and promotions for the next month, for example, wouldn't be yet cleared. The commercial input is provided through a new interface, described in subsection 4.4. The process follows the prioritization matrix: Commercials are expected to provide a forecast for SKUs classified as "M", carefully check any SKU classified as "$S+M$" and only intervene in case of advanced information for the SKUs classified as "S". The following week is reserved for the SAP integration of the forecasts, a high-level communication to the executive team, adjustments if necessary and a final approval, at an S&OP meeting. The forecasts are delivered in time for the MP to plan the following month, as a preliminary Master Plan is defined throughout the last week of the past month and adjusted accordingly in the first week of the month.

4.2.2 Forecast revalidation

The revalidation subprocess aims at addressing deviated forecasts in periodic revision moments. The main motivation for its conception is the benefit expected to be collected by the production, distribution and replenishment areas. As forecasts are timely corrected, operational mistakes are avoided and supply planning loses some of its erratic nature. This subprocess, in particular, is expected to yield significant results in an S&OP context. Figure 4.4 illustrates the subprocess in a monthly time-frame.

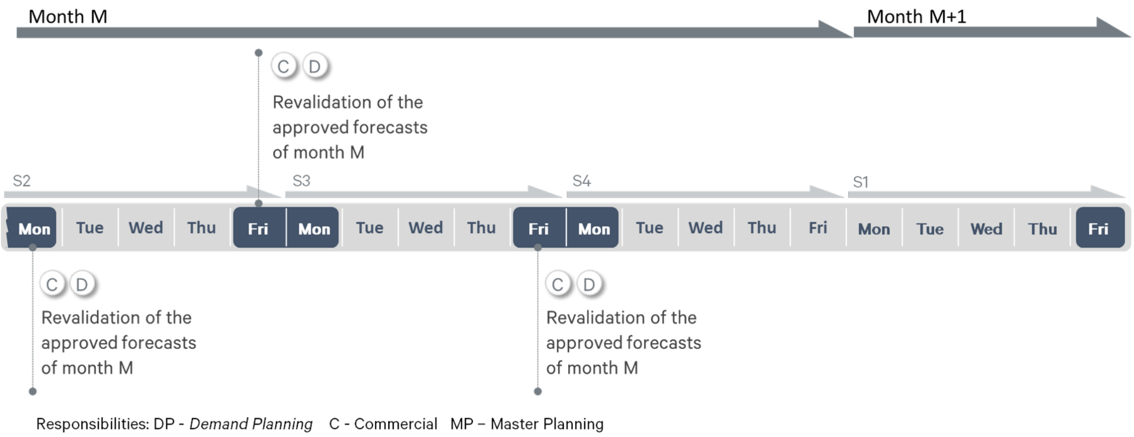


Figure 4.4: New revalidation subprocess

Forecast revalidation is performed in the second, third and fourth week of each month, in a two-day process. Using an interface explained in subsection 4.6, forecasts are signalled as under-forecasting or over-forecasting. The critical cases are communicated to commercial teams, in the case of "M" and "$S+M$", and corrected by the DP for the "S" cases. Afterwards, a weekly report is communicated with the supply planning teams, to absorb the expected benefits. The process is repeated for the other two revalidation moments.

4.2.3 Forecast monitorization

The last sub-process aims at establishing a process of continuous improvement in the DP department, by collecting insights and reporting them to the adequate teams. Figure 4.5 illustrates the sub-process.

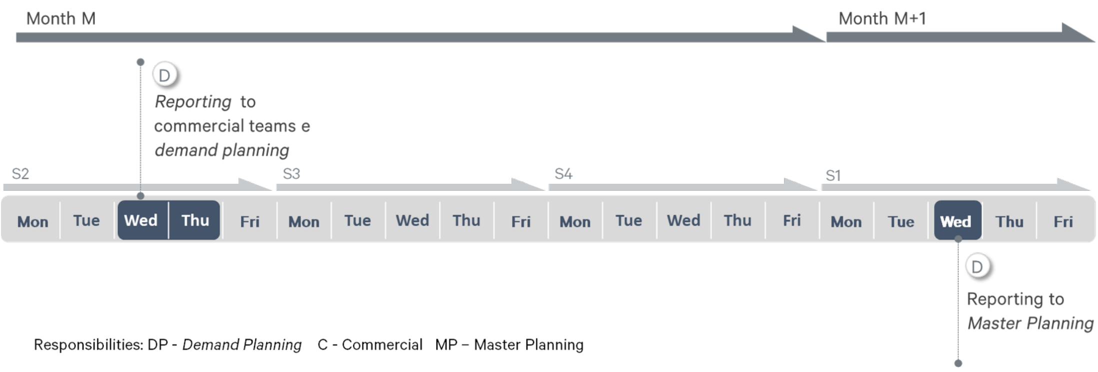


Figure 4.5: New monitorization subprocess

The activities involved in the process are respective to the results of the past month, hence the timing. Past results are collected and analysed by utilizing internal dashboards. The results are then communicated to the commercial team, MP team and discussed within the DP team to collect improvement opportunities.

4.3 Forecast Optimizer

SAP has on itself methods to automatically define statistical methods and parameters to different statistical groups (SAP, 2006). However, the clustering of SKUs into SGs requires manual setup and isn't an easy task. SKUs of the same family may have very different sales patterns, which indicates the needs for a statistical method to perform the clustering. Moreover, the choice of a statistical method is interconnected with the SG's clustering. The overall statistical forecast has to be seen holistically and optimized considering both dimensions. The optimal solution is a cluster of different SGs, with each assigned a statistical method, that provides the most accurate result. Thus, the need for an Optimizer, that suggests the ideal SGs and their respective statistical methods. Furthermore, the prioritization matrix requires continuous revision. Sales patterns and the company's SKU assortment can change throughout time and so can the SKU's predictability. Consequently, such Optimizer has to be tailor-made for the company, to satisfy the identified needs.

To provide the most accurate clusters and methods to SAP, it is necessary to replicate SAP's forecasting process, to ensure that the expected benefits, prototyped in the optimizer, become an effective reality. Consequently, the optimizer aims to replicate the steps that SAP performs when choosing the forecasting method and parameters, as illustrated in SAP (2006).

The optimizer is partitioned in the following segments:

- Data treatment;
- Forecast prioritization;
- Optimization based on current SGs;
- Optimization based on new SGs;

4.3.1 Data treatment

The data set utilized by the optimizer is extracted from the SAP module, monthly, containing two years of monthly sales, budget information, system and commercial forecast. The data is aggregated and available in three granularity levels, SKU x Channel x Client/Region, SKU x Channel and SKU. For the SKUs that are a direct substitution from another older version, the time series of the previous version is utilized for the new version. Furthermore, SKUs are also identified according to their status:

- Valid SKUs to forecasting;
- Innovations (with less than one year of sales), classified as "M" and thus, not requiring statistical forecasting;
- Discontinued (no sales for over 3 months);

4.3.2 Forecast prioritization

The optimizer attributes per SKU x sales channel the "S", "M" and "$S+M$" according to their value and predictability, by applying the rationale explained in Table 4.2. Results are extracted with a prioritization list and a summary of each segment and in order to allow its applicability, the prioritization is aggregated per sales channel x client/Region, to allow each commercial team to have a good overview of the number of SKUs of each type in their own channel.

4.3.3 Optimization based on current statistical groups

Despite the possibility of optimizing statistical groups, in some cases, the implemented clustering do not require tuning. The module aims to assess the accuracy of the current distribution, reparametrized, to allow clear comparisons with new clusterings and assess if a new redistribution yields significant benefits. The optimizer identifies for each SG the ideal statistical method, following the same methodology than SAP, storing the best MAPE value for each SG, for comparisons drawn later. The methodology utilised is described in Appendix C

4.3.4 Optimization based on new statistical groups

The module finalises its algorithm by optimizing clusterings and methods. The algorithm starts by normalizing SKUs (dividing each time series by their average sales value) and extending time series for the past, if necessary due to lack of data, via backcasting (forecasting the past). Such treatment ensures easiness of comparison between different SKUs, each with their own sales pattern. Afterwards, a heuristic is used, with random seeding, to aggregate SKU's into different SGs. The number of SGs and the SKUs assigned to each SG is a random process, inputted to the clustering. Finally, each cluster of SGs is tested, via the algorithm described in appendix C, to identify their final accuracy.

The DP department evaluates the optimizing results and is accountable for updating SAP with the optimal SGs and updated method and parameters.

4.4 Commercial interface

Similar to the automatic forecast, the manual input provided by the commercial teams was also addressed, in order to maximize their expected insights. As illustrated by Figure 3.11, the utilized interface was an Ms Excel sheet, directly extracted from SAP, and ready to be imported again into the system. SAP requires the specific Excel format to upload forecasting values, indicating that potential changes would have to be designed in another sheet, while in the same file, and copied into the original sheet for later import. Despite such limitation, the development of a new interface was considered a priority for the company, not just for overall improvement of the input process, but primarily to apply the prioritization methodology, described in section 4.1, and ensure cohesion between the whole department. The current interface does not allow for the separation of SKUs per the "S", "M" and "$S+M$" categories, neither a detailed look of each SKU. The layout is in a tabular format, hindering potential detailed analysis of the performance of specific products and preventing aggregated analysis per specific product categories, such as brand, container capacity, container type and brand segment. A new interface could potentially leverage on smoother navigation, that allowed for a focused and efficient forecast generation, and potentiate the passage of the prioritization methodology from a conceptual notion to a practical and implemented method.

The new interface was designed together with the input of all commercial teams and tested hands-on via three commercials, each representing a sales team and portraying a role of spokesperson for the rest of the teams. An initial workshop was held to capture the pain points of the current interface:

- Last year's sales hard to compare to current values;
- Trends and seasonality hard to identify in the tabular format;
- No validation mechanisms;
- Lack of overview over the current sales performance;
- No aggregated brand indicators;
- Missing SKU prioritization or focus in a single SKU;
- Hard to focus on the value being forecast;

Based on the input gathered from every commercial team, a new Excel interface was designed to address the identified pain points and tested with two pilots made with the identified commercials. Prior to the development of the interfaces per se, the assignment required the development of a clean back-end programming, designed in VBA, that could smoothly treat the data extracted from SAP and import it at the end of the activity, when forecasts were generated. The interface navigation was influenced by the applicability of the prioritization methodology and how it could be leveraged the best. Figure 4.6 illustrates the rationale behind the interface and how the commercial forecast generation process was designed.

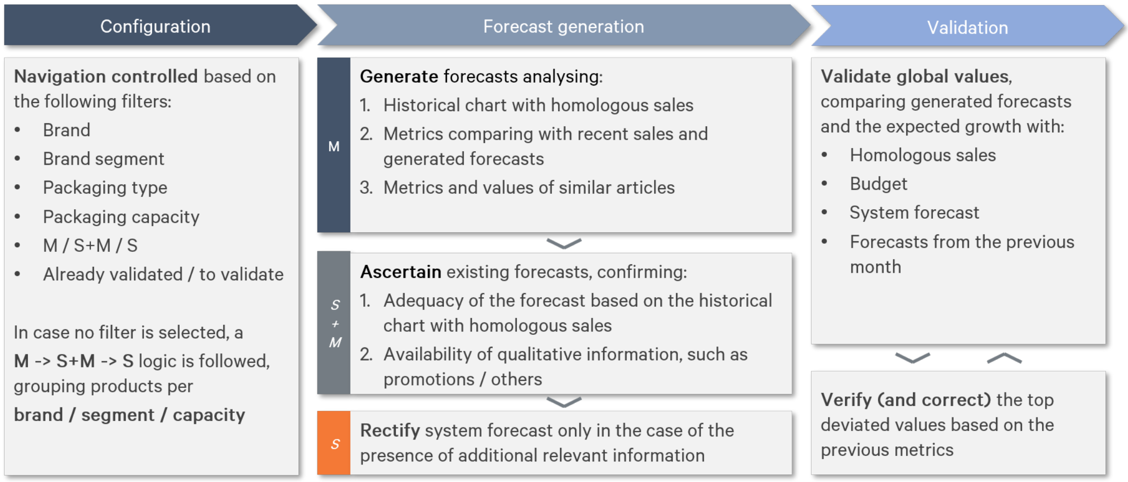


Figure 4.6: Commercial interface rationale

Two views were developed to apply the aforementioned rationale. A first view for forecast generation (SKU view), and a second, a summary view, for a holistic view of the overall process. Figure 4.7 and Figure 4.8 illustrate both views and Appendix D explains each layout.

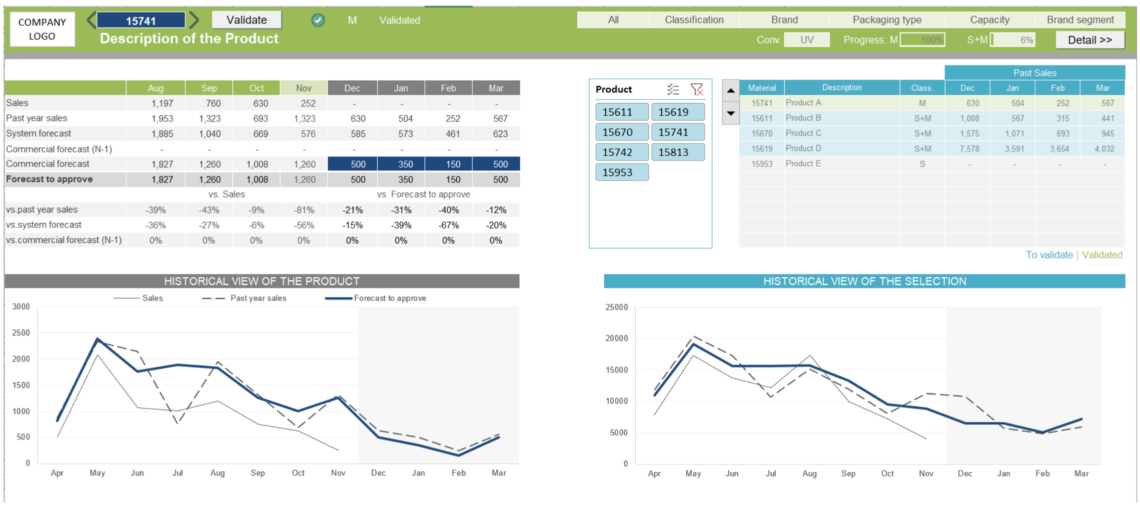


Figure 4.7: SKU view of the commercial input tool

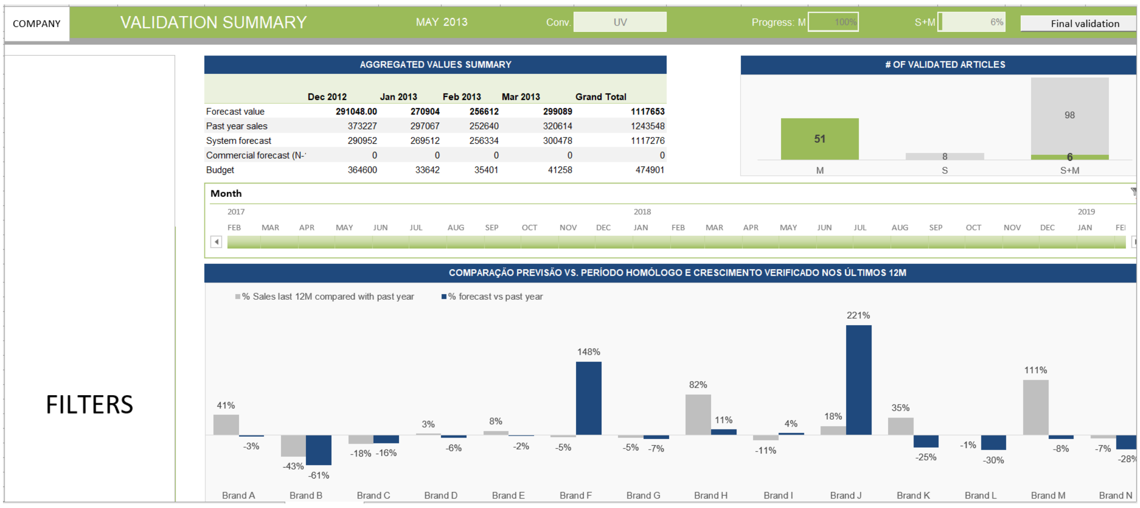


Figure 4.8: Summary view of the commercial input tool

Table 4.6 summarizes the main developments of the interface. The new file was well praised and implemented by the commercial teams.

Area	Improvements
Navigation	Simplification of the mechanism, based on the prioritization methodology
	Easiness of navigation, allowing for high personalization of which SKU group to analyse
Accessory information and graphical support	Graphical layout, allowing for analysis on seasonality, trends and past historical values
	"Vs. past year", "vs. system forecast" and "vs. past commercial forecast" metrics displayed for analysis
	"M" and "$S+M$" progress bar and an option for unit conversion
Aggregated vision & comparison	Easy comparison with any required aggregated selection
	Dynamic and adjusted list of products, allowing for the presentation of past year sales or their forecasts, according to the SKU being visualized
	Summary view, allowing for brand comparison between past year sales and budget information
	Possibility to identify deviated values and correct them

Table 4.6: Interface features

4.5 System forecast validation

A core issue resulting in distrust of system forecasts is the lack of its needed validation. Forecasts would often predict overly deviated values, unrealistic even, increasing the sentiment of doubt over its accuracy. A tool that could potentiate a quick validation, and suggest improvements for deviated forecasts would be ideal for the DP team. Henceforth, an Excel interface was developed to allow such validation.

Figure 4.9 illustrates the Excel interface. Its functionality can be segmented in three major components: a test to identify continuous positive or negative errors, an analysis to the forecast values based on defined thresholds, verifying if they exceed the expected prediction interval, and a forecast suggestion if the value deviates more than expected.

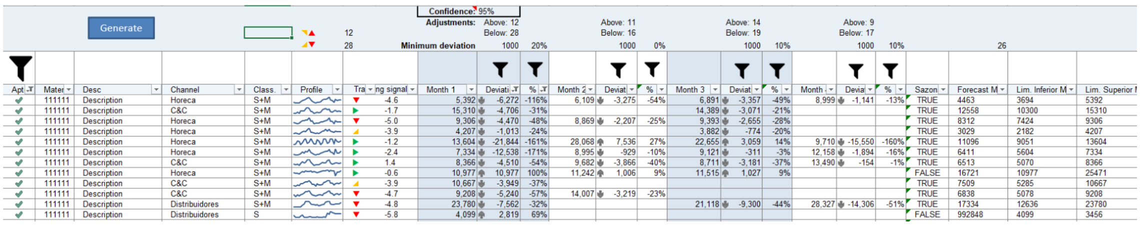


Figure 4.9: System validation interface

The interface is divided per sales channels and verifies each input at the granularity SKU x sales channel x client/region. To ensure proper functioning, the interface is directly connected with SAP, updating the needed data automatically: last year of sales and forecast per SKU x sales channel x client/region.

The tool aims at providing insights to the DP team regarding each SKU if necessary. It analyses each SKU for continuous deviated errors by applying the tracking signal methodology, explained in Appendix A. In the case of demonstrating continuous deviated values, it could potentially indicate a need to adjust the SG of the SKU, or even to reoptimize SAP, if the case is multiplied by various SKUs. Figure 4.10 illustrates the example of the application of the tracking signal, each line is an SKU. In cases of overly deviated values, with an absolute value above 4.5, the standard value commonly defined within the tracking signal methodology, a red arrow indicates those cases. A yellow sign is used for cases that are not yet critical but are indicating deviation, for absolute values between 3 and 4.5. While the tracking signal indicates a continuous forecast deviation, the practicality of its results is dependent on the conclusions withdrew from the DP team. The business insight is valuable in this case, to understand if the deviations have to be addressed, or if their significance is minimal.

Channel	Class.	Profile	Tra ng signal
Horeca	S+M		-4.6
C&C	S+M		-1.7
Horeca	S+M		-5.0
Horeca	S+M		-3.9
Horeca	S+M		-1.2
Horeca	S+M		-2.4

Figure 4.10: Example of the tracking signal applicability

Simultaneously, each of the four-month system forecasts is analysed for each SKU, to provide corrected forecast suggestions in case of high deviations. The process is performed based on the following methodology, using Excel functionalities:

1. Each SKU sales pattern is tested for seasonality, using the autocorrelation method described in Appendix A;
2. A method of exponential smoothing is applied to each SKU, with its variation depending on the presence of seasonality. The exponential smoothing methods are described in appendix A. For each SKU, forecasts for the next four months are generated, to compare with the forecast provided by SAP;
3. Upper and lower prediction interval are calculated for each of the Excel forecasts. A 95% statistical significance interval is employed, serving as limits to evaluate the system forecast provided by SAP;
4. If the system forecast, for each of the four months, is above or below the defined prediction intervals of the respective Excel forecast, a correction suggestion is presented, with the value advised equal to the superior or inferior limit, according to the type of deviation;

The applicability of this method is backed by the rationale that the SAP's proposed value, couldn't be above or below the prediction limits of an exponential smoothing forecast at an SKU x channel x client/region granularity. It is the DP task to analyse the interface's signalled deviated cases and consider if the proposed adjustments should be considered or not based on their business knowledge and insights. Figure 4.11 illustrates the layout used to present suggestions.

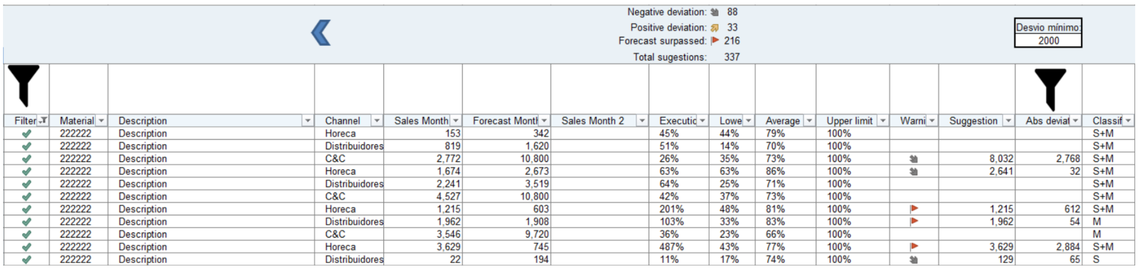
Month 1	Deviati	%	Month 2	Deviati	%	Month 3	Deviati	%	Month 4	Devia	%
15,310	-4,706	-31%				14,389	-3,071	-21%			
9,306	-4,470	-48%	8,869	-2,207	-25%	9,393	-2,655	-28%			
4,207	-1,013	-24%				3,882	-774	-20%			
13,604	-21,844	-161%	28,068	7,536	27%	22,655	3,059	14%	9,710	-15,550	-160%
7,334	-12,538	-171%	8,995	-929	-10%	9,121	-311	-3%	12,158	-1,894	-16%
8,366	-4,510	-54%	9,682	-3,866	-40%	8,711	-3,181	-37%	13,490	-154	-1%
10,977	10,977	100%	11,242	1,006	9%	11,515	1,027	9%			
10,667	-3,949	-37%									
9,208	-5,240	-57%	14,007	-3,219	-23%						
23,780	-7,562	-32%				21,118	-9,300	-44%	28,327	-14,306	-51%
4,099	2,819	69%									

Figure 4.11: System forecast validation suggestions

4.6 Monitorization interface

DP is accountable for correcting forecasts throughout the month and informing the MP team of potential relevant changes to current forecasts. Information, in this case, allows supply planning to adapt their own operations and improve the company's business performance. Therefore, a monthly forecasting monitoring and the consequent forecast rectifications yield results primarily down at the S&OP chain. To support the monitorization subprocess, described in subsection 4.2.3, an interface and its respective methodology were developed to identify erratic monthly sales patterns and enable forecast corrections accordingly.

The interface was designed similarly to the system revalidation interface, to facilitate the learning process and the user experience of the DP team, when utilizing both tools. Figure 4.12 illustrates the Excel interface for the monitorization subprocess. Its functionalities allow for a comparison of current sales performance with its expected result, according to their monthly historical profiles and variability. New forecasts are recommended, in cases of sales underperforming or overperforming, when surpassing defined thresholds.


Negative deviation: 88
Positive deviation: 33
Forecast surpassed: 216
Total sugestions: 337

Desvio mínimo:
2000

Filter	Material	Description	Channel	Sales Month	Forecast Montl	Sales Month 2	Executic	Lowe	Average	Upper limit	Warni	Suggestion	Abs deviat	Classif
✓	222222	Description	Horeca	153	342		45%	44%	79%	100%				S+M
✓	222222	Description	Distribuidores	819	1,620		51%	14%	70%	100%				S+M
✓	222222	Description	C&C	2,772	10,800		26%	35%	73%	100%		8,032	2,768	S+M
✓	222222	Description	Horeca	1,674	2,673		63%	63%	86%	100%		2,641	32	S+M
✓	222222	Description	Distribuidores	2,241	3,519		64%	25%	71%	100%				S+M
✓	222222	Description	C&C	4,527	10,800		42%	37%	73%	100%				S+M
✓	222222	Description	Horeca	1,215	603		201%	48%	81%	100%		1,215	612	S+M
✓	222222	Description	Distribuidores	1,962	1,908		103%	33%	83%	100%		1,962	54	M
✓	222222	Description	C&C	3,546	9,720		36%	23%	66%	100%				M
✓	222222	Description	Horeca	3,629	745		487%	43%	77%	100%		3,629	2,884	S+M
✓	222222	Description	Distribuidores	22	194		11%	17%	74%	100%		129	65	S

Figure 4.12: Monitorization interface

The methodology starts with a developed external module, in R language, provide the needed average and variance per day of the month, for each SKU x sales channel x client/region. Such analysis concedes understanding over how much of the total monthly sales are expected to be sold until a certain day of the month. The algorithm defines cumulative monthly sales curves for each month, providing the expected percentage of the total monthly sales already sold in each day. The daily sales average and the variance for each SKU are a result of the aggregation of all the curves. Algorithm 1 illustrates the general procedure. The insights extracted from the algorithm are indications of the expected cumulative sales percentage sold until a specific day. For instance, indicating that a certain SKU at a certain channel and client sells between 20% and 35% of the total sales of that month until the 13^{th} day. Based on the variance and average of each day, upper and lower thresholds are defined and used to compare the sales performance of the monitored month with its expected behaviour.

Input: SKU's daily sales dataset
for *each SKU x channel x client/region* **do**
  for *each day of the month* **do**
    Remove outliers from dataset
    Calculate mean of the day
    Calculate variance of the day
    Calculate upper prediction interval limit
    Calculate lower prediction interval limit
    Store mean, variance, superior, inferior value
  end
end

Algorithm 1: Revalidation forecast intervals

If the sales of the month are below the lower limit, or above the upper limit, then corrections to the sales forecast should be considered, as the sales pattern for that month, is following an unexpected pattern. Figure 4.13 illustrates the methodological approach for a case of a sales pattern below the lower limit.

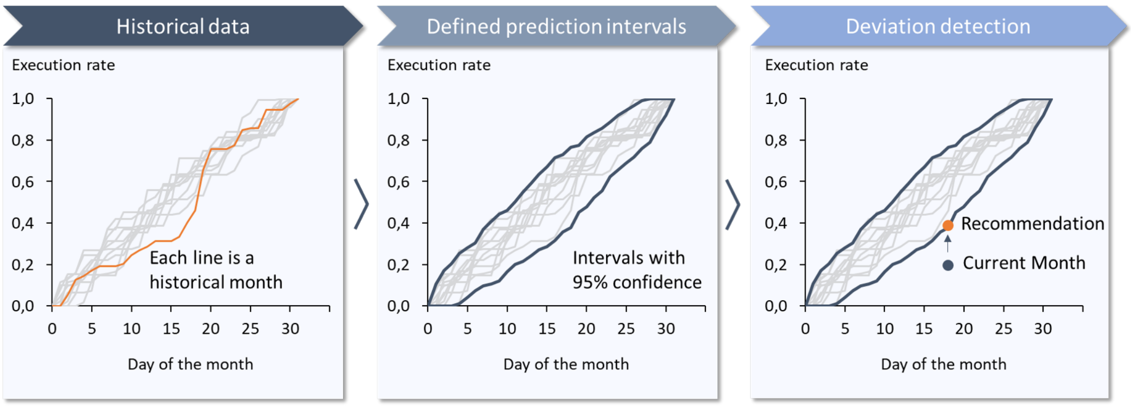


Figure 4.13: Monitorization methodology

Forecast suggestions are provided based on the following method, performed using the Excel functionalities:

1. The execution rate of each SKU is calculated, dividing the cumulative sales until the given day by the monthly forecast. Every change is considered based on a 95% prediction interval;
2. The lower and upper thresholds are extracted from the external module and used to compare with the current execution rate of the SKU:
   a) If the execution rate is between the limits, no action is taken, since the SKU is selling at an expected monthly rate;
   b) If the SKU execution rate is below the lower limit, the monthly forecast for the given SKU is adjusted for the minimum monthly value, at a 95% prediction interval;

c) If the SKU execution rate is above the upper limit, the monthly forecast for the given SKU is adjusted for the maximum monthly value;
d) If the SKU execution rate is above 100%, then the monthly sales already surpassed the forecast value. For those cases, no suggestion is provided, albeit the product is flagged accordingly, for consideration of the DP team;

The interface is divided per sales channels and verifies each input at the granularity SKU x sales channel x client/region. Direct connection with SAP is established to update the required data automatically: last year of sales and forecast per SKU x sales channel x client/region.

The success of the monitorization subprocess and the forecast's revalidation is highly dependent on the business acumen of the DP and commercial teams. Despite the identification of lower / higher than expected sales results, the underlying causes may be very significant to define the actions to undertake. As an example, a large client for a given product may have anticipated its order, flagging the product as surpassing the limit, despite the overall sales volume staying constant. External factors such as the given example may play an important part in the reasons for an unusual sales pattern.

4.7 Stock simulator

To quantify the company's stock level, safety stock and its impact on the company's service level and cost structure, it was necessary the simulation of the company's stock policies and the gathering of all the variables that contribute to the accumulation of inventory. Hence, the necessity for the creation of an Excel stock management simulator.

The simulator takes on data from the company and considers their correlation to calculate results. The simulator is capable of accurately measure the service level, stock level, safety stock and the costs with them implied, per SKU.

The simulator calculates different stock scenarios according to real or estimated data. It requires data to simulate results, which is provided by company sources, in a weekly segmentation, per SKU level. Appendix E indicates all the required inputs, and their meaning, for its proper functioning.

The historical information is used to set up the simulator with stock levels, sales and other relevant information identical to what each factory holds in a real scenario. The results are considered to be based on the restrictions applied.

The methodology utilised by the simulator monitors weekly the stock held for each SKU, based on the initial stock reserves, expected demand for the following weeks, cycle stock necessities, SS necessities and planned production quantities. The simulator accurately simulates the company's stock policy based on the values of each of the aforementioned signatures and considering the inputs described in appendix E. Figure 4.14 illustrates the methodology utilised by the simulator.

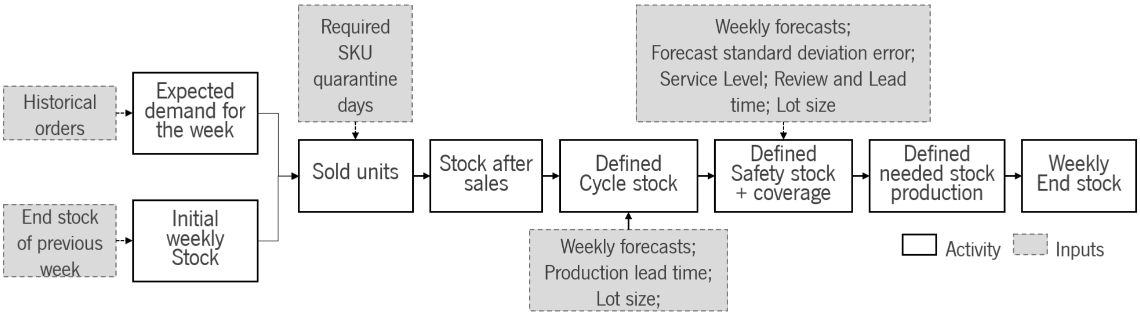


Figure 4.14: Stock methodology

The procedure is replicated for every SKU, weekly, considering the inputs indicated for each of the stages. The simulator is constructed by iteratively following the methodology throughout various weeks, providing a summary indicating the average quantities of each weekly signature. Table 4.7 indicates how the main signatures were measured:

Signature	Method
Sold Units	Minimum quantity between expected demand and the initial weekly stock
Cycle stock	Calculated by the average of the forecast product needs, during the production frequency multiplied by the number of weeks until a new batch of the SKU can be produced again
Safety Stock	Application of the method described by Silver et al. (2009), using forecast deviation errors instead of demand variation errors (since it provides an accurate replication of reality)
Stock order	Necessary stock to be produced, based on the difference between the company needs and the current stock

Table 4.7: Calculation methods for stock signatures

Additionally to the stock simulation, illustrated in Figure 4.14, the simulator quantifies stock gains by adapting the method proposed by Ha et al. (2018) and calculating the stock difference between both scenarios. Due to the scope of the thesis, only inventory costs were considered for the forecast quantification, leading to the following adaption of Ha's formula:

$$
\begin{aligned}
\textbf{Total cost} \qquad & TC_k = \sum_{t=1}^{n} (c_I * I_t + c_S * S_t), \\
\textbf{Inventory units} \qquad & I_t = Max(SS + I_{t-1} + P_t - D_t - S_{t-1}, 0), \\
\textbf{Units stocked out} \qquad & S_t = -Min(SS + I_{t-1} + P_t - D_t - S_{t-1}, 0).
\end{aligned}
\tag{4.1}
$$

Where c_i is the inventory holding cost per unit, I_t the inventory units, c_s the marginal stock-out/backlog cost per unit, S_t the units stocked out, P_t the units produced and D_t the actual demand, all in the month t.

The following Figure 4.15 illustrates the whole process utilized to calculate the costs illustrated in the formula. The costs values were provided by the company.

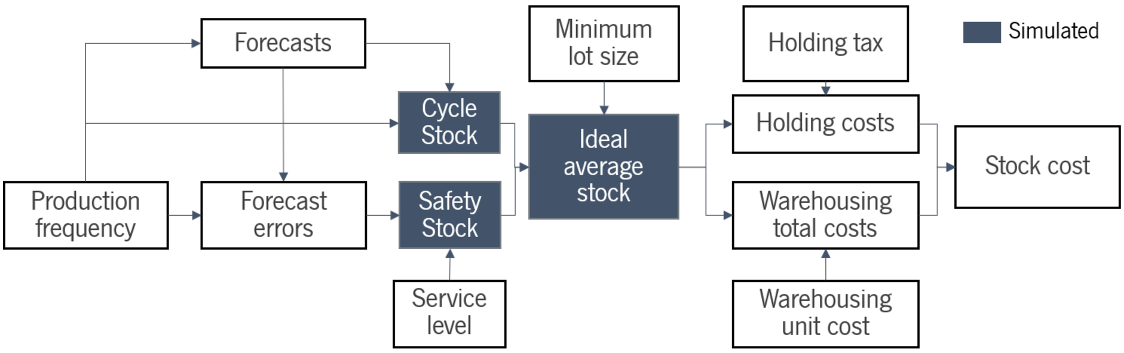


Figure 4.15: Stock costing process

The stock quantification of the forecast gains is possible, as the simulator considers the next week's forecasts to appropriately define necessities. Additionally, the SS formula utilised by the company is based on the forecast error variability, showcasing benefits if the same variability reduces. The results of the simulation, explored in the next chapter, is a consequence of the usage of the newly improved forecasts, reducing the two components mentioned in Figure 3.14. The next chapter presents the results withdrawn from the improvement actions described in this thesis.

Chapter 5

Results

In this chapter, the results obtained are displayed from the application of the different methodologies and algorithms described in chapter 4. The effects are displayed holistically, in most cases, due to the present synergies between the different initiatives. Admittedly, the effectiveness of the DP process is considered globally, through improvements in the forecast accuracy, and thus, a simulation was conducted to examine influences. Simultaneously, the impact of such endeavours was estimated in terms of stock coverage, in days, and overall stock cost reduction through the use of the stock simulator, described in section 4.7. Finally, a qualitative overview of the benefits in an S&OP context is equally provided.

5.1 Benefits withdrew from the new Demand Planning process

The new DP process, depicted in section 4.2, has been iteratively implemented, in an on-going process, transpiring beyond the timeframe of this thesis. A stabilization period was defined, of over six months, to ensure that the transition would be smooth and accordingly fine-tuned, if necessary. The implementation was segmented per two modules. A first, faster to execute, that considers the implementation of the main process and activities to which the DP team is accountable for, and a second, containing the activities requiring coordination with commercial teams and the MP team, such as the implementation of the commercial interface and of the reporting sessions. 2018's December monthly forecasts were generated and validated based on the new process, identifying significant holistic benefits due to its usage:

1. Increased cohesion between different sub-processes and cross-departmental activities;

2. Governance well defined across the spectrum, with the DP team accountable for improved forecasting results;
3. Monthly forecast delivery deadline in tune with MP necessities;
4. Increased efficiency on resource utilization, with greater value extracted from system's forecast;
5. Exploitation of analytical methodologies for greater results;
6. Commercial focus enhanced, for cases of higher added value, through the use of the forecast prioritization methodology and commercial interface;
7. Continuous improvement iterations, allowing for long-term insight's gathering;
8. Higher reactivity to abrupt changes, with formal forecasting follow-up throughout the month;

In a steady state, the implementation of the new process is also expected to involve changes in each team's effort. The DP team is expected to have an increment in the number of dedicated hours to sub-processes that were until the moment disregarded, such as system parametrization, forecast validation, monitorization, and continuous improvement activities. Notwithstanding, the commercial team's effort on forecast generation is optimized and centred around the most-value added products. Thus, the effort is expected to reduce for such sub-process but increase for forecast validation, as each commercial team is now accountable for correcting forecasts for SKUs classified as "M" and "$S+M$"'s manually corrected. The new process is highly influenced by the accuracy and reliableness of the system forecast. The next section provides an overview of the new SAP parametrization.

5.2 Forecast Optimizer

The optimizer described in section 4.3 renders a report, in a six-month periodicity, indicating the attributed forecast prioritization and the necessary changes in SAP APO. Table 5.1 illustrates a summary of the prioritization, per segment, regularly provided through the report, highlighting the sales weight of each category.

Category	Nº Inputs	Sales Weight
S+M	1578	67.71%
S	1483	4.64%
M	196	25.95%
Innovation	377	1.69%

Table 5.1: Attribution per category

A summary of the prioritization is similarly provided, at a sales channel x client/Region granularity, as illustrated per Table 5.2. Concurrently, an external file is provided with the classification rendered to each SKU.

Channel	M	S+M	S	Innovation
HoReCa	26	203	44	29
Retail	95	733	737	210
International	43	381	556	138
Distributors	6	149	109	30
Cash & Carry (C&C)	26	112	37	24

Table 5.2: Attribution per sales channel

The optimization of current parametrization is depicted through several illustrative examples of improved forecast performance. Figure 5.1 show one examples of an improved time series, in which the red line represents sales, the blue line the new forecast and the green line the old one.

Figure 5.1: Example of an improved time series

The module also optimizes the SGs and consequent methods, based on iterative clustering. Figure 5.2 illustrates an example of various solutions, identifying the optimal one, in this case with 81.24% of accuracy, amidst 16 different SGs.

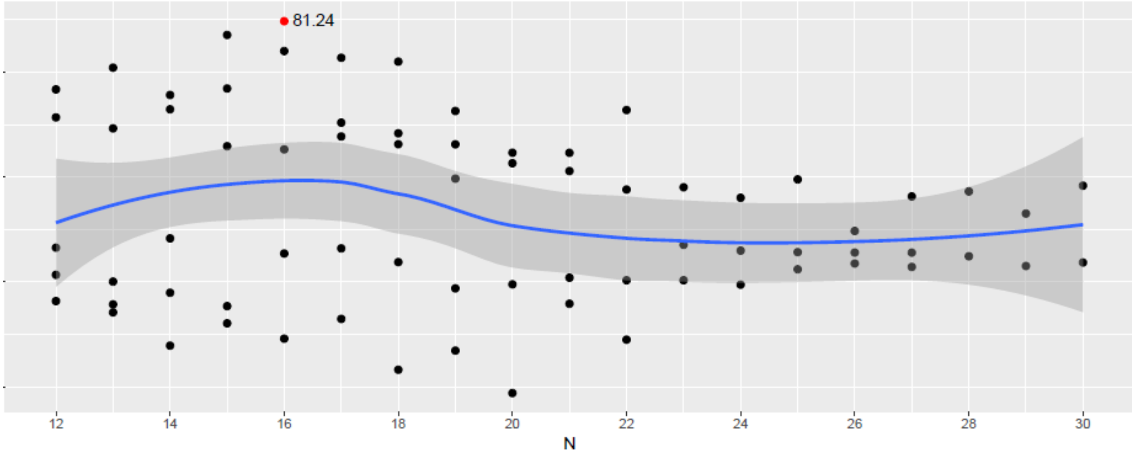


Figure 5.2: Optimal clustering, among the various tested combinations

Finally, a comparison between the current parametrization, the option of only updating the statistical methods and the full optimization, with the new SGs was provided with the best one chosen. Table 5.3 provides a summary of such comparison, referent to the optimization process, conducted in December. SAP was promptly optimized, by the DP team, based on the illustrated simulated results.

	SAP	New methods	New SGs
Accuracy SKU	71.49%	79.46%	81.24%
Accuracy sales channel	65.77%	71.92%	74.38%
Accuracy input	61.21%	67.07%	69%
Bias	-7.70%	-5.04%	-0.96%

Table 5.3: Comparison between current parametrization and suggested combinations

5.3 Forecast & stock simulation

Due to time and project related constraints, it was inconceivable an in-depth practical analysis over the forecast performance, resulting from the implemented solution. The new DP process will take a considerable amount of time for its full implementation, beyond the time-frame defined for the development of this project, eliminating the possibility of hands-on testing of the prioritization methodology. Similarly, the commercial interface is an auxiliary tool to the work of the commercial team, vulnerable to the quality of the monthly qualitative information used by each commercial team. Thus, the quantification of its impact would require the consideration of various monthly processes, in order to reduce the impact of the information's quality variability. Henceforth, the quantification of its impact is also impracticable. Nonetheless, a simulation of four months was performed, to allow for relative conclusions over the impact of the defined methodologies. The DP process was simulated accordingly, following the different sub-process steps, with exception of the revalidation sub-process, quantified later, due to its peculiar nature. The process benefits are quantified in terms of forecast gains and stock benefits, through the use of the aforementioned stock simulator. Figure 5.3 illustrates the defined steps undertaken to obtain the necessary results:

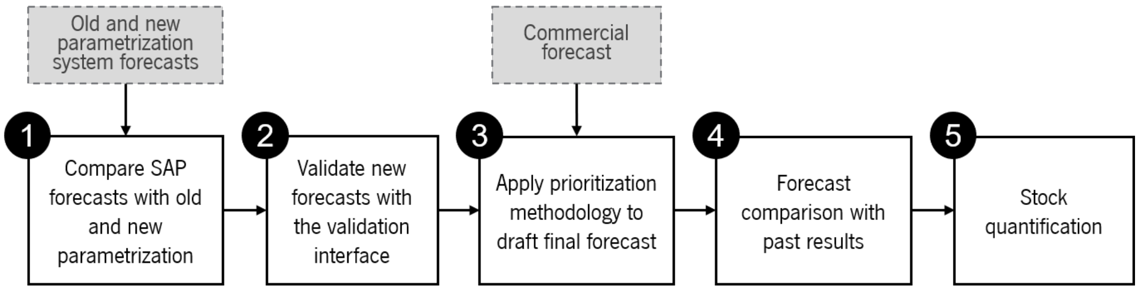


Figure 5.3: Quantification methodology

The methodology allowed the quantification of the benefits in different stages of the process. Initially, the benefits of utilizing an updated system forecast was quantified, followed by the profit of validating such statistical results, using the system forecast validation interface. The corrected system forecasts were then utilized for the final forecast, according to the prioritization methodology:

1. SKUs classified as "M" considered only the commercial forecast provided during the simulated months;
2. SKUs classified as "S" were forecast with the validated system forecasts;
3. SKUs classified as "$S+M$" utilised either the commercial or system forecast, considering which on had the lowest deviation to the sales value;

The accuracy and Bias were calculated per sales channel, across four different months of 2018: April, May, June and July. The global results and gains, in terms of statistical performance, are illustrated in Figure 5.4. The final forecast were compared with the initial SAP forecast and the commercial forecast provided, at the time, during those months.

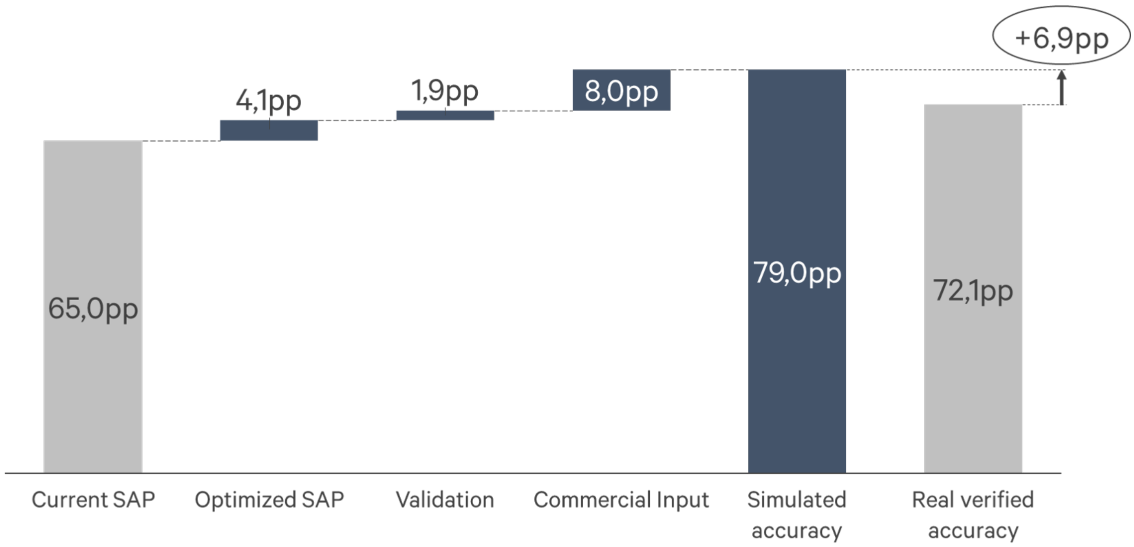


Figure 5.4: Simulation's forecast accuracy

Globally, the applicability of the new SGs, statistical methods and the validation interface yield a significant improvement over the current SAP parametrization, with an increment of 6PP in forecast accuracy. Simultaneously, the applicability of the prioritization methodology carried a similar benefit, by leveraging the expected commercial input for critical cases and thus improving the overall accuracy in over 6PP, when compared to past final forecasts. However, the simulation has also signalled overly negative deviations with the new SAP parametrizations, as illustrated in Figure 5.5.

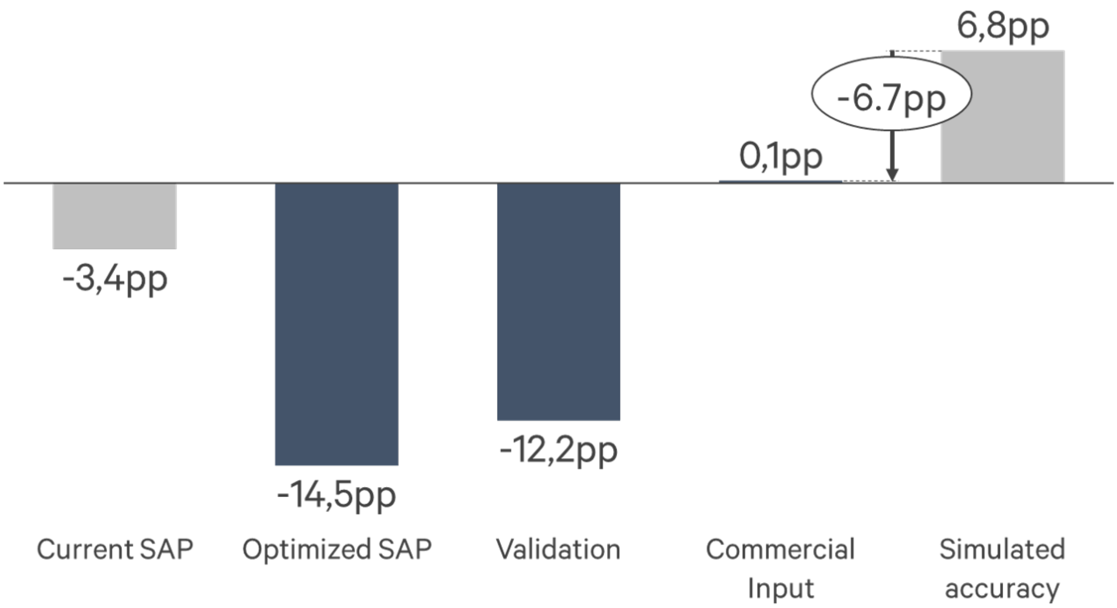


Figure 5.5: Simulation's forecast Bias

The system's Bias deteriorated with the new changes, presenting a negative Bias of -14%, corrected to 12% with the validation tool. Notwithstanding, when applying the prioritization methodology, the Bias was levelled properly, presenting a deviation of 1% and thus contrasting with the positive deviation commonly present in final commercial forecasts.

Despite the necessary caveats that should be taken into consideration with the usage of a simulation, the illustrated results highlight the potential benefit underlined beneath the utilisation of the elaborated process and the aforementioned interfaces. The simulation enhanced the utilization of the statistical forecast, throughout the four months and without considering the expected benefit brought by the commercial and DP team's business expertise. Similarly, the overly negative deviation verified with the SAP parametrizations should be corrected and adjusted, naturally, in future iterations of the module. The "$S+M$" forecast attribution was optimistic since it can't be expected that every change proposed by the commercial team will improve the forecast accuracy. Nevertheless, the results are aligned with the department's expectations and with the expected profits.

The simulation further estimated high-level benefits collected at the S&OP chain of the company, with the use of the stock simulator. Benefits quantified in terms of stock management, while not entirely representative of the impact felt in supply planning areas, are indicative of possible influences felt in the rest of the chain. Table 5.4 summarizes the results, in terms of service level and stock coverage, in days, verified at each *ABC-XYZ* quadrant.

Quadrant	Service Level	Stock	Cycle Stock	Safety Stock
AX	98.60%	17.8	16.8	1.1
AY	98.61%	22.4	18.1	4.3
AZ	99.95%	35.8	26.4	9.4
BX	96.76%	20.0	18.8	1.2
BY	98.47%	29.1	24.2	4.9
BZ	99.86%	46.9	36.5	10.5
CX	100%	23.7	22.4	1.3
CY	100%	38.7	33.6	5.0
CZ	99.20%	54.9	38.9	16.0

Table 5.4: Simulator: stock coverage (in days) and service level per quadrant ABX-XYZ

The simulator considered the same number of SKUs, during the same weeks from which the results shown in Table 3.1 were extracted. The new forecasts were disaggregated, from a monthly to a weekly value and utilized accordingly, to simulate the company's stock management, under the same restrictions and for the same minimum global service level of 94.24%, as defined by the company. Table 5.5 presents the final comparison results, indicating the benefits withdrew from the DP improvements.

Quadrant	Service Level	Stock	Cycle Stock	Safety Stock	Total Cost	SS Cost	CS Cost
AX	-0.30%	-1.7	-2.0	0.4	-	-	-
AY	-0.56%	-2.8	-2.9	0.2	-	-	-
AZ	0.43%	0.0	-0.5	0.4	-	-	-
BX	-1.74%	-1.3	-0.1	-1.2	-	-	-
BY	-0.21%	-1.7	-2.8	1.1	-	-	-
BZ	1.04%	1.6	0.7	0.9	-	-	-
CX	0%	-3.4	-3.2	-0.2	-	-	-
CY	4.52%	-3.0	-3.6	0.6	-	-	-
CZ	2.17%	4.2	1.3	2.9	-	-	-
Total	**-0.1%**	**-1.2**	**-1.6**	**0.4**	**-5.9%**	**-5.4%**	**-7.8%**

Table 5.5: Stock benefits (difference between both scenarios) extracted from the DP improvement

Few insights can be extracted from the stock simulation and from a direct comparison between past and simulated scenarios:

1. Main stock and cost reduction is due to forecast improvement. As the forecast Bias had a significant average reduction of 5%, stock levels were adjusted to the minimum necessary to cover for the expected service level;
2. SS higher for SKUs classified as "Z", in particular for "BZ" and "CZ". Worth exploring the option of providing a lower service level for SKUs belong to B and C quadrants;
3. Global SS coverage increased slightly, with the increment verified in the forecast's error standard deviation. Despite the coverage increase, SS costs reduced, due to a redistribution of the stock towards lower cost products;
4. Overall service level maintained, despite the clear stock and cost reduction;

5.4 Forecast revalidation

The revalidation subprocess was excluded from the stock simulation, due to its iterative nature. The interface was developed to provide suggestions to the DP team, of deviated values, to consider for revision. However, the quality of the process is correlated to the qualitative information that the DP and the accountable commercial team can provide for the deviated values, if any. In spite of it, Table 5.6 showcases the impact on the overall forecast accuracy in each revalidation moment, if every suggestion provided by the interface was considered and accepted.

Moment 1	Moment 2	Moment 3
-0.2pp	+0.1pp	+1.4pp

Table 5.6: Impact of the revalidation subprocess in each revalidation moment

The results illustrate the previous point, as the methodology suggestions improve as time progresses during the month. DP input is particularly important in the first revalidation process. The MP is expected to benefit from corrections for cases where the certainty of over and under-forecast is higher. For those, plans can be adjusted accordingly.

5.5 S&OP benefits

The implemented solutions presents qualitative and quantitative benefits in an S&OP context. The quantitative results illustrated in Table 5.5 are presumed to be felt throughout the S&OP chain, at the production, replenishment and distribution operational areas. Despite each area containing their own set of constraints, costs and influencing aspects towards forecast impact, accuracy improvements enhance operational efficiency, even if at different scales. It is thus expected that each area collects benefits, as the MP indicates improvement in different metrics. The formalization of reporting moments between DP, sales and MP teams foster collaboration between each unit and contributes for greater cohesion towards business objectives. The efficiency of the S&OP process is thus, improved, as the formal meetings are foreseen to yield continuous improvement actions to the process. The reactiveness of the S&OP chain is another key aspect absorbing benefits from the project, as the revalidation subprocess contributes with improved forecasts at different revalidation moments. Adjustments to the plans are supported and early reactions to unforeseen struggles are now possible.

Chapter 6

Conclusion

This closing chapter reviews critically the work developed during the elaboration of this thesis. It concludes with suggestions for possible developments in the field and in the work developed.

6.1 Critical analysis

The major takeaway from the project is that changes in the DP process, the assignment of governance across departments and the elaboration of specific forecast tools impact positively the forecast accuracy. The simulation explained in section 5.3 indicates an improvement of 6 PP in overall MAPE, with an overall stock cost reduction of 6 PP, due to the application of the different improvement initiatives in the analysed months. The improvements are best considered globally, as the cohesion of the department is shown as a critical aspect for the forecast accuracy. Redefining the company's DP process and by proxy ensuring a smart utilization of both statistical forecast and qualitative information was the foundation for a proper leveraging of other improvement initiatives. In the case of maintaining the same DP process, granular gains verified in specific domains of the department wouldn't be capitalized, as the status-quo was highly favouring of a simple, qualitative-based forecasting method, neglecting the benefits of statistical inputs. The procedural change, including the company's mindset shift, was pivotal and carefully considered, adjacent to a novel prioritization methodology, that categorized products according to their relevance for the company and forecast difficulty. As a consequence, each product was provided with the best possible forecast, qualitative or quantitative, according to their own characteristics and placement in the company. Each initiative, such as the new SAP parametrization, the system forecasts' validation, the commercial interface and revalidation tool magnified the performance of the other specific activities or subprocesses, both short and medium-term, consequently leading to forecast performance gains. Despite the benefits quantified with the simulation, the impact of the commercial interface and revalidation tool, in particular, will only be felt over-time as their purpose is towards supporting actions, dependent of other factors, external to this thesis.

The approach of evaluating the company in an S&OP context, prior to addressing pain points undeviatingly was for itself a different approach that yielded significant positive results. Firstly, the holistic perspective provided by such overview supported the development of the DP department. The process, timings and solutions were developed consistently considering the impact it would have further down the S&OP chain. Similarly, the S&OP assessment in terms of efficiency and effectiveness contributed with an enhanced focus on the formalization of necessary subprocesses, until the moment disregarded. In opposite circumstances, of a very myopic view towards the problems encountered in the DP department, such solutions, like the revalidation and continuous improvement subprocesses, would likely not come to fruition. Likewise, the result quantification, based on the simulation of the MP process cemented the benefit that the applicability of the methodology had in the company. The benefits extracted from increasing the accuracy of the forecasts were successfully leveraged, by reducing the overall stock coverage, whilst maintaining the same service level towards its customers. Notwithstanding, the increment of Safety Stock coverage verified in the simulation further validates the previous point, as other projects alike may not incur in similar significant quantifiable results.

This master thesis is a novel practical example of the benefits incurred from considering the S&OP process in transformational initiatives. Few works of literature are available to provide a schematic process that starts with a holistic assessment and further details into an area for a specific development. This thesis aimed at contributing to scientific research in such regard. The methodology summarized by Ha et al. (2018) and utilized during this thesis was essential to transform forecast benefits into quantifiable measurements. Ideally, further case studies should consider the full implementation of the methodology, instead of only considering a partition of it, as this thesis proceeded to by simulating the MP policies. However, it is worth mentioning the various practical hardships that applying such concept carries. Effective utilisation of the methodology requires a simulation of the company procedures, stock management, and if further explored, production and distribution areas. The elaboration of such simulator requires know-how of the different domains and a large data set. Furthermore, only in cases of matured S&OP processes can the methodology be expected to be applied, since in many cases, companies will lack the integration that is necessary to apply it. Consequently, its practical application requires a high degree of effort, integration and time.

While the application of the company's stock management policies contributed to a greater understanding of the impact of forecast improvement projects, the depth of its impact could be further explored with the inclusion of more variables. Nevertheless, the simulation supports the premise present in the S&OP literature, of the impacts felt by forecast improvements. While the cost-benefit expected from such measurements is related to the cost associated with each product, an overall reform will contribute to an average cost reduction.

6.2 Future research and development

A few strings are left requiring future work. The simulation described in section 5.3, albeit fairly accurate, doesn't replace results obtained from the application of the methodology *in loco*. A second analysis should be performed, when such practical analysis is possible, to measure the effect of the methodology and confirm the outcomes extracted from the original simulation. In particular, the registered increase in SS coverage and the high negative deviation registered by the system forecast are strong indications of the presence of improvement opportunities, on one hand, and the necessity for further tweaking to the forecast Optimizer on the other. As such occurrences were expected, a stabilization period was formally established, since the start of the project and in vigour afterwards, to correct expected issues. Concurrently, the prioritization methodology is expected to generate even greater gains as confidence is earned by the methodology. As improvements are felt into the system forecast, an even higher number of SKUs could potentially be predicted based on it, inducing even greater commercial focus on critical products, while reducing their overall effort.

Overall, the project documented by this thesis concerns a roadmap of continuous improvement, with big margins of unexplored profits. A vision of the future implies new developments, raised from the insights yet to collect and from the applicability of complex machine learning methodologies. However, the evolution of this roadmap is highly dependent on the gradual evolution of the S&OP process, in particular of the Data Gathering step, precedent to the one this thesis is concerned with. Only with the presence of additional causal variables, such as promotional information and weather effects, and only with an adaptable and flexible IT system can such degree of forecast improvements be expected.

Future work isn't only restricted to the DP and Data Gathering area. Overall business improvement is best achieved if the entire S&OP process is equally improved. The S&OP assessment leveraged in the DP area, in spite of other areas also indicating significant results. Both the replenishment and distribution area of the company are functioning partially independently from the MP and the forecasts provided by DP. Their integration, by considering one single forecast for the overall chain, as well as considering their own restrictions would contribute for a smoother and efficient S&OP process. The S&OP process described in section 2.2, as well as the forecast methodologies described in section 2.4, were both applied during this project. The observed results are aligned with the approach utilised in other case studies and with the references highlighted during this master thesis. For the future, a continuous focus on the practical applicability of the S&OP literature is required, to ensure the needed development of the field.

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Appendix A

Forecast complementary concepts & statistical methods

Forecast generation requires the use of statistical methods and the comprehension of complementary statistical concepts. This appendix aims to explain complementary concepts and time series models utilised during this thesis.

A.1 Forecast complementary concepts

A.1.1 Autocorrelation

Correlation is often considered the association or dependence between two random variables, due to causality or not. Thus, autocorrelation measures the linear relationship between lagged values from the same time series. Lagged values can be understood as preceding values from the time t being analysed. Autocorrelation coefficients are calculated by measuring the relationship between lagged values (Hyndman and Athanasopoulos, 2018). For instance, the coefficient $r1$ measures the relationship between variables y_t and y_{t-1}, while $r2$ measures the relationship between y_t and y_{t-2}.

The value of R_k is calculated by the following equation:

$$R_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{A.1}$$

where T is the length of the time series.

When the coefficient value surpasses a defined threshold, commonly calculated by $\pm\frac{2}{\sqrt{T}}$, it is considered that there's autocorrelation between the values separated from the defined lag.

A.1.2 White Noise

White noise is a set of values or an entire time series that do not show any autocorrelation. Thus, it is expected from the autocorrelation coefficients to be close to 0 (apart from random variations), with 95% of the calculated values to be within $\pm\frac{2}{\sqrt{T}}$, the threshold limits Brockwell and Davis (2002). Commonly, statistical models can't fully explain the variation identified in the data set. In these cases, it is often considered that some of the data is noise, in the best case white noise. Such a statement is refutable in case of the presence of a large autocorrelation value, or if more than 5% of the coefficients are going beyond the limits. If so, it should be assumed that the set values or the entire series have a correlation yet to be explained (Hyndman and Athanasopoulos, 2018).

A.1.3 Tracking Signal

Due to the erratic nature of sales, forecasts are expected to be capable of adapting and anticipating to sales pattern variations. In some cases, forecasting models are incapable of doing so, inducing themselves in forecasting biases and consequently reducing the model's accuracy. To ensure the adequacy of the forecasting model, it is common the usage of a tracking signal, to monitor the non-existence of bias (Gonçalves, 2000).

$$Tracking\ Signal = \frac{\sum_{t=1}^{n}(forecast - sales)}{MAD} \tag{A.2}$$

The tracking signal is a metric that monitors forecast deviations and signals systematic deviations that go beyond a defined threshold. It is calculated each time a new data entry is added and monitored through the use of a threshold, commonly defined by $\pm\frac{2}{\sqrt{T}}$. The used control limits may change considerably from scenario to scenario. The context of the problem plays a big role in defining the thresholds and how volatile the forecasting model should be (Gonçalves, 2000). In situations of big variation, the forecasting model has to be corrected or even changed to meet the newly identified sales patterns.

A.1.4 Time series data patterns

Trend

A trend underlies growth or decline for a time-series, in a long-term spectrum. It is identified in series, by a straight-line or curves in the values, that suggests a continuous pattern of growth or decline. In figure x, image a) the series presents a positive trend (Hanke and Wichern, 2014).

Seasonality

A seasonal component is present when the time series is affected by seasonal factors such as the time of the year, month or day of the week. Seasonality is of a fixed frequency, in a pattern that repeats itself yearly (Hanke and Wichern, 2014).

Cycle

A cycle occurs when a pattern of change affects the time series in a not fixed frequency. Often due to external conditions, these fluctuations affect the time series in long time periods, often over several years (Hanke and Wichern, 2014).

A.1.5 Identifying data patterns using autocorrelation

Data patterns can be identified using autocorrelation coefficients for different time lags (Hanke and Wichern, 2014). Seasonality is often identified through autocorrelation coefficients when the values are larger for seasonal lags (in multiples of the seasonal frequency) than for other values. If a series has a trend, successive observations are correlated, with the autocorrelation coefficients being significantly different from zero for the first time lags and gradually decrease to 0 as the lag progresses. The formula commonly used is $\pm\frac{2}{\sqrt{T}}$, with the numerator changing accordingly.

A.2 Time series decomposition

Time series decomposition is a method used to study time series data and historical changes over time, by splitting the series into its different components: seasonality, trend, cycle and noise (Hyndman and Athanasopoulos, 2018).

A.2.1 Additive or Multiplicative decomposition

When assuming an additive decomposition, the data can be described by

$$y_t = S_t + T_t + R_t$$

Where y_t is data, S_t the seasonal component, T_t the trend-cycle and R_t the remainder component, during a period t (Hyndman and Athanasopoulos, 2018).

A multiplicative decomposition is written as

$$y_t = S_t \times T_t \times R_t$$

The usage of the multiplicative or additive version depends on the proportionality between the level of the time series and the variation verified in the seasonal and trend-cycle pattern. If the magnitude of the seasonal fluctuation or the trend-cycle variation doesn't seem to be affected as the level of the time series changes, then an additive method is preferred. If both patterns seem to be reactive, then a multiplicative decomposition is ideal (Hyndman and Athanasopoulos, 2018).

The choice of which version to use is relevant when applying the classical decomposition method explained in subsection x.

A.2.2 Moving Average

Moving Average (MA) is a classic method in time series decomposition, widely used for decomposition and to generate forecasts. Since the method is used for classical decomposition, it is worth to define it first.

A MA of an order k is the average between the last k consecutive observations. The most recent MA result is the forecast for the next period (Hanke and Wichern, 2014).

$$\hat{Y}_{t+1} = \frac{Y_t + Y_{t-1} + ... + Y_{t-k+11}}{k} \tag{A.3}$$

where $\hat{Y}_{t+1}$ is the forecast value for the next period, Y_t is the value for period t and k is the number of observations.

As new data points are added, the MA accompanies the evolution, by adding the new data points and maintaining k values of the past.

Despite the equation A.3 being used to forecast, a smoothed version is widely used for decomposition methods:

$$\hat{Y}_t = \frac{\sum_{j=-k}^{k} y_{t+j}}{m} \tag{A.4}$$

Where $m = 2k + 1$.

The smoothed version supports decomposition by estimating the trend+cycle curve of the time series. Such estimation is obtained by averaging out k values of the period t, successfully eliminating the randomness of the data. The application of the smoothed MA throughout the data points showcases a smoothed trend line. When using this form, the smooth MA is commonly used with odd numbers (3,5,7,...) to maintain the symmetry between the values. Despite its effectiveness to eliminate randomness, this method isn't successful in eliminating seasonality, since it doesn't evenly distribute values of even orders (Hyndman and Athanasopoulos, 2018).

A.2.3 Estimating trend-cycle with seasonal data

It is possible to apply a MA of a set of MAs. Such a procedure is beneficial to make even MAs symmetric, thus, eliminating seasonal effects. A notation of $2\times 6-MA$ signifies a moving average of order 6 followed by a moving average of order 2. When an even order MA is followed by an even order MA, or if an odd order MA is followed by an odd order MA, symmetry is established throughout the values of the MA. The formula below exemplifies the result of a $2 \times 4 - MA$ (Hyndman and Athanasopoulos, 2018).

$$\hat{Y}_t = \frac{y_{t-2}}{8} + \frac{y_{t-1}}{4} + \frac{y_t}{4} + \frac{y_{t+1}}{4} + \frac{y_{t+2}}{8} \tag{A.5}$$

Such property is very beneficial to faze out seasonality effects from the time series. When applying the $2 \times 4 - MA$ to quarterly data, for instance, each quarter will be given the same weight, fazing out seasonal variation. Generally, $2 \times m - MA$ is equivalent to a weighted moving average of order $m+1$, where each observation has a $\frac{1}{m}$ weight, except the first and last one, who has a weight of $\frac{1}{2m}$. If the seasonal period is even, with order m, a $2 \times m - MA$ smooth moving average can be used to calculate the trend-cycle. If the seasonal period is odd, then an $m - MA$ will suffice. As an example, $2 \times 12 - MA$ can be used to calculate the trend-cycle on monthly data with yearly seasonality.

A.2.4 Classical Decomposition

The classical decomposition follows a number of steps, which are different depending on if it is the multiplicative or the additive version of the process. For it to work, it is assumed that the seasonal component is constant from year to year. Hyndman and Athanasopoulos (2018) summarizes the steps for both versions:

1. If the seasonal period is referent to an even number, m, the component trend-cycle T_t should use a $2 \times m - MA$. In the case of m being an odd number, the trend-cycle should be calculated using an $m - MA$;
2. Extract the trend-cycle component from the time series. If it is using the additive method, $Y_t - T_t$, if it is with the multiplicative method, $\frac{Y_t}{T_t}$
3. From the new decomposed time series, average the values of the season in particular. In a scenario with monthly data, the seasonality of June is the average of all the detrended values of June in the time series. The seasonal component is obtained by merging the different seasonal indexes from the different months and then replicating the sequence for the time periods in the data. This gives component S_t.

4. The reminiscing is obtained by subtracting or dividing the already identified components. If it is using the additive method, $R_t = Y_t - T_t - S_t$, if it is with the multiplicative method, $R = \frac{Y_t}{(T_t + S_t)}$

There are other methods for decomposition, such as X11 decomposition (Dagum and Bianconcini, 2016), SEATS decomposition (Dagum and Bianconcini, 2016) and STL decomposition (Cleveland et al., 2002). However, since the company's ERP system uses classical decomposition, the methodology used will also be based on the same method, to allow comparable results and the appropriate simulation of the ERP's behaviour. These methods were done with the support of software, more concretely, R programming.

A.3 Forecasting Models

This section presents a collection of the different time series forecasting models, with a special focus on those models capable of being utilized by the company's ERP system.

A.3.1 Naïve Method

The naïve method is the simplest of them all since it assumes the least possible effort to predict the future value.An example of an used naîve model is:

$$\hat{Y}_{t+1} = Y_t \tag{A.6}$$

In other circumstances, the value to be predicted can also be equal to the last seasonal data point. The naïve model could be a solution for problems with very small data sets. However, its usage has big limitations since random fluctuations are considered as any other data point with valid conclusions (Hanke and Wichern, 2014).

A.3.2 Weighted Moving Average

The weighted MA has a similar expression to the MA explained in subsection A.2.2, with the addition of weights to different data entry points, mainly conditioned with their novelty factor: the newest the data point, the more weight it will receive. The model is:

$$\hat{Y}_t = \sum_{j=-k}^{k} \alpha_j y_{t+j} \tag{A.7}$$

with α between 1 and 0.
A combination of MAs, as often happen with time-series decomposition, is also a weighted MA, as different data points receive weights accordingly. A clear benefit of weighted MAs, when compared to the naïve method and a non-weighted MA method is the smoothness that it can provide to its curve. As data points enter and leave the series, the weight MA adapts with slower increases and decreases (Hyndman and Athanasopoulos, 2018).

A.3.3 Exponential Smoothing

The forecasts induced by exponentially smoothed methods are weighted averages of past observations, with the weights diminishing exponentially as the observations grow older. Contrarily, the newer the observation, the higher the weight associated with it. Some of the benefits associated with these types of methods are their reliability and adaptability to a wide variety of different time series (Hyndman and Athanasopoulos, 2018). There are three main methods to be described: A simple exponential smoothing method, Holt's method and the holt-winter's method.

Simple Exponential smoothing Method

First proposed by Brown (1959), the method is based on averaging past values of a series, in an exponentially decreasing way, considering the freshness of the data: how recent or old the data point is. Such method distributes the importance of the data point on the prediction, as the most recent observations receive the largest weight, α (with α between 0 and 1), the second most recent observation receives less weight $\alpha(1-\alpha)$ and the third most receive $\alpha(1-\alpha)^2$, and so forth...
The formal equation is the following:

$$\hat{Y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + ..., \tag{A.8}$$

where $0 \leq \alpha \leq 1$ and $T+1$ is a weighted average of all observations T.

The α, as the weighting factor, indicates the reactiveness of the model. When α is close to 1, the newer forecast will carry more significance in the prediction, causing the model to react more promptly to newer changes. In the case of α being closer to 0, the model will be smoother, with newer prediction carrying less significance.

α, as well as the parameters that follow in proceeding methods, are often calculated using the least square method, summarised in subsection 2.4.2, that aims to minimize the error. The parameter value with the smallest error is chosen.

The simple smoothing method provides a good balance between the naïve method and the MA method. It isn't as reactive as the first nor does it give the same importance to all of the observations. However, the model can't successfully consider linear trends and seasonality, if any is present in the time series. For the case of the sole presence of a trend, the use of the Holt (2004) method will suffice, in case of the presence of both phenomenon, the Winters (1960) method should be used.

Holt's method

Holt (2004) method considers that besides the occasional change of the curve level, there's a continuous trend affecting the time series. For such cases, Holt's considers the tendency in a linear exponential smoothing method, that allows the evolution of the linear tendency in a time series. The model is the following:

$$
\begin{aligned}
\textbf{Forecast equation} \quad & \hat{Y}_{T+h|t} = l_t + hb_t, \\
\textbf{Level Equation} \quad & l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}), \\
\textbf{Trend Equation} \quad & b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}.
\end{aligned} \tag{A.9}
$$

Holt (2004) considers two equations when forecasting: A level equation with an added trend component (If the trend is 0, the equation is the same as A.8); A trend equation, with β as the smoothing parameter ($0 \leq \beta \leq 1$), that considers the slope of the series. The forecast is then calculated based on the result of both equations. A small value of β indicates that the slope hardly changes over time, while a high value of β indicates a reactive slope.

A problem with Holt's linear method is its tendency to over-forecast for longer forecast horizons, due to displaying a constant trend for an indefinite future. Gardner and McKenzie (1985) introduced a parameter to contradict this observation, that aims to dampen the trend to a flat line after some time. The method as proven to be widely successful.

$$
\begin{aligned}
\hat{Y}_{T+h|t} &= l_t + (\phi + \phi^2 + ... + \phi^h)b_t, \\
l_t &= \alpha y_t + (1-\alpha)(l_{t-1} + \phi b_{t-1}), \\
b_t &= \beta(l_t - l_{t-1}) + (1-\beta)\phi b_{t-1}.
\end{aligned} \tag{A.10}
$$

If ϕ value assumes 1, then the equation is the same as A.9. Otherwise, the trend will progressively dampen out over time. In normal cases, $0.8 \leq \phi \leq 0.98$ ensures the effect that is expected (a slow reduction of the tendency over time) (Hyndman and Athanasopoulos, 2018).

Due to the high revision of forecasts in the company, the Holt's method will be the one used for the methodology of this thesis.

Holt winters method's

Winters (1960) extended the method previously defined by Holt's, by adding a component for seasonality. An extra equation is added, with an additive and a multiplicative version. The additive version sums up similarly as the other equations do, while in the multiplicative case, the seasonality is presented as a seasonal index. Only the additive method will be here illustrated, since the seasonality with which this thesis address isn't influenced by the sales level of the series. The method is the following:

$$\begin{aligned}
\textbf{Forecast equation} \quad & \hat{Y}_{T+h|t} = l_t + hb_t + S_{t+h-m(k+1)}, \\
\textbf{Level Equation} \quad & l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}), \\
\textbf{Trend Equation} \quad & b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}, \\
\textbf{Seasonality Equation} \quad & s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m},
\end{aligned} \tag{A.11}$$

where k is the integer part of $\frac{h-1}{m}$, which ensures that the seasonal indices used comes from the final year of the data.

The level equation show a weighted average between the seasonally adjusted observations $(y_t - s_t - m)$ and the forecasts that are non-seasonal $(y_t - s_t - m)$ for time t. The trend equation is the same as the one in equation A.9. The seasonal equation performs a weighted average between this year's seasonal index $(y_t - l_{t-1} - b_{t-1})$ and the last year's, in the same season (m time periods ago).

A.3.4 Croston Method

The Croston (1972) method is a forecasting strategy used for products of intermittent demand. In situations in which the time-series contains various data points with zero quantity, the usage of one of the methods described before is vastly reduced since each method will react poorly to continuous null values.

Croston's method constructs two-time series from the sample provided, by separating non-zero values from null values and registering the time periods for each type of cases. Croston's then separates simple exponential smoothing forecasts into two new time series, a and q, being q_i be the ith non-zero quantity and a_i the time difference between q_i and q_{i-1}. q is often called the demand and a the "inter-arrival time".

$$\begin{aligned} \hat{q}_{i+1|i} &= (1-\alpha)\hat{q}_{i|i-1} + \alpha q_i, \\ \hat{a}_{i+1|i} &= (1-\alpha)\hat{a}_{i|i-1} + \alpha a_i, \end{aligned} \tag{A.12}$$

$\hat{q}_{i+1|i}$ and $\hat{a}_{i+1|i}$ are one step forecasts for the $(i+1)$th demand and inter-arrival time, based on demand until time point i. $0 \leq \alpha \leq 1$ and is the same value both equations.

$$\hat{y}_{T+h|T} = \frac{q_{j+1|j}}{a_{j+1|j}}, \tag{A.13}$$

Finally, y_{t+h} is the h-step ahead forecast for demand at any time, $T+h$. Let j be the time for the last observed positive observation.

Appendix B

Demand Planning process mapping

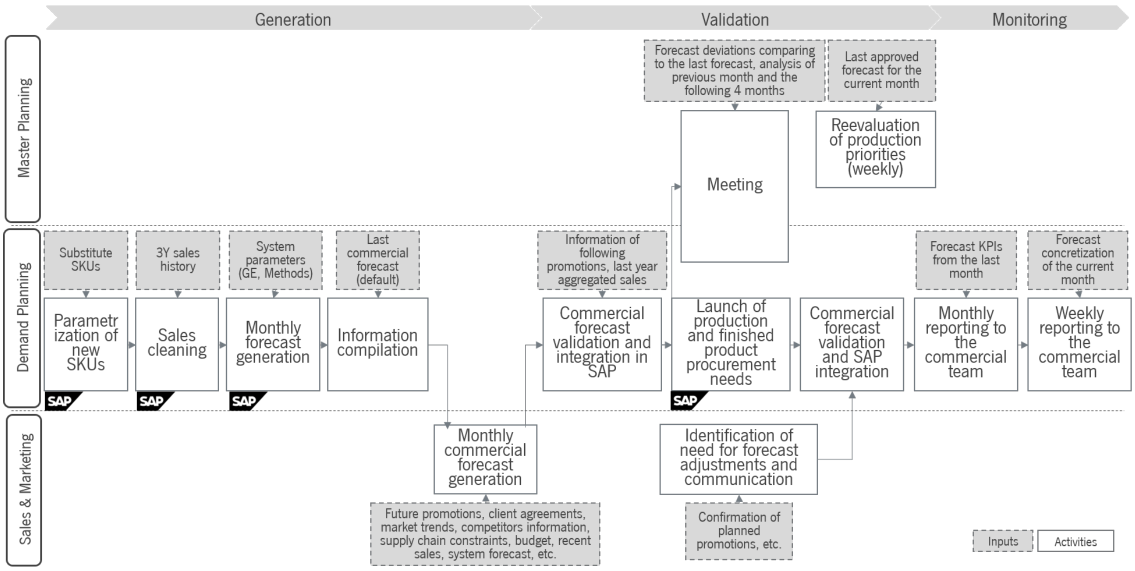

Figure B.1: Demand planning process mapping

Appendix C

Statistical groups and forecasting models tuning and selection procedure

The optimizer performs clustering to elaborate newer combinations of SKUs into SGs, attributing afterwards the ideal statistical method to each SG. The procedure is described in algorithm 2, the optimization of SGs, and algorithm 3, the attribution of statistical methods. For cases where only the statistical methods are updated, algorithm 3 suffices as the main explanation for the operation.

The main challenge surrounding the elaboration of new SGs is the number of different combinations that can be considered. With over 500 SKUs, and without a restricted number of SGs to be created, the combinational factor is massive, becoming a burden in terms of software performance. Thus, to overcome such a challenge, a partitional clustering method is utilized, booted with random seeding to ensure that good SG combinations are considered, even if possibly not optimal. Partitional clustering aims at identifying the combination of clusters that minimize the distance between the provided centroids (the central point of the cluster) and the other assigned points to the given clusters (Jin and Han, 2010). Eq C.1 illustrates the objective function. The objective is to find the ideal combination, that minimises the sum of the clustering distances, considering the number of clusters and the centroid locations that were provided.

$$\sum_{i=1}^{K}\sum_{j=1}^{|C_i|} Dist(x_j, center(i)), \tag{C.1}$$

where $|C_i|$ is the number of points in cluster i, $Dist(x_j, center(i))$ is the distance between point x_j and center i.

In the case of forecast optimization, the position of the centroid is randomly provided through n different random seeds, each rendering a different centred time series to the number of inputted clusters. As an example, if the number of defined clusters is five, then n iterations are run (the number of seeds), in which in each of the five different clusters, a different main time series is provided. The distance is then measured by the difference between all the time series. The clusters are optimized by minimizing the sum of all differences between the time series in each cluster. The optimal SGs are then the groups of time series that most resemble each other in terms of time series patterns. The use of random seeding ensures that different combinations are continuously considered. The number of different seeds that are provided is a result of the trade-off between the consideration of more combinations and computational performance. The clustering isn't per itself the only domain to which forecast accuracy depend on. The choice of the ideal statistical method yields different accuracy results regardless of the clustering.

Set Seeds = 1 to 5
Set SG_{Min} as Minimum number of SGs
Set SG_{Max} as Maximum number of SGs
Input: Respective sales dataset
for $SG_{Min} < n < SG_{Max}$ **do**
    for *each seed* **do**
        generate: n clusterings based on seed
        optimize: n clusterings
        Choose clusters with optimized minimum distances
        Assign forecast methods: Call algorithm 3
    end
end
Choose best SGs and models
Store SGs, method, alpha, beta, gamma

Algorithm 2: Optimizing statistical groups

```
for each SG do
    Input: Respective sales dataset
    Run White noise test (SG)
    Run Intermittent test (SG)
    Run Trend significance test (SG)
    Run Seasonal significance test (SG)
    if intermittent = 1 then
        for i ∈ months do
            Run Cronston's method for 12 months
        end
    else
        if Trend significance=1 & White Noise=0 then
            if Seasonal significance=1 then
                for i ∈ months do
                    Set Parameters restrictions
                    Run Holt Winter's method for 12 months
                end
            else
                for i ∈ months do
                    Set Parameters restrictions
                    Run Holt's method for 12 months
                end
            end
        else if Seasonal significance=1 & White Noise=0 then
            for i ∈ months do
                Set Parameters restrictions
                Run Double exponential smoothing method for 12 months
            end
        else
            for i ∈ months do
                Set Parameters restrictions
                Run Simple exponential smoothing method for 12 months
            end
        end
    end
    Store method and parameters
end
```

Algorithm 3: Optimizing statistical methods

Appendix D

Commercial interface features overview

The commercial interface is divided in two main views: SKU and summary view. A description of the main features of each view unfollows.

D.1 SKU view

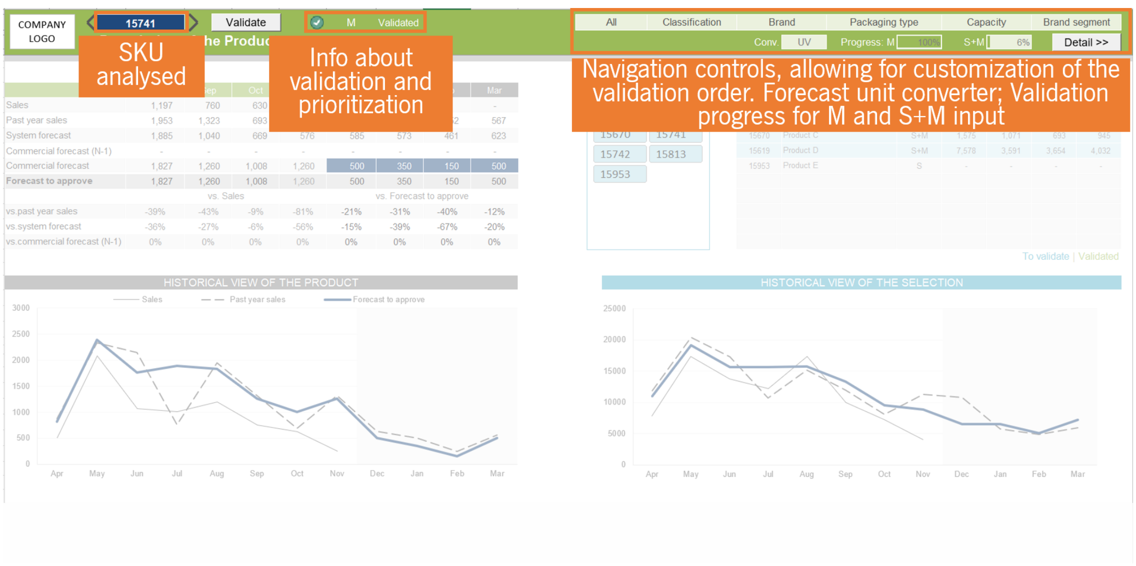

Figure D.1: Navigation feature

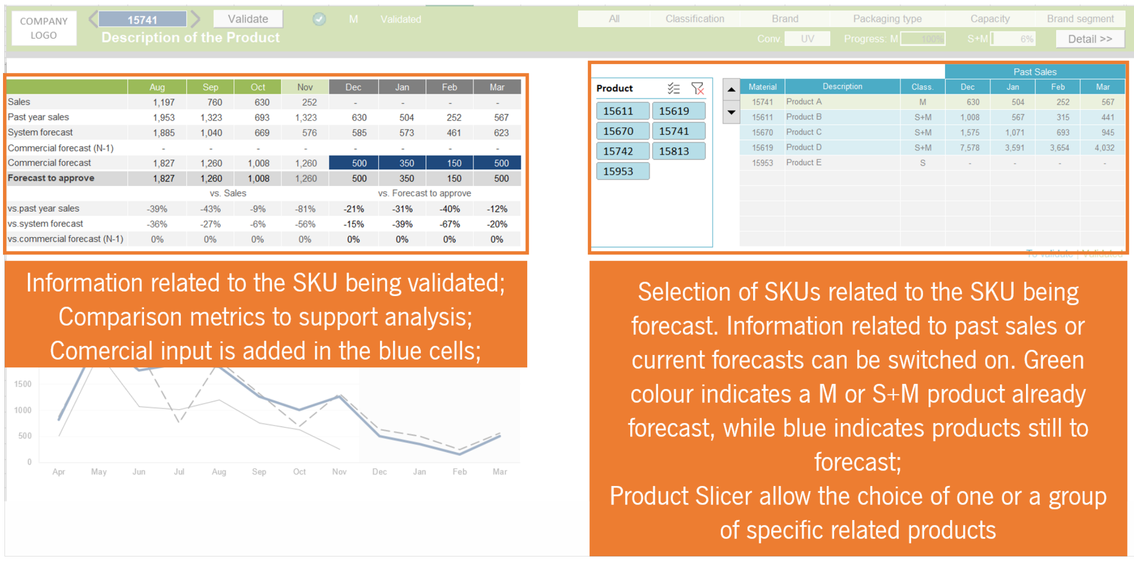

Figure D.2: Auxiliary information and forecast insertion features

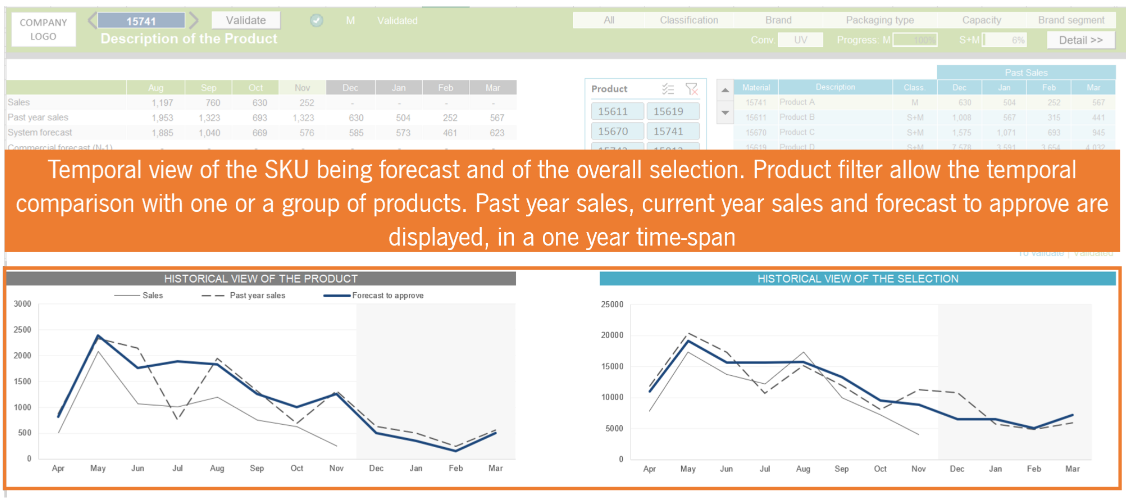

Figure D.3: Historical graphical display of SKU and selection feature

D.2 Summary view

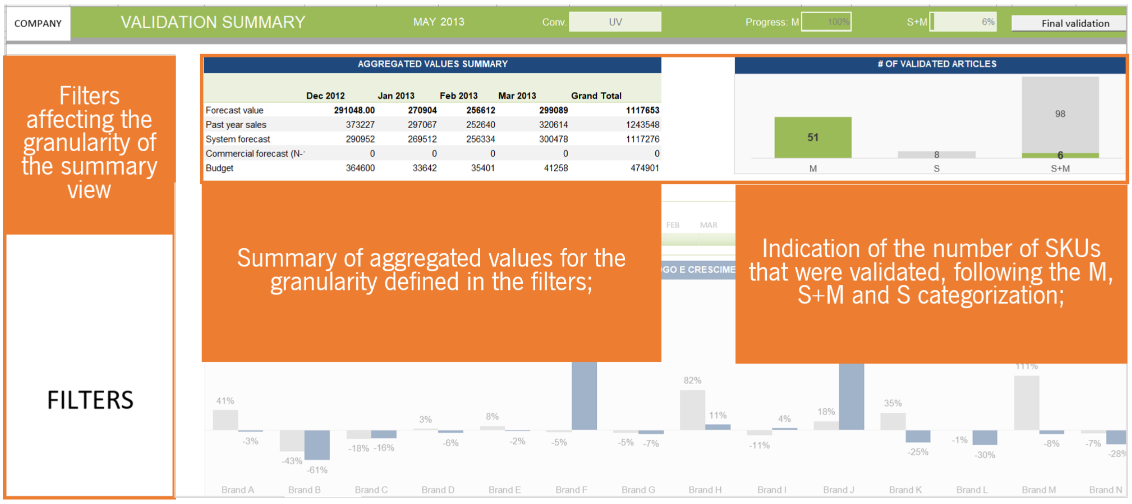

Figure D.4: Aggregated value perspective and summary of validated articles

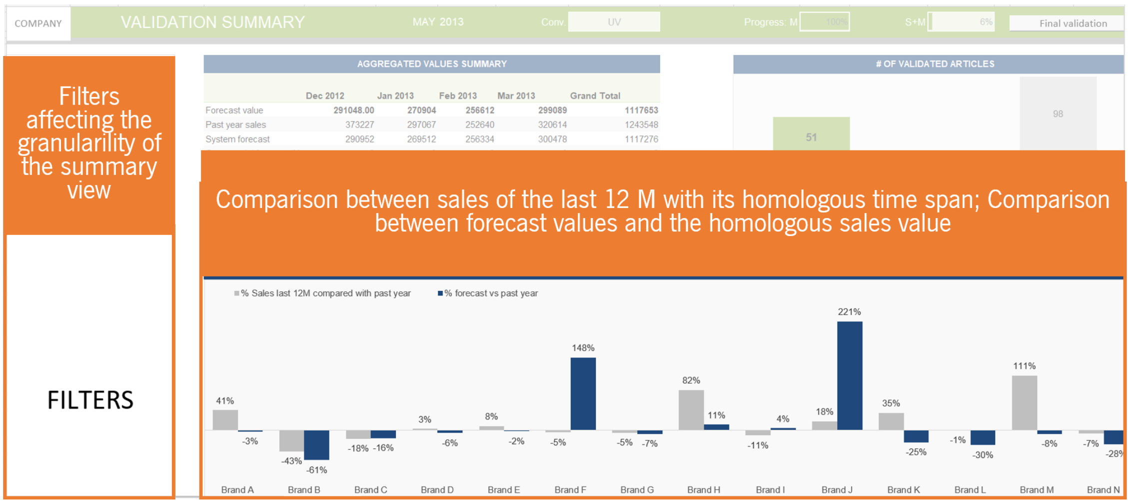

Figure D.5: Comparison with past year sales

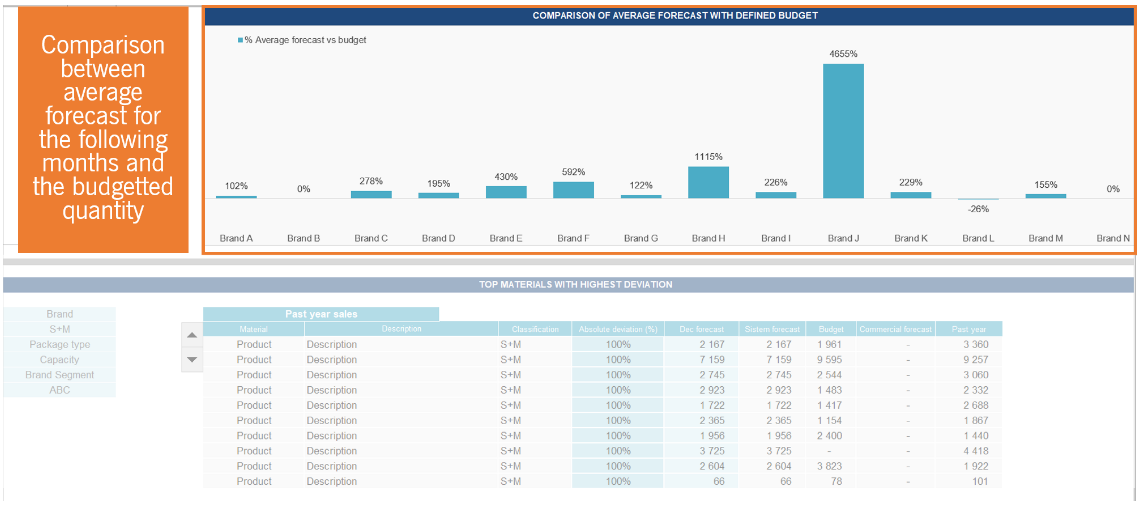

Figure D.6: Comparison with budgeted expected sales

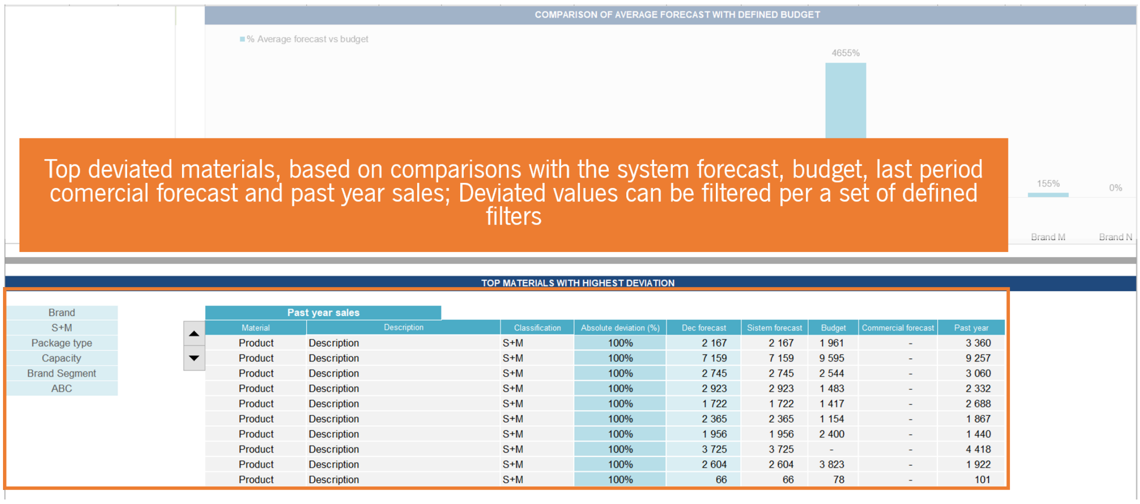

Figure D.7: identification of deviated values

Appendix E

Inputs to the Stock Simulator

Category	Description
Factory	The factory at which the SKU is produced.
Line	The factory line at which the SKU is produced.
Basic Unit	The measurement unit used for each SKU. It is necessary to convert all SKU's for the same measurement unit, for comparison purposes.
ABC Classification	Identifies if an SKU is A, B or C for the company.
Lot Size	The number of units produced by each manufactured batch.
Minimum Lot	Minimum required batch quantity to produce an SKU due to production restrictions.
Review Time	Number of weeks until a new SKU batch can be produced again.
Lead Time	Number of weeks necessary to produce an SKU batch.
Deviation Error	Average forecast error.
Service Level	Expected service level, considering if the SKU is an A, B or C for the company.
Sales	Weekly planned sales for each SKU.
Forecast	Expected units to be sold for the SKU in the next 10 weeks.
Quarantine	Number of days required for an SKU to stay idle. Not all SKU's require quarantine time.

Table E.1: Inputs to the stock simulator